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Stochastic Programming for Optimizing Sustainable Urban Logistics: Multi-Period Production-Routing and Reverse Logistic

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SUMMARY OF THESIS

The increasing need for sustainable logistics and efficient urban transportation systems has driven significant research in integrated optimization models. This thesis addresses the development of multi-period production-routing models tailored to enhance sustainable urban logistics, focusing on reverse logistics and the use of green vehicles. The research introduces a two-stage model that integrates real-time data from IoT systems to optimize vehicle routing and resource allocation across multiple echelons of logistics networks. In the first stage, an innovative model is proposed to address the production and routing of goods in urban environments, accounting for demand variability and transportation constraints. The second stage focuses on reverse logistics, where the allocation of returned goods to recovery centers is optimized to maximize resource utilization and minimize environmental impacts. The optimization models employ stochastic programming techniques, including Chance-Constrained Programming (CCP), and are solved using novel heuristic and metaheuristic algorithms. The results, validated through computational experiments and sensitivity analysis, highlight the effectiveness of these models in reducing operational costs, improving service levels, and enhancing the sustainability of urban logistics systems through the adoption of green vehicle technologies.

Keywords: Multi-Period Production-Routing; Green Vehicle Routing; Vehicle Routing Problem; Heuristics and Metaheuristic Algorithms; Reverse Logistics; IoT-Based Optimization.

CONTENTS

CHAPTER 1

1.1. INTRODUCTION

In the current era of rapid urbanization, cities are experiencing unprecedented growth, leading to complex challenges in managing resources, infrastructure, and services. Among these challenges, urban logistics stands out as a critical component that significantly influences the sustainability and livability of urban environments. Urban logistics encompasses the planning, implementation, and control of the efficient flow and storage of goods, services, and information within cities. Its optimization is imperative for sustainable development as it directly impacts environmental quality, economic efficiency, and social well-being.

The escalating environmental concerns, such as air pollution, traffic congestion, and increasing waste generation, necessitate innovative approaches to urban logistics. Traditional logistics models are often inadequate to address the dynamic and complex nature of modern urban systems. Therefore, integrating advanced technologies like the Internet of Things (IoT), electric vehicles (EVs), and sophisticated optimization algorithms becomes essential. These technologies offer transformative potential to revolutionize waste management and urban delivery systems by enabling real-time data analytics, dynamic routing, and sustainable transportation solutions.

Urban logistics significantly impacts various aspects of city life. Environmentally, inefficient logistics contribute to increased greenhouse gas emissions, noise pollution, and resource depletion. Economically, logistics costs constitute a substantial portion of the total expenses in urban supply chains, affecting the competitiveness of businesses and the affordability of goods and services. Socially, logistics activities influence the quality of life through their effects on traffic congestion, road safety, and accessibility of essential goods.

Several elements affect urban logistics, including location decisions, inventory management, production planning, and transportation routing. For instance, the location of facilities such as warehouses, distribution centers, and waste processing plants plays a crucial role in determining transportation distances, costs, and environmental impacts.

Optimizing facility locations can lead to significant improvements in logistics efficiency and sustainability, as highlighted in the third study of this thesis, where a green, multi-objective location-allocation model is proposed for waste management facilities.

Inventory management and production planning are other critical factors influencing urban logistics. Efficient coordination between production schedules and inventory levels can reduce unnecessary storage costs and ensure timely delivery of goods. The fourth study addresses this by introducing a mixed-integer linear programming model for a multi-period dynamic electric vehicle production-routing problem. By synchronizing production, inventory, and distribution decisions, the model enhances the overall efficiency of the supply chain while considering the limitations and energy consumption of electric vehicles.

Transportation routing is perhaps the most visible element of urban logistics, directly affecting traffic congestion, delivery times, and environmental emissions. Dynamic routing strategies, supported by real-time data from IoT devices, enable logistics providers to adapt to changing conditions such as traffic fluctuations and varying demand levels. The first study demonstrates the application of a discrete choice model in dynamic vehicle routing for waste collection, accounting for fluctuations in waste generation and transportation conditions. This approach not only optimizes routing efficiency but also ensures regulatory compliance through waste segregation using multi-compartment vehicles.

Waste management is a significant component of urban logistics due to the increasing rates of municipal solid waste generation in urban areas. Efficient waste collection, processing, and disposal are essential to minimize environmental impacts and promote resource recovery. The integration of advanced technologies in waste management can lead to smarter operations, as seen in the second study's allocation-routing optimization model for integrated solid waste management. By leveraging IoT technology and considering uncertainties in recycling and recovery activities, the model maximizes probabilistic profit while minimizing transportation costs and travel time.

The deployment of electric vehicles in urban logistics presents both opportunities and challenges. EVs offer the potential to reduce emissions and reliance on fossil fuels. However, their limited range and the need for recharging infrastructure require careful planning and optimization. The fifth study addresses these challenges by developing a decision support system for urban deliveries using electric vans. The system incorporates metaheuristic algorithms to minimize operational costs while considering battery capacities and the availability of fast recharging options during delivery tours.

Advanced optimization algorithms play a pivotal role in enhancing urban logistics. They enable the handling of complex, multi-objective problems that involve numerous variables and constraints. By employing methods such as hybrid Genetic and Particle Swarm Optimization algorithms, as in the first study, or using the Taguchi parameter design method for algorithm performance improvement, as in the second study, these algorithms contribute to generating high-quality solutions that balance efficiency, cost, and environmental considerations.

In conclusion, optimizing urban logistics is critical for addressing the multifaceted challenges posed by rapid urbanization and environmental concerns. By integrating advanced technologies and considering various influencing elements such as facility location, inventory management, production planning, and transportation routing, it is possible to develop sustainable and efficient logistics systems. This thesis contributes to this endeavor by exploring innovative solutions across different facets of urban logistics, emphasizing the transformative potential of technologies like IoT, electric vehicles, and advanced optimization algorithms. The collective insights from the studies provide a comprehensive approach to enhancing operational efficiency, reducing environmental impacts, and ultimately contributing to the development of smarter and more sustainable cities.

The first study presents an innovative dynamic approach to the multi-compartment vehicle routing problem (MCVRP) in waste management, addressing the pressing challenges posed by increasing municipal solid waste in urban areas. Traditional waste collection systems often rely on static routing methods that do not account for real-time fluctuations in waste generation or changes in transportation conditions. This can lead to inefficiencies such as missed collections, unnecessary fuel consumption, and increased operational costs. To overcome these limitations, the study introduces a dynamic municipal solid waste collection scheme that optimizes vehicle routing by incorporating real-time data on waste levels and transportation networks.

A key contribution of this research is the application of a discrete choice model (DCM) within the context of dynamic vehicle routing problems (DVRP), marking the first time DCM has been utilized in this manner for waste management. At each decision point during the collection process, the DCM is employed to determine the probability of selecting the next geographical zone to visit based on current waste generation levels and traveling costs. This probabilistic approach allows the routing system to be more responsive and adaptable, efficiently handling the variability in waste generation and transportation conditions that are typical in urban environments.

Moreover, the study emphasizes the importance of maintaining waste segregation during transportation to enhance operational efficiency and comply with regulatory standards. To achieve this, multi-compartment vehicles are utilized, allowing different types of waste to be collected and transported separately within the same vehicle. This not only preserves the integrity of waste segregation but also reduces the need for multiple collection trips, thereby decreasing fuel consumption and emissions.

Another significant aspect of the research is the method developed to prioritize bin visits by adjusting time windows based on threshold waste levels. Bins that reach a certain waste level threshold are assigned higher priority, ensuring they are serviced promptly to prevent overflow and associated environmental and public health issues. This dynamic adjustment of time windows enhances the efficiency of the waste collection system by focusing resources where they are most needed at any given time.

To solve the complex optimization problem posed by the dynamic, multi-compartment vehicle routing, the study develops a hybrid Genetic and Particle Swarm Optimization (GA-PSO) algorithm. This hybrid algorithm leverages the exploration capabilities of genetic algorithms and the exploitation strengths of particle swarm optimization, resulting in a robust tool capable of finding high-quality solutions within reasonable computational times. The performance of the hybrid GA-PSO algorithm is benchmarked against other advanced metaheuristic algorithms, demonstrating superior results in terms of solution quality and computational efficiency.

Furthermore, the study employs the Best Worst Method (BWM), a multi-criteria decision-making approach, to evaluate and select the most effective algorithm for solving the presented problem. The BWM analysis considers various performance criteria such as solution quality, computational time, and algorithm robustness. The results confirm that the hybrid GA-PSO algorithm outperforms other considered algorithms, making it the preferred choice for the dynamic routing problem in waste management.

Overall, this study offers a comprehensive framework for sustainable, efficient, and effective waste management practices by integrating dynamic routing, discrete choice modeling, and the use of multi-compartment vehicles. By addressing the challenges of fluctuating waste generation and dynamic transportation conditions, the proposed approach enhances operational efficiency, reduces environmental impacts, and ensures compliance with waste segregation regulations. The incorporation of real-time data and advanced optimization techniques exemplifies how urban logistics can be transformed to meet the demands of modern cities, contributing significantly to the development of smarter and more sustainable urban environments.

This innovative approach not only optimizes the logistical aspects of waste collection but also has broader implications for urban sustainability. By reducing the number of trips required and optimizing routes, the system decreases fuel consumption and associated greenhouse gas emissions. The efficient allocation of resources and timely collection of waste improve public health outcomes and enhance the quality of life for city residents. Additionally, the use of multi-compartment vehicles supports recycling and waste reduction initiatives by maintaining the integrity of segregated waste streams, facilitating more effective recycling and disposal processes.

The study's methodology demonstrates the potential of combining advanced mathematical modeling with practical considerations in urban logistics. The dynamic routing framework can be adapted to other areas of urban logistics beyond waste management, such as delivery services and public transportation, where real-time data and adaptability are crucial. The successful application of the hybrid GA-PSO algorithm and the use of the Best Worst Method for algorithm selection also provide valuable insights for researchers and practitioners seeking to address complex optimization problems in dynamic and uncertain urban environments.

In conclusion, the first study makes a substantial contribution to the field of urban logistics by presenting a dynamic, responsive, and efficient approach to waste management. It showcases how integrating advanced technologies and optimization algorithms can address the multifaceted challenges of waste collection in rapidly growing urban areas. By enhancing operational efficiency and sustainability, the study lays the groundwork for future innovations in urban logistics that can lead to smarter, cleaner, and more livable cities.

While the first study successfully addresses the challenges of dynamic waste collection through advanced vehicle routing and optimization techniques, it primarily concentrates on optimizing the collection phase of waste management. The introduction of a dynamic approach using discrete choice models and multi-compartment vehicles enhances operational efficiency and ensures compliance with waste segregation regulations. However, waste management is a multifaceted process that extends beyond collection; it encompasses subsequent stages such as recycling and recovery, which are crucial for achieving sustainable waste management practices.

Recognizing the need to consider the entire waste management lifecycle, the next study expands the scope from optimizing just the collection phase to developing an integrated smart waste management (ISWM) framework. This holistic approach not only includes waste collection but also incorporates recycling and recovery processes, aiming to improve the overall performance of the waste management system. By integrating these stages, the study seeks to maximize the economic benefits derived from waste recycling and recovery while minimizing operational costs and environmental impacts.

The transition to this integrated framework is driven by the realization that optimizing individual components of waste management in isolation may not yield the most sustainable or efficient outcomes. While the first study focuses on dynamic routing to adapt to fluctuations in waste generation and transportation conditions, it does not fully address the uncertainties and complexities involved in the recycling and recovery stages. The second study introduces a novel multi-objective optimization model that accounts for various sources of uncertainty affecting the ISWM, such as variable market prices for recycled materials, fluctuating waste generation rates, and the stochastic nature of recycling and recovery yields.

To effectively handle these uncertainties, the study employs chance-constrained programming within its optimization model. This approach allows for the incorporation of probabilistic constraints, ensuring that the solutions generated are robust under different scenarios of uncertainty. By maximizing the probabilistic profit from recycling and recovery activities while minimizing total travel time and transportation costs, the model provides a balanced solution that considers both economic and operational objectives.

Moreover, the second study leverages IoT technology to enhance data collection and communication within the waste management network. The integration of IoT devices enables real-time monitoring of waste levels, vehicle locations, and facility operations. This real-time data is crucial for optimizing waste collection schedules, routing decisions, and facility allocations. The use of IoT represents an advancement from the first study, which, while dynamic in its routing approach, does not incorporate real-time technological innovations to the same extent.

Another significant development in the second study is the inclusion of facility location decisions within the optimization model. The strategic placement of recycling and recovery facilities can have a profound impact on the efficiency of the waste management system. By optimizing the location of these facilities alongside routing and allocation decisions, the study addresses a critical element that was not the primary focus of the first study. This integrated approach ensures that waste is transported to the most appropriate facilities in a cost-effective and timely manner, further enhancing the system's overall efficiency.

Additionally, the second study acknowledges the involvement of multiple stakeholders in the waste management process, such as municipal authorities, private waste collectors, recycling companies, and the community. By considering the perspectives and objectives of these stakeholders, the model becomes more comprehensive and applicable to real-world scenarios where collaboration and coordination are essential.

The methodologies used in the second study also build upon and extend the optimization techniques applied in the first study. While the first study develops a hybrid Genetic and Particle Swarm Optimization algorithm to solve the dynamic routing problem, the second study applies some of the most proficient multi-objective metaheuristic algorithms to tackle the increased complexity of the integrated model. The Taguchi parameter design method is utilized for optimal parameter tuning, improving the performance of the optimization algorithms. Furthermore, the Best Worst Method (BWM) is employed to identify the most reliable algorithm for solving the problem, demonstrating a commitment to methodological rigor and solution quality.

In summary, the transition from the first to the second study represents a progression from focusing on a specific aspect of waste management—dynamic vehicle routing in the collection phase—to embracing a comprehensive, integrated approach that encompasses collection, recycling, and recovery processes. This shift acknowledges that optimizing the entire waste management system can lead to greater sustainability benefits than optimizing individual components in isolation. By incorporating advanced technologies like IoT, addressing uncertainties through chance-constrained programming, and involving multiple stakeholders, the second study offers a more holistic solution to the challenges of urban waste management.

This evolution in focus reflects a deeper understanding of the complexities inherent in waste management and the necessity of integrated solutions for sustainable urban development. It underscores the importance of considering various elements that affect urban logistics, such as facility location, inventory levels, production planning, and the dynamic interactions between different stages of the supply chain. By building upon the foundations laid in the first study, the second study advances the discourse on how advanced technologies and optimization methods can be synergistically applied to enhance the efficiency, profitability, and sustainability of waste management systems.

The second study delves into the development of an allocation-routing optimization model tailored for integrated solid waste management (ISWM). The primary objective is to enhance the overall efficiency and sustainability of waste management systems by optimizing the collection, recycling, and recovery processes. One of the critical challenges addressed in this study is the inherent uncertainty present in waste management operations, particularly concerning the profit derived from recycling and recovery activities. Factors such as fluctuating market prices for recyclable materials, variable waste generation rates, and unpredictable processing yields introduce significant uncertainty that can impact the profitability and feasibility of waste management strategies.

To effectively handle these uncertainties, the study employs chance-constrained programming, a mathematical optimization technique designed to manage problems with probabilistic constraints. Chance-constrained programming allows decision-makers to formulate constraints that are satisfied with a certain predefined probability level, thereby providing a more realistic and robust solution under uncertainty. In the context of this study, the chance constraints are applied to the profit function derived from recycling and recovery activities, ensuring that the profit meets or exceeds a target value with a specified probability. This approach acknowledges the stochastic nature of the profit while allowing for a controlled level of risk in decision-making.

Implementing chance-constrained programming within the optimization model introduces additional complexity, as it transforms the deterministic problem into a stochastic one. Solving such problems analytically is often infeasible due to the non-linearity and non-convexity introduced by probabilistic constraints. To overcome this challenge, the study turns to advanced multi-objective metaheuristic algorithms, which are well-suited for handling complex optimization problems with multiple conflicting objectives and constraints.

Metaheuristic algorithms, such as genetic algorithms, particle swarm optimization, and others, are iterative search methods that explore the solution space by mimicking natural or physical processes. They are particularly effective in finding near-optimal solutions within reasonable computational times, even for large-scale and complex problems where traditional exact methods may fail or be computationally prohibitive.

In this study, the metaheuristic algorithms are adapted to handle the chance-constrained programming model by incorporating mechanisms to evaluate and satisfy the probabilistic constraints. This involves generating a population of potential solutions and assessing their feasibility concerning the chance constraints. For each solution, simulations or probabilistic evaluations are performed to estimate the likelihood that the profit constraints are satisfied. Solutions that meet the predefined probability levels are considered feasible and are selected for further optimization, while those that do not are discarded or penalized.

To enhance the performance of the metaheuristic algorithms, the study utilizes the Taguchi parameter design method for parameter optimization. The Taguchi method is a statistical approach that systematically investigates the effects of various algorithm parameters on performance, identifying the optimal settings that lead to the best results. By conducting controlled experiments with different parameter combinations, the method determines the most influential factors and their optimal levels, thereby improving the efficiency and effectiveness of the algorithms.

The integration of chance-constrained programming with metaheuristic algorithms allows the model to navigate the complex landscape of uncertainties in waste management operations. It provides decision-makers with robust solutions that account for variability in profits while balancing other objectives such as minimizing total travel time and transportation costs. This approach ensures that the strategies developed are not only theoretically sound but also practically viable under real-world conditions where uncertainties are inevitable.

Furthermore, the model's ability to handle multiple objectives and uncertainties makes it a powerful tool for municipalities and waste management organizations. It facilitates better planning and resource allocation by providing insights into the trade-offs between profitability, cost-efficiency, and risk levels. The application of this model can lead to more sustainable and resilient waste management systems that can adapt to changing conditions and uncertainties in the market and operational environment.

In summary, the second study makes significant contributions by addressing the technical challenges of uncertainty in integrated solid waste management using chance-constrained programming. By effectively incorporating probabilistic constraints into the optimization model and solving it using advanced metaheuristic algorithms optimized via the Taguchi method, the study offers a robust and practical solution to enhance waste management operations. This work not only advances the methodological approaches in handling uncertainties in optimization problems but also provides tangible benefits for sustainable urban development.

Building upon the advancements achieved in the first two studies, the third study represents a significant progression in the pursuit of sustainable urban waste management by integrating the insights from dynamic optimization, uncertainty handling, and strategic infrastructural planning through the lens of Industry 4.0 technologies. The first study introduced a dynamic approach to waste collection by employing discrete choice models and multi-compartment vehicles, optimizing routing efficiency in response to real-time fluctuations in waste generation and transportation conditions. This approach enhanced operational efficiency and regulatory compliance within the waste collection phase, demonstrating the benefits of integrating advanced optimization algorithms and dynamic decision-making processes.

The second study expanded the scope by developing an allocation-routing optimization model for integrated solid waste management (ISWM), incorporating the recycling and recovery stages of waste management. It addressed the inherent uncertainties in profit from recycling and recovery activities by applying chance-constrained programming, thus ensuring robust decision-making under uncertainty. Advanced multi-objective metaheuristic algorithms were employed to tackle the complexity of the problem, and the Taguchi method was utilized for parameter optimization, enhancing the algorithm's performance. This study underscored the importance of considering uncertainties and the involvement of various stakeholders in waste management, moving towards a more holistic and integrated approach.

Transitioning from these foundations, the third study delves deeper into the strategic aspects of waste management by embracing Industry 4.0 technologies to not only optimize operational processes but also reimagine the waste management infrastructure. While the first study focused on dynamic routing within the collection phase and the second study incorporated recycling and recovery processes under uncertainty, both primarily operated within the constraints of existing infrastructural setups. The third study recognizes that to achieve greater sustainability and efficiency, it is imperative to address infrastructural decisions such as the strategic placement of facilities and the adoption of environmentally conscious routing practices.

By integrating the Internet of Things (IoT) technology, the third study harnesses real-time data from IoT-equipped bins to inform both operational and strategic decisions. This approach enables a more responsive waste collection system that adapts to actual waste generation patterns, thereby reducing unnecessary trips and associated emissions. The study introduces an IoT-based framework that not only optimizes waste collection routes but also strategically locates separation centers where waste is sorted into organic and non-organic categories. This sorting process enhances the value output of the waste management system by improving the efficiency of recycling and recovery operations, a consideration that extends beyond the scope of the first two studies.

Furthermore, the third study addresses the vehicle routing problem as a multi-depot green vehicle routing problem with split pickup, incorporating real-time information to minimize cost, CO_2 emissions, and visual pollution. This environmentally conscious routing strategy represents an evolution from the routing optimizations in the first study by explicitly incorporating environmental objectives and leveraging real-time data for greater efficiency. The inclusion of facility location decisions introduces a strategic dimension that was not the primary focus of the previous studies, recognizing that the placement of facilities can significantly impact operational costs and environmental outcomes.

By connecting the advancements from the first study's dynamic routing optimization and the second study's integrated management under uncertainty, the third study offers a comprehensive solution that addresses both operational efficiencies and strategic infrastructural planning. It embodies a shift towards a more holistic model of waste management that aligns with the principles of Industry 4.0 and smart city development. This progression reflects an understanding that optimizing individual components of waste management in isolation is insufficient; instead, a synergistic approach that integrates advanced technologies, strategic planning, and environmental considerations is necessary to tackle the complex challenges of urban waste management effectively.

In essence, the transition to the third study signifies a convergence of dynamic operational optimization, robust uncertainty handling, and strategic infrastructural decision-making, all empowered by cutting-edge technologies. It demonstrates how the integration of IoT, advanced optimization algorithms, and green logistics practices can revolutionize waste management systems, leading to smarter, more sustainable cities. By building upon the foundations laid by the first two studies and expanding the scope to include strategic infrastructural considerations, the third study marks a significant advancement in the quest for sustainable urban logistics solutions.

The third study presents a comprehensive integration of Internet of Things (IoT) technology and advanced optimization techniques in waste management, framed within the context of Industry 4.0. Recognizing the escalating production of solid waste in urban areas and its critical impact on sustainable development, the study aims to mitigate adverse environmental effects while enhancing the efficiency of waste management systems. It introduces a holistic framework that not only optimizes waste collection but also strategically determines facility locations and implements green vehicle routing strategies, thereby providing a multifaceted solution to reduce costs and environmental impacts.

A key innovation in this study is the incorporation of waste sorting at separation centers, which significantly enhances the value output of the waste management system. Traditional waste management practices often overlook the simultaneous optimization of waste collection and sorting processes. This study addresses this gap by proposing an integrated approach where waste is collected using various types of bins, transported to strategically located separation centers, and then sorted into organic and non-organic waste. The sorted waste is subsequently dispatched to recovery centers at a secondary level, optimizing the entire waste processing chain.

To model this complex system, the study formulates a green, multi-objective location-allocation model that simultaneously determines the optimal number and locations of separation centers while optimizing vehicle routing decisions. The model aims to minimize three primary objectives: the total cost, CO_2 emissions, and visual pollution associated with waste management operations. By integrating these objectives, the model ensures that economic efficiency does not come at the expense of environmental sustainability or social well-being.

The vehicle routing problem is addressed as a multi-depot green vehicle routing problem with split pickup, which is a significant advancement over traditional routing models. The split pickup feature allows vehicles to collect waste from multiple bins without the constraint of collecting an entire bin's content in one visit. This flexibility leads to more efficient routing and better utilization of vehicle capacity. The model also incorporates real-time information from IoT-equipped bins, enabling dynamic routing adjustments based on actual waste levels. This real-time data integration enhances the responsiveness of the waste collection system, reduces unnecessary trips, and minimizes fuel consumption and emissions.

From a methodological standpoint, the study employs both exact methods and proficient metaheuristic algorithms to solve the formulated mathematical models. The exact methods are implemented using GAMS optimization software, which provides precise solutions for smaller problem instances. However, given the computational complexity and NP-hard nature of the problem, especially for larger instances, the study also utilizes advanced metaheuristic algorithms such as Social Engineering Optimization (SEO) and Keshtel algorithms. These algorithms are adept at finding high-quality solutions within reasonable computational times, making them suitable for practical, large-scale applications.

The SEO algorithm is inspired by human social behaviors and interactions, simulating the way individuals influence each other to converge on optimal solutions. The Keshtel algorithm, on the other hand, is based on the behavior of kestrels, a type of bird of prey, in their hunting strategies. Both algorithms are tailored to handle the multi-objective nature of the problem, efficiently exploring the solution space to identify Pareto-optimal solutions that balance cost, environmental impact, and social considerations.

To validate the effectiveness of the proposed framework and optimization approaches, the study conducts extensive computational experiments using real-world data. The results demonstrate that the integrated model significantly reduces total operational costs, CO_2 emissions, and visual pollution compared to traditional waste management practices. The strategic placement of separation centers leads to shorter transportation distances and better accessibility, which in turn reduces fuel consumption and emissions. The incorporation of split pickup in vehicle routing enhances the flexibility and efficiency of collection routes, ensuring that vehicles operate closer to their optimal capacity and reducing the number of trips required.

The study also highlights the social benefits of the proposed framework. By minimizing visual pollution through efficient waste collection and timely removal of waste from public spaces, the model contributes to improved urban aesthetics and public health. The reduction in CO_2 emissions aligns with global efforts to combat climate change and promotes a healthier environment for urban residents.

In addition to its practical contributions, the study advances the theoretical understanding of integrating IoT technology and advanced optimization in waste management. It demonstrates how real-time data can be effectively utilized within complex optimization models to enhance decision-making processes. The successful application of metaheuristic algorithms to solve the multi-objective location-allocation model provides valuable insights into handling large-scale, complex problems that are otherwise intractable using exact methods alone.

Furthermore, the study underscores the importance of considering multiple objectives and stakeholder perspectives in urban logistics planning. By addressing economic, environmental, and social objectives simultaneously, the proposed framework ensures that solutions are balanced and sustainable in the long term. This multi-faceted approach is essential in the context of Industry 4.0, where technological advancements should be leveraged to create systems that are not only efficient but also socially responsible and environmentally friendly.

In conclusion, the third study makes significant contributions to the field of sustainable urban waste management by integrating IoT technology, strategic facility location, and green vehicle routing within a holistic framework. By addressing the challenges of waste sorting, facility placement, and environmentally conscious routing, the study provides a comprehensive solution that enhances the efficiency and sustainability of waste management systems. The innovative modeling approaches and optimization techniques employed offer practical tools for municipalities and waste management organizations seeking to improve their operations in line with Industry 4.0 principles. The findings of this study pave the way for future research and implementation of smart waste management solutions that can adapt to the dynamic and complex nature of urban environments.

Building upon the methodologies and insights from optimizing waste management in the previous studies, the fourth study shifts focus to the broader realm of supply chain logistics by examining the optimization of production and routing decisions using electric vehicles. This study extends the problem scope by integrating production planning, inventory management, and distribution routing within a multi-period framework. By considering production levels over multiple time periods, the research addresses the dynamic nature of supply chains where demand, production capacities, and inventory levels vary over time.

A key innovation of this study is the development of a mixed-integer linear programming model that simultaneously optimizes production schedules, inventory holdings, and distribution routes utilizing electric vehicles with heterogeneous characteristics. The model accounts for energy consumption and incorporates traffic-induced variations in travel speeds by dividing each production period into several hourly time intervals. This approach captures the impact of fluctuating traffic conditions on energy usage and delivery times, which is crucial for electric vehicles due to their limited range and battery capacity.

By integrating production decisions with routing in a multi-period setting, the model allows for more efficient coordination between manufacturing and distribution activities. It considers factors such as fixed and variable production costs, holding inventory costs, routing costs, and the fixed costs associated with using electric vehicles. The mileage limitations and energy consumption of electric vehicles are critical constraints in the model, requiring careful planning to ensure deliveries are completed within the vehicles' operational capabilities.

To solve this complex and dynamic problem, the study designs capable and hybrid metaheuristic algorithms tailored to handle large-scale, real-world scenarios. These algorithms efficiently search for high-quality solutions by balancing exploration and exploitation of the solution space, addressing the computational challenges posed by the multi-period, multi-objective nature of the problem. The effectiveness of these algorithms is demonstrated through extensive computational experiments, highlighting their ability to produce practical solutions within reasonable computational times.

By considering production levels and extending the problem to a multi-period context, the fourth study contributes significantly to the field of sustainable supply chain management. It emphasizes the importance of synchronizing production schedules with distribution plans to minimize costs and environmental impacts. The inclusion of energy consumption considerations and traffic-induced travel speed variations underscores the necessity of accounting for real-world operational challenges when planning with electric vehicles.

This study not only advances the application of advanced optimization techniques in supply chain logistics but also reinforces the central theme of optimizing urban logistics for sustainable development through advanced technologies. It demonstrates how integrating production planning with dynamic routing and energy considerations can lead to more efficient and sustainable supply chain operations. By doing so, it provides valuable insights into how urban logistics systems can be optimized to meet the growing demands of urbanization while minimizing their environmental footprint.

The fourth study presents an innovative approach to optimizing supply chain logistics by developing a mixed-integer linear programming (MILP) model that integrates multi-period production planning with dynamic electric vehicle routing. This integration addresses several complex challenges, notably the coordination of different planning horizons—production planning on a weekly basis and vehicle routing on a daily basis—and the incorporation of travel time variations within a day due to fluctuating traffic conditions. The study's primary objective is to enhance sustainability in supply chain operations by optimizing production schedules, inventory levels, and distribution routes while considering the unique constraints and capabilities of electric vehicles (EVs).

One of the significant technical challenges tackled in this study is the synchronization of production and routing plans that operate on different time scales. Production planning typically spans multiple days or weeks, focusing on scheduling manufacturing processes to meet demand while minimizing costs associated with production and inventory holding. In contrast, vehicle routing is planned daily, aiming to deliver products to customers efficiently within specific time windows. The challenge lies in aligning these two planning processes so that production outputs are available when needed for distribution, and deliveries are scheduled when customers can receive them, all while optimizing overall operational efficiency.

To handle this, the study introduces a novel time-indexed formulation that divides each production period into several hourly intervals. This granularity allows the model to capture the variations in travel times throughout the day due to changing traffic conditions, which significantly affect the energy consumption and range limitations of electric vehicles. By indexing travel time, the model accounts for the fact that delivering to a customer in a congested area during peak traffic hours may consume more energy and take longer than during off-peak times.

The coordination between production and routing is achieved by integrating the travel time information directly into the production scheduling decisions. Specifically, the model adjusts the sequence of producing corresponding products based on the travel times to specific customers in specific regions. For example, if the model identifies that delivering to a particular customer is more efficient during certain hours, it will schedule the production of that customer's order accordingly to ensure it is ready for dispatch at the optimal time. This dynamic adjustment enhances the synchronization between production outputs and delivery schedules, leading to more efficient use of resources and improved customer service levels.

Another technical challenge addressed is the limited range and energy consumption of electric vehicles, which are significantly influenced by factors such as vehicle load, travel speed, and route distance. The model incorporates these factors by considering the energy required for each potential route segment, factoring in the vehicle's characteristics and the time-dependent travel speeds due to traffic conditions. By doing so, it ensures that the routing plans are feasible within the EVs' operational constraints and that energy consumption is minimized.

The heterogeneity of electric vehicles is also considered, acknowledging that different vehicles may have varying capacities, battery ranges, and energy efficiencies. This adds complexity to the model but results in more realistic and applicable solutions. The model determines which vehicles are best suited for specific routes and deliveries, optimizing the fleet's overall performance.

To solve this highly complex and computationally intensive problem, the study develops capable and hybrid metaheuristic algorithms. These algorithms combine elements of various optimization techniques to effectively search the solution space for high-quality solutions. They are particularly well-suited for handling large-scale, real-world scenarios where exact methods become impractical due to the problem's NP-hard nature.

The metaheuristic algorithms are designed to manage the integrated planning problem's multi-period, multi-objective characteristics. They simultaneously optimize production schedules, inventory levels, and routing plans while accounting for time-dependent travel times and energy constraints. The algorithms employ strategies to balance exploration and exploitation of the solution space, ensuring that diverse solutions are considered and that the best-performing ones are refined over successive iterations.

The effectiveness of the proposed model and solution methods is demonstrated through extensive computational experiments using realistic data. The results indicate significant improvements in operational efficiency, cost reduction, and sustainability metrics compared to traditional planning approaches that consider production and routing separately. By integrating the planning processes and accounting for dynamic travel times and energy consumption, the model enables more accurate and efficient decision-making.

In practice, this integrated approach allows companies to better align their production and distribution activities, leading to several benefits:

- Improved Resource Utilization: By synchronizing production with optimal delivery times, the model reduces idle times for both production facilities and delivery vehicles, enhancing overall productivity.
- Energy Efficiency: Considering time-varying travel speeds and energy consumption ensures that electric vehicles are used within their operational limits and that energy usage is minimized, supporting sustainability goals.
- Enhanced Customer Service: Adjusting production sequences based on delivery schedules allows for more reliable and timely deliveries, improving customer satisfaction.
- Cost Savings: Optimizing production and routing together reduces costs associated with production, inventory holding, and transportation, contributing to better financial performance.

This research is pioneering in its simultaneous consideration of multi-period production routing with heterogeneous electric vehicles in a dynamic urban setting. By addressing the coordination of production and routing over different time horizons and incorporating real-world complexities such as variable travel times and energy constraints, the study provides a robust framework for enhancing sustainability and efficiency in supply chain operations.

In summary, the fourth study tackles the intricate challenge of integrating production planning and vehicle routing in a multi-period context, considering the nuances of electric vehicle operations in urban environments. The model's innovative use of time-indexed travel times enables it to capture the impact of traffic variations on delivery schedules and energy consumption. By adjusting production sequences to align with optimal delivery times, the model ensures a cohesive and efficient supply chain. The development of specialized metaheuristic algorithms to solve this complex problem underscores the study's contribution to advancing optimization techniques in sustainable urban logistics.

Transitioning from the optimization of production and routing decisions in supply chains using electric vehicles, the fifth study further advances the exploration of electric vehicles in urban logistics by developing a practical decision support system (DSS) for urban deliveries using electric vans. While the fourth study focused on integrating production planning and dynamic routing under energy consumption constraints, it primarily addressed the synchronization of production and distribution activities within a theoretical framework. The fifth study builds upon this foundation by shifting the emphasis toward operational planning and real-time management in practical, real-world scenarios. It addresses the challenges of vehicle range limitations, battery recharging constraints, and unexpected events that can disrupt delivery schedules. By developing a software tool that optimizes daily delivery tours within urban networks, this study bridges the gap between theoretical optimization models and their practical implementation, offering valuable insights for both logistics' operators and urban planners.

The fifth study presents a comprehensive decision support system (DSS) developed to optimize urban deliveries using electric vans (Battery Electric Vehicles or BEVs), with a specific focus on the optimization simulation framework and the real-time recovery and update function. This study moves beyond theoretical models by addressing practical challenges encountered in real-world urban logistics, particularly for electric vehicles, where constraints like limited battery range and recharging logistics are critical.

The key innovation in this paper lies in the development of an advanced optimization simulation framework specifically designed for routing electric vehicles. The framework simulates delivery operations, incorporating factors such as vehicle energy consumption, charging station locations, and delivery time windows. Traditional vehicle routing problems (VRP) are extended in this framework to address the limited range of electric vehicles, requiring a balance between energy capacity and the operational demands of urban logistics.

The optimization simulation framework manages the complexities introduced by electric vehicle constraints. It integrates various data inputs, such as vehicle load, traffic conditions, and energy consumption per route segment, ensuring that the planned routes do not exceed battery capacity without factoring in strategically placed recharging stops. The framework further optimizes recharging operations, accounting for the availability and location of charging stations, charging times, and their effects on delivery schedules. This simulation-based approach enables logistics operators to efficiently minimize delivery times while adhering to the electric vehicle's limitations.

A critical and innovative feature of the DSS is the recovery and update function, which is fully integrated into the simulation phase. This ensures that disruptions, such as traffic congestion, vehicle breakdowns, or charging station availability issues, are dynamically addressed as part of the simulated delivery process. During the simulation phase, the system continuously monitors potential deviations in planned routes using real-time data gathered through Internet of Things (IoT) technologies. Data from vehicles, road networks, and charging stations are fed into the simulation in real time, allowing the system to simulate and preemptively address potential disruptions before they affect operations.

If any unexpected event is detected during the simulation, the system immediately triggers the recovery process. The optimization simulation framework then re-optimizes the remaining routes and tasks within the simulation, adjusting for the new conditions. For example, the system may assign deliveries to different vehicles, reroute vans to avoid traffic, or schedule additional charging stops—all within the same simulation phase. This ensures a seamless transition from the planned delivery routes to updated, more efficient ones, without waiting for real-world execution.

Moreover, the framework employs metaheuristic techniques that handle the computational complexity required for such real-time adjustments. These techniques enable the system to quickly generate high-quality solutions that accommodate changes without significantly impacting delivery efficiency. The simulation capability of the DSS is key to both planning and responding to uncertainties. By simulating potential disruptions like traffic delays or unexpected changes in delivery demand, the system helps operators test and refine their delivery strategies before execution. This preemptive recovery within the simulation phase allows for better preparedness and response, ensuring that the overall efficiency of delivery operations is maintained even in the face of unforeseen challenges.

In conclusion, the fifth study makes a significant contribution to urban logistics by developing a decision support system that incorporates a sophisticated optimization simulation framework with a dynamic recovery and update function, both of which are executed within the simulation phase. This approach not only addresses the operational constraints of electric vehicles, such as limited range and recharging needs, but also ensures that the system can adapt quickly and efficiently to unexpected events. The integration of simulation, real-time data, and dynamic re-optimization offers logistics operators and urban planners a powerful tool for enhancing the sustainability and reliability of urban delivery operations.

The remainder of this dissertation is organized as follows: Chapter 2 introduces a dynamic approach for optimizing multi-compartment vehicle routing in waste management, addressing the complexities of waste collection logistics. Chapter 3 presents an allocation-routing optimization model for integrated solid waste management, offering a comprehensive framework for improving operational efficiency. Chapter 4 focuses on the integration of Industry 4.0 and IoT technologies for optimizing facility location and green vehicle routing in waste management, highlighting the potential for technology-driven solutions. Chapter 5 details the development of a multi-period dynamic production-routing model for electric vehicles in supply chains, emphasizing energy consumption considerations. Chapter 6 examines urban delivery optimization using electric vans, providing valuable insights into sustainable urban logistics. Finally, Chapter 7 synthesizes the findings from the individual papers, discusses the broader implications of the research, and offers recommendations for future research directions in the field of sustainable logistics and supply chain optimization.

CHAPTER 2

PAPER 1:

A Dynamic Approach for Multi-Compartment Vehicle Routing Problem in Waste Management

Urban areas worldwide face a significant environmental challenge which is increasing municipal solid waste rate. Addressing its negative consequences necessitates advancements in waste management systems. Although the previous research focused on the static routing approach in the collection phase, this paper adds a dynamic municipal solid waste collection scheme to optimize vehicle routing, accounting for fluctuations in waste generation and changes in transportation systems. This study employs, for the first time, the application of a discrete choice model (DCM) to streamline the process of re-optimization in dynamic vehicle routing problems (DVRP). At each decision epoch, DCM is applied to determine the likelihood of choosing the next geographical zone to visit bins based on current waste generation levels and traveling costs. Moreover, the multi-compartment vehicles are considered to preserve waste segregation during transportation, thereby increasing operational efficiency and regulatory compliance. Another contribution of this paper is to determine visiting priority for each bin by adjusting the time window based on the threshold waste level. Hence, this paper proposes a framework for sustainable, efficient, and effective waste management practices by integrating the benefits of dynamic and multi-compartment routing. Furthermore, a hybrid Genetic and Particle Swarm Optimization algorithm has been designed to find the best solution for the studied problem as well as some of the latest and most proficient metaheuristic algorithms. Finally, the Best Worst Method is applied to find the best-proposed algorithm to solve the presented problem, indicating that the hybrid algorithm has the highest performance in providing high-quality route plans.

Keywords: Waste Management System; Internet of Things; Discrete Choice Model; Dynamic Vehicle Routing Problem; Sustainability; Multiple Compartments.

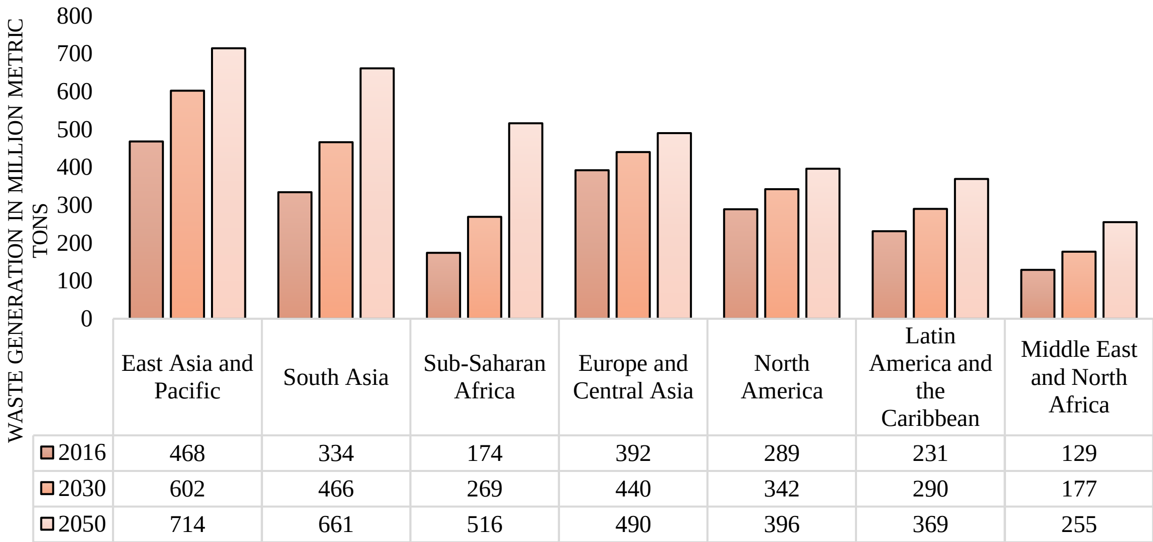
2.1. INTRODUCTION

The Dynamic Municipal Solid Waste Collection Problem, as a crucial logistical challenge in urban areas, is addressed in this paper. A crucial aspect, often overlooked, of this problem is that multiple bins usually are located at specific city locations, each bin dedicated to a different waste category like glass or wet waste (Martikkala et al., 2023). The logistical challenges of the collection task are that the collected waste must be transported to processing facilities without mixing different waste categories (N. Guo et al., 2022). Although using a separate vehicle for each type of waste can maintain waste segregation, it necessitates sending multiple trucks to a single location, thereby increasing environmental impact and transportation costs. Instead, different waste categories can be collected in one visit, with each compartment dedicated to a specific waste type, which can result in preserving segregation during transportation (Eshtehadi et al., 2020).

The problem can be characterized by a set of known fixed demand points, each with different waste generation rates that can change over time, and traffic conditions that fluctuate across the service period. A significant complexity arises from the essential role of vehicles, specifically designed to collect diverse waste categories and uphold segregation, amplifying the complexity of this logistical challenge (J. Chen et al., 2020). Previous research has proposed different methodologies to address the challenges arising from variable waste generation rates and changing traffic conditions, such as employing stochastic information to optimize initial route planning to consider future changes at the beginning of planning periods (Tasouji Hassanpour et al., 2023). Moreover, approximated dynamic programming combines an initial plan with an online policy to determine the initial plan to visit demand points and modify routes as changes occur throughout the service period (H. Zhang et al., 2019).

The application of the discussed methods is often diminished when confronted with large-scale problems (H. Zhang et al., 2019). In addition, the increasing rates of global waste generation (see Fig.2. 1), have outpaced the efficiency of traditional waste management (WM) techniques (di Maria et al., 2020; Hannan et al., 2020). In response, this study implements metaheuristic approaches in which the problem is decomposed into a sequential static routing problem and re-optimizes routes based on the current information (Ferrucci & Bock, 2015a; Vamsi Krishna Reddy & Venkata Lakshmi Narayana, 2022). To improve algorithm performance, events such as a vehicles' arrival at nodes are leveraged to trigger route re-optimization process (Hvattum et al., 2006). Therefore, a solution is developed that initially establishes a static routing plan at the start of the service period, followed by dynamic modifications during the service period using real-time information(Keskin et al., 2023).

The IoT based systems that can exploit real time information to solve a specific problem are increasingly gaining attention in city management for protecting the environment, cost reduction, and boosting productivity (Rahman et al., 2022). Fig.2. 2 provides a comprehensive insight into the number of connected devices based on various use cases worldwide between 2019 and 2030 (World bank). Typically, standard components of IoT-oriented systems encompass endpoint devices (sensors), cloud infrastructures, gateways, along with web and mobile applications (Keshari et al., 2021). The powerful cloud-based platform, utilizing multiple IoT communication protocols, empowers municipalities to monitor all bins on a digital map. This includes information on capacity, waste category, previous measurements, GPS positioning, collection timetable, along with real-time data on the road network (Aytaç & Korçak, 2021; Dubey et al., 2020; Nakandhrakumar et al., 2021). Hence, the provision of real-time data through IoT-driven waste management presents an opportunity to develop novel optimization methodologies in the field of waste collection.



	East Asia and Pacific	South Asia	Sub-Saharan Africa	Europe and Central Asia	North America	Latin America and the Caribbean	Middle East and North Africa
2016	468	334	174	392	289	231	129
2030	602	466	269	440	342	290	177
2050	714	661	516	490	396	369	255

Fig. 2.1. Forecasting regional waste production for the years 2016, 2030, and 2050.
Source: World Bank; ID 233613.

Waste management (WM), in general, entails processes such as waste collection, separation, recycling, and treatment (Jatinkumar Shah et al., 2018; Rahmanifar et al., 2023a). Conventional WM methods often result in unnecessary waste collection or, alternatively, significantly delayed pickups. Such unnecessary pickups can increase annual collection costs by approximately 70% and inefficiently planned routes can result in increased traffic, demanding more fuel and trucks to fulfill the collection tasks. Without considering multi-compartment vehicles, these challenges become even more amplified and neglecting their use in the planning and execution of waste collection can significantly heighten transportation costs and environmental impacts. Moreover, it can pose a risk of cross-contamination between various waste types during transportation. Utilizing single-compartment vehicles tends to worsen these problems, leading to increased fuel costs and the need for more vehicles. Ultimately, these factors cumulatively can lead to a 50% increase in the carbon footprint (Shang et al., 2023).

IoT solutions can provide a customized and dynamic waste management system that offers benefits to different stakeholders by suggesting more efficient routes for waste collection vehicles (Hashemi-Amiri, Mohammadi, et al., 2023). Therefore, a solution composed of a static routing plan at the start of the service period which is then dynamically modified throughout the service period leveraging IoT technology (Faccio et al., 2011; J. Zhang et al., 2023). The primary methodological contribution of this paper lies in determining the decision epoch for DVRP in waste management WM systems using a DCM and real-time information provided by IoT devices (Huang et al., 2017). The study area is partitioned into distinct zones, each has its own separation center where the collected waste undergoes sorting and storage processes. The variation of travel time in the road network and the waste generation rate are the main considered sources of uncertainty and dynamism of the problem in this paper to determine the decision epochs. While one approach can be involving re-optimization after visiting each bin, this method often leads to many unnecessary calls of re-optimizations process since bins are usually located near each other.

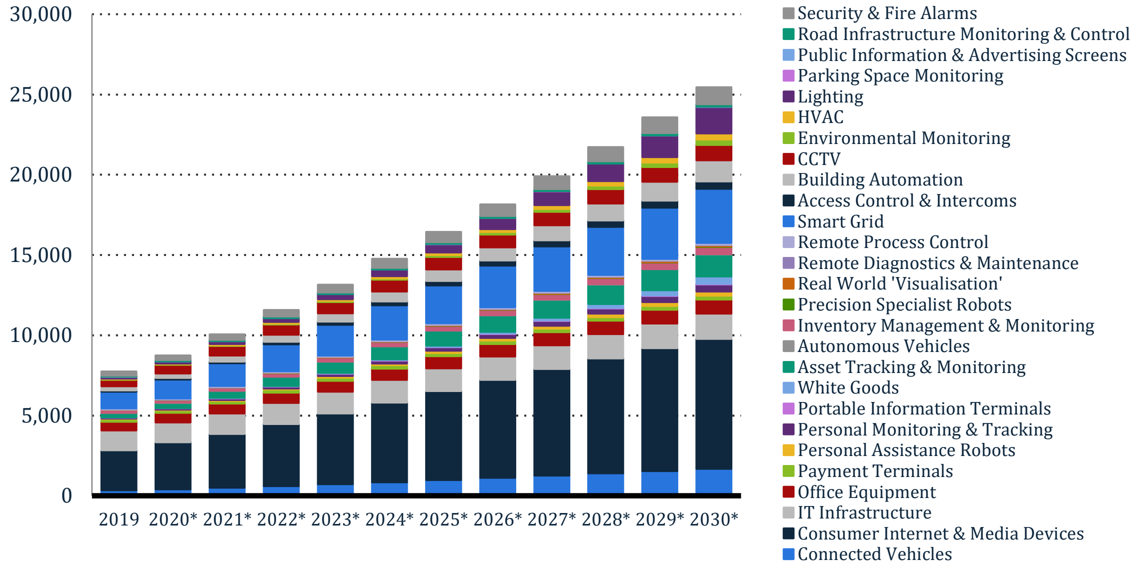


Fig. 2. 2. Number of Internet of Things (IoT) connected devices worldwide from 2019 to 2030, by use case (in millions). Source(s): Transform Insights; ID 1194701.

To address the travel time variation within the road network because different traffic conditions, one approach is to incorporate a time-dependent travel time function based on historical data (Huang et al., 2017). In this case, the planning horizon is divided into one-hour time slices, and re-optimization occurs at the start of each time slice. However, a drawback of this approach is that any new updates must wait until the end of the time interval to be responded by the algorithm (J. Zhang & Woensel, 2023). Hence, this paper proposes a structured decision epoch framework that encompasses both conditions to overcome mentioned limitations. It involves dividing each zone into several sub-zones, where the road network exhibits similar characteristics. Re-optimization is then performed either at the end of each time interval or after visiting the last bin within the current sub-zone. The former is achieved by utilizing a DCM that responds to changes in waste generation (Hassan et al., 2019; Lee & Waddell, 2010). The DCM model determines the likelihood of selecting the next sub-zone based on the waste amount generated and the corresponding travel cost. By incorporating this structure, the proposed model can effectively manage the decision epochs, ensuring timely re-optimization while considering the specific characteristics of the waste generation and road network.

The main contributions of the present study are summarized below:

- Designing an applicable multi-compartment dynamic vehicle routing model for an IoT-based waste collection system by utilizing real-time data from bins and time-dependent functions in the route network.
- Developing a mathematical model in which the priority of visiting of bins is determined based on adjusting time windows. It is done by sensing TWL and hazardous waste in bin.
- Designing a structure to determine the decision epochs by considering travel time variation and waste generation rate.
- Applying the DCM to determine the next sub-zone for re-routing.
- Applying recent metaheuristic algorithms, including Tree Growth Algorithm (TGA), Tabu search (TS), Particle swarm optimization (PSO), and Genetic Algorithm, which is hybridized with PSO Algorithm (GAPSO).

2.2 LITERATURE REVIEW

As a consequence of the latest advances in technology, which resulted in improvements in real-time data transmission and intelligent transportation systems, more recent attention has focused on the DVRP (da Silva Júnior et al., 2021; H. Zhang et al., 2019). Because of the emergence of new abilities of infrastructure, which are offered by the IoT, advanced fleet management systems, and global positioning systems (Akbarpour et al., 2021a). Against the static approach in which information about the problem is assumed to be time-invariant, the information in DVRP can be varied within the planning horizon (Jatinkumar Shah et al., 2018). So, because of different sources of uncertainty in both nodes and/or links in the VRP problem, the vehicles routes cannot be fixed at the beginning of the service period when vehicles are at the depot (Janssens et al., 2009). The key aspects of variation in nodes could be the number of nodes, the arrival time of the new request, and demand quantity (Kuo et al., 2009). Moreover, travel time, traffic flow, and congestion are links' main characteristics, which can vary during the service time (S. N. Kumar & Panneerselvam, 2012).

In (Cheng et al., 2019), the authors considered the uncertainty related to road networks in disaster waste management to transfer waste from disaster-affected areas to landfills. The reliability of the waste management system is estimated by considering each route reliability in the two-stage framework. Since the reliability of the whole system depends on the routes' reliability, each route is estimated to have system reliability. A multi-objective optimization model was developed by (X. Wang, 2018) to tackle a DVRP with a time window for delivering tasks utilizing an ensemble learning-based multi-objective evolutionary algorithm. Customer location during the distribution process can be varied, which is considered a source of uncertainty(Xiang et al., 2021). This paper attempts to develop a model utilizing IoT devices in waste collection, the demand of each node is known in real-time. A review of recent studies in DVRP is illustrated in Table 2.1 to compare them in terms of the applied solution methodology, objective function, travel time, and quality of information.

Table. 2. 1.
Review of recent studies in DVRP.

	Applied methods						Objective						source of changes							
													Travel time				Quality of information			
Article	Exact methods	Heuristics	Metaheuristics	Simulation	Machine Learning methods	Real-time solution methods	Travel time-dependent	Distance dependent	Vehicle dependent	Function of lateness	Implied hazard/risk related	Other	Deterministic	Function dependent (a function of current time)	Stochastic	Unknown	Known (deterministic)	Stochastic	Forecast	Unknown (Real-time)
(Janssens et al., 2009)				×								×				×				×
(Kuo et al., 2009)			×				×						×	×			×			
(X. Li et al., 2010)			×					×	×						×			×		
(Balseiro et al., 2011)			×				×		×				×	×			×			
(Juan et al., 2011)			×	×				×					×					×		
(Lorini et al., 2011)		×				×	×			×				×		×				×
(X. Chen et al., 2012)			×					×					×					×		
(Goodson et al., 2012)		×	×					×					×					×		
(Khouadjia et al., 2012)			×					×					×							×
(Dabia et al., 2013)	×						×						×	×			×			
(Ferrucci et al., 2013)			×			×				×			×						×	
(Pandelis et al., 2013)	×							×					×					×		
(Taş et al., 2013)			×					×	×	×		×			×			×		
(Vidal et al., 2014)			×					×	×					×			×			
(Zhu et al., 2014)		×				×		×					×					×		
(Euchi et al., 2015)			×					×					×							×
(G. Kim et al., 2016)	×						×								×			×		
(Ng et al., 2017)	×		×				×							×			×			
(S. Chen et al., 2018)		×	×					×	×				×							×
(Abdirad et al., 2021)		×	×					×					×							×
(Xiang et al., 2020)		×	×					×	×			×	×				×			
(da Silva Júnior et al., 2021)		×						×		×		×	×				×			×
(F. Wang et al., 2021)			×					×		×			×						×	
(Frohner et al., 2021)					×		×								×					×

Regarding the objective function, as shown, the most frequently objective function considered to optimize DVRP is the travel distance-related objectives. However, metaheuristic approaches have been mainly employed for solving the DVRP because of the complexity of the problem and the need for re-optimization of routes during the distribution process. Although some papers have investigated different type of uncertainty, travel time on the network links is assumed to be known and fixed beforehand in the most previous research.

In (Cheng et al., 2018a), the authors proposed a framework to consider uncertainties related to the waste collection after extreme events because the generated waste must be cleared from the affected area as soon as possible. The scale of the disaster considered is the only uncertain factor considered among disaster type, disaster scale, and disaster location considered as impact variable in this paper. The required total time and capacity for cleaning-up the waste after a disaster is investigated by (Cheng et al., 2018b). The authors considered the uncertainty related to the type and quantity of waste which is affected by the type of disaster. A nonlinear model was developed to optimize the reliability of the system, which was solved by the GA by providing the required information about the end of cleaning-up process.

In (Archetti et al., 2021), the authors proposed a solution algorithm to consider both known customer requests and real-time requests of customers, which should be delivered within a time window. The distribution center was assumed to have a predefined number of vehicles, and a set of occasional drivers could be applied to carry out all the services. A variable neighborhood descent generated an initial solution, and new customers were inserted into the solution iteratively. In addition, (Cheng et al., 2021) applied a reliability analysis to identify the level of risk in the solid waste management systems and then optimized the different transferring facilities' location and their capacity. A multi-stage waste system is considered in which the capacity and demand of each facility are assumed to be uncertain. On the other hand, DVRP makes it possible to start with the static plan and then adjust the routes at each decision epoch within the service period to consider the changes in the problem characteristics. The application of DVRP in the context of WMS is provided in Table 2.2.

Since the application of IoT in the WM system makes it possible to trace the situation of each bin concerning the weight of waste and existing hazardous waste, more studies have been recently investigated application of the DVRP model based on IoT-devices in the WM system. (Akbarpour et al., 2021a; Anagnostopoulos, Kolomvatsos, et al., 2015; Salehi-Amiri, Jabbarzadeh, et al., 2022). So, the information has been considered available as soon as changes happen to the current situation. In terms of methodological aspect, the metaheuristic algorithm is the main approach utilized to deal with the DVRP in the context of WM system. Consequently, it is required to decompose the DVRP into several static problems and carry out re-optimization at the end of each time interval. However, determining the time interval and the decision epochs is a critical issue in implementing the algorithm.

Table. 2.2.
The application of DVRP in the context of WMS.

Article	Exact methods	Heuristics	Metaheuristics	Simulation	Machine Learning Methods	Real-time solution methods	Travel time dependent	Distance dependent	Vehicle dependent	Function of lateness	Implied hazard/risk related	Other	Deterministic	Function dependent (a function of current time)	Stochastic	Unknown	Known (deterministic)	Stochastic	Forecast	Unknown (Real-time)
(Anagnostopoulos, Kolomvatsos, et al., 2015)		x						x					x							x
(Anagnostopoulos, Zaslavsky, et al., 2015)		x		x			x	x					x							x
(Nesmachnow et al., 2018a)			x					x				x		x					x	x
(Ramos et al., 2018)		x						x			x		x						x	x
(Abdallah et al., 2019)				x				x			x		x							x
(H. Wu et al., 2020)			x					x	x		x	x	x							x
(Nidhya et al., 2020)				x									x							x
(Akbarpour et al., 2021b)	x		x					x				x	x				x			
(Mamashli et al., 2021)	x		x					x			x	x	x					x		
(Mojtahedi et al., 2021a)	x		x					x	x		x		x				x			
This study	x	x	x					x	x		x			x						x

Generally, DVRP is an extension of a well-known NP-hard combinatorial optimization problem called VRP and plays a crucial role in logistics systems. On the other hand, metaheuristics are the heart of the combinatorial optimization research field, as reported by many papers (Boussaïd et al., 2013; Elshaer & Awad, 2020). The real-world application of VRP made it more complex and larger in scale. So, exploring the effective method for finding a feasible solution in a reasonable time is inevitable. Because of these reasons, metaheuristics are often more suitable for practical applications concerning one or multiple objectives in an affordable amount of time (Gendreau et al., 2008). Metaheuristics can quickly determine the solution space without settling for local or global optimum solutions (Asih et al., 2017). Based on a taxonomic review by Braekers et al between 2009 and mid-2015, around 70% of articles with the core topic of VRP employed a metaheuristics algorithm as a solution technique(Braekers, Ramaekers, & van Nieuwenhuyse, 2016). We employed a metaheuristic approach to tackle our presented waste collection routing problem.

Many studies utilized metaheuristic algorithms and compared them to select the best one to increase the efficiency of their proposed solution. Jorge et al (2022) presented a hybrid metaheuristic for solving intelligent waste collection regarding the workload concern. Based on current and prediction fill statuses, they employed a look-head heuristic to determine collection day and which bin must be empty. A simulated annealing/neighborhood search algorithm was applied to select the best bins to visit and the best visiting routes within a relatively short time(Jorge et al., 2022a). Another recent work (Okulewicz & Mańdziuk, 2019) utilized metaheuristic approaches to solve DVRP in continuous search space. PSO algorithm and differential evolution (DE) with continuous search spaces and a Genetic Algorithm with discrete search space were applied to solve their proposed model. They compared all proposed algorithms to see which was more efficient for their suggested problem. The findings of both continuous algorithms outperformed those of the discrete solution representation algorithm, although the performance differences between PSO and DE are negligible.

A DVRP with a soft time window to deliver urgent goods is considered (Ferrucci & Bock, 2015b), which the planned routes require to be adopted after arriving at the new customer request. Two different approaches are introduced in this paper to address the problem, and TS metaheuristic is utilized in both approaches to address the problem. In the first approach, new requests are considered after static plans when they arrive, but stochastic knowledge is considered in static plans to enrich it in the second approach. However, a single-day profile is used to predict future requests, which can not apply to real-world problems. Hence, the real-time routing solution methodology considers multiple profiles for different day types proposed by Ferrucci & Bock (2016)(Ferrucci & Bock, 2016). Profile with a similar request arrival pattern is grouped, and stochastic information is extracted in the static plan. TS metaheuristic algorithm was implemented to solve the problem. Changing between different operators that control neighborhood search is proposed to enhance the diversification and intensification of operators. Although it is suggested in several studies that metaheuristic algorithms can be applied to adopt routes in DVRP efficiently, in this paper, a framework is proposed to exploit the advantages of metaheuristics and avoid large computation time for rerouting by combining them with a discrete choice model in waste collection. Most of the previous research has considered a fixed time interval and triggering the decision time by an event such as arrival to the next node in the tour. One of the main obstacles to implementing this approach in the waste collection is that nodes (bins) are usually located densely, especially in a local neighborhood and it is rare to have a big change in the subsequent links of the tour unless the vehicle traverses to another part of the city with different road network characteristic. Therefore, calling the re-optimization process after visiting each bin is associated with an increased risk of unnecessary re-optimization. On the contrary, assigning the decision epoch just to the end of each time interval is more likely to result in poor responsiveness to the changes that occurred during the service period. This paper attempts to fill this gap by considering the characteristics of both related to both nodes and links that can impose uncertainty on the problem.

A stepwise travel time function is suggested to consider the effect of travel time variation at different times of the day. So, re-optimization is proposed to be performed at the end of each time interval. Moreover, after visiting the last bin of the current sub-zone to consider the effect of changes in waste generation rate in bins, re-optimization is proposed to perform rather than re-routing after visiting each bin. A DCM model is proposed to apply after unloading the last bin of the current sub-zone to calculate the probability of selecting the next sub-zone based on the weight of collected waste in the other sub-zones and the current transportation cost to associated sub-zones.

2.3 PROBLEM STATEMENT AND MATHEMATICAL REPRESENTATION

The study area is divided into several distinct zones with separation centers in the offered model to collect waste from bins, conducting a separation process and temporary storage (see Fig.2.3). In this model, due to the dynamism of road networks and waste generation rate, a dynamic approach for routes optimization is suggested. After optimization of the initial routes, the optimization process must be re-run to solve the model at sequential decision epochs to consider the parameters' dynamism for determining the vehicle tour visit. Since, in the real world, the position of the bins is too close in a local distinct, it is rare to have changes in the road network status and waste generation level during traversing between two consecutive nodes. Because of that, this model neglected to adjust the fixed tour after visiting each bin. So, each zone is divided into different sub-zone based on similar characteristics of the local network for solving the problem of decision epochs in DVRP to answer two important questions regarding the re-optimization time and the best strategy to identify the order of remaining nodes.

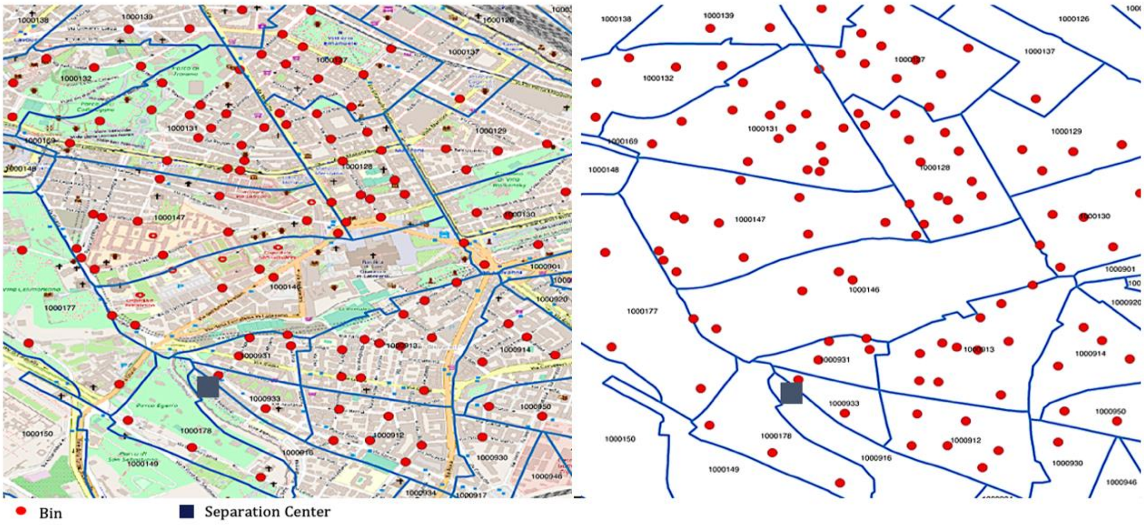


Fig. 2. 3. An example of sub-zone and location of bins by QGIS software.
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In terms of re-optimization time, it is crucial to pay attention to both sources of changes in the model to determine the time of re-optimization regarding the travel time variation. A time-dependent travel time function that is extracted based on historical data is proposed. The planning horizon is divided into a one-hour time slice, and the problem must be re-optimized at the end of each time slice. In addition, a DCM is suggested to apply to react to the changes in waste generation after visiting the last bin of the current zone to trigger a decision epoch and improve the responsiveness of the algorithm in the current time slice. DCM model calculates the probability of choosing the next sub-zone based on the amount of waste generated and the cost of traversing to that zone. Besides, the information for our problems comes from smart bins equipped with a sensor, and the data related to the road network are based on time-dependent travel time functions.

A Time Window Capacitated Multi-Compartment Vehicle Routing Problem (TWCMVRP) with heterogeneous vehicles is proposed to address the routing problem for collecting waste from bins to separation centers. Since there are different links in the road network in terms of capacity, the waste collection service should cover all parts of the city. Because applying a set of homogeneous vehicles cannot meet the objectives of the waste management system, a heterogeneous variant of the VRP problem is considered for the collection phase in this paper.

Besides, a time window is defined for each bin that is assigned to a truck. With the help of IoT devices, a concept of TWL is proposed to determine which bin must be emptied to avoid the weakness of traditional systems, such as having overload bins or visiting empty bins. TWL and the amount of hazardous waste in each bin are considered to determine a priority for each bin. The priority is determined by calculating the time window considering these rules: how much TWL is exceeded and how much dangerous waste is sensed by IoT devices embedded in each bin. The more waste level or dangerous waste results in limited time window intervals.

The main assumptions of the problem can be outlined as follows:

- A heterogeneous fleet is used in each separation center visiting bins.
- Study areas are segmented into various zones, and each zone is divided into multiple sub-zones.
- The links belong to a local network (sub-zone) have similar characteristics.
- A bin should be only visited by one truck.
- The capacity of trucks is bigger than that of bins.
- The TWL is continually observed and is expected to be 75%. All bins attaining this capacity necessitate a visit.
- The time window is calculated based on TWL and the existence of hazardous waste.
- The re-routing optimization should be done in the last bin in the current zone and beginning of each time slice.

2.3. 1. DISCRETE CHOICE MODEL

In general, a DCM is utilized to determine the probability of an alternative being chosen when a predefined set of discrete alternatives exists. The random utility model (RUM) is a form of DCM, a behavioral model that can represent transport-related choices (Walker & Ben-Akiva, 2002). In RUM, the probability of choosing each alternative is calculated based on the perceived utility, which is composed of systematic utility and random residual (Cascetta, 2009). This paper proposes the logit model as a well-known RUM model to determine the probability of choosing the next sub-zone.

The formulation of the proposed model for specifying the selection probability of the next sub-zone is represented in Eq. (2.1). The average cost of travel time from the last bin of the current zone to the other subzone (the average distance to the other sub-zone) is represented by C_{az} which plays the role of random residual in RUM and the value of parameters β is estimated through model calibration. While A_z represents a systematic utility associated with each alternative (sub-zone) calculated based on the summation of waste in all bins of each sub-zone at the current time. So, the higher waste in each sub-zone (attraction), the higher probability of that sub-zone. While the higher cost of traveling can lead to a lower probability to select that sub-zone.

$$Probability_{Sub-zone} = \frac{A_Z \exp(-\beta . C_{az})}{\sum_Z(-\beta . Az)} \tag{2. 1}$$

2.3.2. MATHEMATICAL Model

The mixed integer linear programming is used to develop an innovative application of TWCMVRP for optimizing waste collection practices to address the routing problem by minimizing total trip length and carbon dioxide emissions. The presented framework finds the optimized routes for trucks to streamline the collection and transportation of different waste types, whilst keeping them separated which is done by defining several compartments for the trucks. Simultaneous transportation of diverse waste types in one vehicle from the collection points to the depot is offered by the presented model. It can reduce the total traveled distance and total operational costs, including the optimal number of vehicles, labor costs, as well as fuel costs. This eventually leads to more sustainable and cost-effective waste collection practices. Since different factors contribute to the carbon dioxide emission penalty, such as acceleration, engine characteristics, and speed which the former again depends on the characteristics of the road network, such as slope of links, it is required to be adjusted based on each study area. To construct a model to estimate the carbon dioxide penalty rate considering a range of different contributors, readers are referred to (Ji et al., 2022).

Having different compartments for the trucks is highly beneficial in addressing waste collection, particularly when dealing with multiple types of waste that are pre-separated into different bins and must be kept separated during transportation phase. This can lead to operational efficiency improvement by allowing simultaneous transportation of diverse waste types in one vehicle, thereby saving time and fuel. Moreover, it eliminates the risk of cross-contamination between different waste fractions and upholds the initial segregation efforts at bins. Then through MCVRP, collected waste can be directly transported to the appropriate processing facilities such as composting, recycling, and landfill with consolidated waste collection trips which can be translated into less fuel consumption, transportation, and environmental costs. It is also providing the opportunity of being in compliance with regulations. Because the proposed model provides the opportunity to comply with regulation regarding waste separation and disposal. For example, for Certain types of waste, such as hazardous waste or medical waste, a region may have specific regulations governing their handling and transport. With separate compartments, these waste types can be safely isolated from others, thereby meeting the required safety and handling standards. Tables 2-3 to Table 2-5 represent the sets, and indices, parameters, and variables of the proposed model.

Table. 2.3.
Sets and indexes.

Sets and indices	Description
V	Set of bins and separation center which denoted by 0,
V'	Set of bins,
E	Set of edges,
K	Set of trucks,
S	Set of time intervals,
M	Set of waste types generated at bins,
S	Set of time intervals representing different traffic conditions;
L^k	Compartment set in truck k to carry different types separated,
m	Index of waste types,
l	Index of truck's compartment,
k	Vehicles' index,
s	Time slice index,
i, j	Bin index including bins and separation center.

Table.2. 4.
Parameters.

Parameters	Description
d_{ij}	Distance between number i and j,
C_{lk}	The capacity of compartment l of truck k,
FC_k	The fixed cost of using truck k,
PCO_k	The CO_2 consumption penalty per unit distance for each truck k,
WB_{im}	The generated waste type m in the bin number i,
id_{im}	Unloading time of waste type m at the bin i,
T_{ijs}	Travel time between node number i and j in the time slice s,
ST_i	Earliest time to be allowed to unload the bin i,
FT_i	Last time to be allowed to unload the bin i,
ET_s	Upper bound at each time interval s,
ql_i	A number which representing the degree of waste quantity surpassing the specified TWL in bin i: If $0.75 * TWL \leq WB_{im} < 0.85 * TWL, \;\; ql_i = 1$, If $0.85 * TWL \leq WB_{im} < 0.95 * TWL, \;\; ql_i = 2$, If $0.95 * TWL \leq WB_{im}, \;\; ql_i = 3$,
hw_i	The degree of hazardous waste in bin i can be shown in a range of (1,2,3) based on the level of risk associated to that bin while 3 represents the highest risk.

Table. 2.5.
Decision variables.

Variables	Description
Z_{imlk}	A binary variable equal to 1 if k^{th} truck uses the compartment *l* to carry waste type *m* of bin *i* and 0, otherwise.
X_{ijks}	Number of times that the arc (i,j) is utilized by truck k in time interval s,
Y_{ik}	A binary variable equals to 1 if the i^{th} bin is unloaded by k^{th} truck and 0, otherwise,
W_{mlk}	A binary variable equal to 1 if k^{th} truck uses the compartment *l* to carry waste type *m* and 0, otherwise.
DT_{ik}	Departure time from bin *i*;

2.3.2.6. MODEL

$$\text{minimize} \sum_{(i,j)\in E}\sum_{k\in K}\sum_{s\in S} d_{ij}\, X_{ijks}(1+PCO_k) + \sum_{k\in K} FC_k Y_{0k} \quad \text{Eq. (2.2)}$$

subject to

$$Z_{imlk} \le X_{ijks} \quad \forall i \in V', k \in K, l \in L^k, m \in M, s \in S \quad \text{Eq. (2.3)}$$

$$Z_{imlk} \le W_{mlk} \quad \forall i \in V', k \in K, l \in L^k, m \in M \quad \text{Eq. (2.4)}$$

$$W_{mlk} \le \sum_{i\in V'} Z_{imlk} \quad \forall k \in K, l \in L^k, m \in M \quad \text{Eq. (2.5)}$$

$$\sum_{i\in V'} W_{mlk} \le 1 \quad \forall k \in K, l \in L^k \quad \text{Eq. (2.6)}$$

$$\sum_{j\in V, i<j} X_{ijks} - \sum_{j\in V, j<i} X_{jiks} = 2Y_{ik} \quad \forall i \in V, k \in K, s \in S \quad \text{Eq. (2.7)}$$

$$\sum_{i\in V'} WB_{im}\, Z_{imlk} \le C_{lk} \quad \forall k \in K, l \in L^k, m \in M \quad \text{Eq. (2.8)}$$

$$DT_{jk} \ge DT_{ik} + T_{ijs} + id_{im} - M\left(1 - X_{ijks}\right) \quad \forall (i,j) \in E, k \in K, m \in M, s \in S \quad \text{Eq. (2.9)}$$

$$ST_i + id_{im} \le DT_{ik} \le FT_i + id_{im} \quad \forall i \in V', m \in M \quad \text{Eq. (2.10)}$$

$$DT_{ik} + MX_{ijks} \le ET_s + M \quad \forall (i,j) \in E, k \in K, s \in S \quad \text{Eq. (2.11)}$$

$$DT_{ik} + ET_{s-1}X_{ijks} \ge 0 \quad \forall (i,j) \in E, k \in K, s \in S \quad \text{Eq. (2.12)}$$

$$ST_i = ST_i + ST_i * \left(ql_i * hw_i * \frac{10}{100}\right) \forall i \in V' \quad \text{Eq. (2.13)}$$

$$FT_i = FT_i - FT_i * \left(ql_i * hw_i * \frac{10}{100}\right) \forall i \in V' \quad \text{Eq. (2.14)}$$

$$X_{0jks} \in \{0,1,2\} \ \forall j \in V', k \in K, s \in S \quad \text{Eq. (2.15)}$$

$$X_{ijks} \in \{0,1\} \ \forall i,j \in V', k \in K, s \in S \quad \text{Eq. (2.16)}$$

$$Z_{imlk}, W_{mlk}, Y_{ik} \in \{0,1\} \ \forall i \in V, j \in V', k \in K, l \in L^k, m \in M \quad \text{Eq. (2.17)}$$

The objective function, expressed as Eq. (2.2), comprises of two components: minimizing the overall transportation cost and the associated penalty for CO2 consumption. Additionally, the second term represents the fixed cost incurred when utilizing each truck. Eq. (2.3) guarantees that a specific waste type from a bin can be loaded into a vehicle compartment only if that bin has been visited by the vehicle during the designated time interval. Eq. (2.4) and Eq. (2.5) are defined to allow the truck to carry a waste type in a compartment if that waste type is generated at the visited bin. Eq. (2.6) guarantees that each compartment of a truck is used to transfer only at most one type of waste. Eq. (2.7) indicates the degree elimination constraint and represent that if a truck can visit a bin once. it also holds the continuity of the flow in. away that if a truck arrives to a bin to collect the generated waste, it must be departure from that bin. Eq. (2.8) satisfies the capacity constraint. This constraint ensures that the accumulated loaded waste generated at each bin into compartment of the vehicle does not exceed the capacity of that compartment and prevent overloading. Eq. (2.9) calculates the departure time of the truck from current bin, which is the summation of the time required to travel from previous bin and service time of the truck at current bin. Eq. (2.10) respects the time window at each bin to be visited by a vehicle. Eq. (2.11) and Eq. (2.12) determine the correct time interval of traffic conditions based on the departure time. Eq. (2.13) and Eq. (2.14) update the time window of each. bin according to the presence of the degree of hazardous waste and degree of waste quantity surpassing the specified TWL. Eq. (2.15) to Eq. (2.17) state the domain of the decision variables of the model.

2.4. SOLUTION APPROACH

Addressing the ever-increasing municipal solid waste issue in urban areas requires an innovative, sustainable, and effective waste management system. This paper proposes a comprehensive and dynamic approach towards managing this environmental challenge. The solution primarily focuses on three crucial aspects: DVRP, the multi-compartment vehicle system, and the application of metaheuristic algorithms. Firstly, the paper introduces a dynamic municipal solid waste collection scheme to optimize vehicle routing. This dynamic approach is significantly different from the previously researched static routing approach, as it is designed to adapt to the ever-changing factors in urban waste management such as fluctuations in waste generation and changes in transportation systems. The re-optimization process in DVRP can be demanding, hence, for the first time, a DCM is employed in this study. DCM is a critical tool used at each decision epoch to predict the likelihood of choosing the next geographical zone to visit bins based on current waste generation levels and traveling costs.

The second aspect is the multi-compartment vehicle system which has been considered to preserve waste segregation during transportation. This is a critical improvement as it not only increases operational efficiency but also ensures regulatory compliance, both of which are essential in a sustainable waste management system. Thirdly, the time window for each bin visit is adjusted based on TWL. This innovative approach allows for determining the visiting priority for each bin, ultimately reducing the cost of waste transferring from bins to the separation center. Finally, the application of metaheuristic algorithms, specifically a hybrid of the GA and PSO, has been designed to find the best solution for the studied problem.

Various solution methodologies have been outlined in the existing literature, categorically divided into two primary classifications. The first category encompasses exact methods, typically deployed to tackle small-scale problems. Nevertheless, given that the DVRP is a complex, NP-Hard combinatorial optimization issue, these exact methods often fall short when faced with real-world, large-scale problems. The second classification comprises heuristic and meta-heuristic approaches, structured to identify near-optimal solutions. Moreover, applying the exact methods appears to be irrelevant in the case of DVRP where changes in input over time impose dynamism on the problem. Therefore, heuristic algorithms and metaheuristics have gained widespread acceptance and usage in dynamic waste collection processes(Jorge et al., 2022b). Because in this paper several metaheuristic approaches are applied to do optimization of the initial routes and for re-optimization at different decision epochs. In addition, a hybrid metaheuristic algorithm is introduced in this paper to enhance algorithm efficiency. A dynamic framework is represented to consider changes in input parameters of nodes and links (bins and road networks respectively) by utilizing DCM and metaheuristic to make the method applicable for real-world problems.

2. 4. 1. ENCODING AND DECODING PLAN

Solution representation plays a key role in the implementation of each metaheuristic algorithms to solve a problem (Gholian-Jouybari et al., 2022). A different strategy has been explicated to represent vehicle routes. The VRP problem is divided into two sub-problems composing the problem of assigning customers to vehicles and determining the sequence of visiting for each vehicle. Depending on the approach to deal with the mentioned sub-problems, VRP solution representation strategy can be categorized into direct or indirect methods. Direct representation refers to the solution in which both sub-problems are addressed in one step, while indirect representation consists of two parts: The first focuses on customers, and the second is related to the vehicles (Okulewicz & Mańdziuk, 2019). In addition, in both methods, discrete and continuous representation can be used. The problem encoding proved its advantages over the discrete and indirect methods for DVRP. So, a direct continuous problem encoding method is used in this paper.

A random permutation of all customers can be a solution representation for the travel salesman problem since it necessitates the selection of a visitation sequence for the tour. However, to adapt the TSP solution for the multi compartment vehicle routing problem, firstly a set of delimiters must be incorporated within the permutation of demand points to cluster them among vehicles. Consequently, n-1 delimiters are required to transform a TSP route into a VRP route when n represents the number of vehicles. In this scenario, any number exceeding the maximum number of customers can function as a delimiter. For instance, consider a situation involving five bins and three trucks. To convert the Traveling Salesman route into a VRP route, two delimiters are needed. As such, a random permutation of seven elements can effectively represent the VRP solution.

After transforming the TSP solution to VRP solution, it is required to consider different waste types to consider multi compartments. Hence, the number of bins must be multiplied with number of waste types to consider different waste types and allocated compartments in trucks. Hence, assume to have two types of wet waste and dry waste in the previous example which implies to have two allocation problems for each bin including allocation of wet waste to a compartment of a truck and accordingly for dry waste. therefore, instead of having five elements, it is needed to have $(number\ of\ waste\ types * number\ of\ bins) + number\ of\ trucks - 1$ elements. For the generated example, it equals to twelve elements that the number nine and ten play the role of delimiters.

As depicted in Fig. 2.4. the positions of 11 and 12 serve as delimiters to determine the tour visit sequence for each vehicle. The random key technique, a continuous encoding strategy, is employed to develop a multi compartment VRP route due to its confirmed superior performance for VRP. Several steps must be executed to decode the presented solution for the problem in which the assignment of substantial penalties is crucial aspect of the decoding stage. These penalties to solutions deemed infeasible due to constraints, such as time windows, load capacity, and state of charge. Additionally, it is imperative to account for varying traveling speeds and, consequently, different travel times at a specific time interval for each link when calculating the total travel time in the decoding phase. The procedure of this method is represented in Fig. 2.5. Some steps must be taken to decode the represented solution for VRP. The key part in the decoding phase is to assign a high penalty to those solutions which are not feasible because of constraints handling.

0. 709	0. 754	0. 276	0. 679	0. 655	0. 162	0. 118	0. 498	0. 959	0. 340	0. 585	0. 223

7	6	12	3	10	8	11	5	4	1	2	9

Fig. 2.4. Representation of random key method.

The decoding method starts with determining the position of the delimiter and then extracting the list associated with each vehicle. Afterward, the distance traveled by each vehicle, the arrival time of each vehicle at each customer, and the used capacity of each vehicle are calculated. Furthermore, the violation of constraints is calculated and assigned as a penalty to the solution.

```
Decoding proposed solution representation into vehicle routing problem
Calling propped solution and input
Finding the position of delimiters
Extraction of list of bins for each truck
    for (each truck)
if (the current list is not empty)
Traveled Distance <- Distance from separation center to the first bin
   for (list of current vehicles)
Arrival time of each truck to each bin
Traveled Distance <- Traveled Distance + Distance between current bin and next bin
   end
Traveled Distance <- Traveled Distance+ Distance from last bin to separation center
Used Capacity <- summation of weight of waste in all bins assigned to the current truck
  end
  end
Capacity Violation <- maximum (Used Capacity. /Capacity of vehicles -1)
Capacity Violation <- Average of Capacity Violation
TWV=zeros(1,I);
   for (number of bins)
Time Window Violation <- maximum (0, 1-Arrival time/Starting time of time window, Arrival time/Ending time
of time window, -1]);
    End
Time Window Violation <- Average of Time Window Violation
```

Fig. 2.5. Representation of decoding method.

2. 4. 2. METAHEURISTICS AND HYBRID ALGORITHM

As explained by Cheraghalipour and Paydar (2018), the "No Free Lunch" theory (Wolpert & Macready, 1997) indicates that there is no single algorithm can address all optimization problems universally. This inherent complexity underscores the necessity for the proposal of various metaheuristics to tackle the proposed problem(Cheraghalipour et al., 2017). The objective here is to locate the ideal solution and to examine the most recent, competent, and hybrid algorithms to assist decision-makers in selecting the most effective strategy to resolve this pressing issue. For this purpose, this study explores four distinct algorithms: TS, PSO, TGA, and the hybrid GA and PSO (GAPSO).

2. 4. 2. 1. TABU SEARCH

Tabu search (TS) algorithm is a metaheuristic optimization search method that was invented by Fred W. Glover in 1986 and utilized a local search approach (Glover & Laguna, 1997). TS improves the quality of local search by relaxing its fundamental rule. If no bettering move is available at the start, worsening moves can be accepted at each stage which can result in selecting previously visited solutions. Prohibitions are also implemented to dissuade the search process from revisiting solutions that have been previously evaluated (Gendreau, 2003). Hence, recently searched solutions are managed by introducing a tabu list. Since all visited solutions cannot be stored, the tabu list is updated at each iteration, and it is composed of a specific number of tabu movements. By having the concept of tabu movements, even some solutions which have not been generated can be rejected. Therefore, aspiration criteria are introduced to accept a solution that is in the tabu list. TS algorithm steps are depicted in Fig.2.6.

```
TabuList ← Creating empty list to store tabu moves
Best solution ← generating initial random solution
Defining TabuList size
Updating the TabuList with Best solution
While (stopping condition is not true)
      Neighborhood solution ← creating neighbors
        Best Candidate ← first neighborhood solution
        for i in Neighborhood solution:
             if (( i not in TabuList) and (i > Best candidate) )
                   Best Candidate ← i
             end
        end
        If objective value of best candidate > objective value of best solution
             Best solution ← best candidate
        end
        Updating th TabuList by adding best candidate
        If TabuList size >   TabuList size
             Removing the first element of TabuList
        end
end
Return Best solution
```

Fig. 2.6. The Pseudocode of TS algorithm.

Neighbors of the best solution at each iteration are generated based on two different strategies, including moves and exchange type neighbors, which are proposed in (Hedar & Bakr, 2014). Moves type neighbors are generated by randomly selecting two solutions. The closest distance between two routes is calculated and determined by n_1 and n_2 from corresponding routes. $n_1$must be shifted into the second route before n_2. While n_1 and n_2 are changed between two routes in the exchange type operator. An example of generated neighbor according to the move type strategy and exchange type are illustrated in Fig. 2.7. it is important to mention that the encoding plan proposed in this approach is not utilized in this section for the sake of simplicity and direct visualization of initial routes and generated routes according to each strategy.

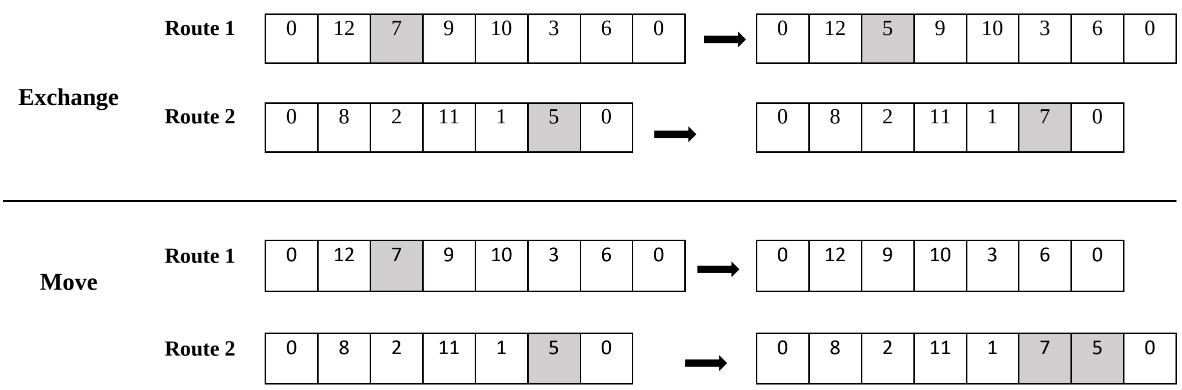


Fig. 2.7. An example of generated neighbor according to the move type strategy and exchange type.

2.4. 2.2. TREE GROWTH ALGORITHM

TGA is a new metaheuristic algorithm based on the greedy behavior of trees to attract sunlight invented by (Cheraghalipour, Hajiaghaei-Keshteli, et al., 2018) . The TGA is divided into two steps: intensification and diversification. During the intensification step, the best trees compete for the food source because they are satisfied with light absorption. In the latter stage, the algorithm allowed some trees to compete for light absorption and move to new or virginal locations. Different steps of the algorithm are elaborated as follows.

1. Creating the initial population based on solution representation approach represented in section 2.4.1.
2. Evaluating the objective function for the generated routes and assigning the best value of each iteration to T_{GB}^{j}.
3. Performing several local searches for N_1 best routes constructed based on Eq. (2.18) and replaced with the current one if they are improved. θ is the effect of aging and high growth and represents a reduction rate of power. r is generated uniformly between (0,1) to represent the process of root movement to absorb food at a rate of rT_i^j.

   $$T_i^{j+1} = \frac{T_i^j}{\theta} * rT_i^j \tag{2.18}$$

4. Selecting two closest solutions for N_2 solutions. Any of these, N_2must move towards two nearest trees at different angle α. The distance of selected trees and neighbors is calculated based on Eq. (2.19), and then Eq. (2.20) provides a linear combination of selected trees to determine the distance for movement of N_2 solutions. Eq. (2.21) is used to move selected tree with angel α toward the nearest trees.

   $$d_{\mathrm{i}} = \sqrt{\sum_{i=1}^{N_1+N_2} \left(T_{N_2}^{j} + T_i^{j}\right)^2} \qquad and \qquad d_{\mathrm{i}} = \infty \quad if \quad \left(T_{N_2}^{j} = T_i^{j}\right) \tag{2.19}$$

   $$\mathrm{y} = \lambda x_1 + (1-\lambda)x_2 \tag{2.20}$$

   $$T_{N_2}^{j+1} = T_{N_2}^{j} + \alpha y \tag{2.21}$$

5. Replacing, N_3worse solution randomly new generated solutions.
6. Creating, N_4new solution and adjust them by utilizing a mask vector considering N_1best solutions. If an element in the mask is zero, it holds the corresponding cell from new generated solution. Otherwise, the corresponding element is selected from the best solution. New populates are composed of N_1, N_2, N_3, N_4
7. Sorting all individuals based on their fitness values and selecting number initial population size of them to start the next iteration.

2. 4. 2.3. PARTICLE SWARM OPTIMIZATION ALGORITHM

PSO solves a problem by generating a population of candidate solutions, dubbed particles, and moving them around in the search space by inspiration of social behavior (Shi & Eberhart, 1998). The best position of each particle and the global best positions express cognitive behavior and social behavior, respectively. The first one is defined as the best objective function visited by each particle so far. While the second one is the position of the best objective function among all particles, which both are updated once the position of the particle is improved (Zahedi et al., 2021a). Particle velocity, which is affected by inertia which tries to exploit the direction of previous iterations to search based on the product of current velocity and inertia rate (w). The cognitive term keeps the particle returning to its best position as a product of the difference between the current position with the individual best position with a random number (u), and the personal best acceleration constant (c_1). Whereas the social term directs particles toward the global best position and is calculated based on product of the difference of the current position with the global best position by a random number (u), and global best acceleration constant (c_2) (Baños et al., 2011). The main steps of proposed algorithm are elaborated in Fig.2.8.

$$w_{\mathrm{i}}(t) = w_{\mathrm{i}}(t-1) + c_1 r_1 (Pbest_{\mathrm{i}} - x_{\mathrm{i}}(t-1)) + c_2 r_2 (Gbest_{\mathrm{i}} - x_{\mathrm{i}}(t-1)) \quad (2.22)$$

$$x_{\mathrm{i}}(t) = x_{\mathrm{i}}(t-1) + w_{\mathrm{i}}(t) \quad (2.23)$$

```
Initialize the problem with number of particles, c1, c2, maximum number of iterations,
for each particle
    initialize route with represented encoding plan, initial position, and initial velocity
end
while stopping condition is not satisfied
    for each particle
        Calculating objective function
        if objective function of particle < c1
            setting current objective value as a new c1
        End
    End
selecting particle with best objective value as c2
for each particle
    updating the velocity of each particle according to Eq.22.
    updating the position of each particle according to Eq.23.
end
```

Fig. 2.8. The Pseudocode of TS algorithm.

2.4.2.4. GAPSO ALGORITHM

Generally, meta-heuristic algorithms are categorized into two categories, single-based solutions, and population-based solutions. One solution is used in the single-based solution algorithms to find the best possible solution. Whereas a population of solutions is utilized in each iteration to search solution space to increase the likelihood of finding the optimal solution. GA is an efficient algorithm to address the real-scale problem by using genetic operators. This paper proposes the GAPSO to improve algorithm effectiveness by balancing intensification and diversification steps. Based on this, two population-based metaheuristic algorithms, PSO and GA, which, the second one inspired by the natural selection process, are proposed to be hybridized. Using the GA algorithm allows you to search multiple spaces simultaneously, and its uniqueness allows it to avoid infeasible solutions. The proposed algorithm is designed to improve the diversification phase of GA, which the crossover operator is responsible for in the general form of the algorithm. Instead of going through the crossover operator of the algorithm, PSO is utilized to generate new solutions by following the basic steps of the algorithm. The pseudo-code of the designed GAPSO is depicted in Fig. 2.9.

```
Initialization of the population for problem
Evaluation of the generated solutions
% main loop of GA
while iteration <MaxIteration
        Applying roulette wheel to perform selection
        Determining crossover population
        % main loop of PSO
         Initialize the problem with number of particles, c_1, c_2, number of iteration,
         for each particle
              initialize route, initial position and initial velocity
         end
         while stopping condition is not satisfied
                for each particle
                     Calculating objective function
                     if objective function of particle < c_1
                          setting current objective value as a new c_1
                     end
                end
          selecting particle with best objective value as c_2
          for each particle
               updating the velocity of each particle according to Eq.22.
               updating the position of each particle according to Eq.23.
          end
          creating new solutions
          performing mutation
          merging populations
          evaluating the solutions
          sorting solution based on ascending order
          update the population
          iteration=iteration1
end while
```

Fig.2. 9. The pseudo-code of the GAPSO algorithm.

2. 5. PARAMETER SETTING

This section outlines the parameter configurations employed to assess the effectiveness of the proposed metaheuristics in addressing the model. The application of the Taguchi experiment is utilized to fine-tune the algorithm parameters prior to conducting the tests [129]. Additionally, a random dataset is generated for testing purposes. Given the novelty of the proposed model, a collection of standard benchmark functions is employed to evaluate the performance of the hybrid metaheuristic algorithm (Liao et al., 2020).

2.5.1. TUNING OF ALGORITHMS PARAMETERS

The effectiveness of metaheuristic algorithms is significantly influenced by their parameter settings. In this section, the Taguchi method is employed to determine the optimal parameter values for the algorithm. This method enables the control of process quality while minimizing the number of required tests(Salehi-Amiri, Jabbarzadeh, et al., 2022). Taguchi experiments usually utilize a two-step optimization procedure. The first step utilizes the signal-to-noise (S/N) ratio in order to determine control factors for reducing variation. In the second step, control factors are determined, which move the mean to target and have a small or, in some cases, no effect on the S/N ratio. S/N ratio estimates how the response changes close to the nominal or target value under various noise circumstances. The Nominal is Best and smaller is better S/N ratios are utilized, which are calculated based on Eq. (2.24) and Eq. (2.25) (Colombaroni et al., 2020).

$$S/N_{\ Smaller\ is\ better} = -10\log\left(\sum_{i=1}^{n} Y_i^2 \,/\, n\right) \tag{2.24}$$

$$S/N_{\ Nominal\ is\ best} = -10\log(\sigma^2) \tag{2.25}$$

As reported in Table 2.6, three levels are proposed for each parameter of the algorithm, and one of them will be selected for each parameter by implementing the Taguchi approach. The orthogonal arrays suggested by Taguchi design for all proposed metaheuristics algorithms are L_{27}. The S/N ratio plots for finding optimal level is illustrated in Fig.2.10, 2.11 ,2.12, and Fig.2.13. For parameter tuning, a series of test problems with varying dimensions is utilized. To ensure comparability of the objective function across different trials, the relative percentage deviation (RPD) method is employed. This method normalizes the objective function values, allowing for a consistent scale of comparison. To calculate the RPD the objective function values in algorithm (Alg_{sol}) and the best solution for the trial (Min_{sol}) are utilized. The RPD is then computed, and the average RPD is determined for each trial. The Taguchi approach develops orthogonal arrays according to the mean signal-to-noise ratio estimated by RPD (see Eq. (2.26).

$$RPD = \frac{|Alg_{sol} - Min_{sol}|}{Min_{sol}} \tag{2.26}$$

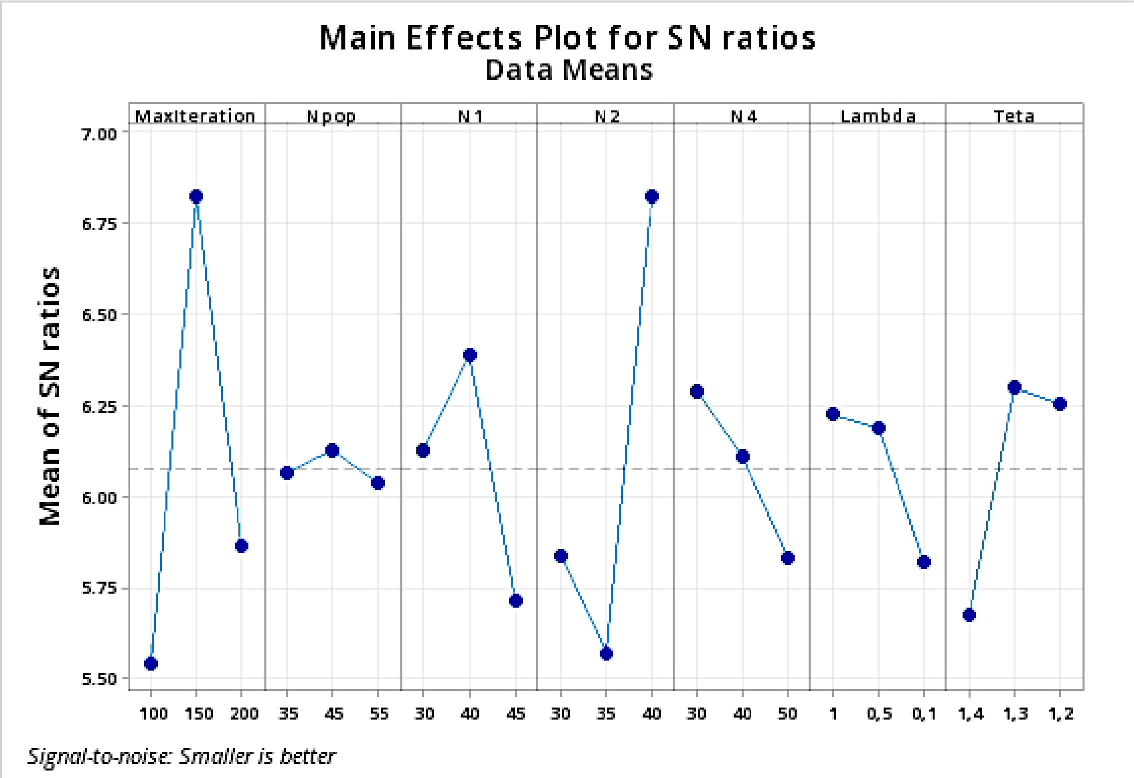


Fig.2.10. The S/N ratio plot for TGA

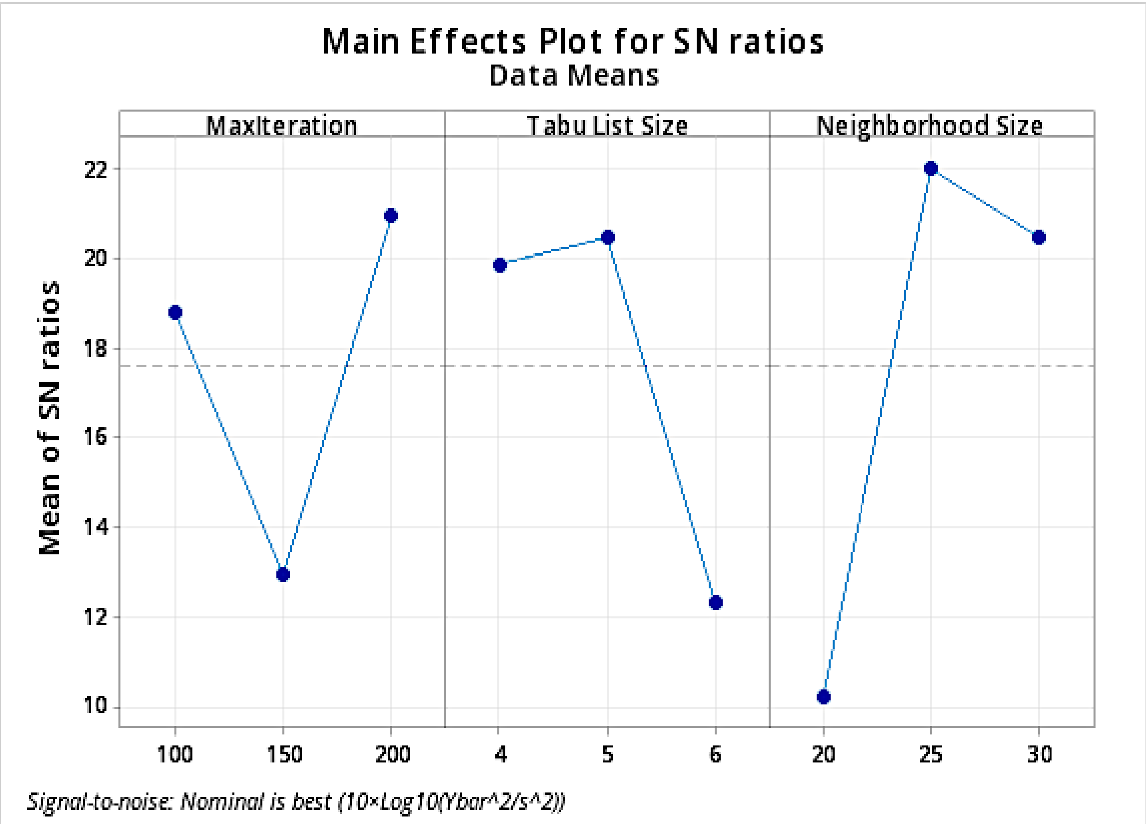


Fig.2.11. The S/N ratio plot for TS.

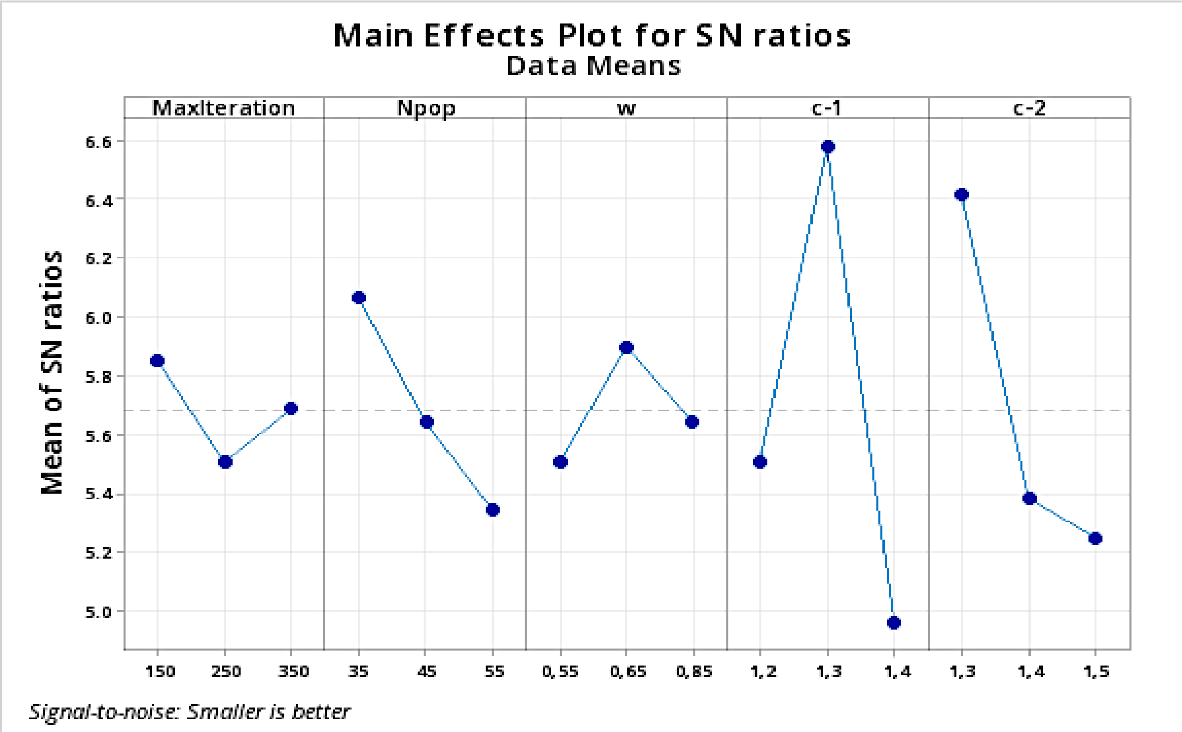


Fig.2.12. The S/N ratio plot for PSO.

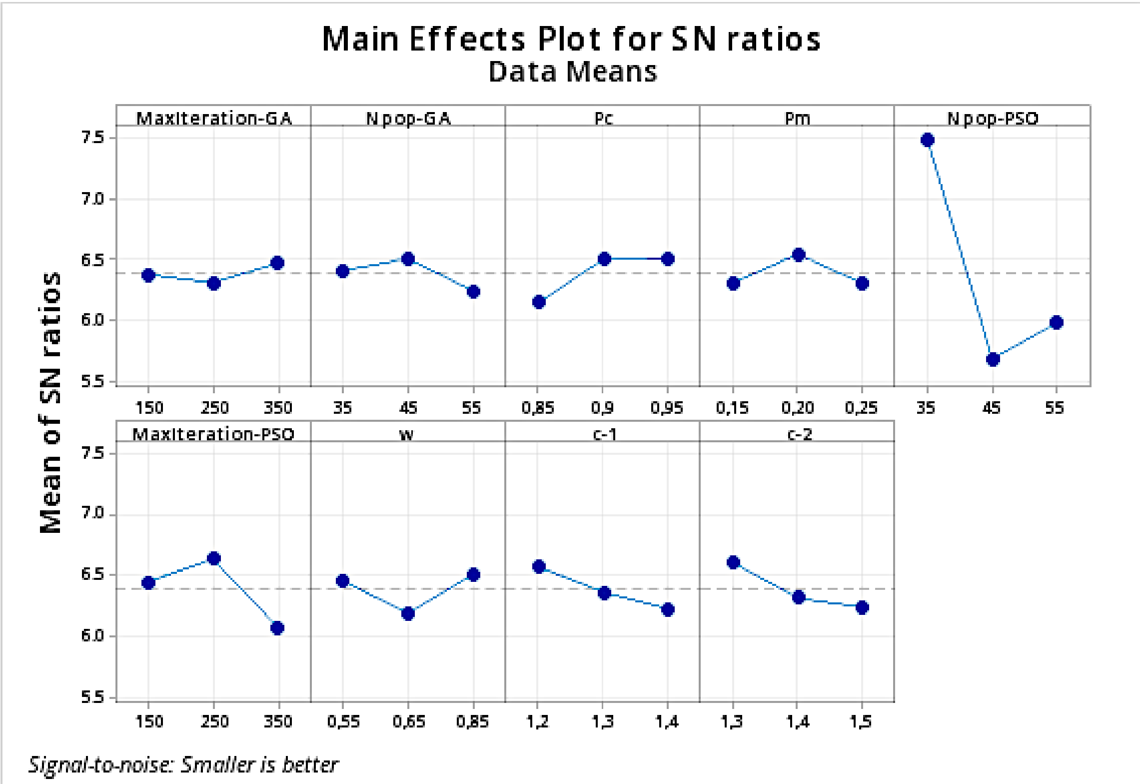


Fig.2.13. The S/N ratio plot for GAPSO.

Table.2.6. The proposed level for parameters of metaheuristics algorithm.

Algorithm	Parameters	L1	L2	L3	L*
TGA	MaxIteration	100	150	200	**100**
	Npop	35	45	55	**55**
	N1	45	40	30	**45**
	N2	40	35	30	**35**
	N4	50	40	30	**50**
	Lambda	1	0.5	0.1	**0.1**
	Teta	1.4	1.3	1.2	**1.4**
TS	MaxIteration	100	150	200	**150**
	Tabu List Size	4	5	6	**6**
	Neighborhood Size	20	25	30	**20**
PSO	MaxIteration	150	250	350	**250**
	Npop	35	45	55	**55**
	w	0.55	0.65	0.85	**0.55**
	c1	1.2	1.3	1.4	**1.4**
	c2	1.3	1.4	1.5	**1.5**
GAPSO	MaxIteration-GA	150	250	350	**250**
	Npop-GA	35	45	55	**55**
	Pc	0.85	0.9	0.95	**0,85**
	Pm	0.15	0.20	0.25	**0.15**
	MaxIteration-PSO	150	250	350	**350**
	Npop-PSO	35	45	55	**45**
	w	0.55	0.65	0.85	**0.65**
	c-1	1.2	1.3	1.4	**1.4**
	c-2	1.3	1.4	1.5	**1.5**

2.5.2. MODEL PARAMETERS

The efficiency of the designed algorithms is evaluated by obtaining results for a diverse range of problem sizes, allowing for an investigation of their performance across different settings. Table 2.7 depicts the different classes of the test cases by the number of bins and number of trucks to have problems under various conditions. The coordination of the different problems is shown in Table 2.8. As stated, each test instance is represented by several bins and a number of trucks. Uniform distribution is utilized to generate coordinates (x_i,y_i) of bins within [0,200] and [0,100] for x and y, respectively. Then the distance between all nodes is calculated based on Euclidean distance. However, another main feature of each test is the capacity of the truck per problem and the number of required trucks to ensure the feasibility of the test.

The weight of pickup load at each bin for each type is generated randomly between 50 and 150 kilograms, and the capacity of each compartment of the trucks is generated within [$\frac{total\ generated\ waste}{number\ of\ trucks}$, 1.5*[$\frac{total\ generated\ waste}{number\ of\ trucks}$] using a uniform distribution which must be between 1000 and 2000 kilograms. Hence, a test can be generated in which all vehicles must be loaded near to their capacity, or fifty percentage bigger supply can be provided in comparison with total demand. The test beds are generated by assuming to have only two types of waste including wet waste and dry waste and consequently two compartments for the trucks.

Travel time associated with each link for each truck is calculated based on distance divided by the average speed of the corresponding truck. The average speed of each truck which is expressed in meters per second generated uniformly from [8.5, $\frac{18000}{Capacity\ of\ each\ truck}$] to ensure lower speed for larger capacity trucks. The biggest value for capacity results in 9 meters per second as the maximum possible value for average speed, while 18 meters per second is the maximum value of average speed for low-capacity trucks. According to the approach presented by (Solomon, 1987), [ST_i, FT_i]= [CEN_i-0.5TW_i, CEN_i+0.5TW_i] is utilized to assign time window to each node. CEN_i and TW_i are generated uniformly [0, max ($\frac{d_{ij}}{average\ speed_l}$)*$\frac{N}{2}$] and [2,10], respectively. Idle time to perform unloading tasks for each visited bin is depended on the amount of waste in that bin. It is specified linearly between 3 and 7 minutes based on [$\frac{weight\ of\ waste\ in\ bin - minimum\ weight\ amon\ all\ bins}{maximum\ weight\ amon\ all\ bins - minimum\ weight\ amon\ all\ bins}$*(7-3)+3].

Table.2.7.
Problem classification.

Classification	Instance	Problem size (*I*, *K*, *S*)
Small	SP1	(10,2,6)
	SP2	(15,2,6)
	SP3	(20,2,6)
	SP4	(25,3,6)
	SP5	(30,3,6)
Medium	SP6	(40,4,6)
	SP7	(55,4,10)
	SP8	(70,5,10)
	SP9	(85,5,10)
	SP10	(100,6,10)
Large	SP11	(120,10)
	SP12	(140,7,12)
	SP13	(160,8,12)
	SP14	(180,8,12)
	SP15	(200,9,12)

Table.2.8.
The values of the implemented parameters.

Parameter	**Values**	**Unit**
FC_k	Uniform ~ [15,25] ×10^6	Dollar ($)
PCO_k	Uniform ~ [10,15]	Dollar ($)
ST_i	Uniform ~ [480,840] (real Time)	Minute
FT_i	Uniform ~ [480,840] (real Time) and > ST_i	Minute
ql_i	~ [1,2,3]	-
hw_i	~ [1,2,3]	-

Moreover, in this study, to address the proposed model in DVRP, a new hybrid metaheuristic GAPSO is presented. To evaluate the performance of GAPSO and other selected metaheuristics in this paper, we utilized a different benchmark function which is presented by (Plevris & Solorzano, 2022). Plevris and Solorzano presented a series of 30 mathematical benchmark functions in multiple dimensions that can be employed for the optimization problem. These benchmark functions are utilized for unconstrained multi-dimensional single-objective optimization problems. We analyze the performance of GAPSO algorithms and other three metaheuristic algorithms, namely TGA, TS, and TS, by using Sphere in the bowl-Shaped group, Ackley and Drop-Wave in the benchmark group of Many Local Minima, Zakharov in the Plate-Shaped group, and Rosenbrock in Valley-Shaped group. The applied benchmark functions are listed in Table 2.9.

The implementations of all used benchmarks are run in MATLAB, focusing on objective functions. The selected metaheuristics are run thirty times based on the proposed parameter level reported in Table 2.6. Four dimensions of benchmark function, D= [5, 10, 15, 20], are supposed to have an extensive evaluation on a different problem scale per metaheuristic. The benchmark average objective function and standard deviation results are reported in Tables 2.10 to Table 2.13.

Table.2.9.
Benchmark Functions.

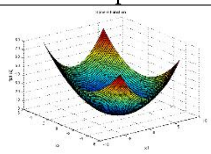
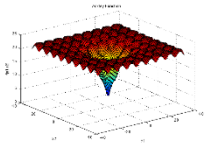
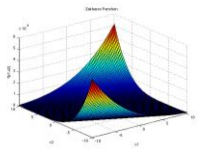
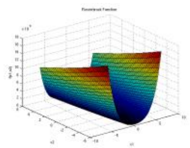
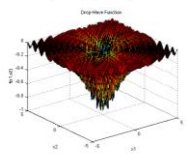
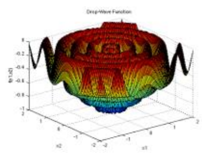
Function Name	Type	Equation	Shape
Sphere	Bowl-Shaped	$f(\mathbf{x}) = \sum_{i=1}^{d} x_i^2$	
Ackley	Many Local Minima	$f(\mathbf{x}) = -a \exp\left(-b\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(\frac{1}{d}\sum_{i=1}^{d}\cos(cx_i)\right) + a + \exp(1)$	
Zakharov	Plate-Shaped	$f(\mathbf{x}) = \sum_{i=1}^{d} x_i^2 + \left(\sum_{i=1}^{d} 0.5ix_i\right)^2 + \left(\sum_{i=1}^{d} 0.5ix_i\right)^4$	
Rosenbrock	Valley-Shaped	$f(\mathbf{x}) = \sum_{i=1}^{d-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	
Drop-Wave	Many Local Minima	$f(\mathbf{x}) = -\frac{1+\cos\left(12\sqrt{x_1^2+x_2^2}\right)}{0.5(x_1^2+x_2^2)+2}$	 

Table.2.10.
The result of metaheuristic algorithms for benchmark problem with dimension d=5.

	Average of Objective Function				Standard Deviation of Objective Function			
Function name	**TS**	**PSO**	**TGA**	**GAPSO**	**TS**	**PSO**	**TGA**	**GAPSO**
Sphere	2.469E-30	2.077E-27	**1.143E-36**	1.441E-27	9.409E-30	4.354E-27	2.552E-36	**1.175E-27**
Ackley	2.961E-15	7.816E-15	3.553E-15	**2.487E-14**	3.856E-15	**1.162E-14**	2.512E-15	5.024E-15
Zakharov	6.85E-30	2.828E-26	8.743E-31	**1.652E-29**	2.02E-29	2.547E-26	1.501E-30	**1.382E-29**
Rosenbrock	**0.000653**	0.3865344	0.9497473	2.253E-21	0.0015649	0.1057249	0.4286826	2.084E-21
Drop-Wave	**0**	0.0637547	0.0637547	**0**	**0**	8.882E-11	3.965E-10	**0**

Table.11.
The result of metaheuristic algorithms for benchmark problem with dimension d=10.

	Average of Objective Function				Standard Deviation of Objective Function			
Function_name	**TS**	**PSO**	**TGA**	**GAPSO**	**TS**	**PSO**	**TGA**	**GAPSO**
Sphere	6.60E-30	**1.80E-14**	1.92E-19	9.59E-23	1.508E-29	3.678E-14	2.486E-19	2.745E-23
Ackley	3.671E-15	9.021E-09	**2.133E-10**	2.521E-12	6.629E-15	**1.117E-08**	2.473E-10	6.557E-13
Zakharov	7.444E-27	3.064E-08	**1.309E-13**	4.282E-24	2.493E-26	2.878E-08	**2.066E-13**	3.48E-26
Rosenbrock	**0.0019116**	3.0838732	5.7460856	2.983E-17	**0.0019912**	2.37501	0.3330723	4.117E-17
Drop-Wave	**0**	0.0637547	0.0637547	0.0637547	**0**	8.005E-10	1.183E-10	**0**

Table.12.
The result of metaheuristic algorithms for benchmark problem with dimension d=15.

	Average of Objective Function				Standard Deviation of Objective Function			
Function_name	**TS**	**PSO**	**TGA**	**GAPSO**	**TS**	**PSO**	**TGA**	**GAPSO**
Sphere	5.678E-29	**2.066E-09**	5.167E-13	8.377E-19	7.333E-28	4.799E-06	6.363E-13	**1.004E-19**
Ackley	4.5E-15	8.928E-06	**1.301E-07**	3.412E-10	**1.257E-14**	9.929E-05	6.821E-08	1.592E-11
Zakharov	4.505E-24	**0.0275848**	3.76E-08	5.72E-20	1.615E-23	**0.0159078**	4.339E-08	3.41E-20
Rosenbrock	**0.0021985**	11.651609	11.274488	2.517E-07	0.0028655	0.957937	**0.5163775**	3.557E-07
Drop-Wave	**0**	0.0637547	0.0938535	0.0637547	**0**	3.879E-09	0.067303	**0**

Table.13.
The result of metaheuristic algorithms for benchmark problem with dimension d=20.

	Average of Objective Function				Standard Deviation of Objective Function			
Function_name	**TS**	**PSO**	**TGA**	**GAPSO**	**TS**	**PSO**	**TGA**	**GAPSO**
Sphere	1.747E-28	5.632E-06	1.99E-10	**1.196E-15**	7.333E-28	2.909E-09	**1.245E-10**	1.471E-16
Ackley	4.974E-15	0.0003054	3.46E-06	**1.175E-08**	**1.257E-14**	2.881E-06	9.826E-07	2.268E-09
Zakharov	9.753E-23	14.138764	4.403E-05	**2.434E-16**	3.111E-22	8.8648564	**2.995E-05**	5.338E-17
Rosenbrock	0.004422	16.609178	16.503618	**0.0007223**	**0.0065851**	0.3394418	0.4837657	0.0009188
Drop-Wave	**0**	0.0952966	0.1540511	0.0637547	**0**	0.0665499	0.082429	**0**

2.6. COMPUTATIONAL RESULTS

In this section, the performance of the proposed algorithms is assessed by evaluating their applicability and efficiency. The algorithms are first optimized by determining the best parameters for them. Test problems of varying dimensions are generated to assess the algorithms' performance. For small-scale problems, the best solution is obtained using an exact method, while for large-scale problems, the best solution attained by all algorithms serves as the benchmark for comparison. To ensure reliability, each test problem is solved thirty times by each algorithm due to the stochastic nature of metaheuristic algorithms. General Algebraic Modeling System software (GAMS) is employed to solve the generated test problems in small size. The evaluation criteria include the objective function (OF), hitting time (HT), computational time (CT), and the average computational time per iteration (MCT), all of which are reported for each problem.

2.6.1. COMPARISON OF PROPOSED ALGORITHMS

In this section, the outcome of this paper is presented by carrying out a comprehensive comparison to check the quality of each algorithm. Four performance indicators, including OF, HT, CT, and MCT, are extracted to make a comparison among algorithms. In addition, two nonparametric statistical tests are applied because of the stochastic nature of metaheuristic algorithms. Hence, using nonparametric statistical tests are inevitable to have a precise analysis of solutions which are reached by different algorithms. Firstly, a nonparametric statistical test that can perform pairwise comparisons is proposed to investigate if the two algorithms are significantly different from each other. Then, a statistical test is applied to compare multiple algorithms together and rank them. We conduct the Wilcoxon signed-rank test in our study that is one of the appreciated pairwise nonparametric tests. The Friedman test is applied to have a multiple comparison test.

The result of all indicators, which are the mean of thirty trails for metaheuristic algorithms, for each test problem is reported in Table 2.14. The CT is the computational time of running each algorithm, while the first time that the algorithm obtains the final solution obtains the final solution in each run is reported as an HT indicator, and in Table 11, the mean value of them is reported. Moreover, each algorithm's average of MCT is reported to determine the running time for each iteration. The CT is divided by the tuned number of iterations for each algorithm. Moreover, the solution and corresponding computational time obtained by Gams are also reported for the first six test problems. However, because of the complexity of the problem under study, running time increases dramatically as the dimension of the problem increases. Because of that, the program for solving test problem SP6 by the exact method is stopped manually by the user after 150 minutes.

To compare test problems of differing scales more effectively, we have computed the mean relative percentage deviation (RPD) of objective functions for each individual problem. This data is visually presented in Fig 2.14 to facilitate a comprehensive comparative analysis. As displayed in Fig 2.14, it becomes evident that the discrepancy intensifies as the dimensionality of the problems escalates. The GAPSO algorithm has demonstrated the least amount of variation, outperforming the other tested algorithms in this regard. This minimal deviation signifies a high degree of accuracy and reliability, indicating GAPSO's superiority in these testing scenarios. When considering problems of larger dimensions, a distinct trend is observed. The PSO, a population-based method, achieved a lower deviation from the optimal solution in comparison to the TGA algorithm, which adheres to a single-based methodology. This finding reveals the PSO's increased proficiency in addressing complex, high-dimensional challenges. On inspecting the results for smaller-scale problems, TS and PSO algorithms yielded remarkably similar outcomes. However, as the dimensionality of the test problems amplified, PSO demonstrated a lower deviation and neared the optimal solution more closely than TS. Thus, PSO shows remarkable adaptability and robustness, delivering superior results even as the complexity and scale of the problem set increases.

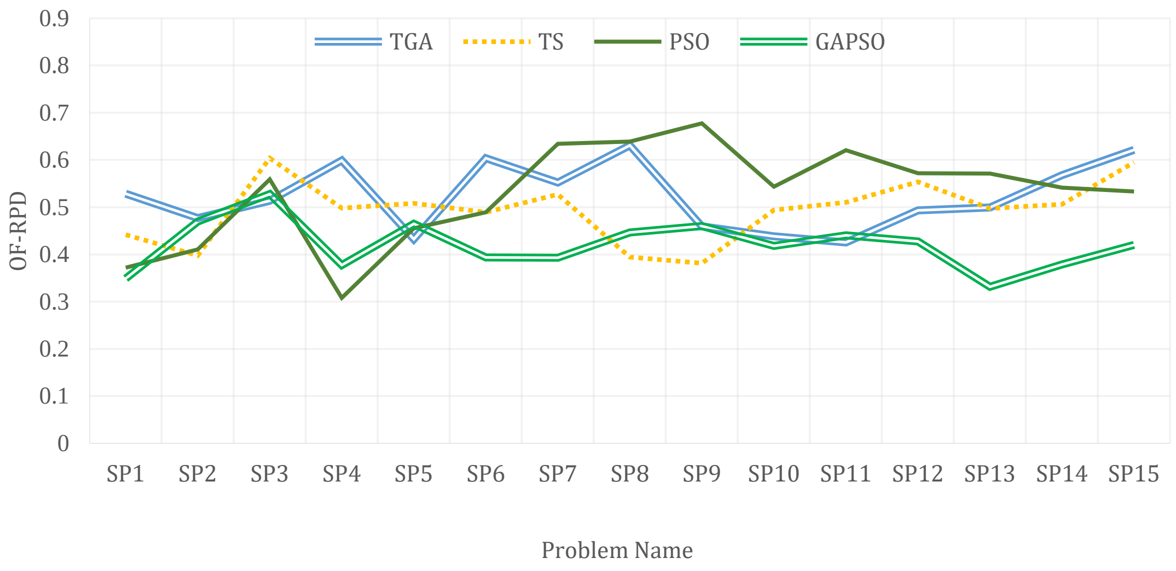


Fig. 2.14. The comparison of algorithms behavior concerning RPD of Objective Function.

To provide a more in-depth analysis, interval plots for the mean objective function of each test problem are presented in Fig 2.15, 2.16, and 2.17. Moreover, to provide a comprehensive comparison, the RPD of the mean objective function has been calculated for all test problems, with the resulting interval plot shown in Fig2.18. Upon examination of these figures, it becomes evident that the GAPSO and TS algorithm exhibit similar intervals, however GAPSO algorithm has a smaller mean. When considering the overall performance, TS, GAPSO, and PSO show comparable effectiveness, all of which outperform the TGA. Nevertheless, it is important to note that for large-scale problems, TGA and PSO yield nearly identical mean values of the objective functions. In general, GAPSO algorithm has the best performance both in terms of the mean values and the discrepancy. This emphasizes GAPSO's strength in navigating complex, large-scale problems while maintaining accuracy and minimizing deviation from the optimal solution. It substantiates GAPSO's effectiveness as a robust algorithm capable of maintaining high performance across a range of testing scenarios.

Table.2. 14.

Evaluation metrics value of metaheuristic algorithm.

Test Problem		TGA	TS	PSO	GAPSO	GAMS
1	OF	614.68	459.24	402.24	419.19	322.66
	HT	2.32	0.00	0.41	4.79	-
	CT	10.04	2.98	3.94	15.88	96.70
	MCT	0.05	0.02	0.02	0.04	-
2	OF	838.48	477.67	500.94	652.15	503.65
	HT	3.60	0.17	0.97	7.26	-
	CT	13.33	3.50	5.39	21.26	5001.67
	MCT	0.06	0.03	0.02	0.06	-
3	OF	975.35	664.83	545.84	989.17	389.09
	HT	5.12	0.85	1.23	9.74	-
	CT	17.69	4.33	6.69	27.58	7329.82
	MCT	0.08	0.04	0.02	0.07	-
4	OF	1090.15	704.77	712.01	1021.27	403.27
	HT	6.93	1.21	2.32	11.76	-
	CT	21.66	6.46	9.85	34.51	8057.22
	MCT	0.10	0.06	0.03	0.09	-
5	OF	1347.73	855.84	885.53	1197.54	599.70
	HT	8.80	1.76	2.76	12.37	-
	CT	25.96	7.80	8.46	39.24	8684.18
	MCT	0.12	0.08	0.04	0.11	-
6	OF	1738.86	905.86	1115.50	1739.51	605.88
	HT	10.74	1.80	3.11	16.31	-
	CT	31.14	8.15	11.07	45.45	**9000***
	MCT	0.15	0.07	0.04	0.12	-
7	OF	2419.94	1221.62	1380.84	2405.17	805.41
	HT	12.01	2.63	3.20	17.53	-
	CT	35.63	8.65	13.04	54.17	-
	MCT	0.17	0.08	0.05	0.14	-
8	OF	3194.06	2075.03	1977.03	3322.23	-
	HT	14.00	2.72	4.69	23.51	-
	CT	41.97	10.45	15.41	63.07	-
	MCT	0.19	0.10	0.06	0.17	-
9	OF	3763.68	2996.37	2535.35	3887.93	-
	HT	15.58	3.43	5.30	22.42	-
	CT	48.64	11.79	17.74	73.89	-
	MCT	0.22	0.11	0.07	0.20	-
10	OF	4614.55	3731.93	3806.25	4496.68	-
	HT	17.93	4.26	6.39	24.79	-
	CT	55.21	13.65	19.96	80.07	-
	MCT	0.26	0.13	0.07	0.22	-
11	OF	5798.04	3992.46	4052.08	6040.24	-
	HT	20.61	4.87	7.96	33.53	-
	CT	65.95	15.53	23.65	98.60	-
	MCT	0.30	0.15	0.09	0.27	-
12	OF	6817.05	3505.28	5373.88	7224.20	-
	HT	23.40	5.62	9.15	39.12	-
	CT	74.07	17.73	26.81	108.55	-
	MCT	0.35	0.17	0.10	0.29	-
13	OF	7745.97	3905.28	5408.20	7922.17	-
	HT	29.84	7.02	10.06	37.90	-
	CT	80.54	19.71	29.82	120.13	-
	MCT	0.36	0.18	0.11	0.32	-
14	OF	9283.07	4265.17	6855.34	9222.01	-
	HT	29.44	7.38	10.45	45.90	-
	CT	92.29	21.65	33.31	135.12	-
	MCT	0.43	0.20	0.13	0.35	-
15	OF	9984.79	5402.25	7997.23	1139.54	-
	HT	36.75	7.65	12.99	55.19	-
	CT	103.46	24.31	37.28	152.05	-
	MCT	0.49	0.23	0.14	0.40	-

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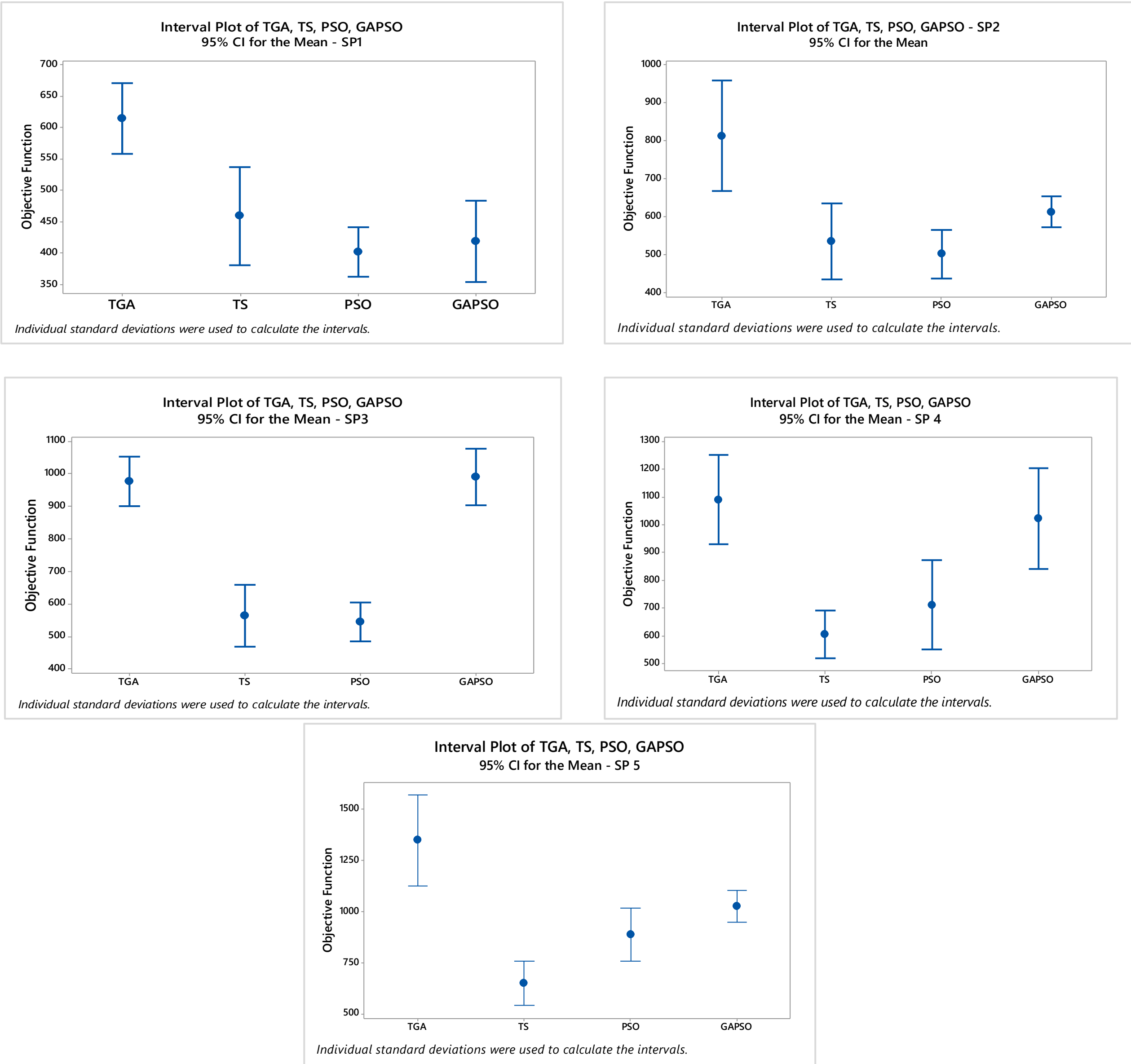


Fig. 2.15. Interval Plot of all selected algorithms for small-size test problem.

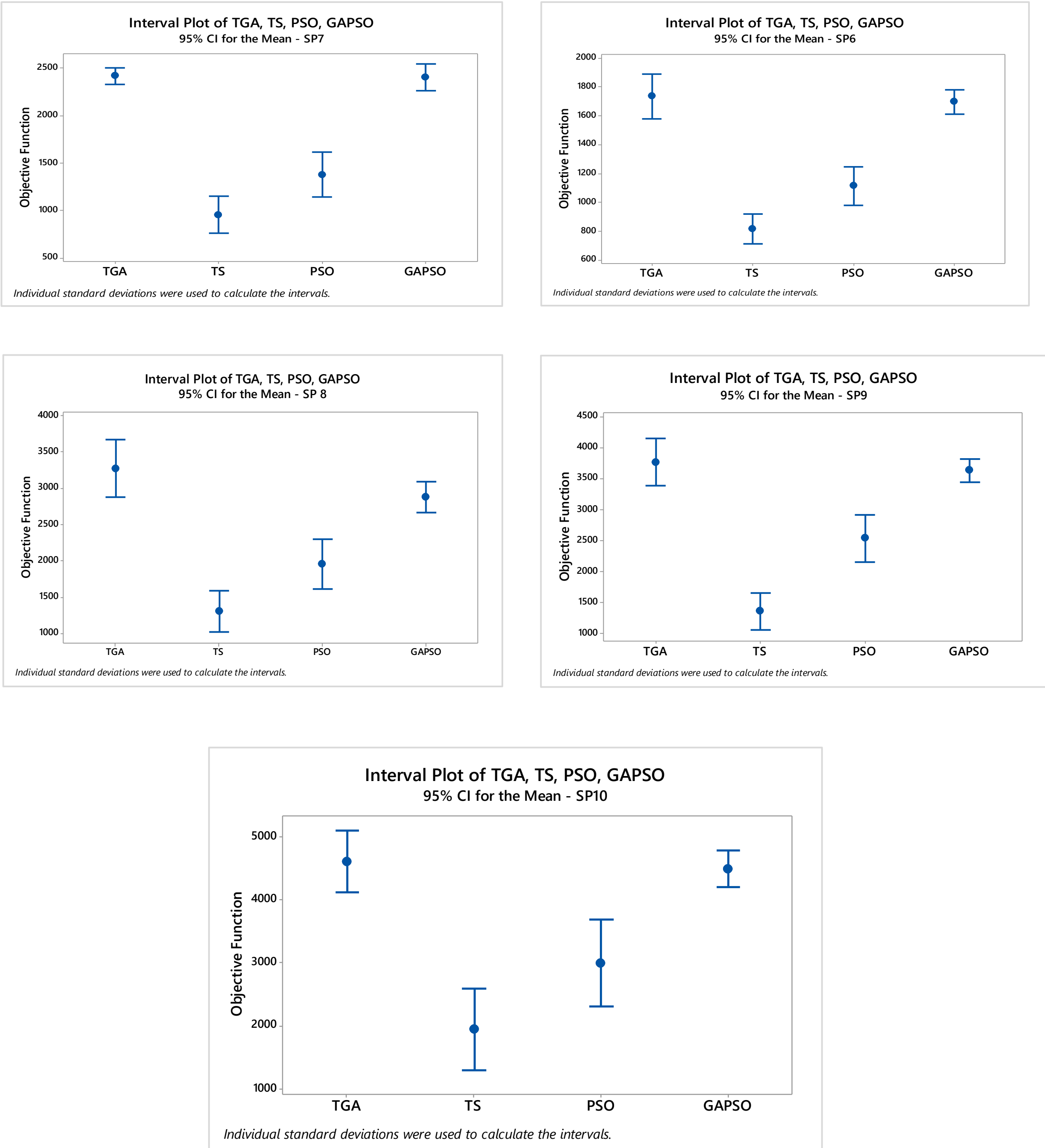


Fig. 16. Interval Plot of all selected algorithms for medium-size test problem.

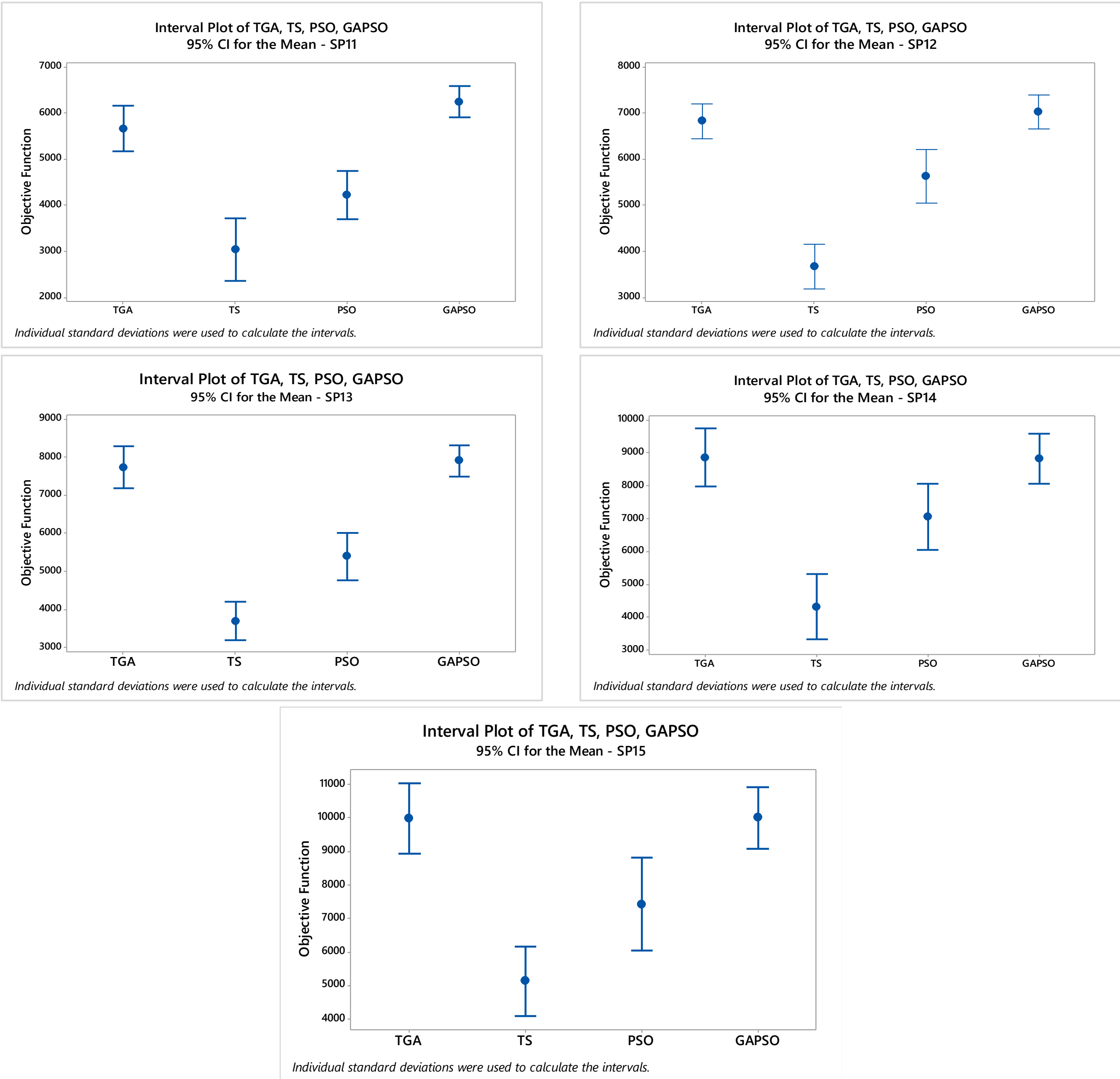


Fig. 2.17. Interval Plot of all selected algorithms for large-size test problem.

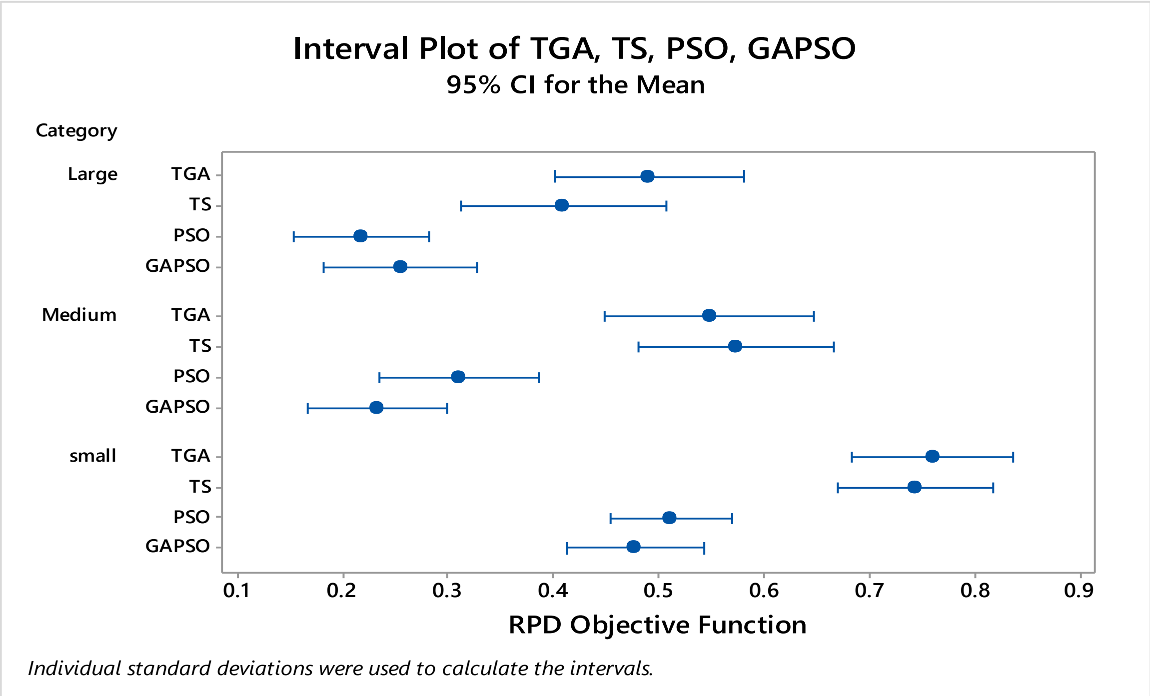


Fig. 2.18. Interval Plot of all selected algorithms for all tests.

Another critical metric to consider is the hitting time, a measure that designates the precise moment or iteration at which the optimal solution is first achieved, and no further improvements can be made in subsequent iterations. Fig 2.19 provides a visual representation of the of the hitting time. As the problem's dimensionality increases, so does its complexity, subsequently leading to a rise in the hitting time. GAPSO algorithm has the highest RPD-HT, whereas TS has a lower value of RPD-HT. The hitting time and optimized objective values (best-found solution) and value of the objective function for a non-optimized solution are reported in Fig. 2.20. The benefits of the proposed framework have been shown in Fig. 2.20. by making a comparison of the objective values obtained by algorithms and a base solution which the optimization process is not involved. The right vertical axis represents the scale for non-optimization involved solution, and the left one presents the axis for optimized objective values. While the height of the bar chart is based on their objective values. The objective value for the non-optimization involved test is shown by a line chart as the worst solution in hand to compare the performance of the algorithm. The CT of the algorithms is illustrated in Fig.2. 21 for TS, TGA, PSO, and GA-PSO by the range of time. The TS reached the lowest CT in terms of time, while the PSO has the best solution in an extended time.

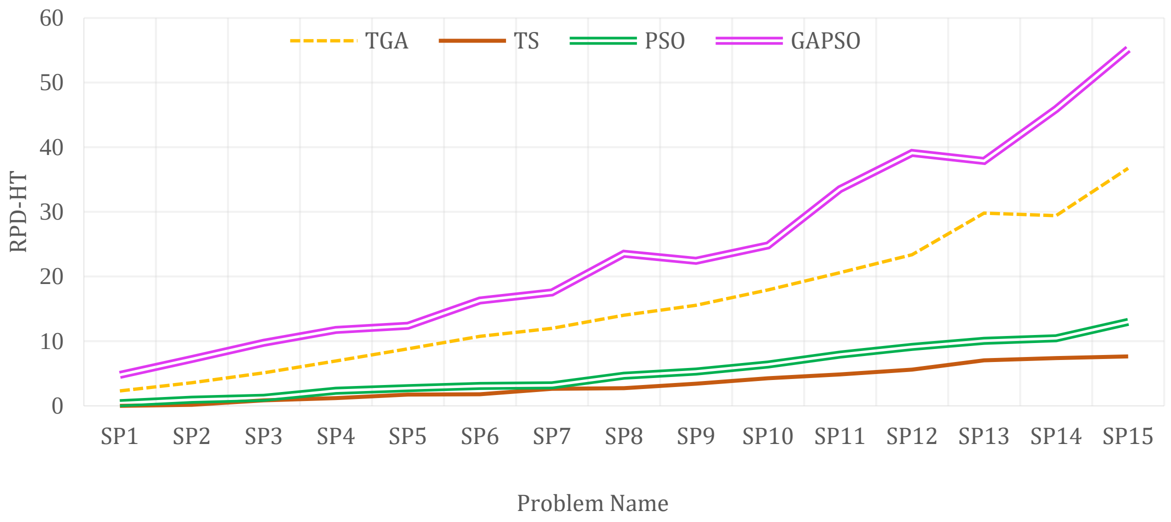
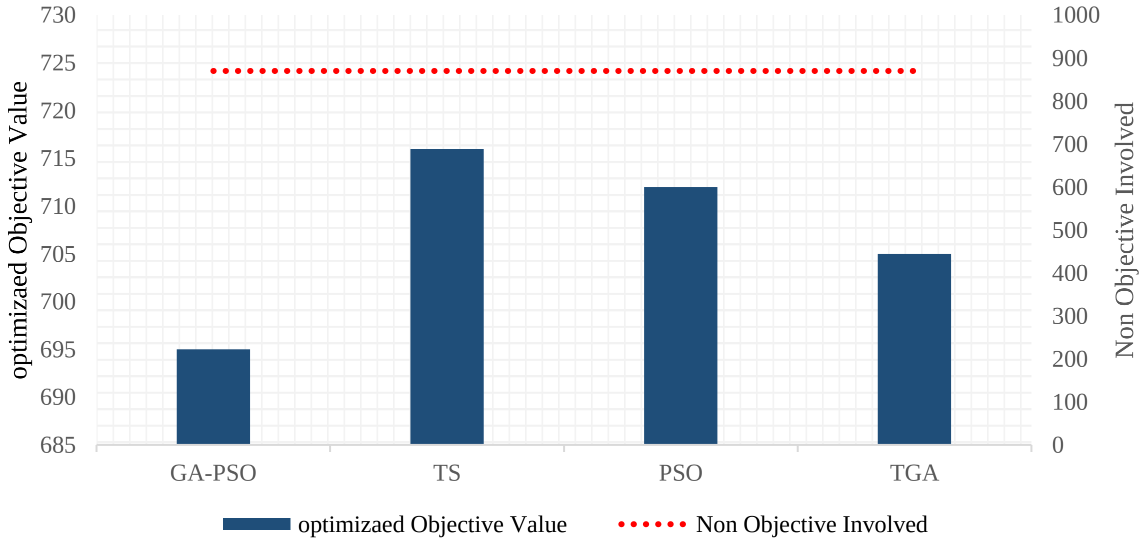


Fig. 2.19. The comparison of algorithms behavior concerning RPD of HT.



	GAPSO	TS	PSO	TGA
Hitting Time	785	498	568	628
Objective Function	695	716	712	705

Fig. 2.20. Hitting Time and Objective Function of the model.

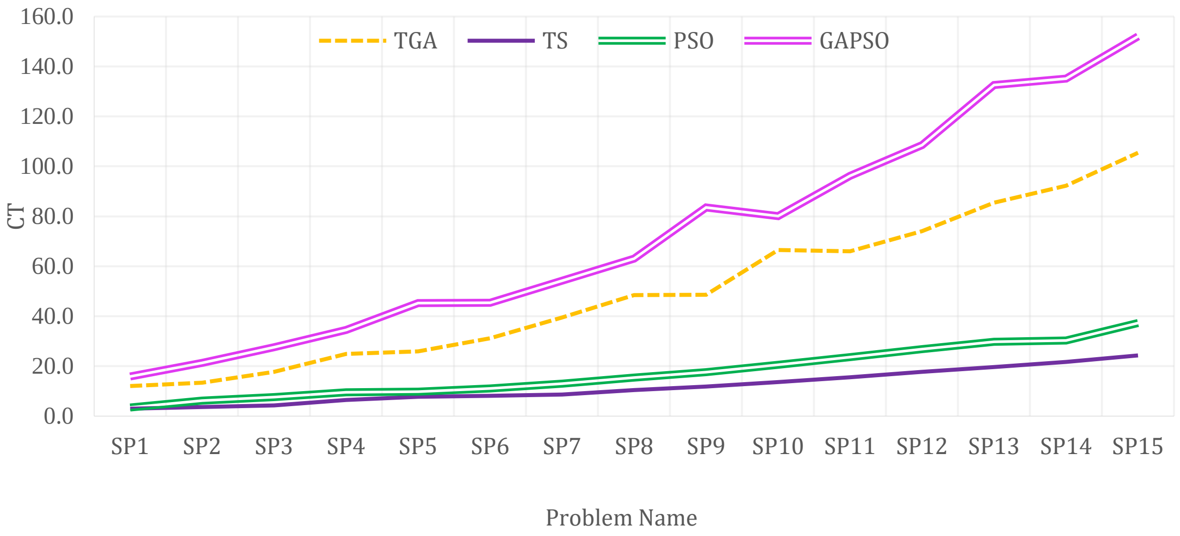


Fig. 2.21. The comparison of algorithms behavior concerning RPD of CT.

As it investigated, solutions of proposed metaheuristics algorithms are very similar to each other based on different criteria. Hence, different statistical tests are applied to have more precise comparisons among them. Wilcoxon signed-rank test and Friedman test are utilized as the pairwise comparison and multiple comparison tests, respectively. The definition of required terms and elements to perform mentioned statistical tests are provided in Table 2.15. Before making a comparison by the mentioned tests, we convert all the performance values to the Relative Deviation Index (RDI) by applying Eq. (2.23). RDI is a statistical analysis that makes it possible to find the standard deviation of algorithms for each problem by converting the results into a reliable metric to have another indicator for comparison. The objective values (Alg_{sol}), the maximum objective value among all trails (Max_{sol}) and the best solution of algorithms among all trails (Min_{sol}) are used to calculate the RDI (see Eq.2.27).

$$RDI = \frac{|Alg_{sol} - Min_{sol}|}{Max_{sol} - Min_{sol}} \tag{2.27}$$

Table.2.15.
Definition of statistical test terms.

Term	Definition
Null hypothesis (H_0)	States that there is no significant difference between the two metaheuristics.
Alternative hypothesis (H_1)	States that there are significant differences between the two metaheuristics.
Statistical significance level (α)	The probability of mistakenly rejecting H_0. For P-value, less than α H_0 is rejected.

So, it is important to mention that the null hypothesis in our statistical tests represents that two investigated algorithms are significantly similar, and if the P-value of a test to compare two alternatives is lower than 0.05 means that the null hypothesis is rejected. In other words, it will be approved that the two metaheuristics are significantly different from each other. To do so, Wilcoxon signed ranked test is applied for the RDI value of objective functions for all pairs of alternatives. The results and P-value of these comparisons are summarized in Table 16. The results are obtained by running the tests with a statistical significance level (α) of 0.05 using SPSS software. Although we have some values near to α, P-values are still less than the significance level (α) of 0.05 for different categories of problems which implies that all algorithms are not significantly similar to each other. Another statistical test is required to make multiple comparisons for ranking proposed algorithms.

Table.2.16.
Wilcoxon signed the ranked test according to OF values for all test problems.

Comparison	**P-value (Wilcoxon test)**		
	SMALL	**MEDIUM**	**LARGE**
TGA versus TS	0.025	0.019	0.028
TGA versus PSO	0.022	0.021	0.048
TGA versus GAPSO	0.033	0.028	0.038
TS versus PSO	0.038	0.048	0.026
TS versus GAPSO	0.046	0.045	0.047
PSO versus GAPSO	0.023	0.047	0.034

The Friedman test, as multiple statistical comparisons, is applied using SPSS software for each category of test problems with a statistical significance level of 0.05. Tables 2.17, 2.18, and Table 2.19 elaborate the results of the Friedman test, which is carried out based on RDI of objective values and CT. The P-values of all tests are less than 0.05, and GAPSO is the first rank for small and large size problems, while TS has the first rank for medium size problems. However, in terms of CT, TS shows the best performance for all categories of generated test problems. Although different tools are utilized to compare the proposed algorithms from different points of view, we could not select the best one by considering all indicators together. Because of representing various behavior according to different indicators, utilizing multi-criteria decision-making methods (MCDM) is inevitable to have a clear comparison and select one algorithm. MCDM makes it possible to have an integrated approach to compare algorithms by considering different indicators simultaneously.

This paper applies the BWM to choose the most suitable option from a group by taking into account various factors (Rezaei, 2015). In this research, the group of alternatives consists of algorithms and the criteria are composed of RPD, RDI, and hitting time. The BWM is a comparative method used for evaluating the importance of different criteria and alternatives. In contrast to other methods that necessitate exhaustive comparisons among all criteria, the primary benefit of this technique is that it requires less information for pairwise comparisons, as these are conducted in an organized way. This implies that instead of comparing all the criteria to ascertain their relative importance, the comparison is only done between the best and worst criteria. Following this, a linear mathematical model is employed to determine the value of the criteria, which is accomplished by maximizing the coherence of the comparisons (Gholian-Jouybari et al., 2022). The output of the mathematical model of BWM is the weights of criteria, and GA-PSO is selected as the best algorithm considering all criteria by weighted sum.

Table.2.17.
The result of the Friedman test for small-size problems.

SMALL				
Metaheuristic	RDI-Objective Function	Rank (RDI-OF)	CT	Rank CT
TGA	4	4	2.8	3
TS	2.1	2	**1.6**	**1**
PSO	2.8	3	1.8	2
GAPSO	**1.1**	**1**	3.8	4
P-value	0.003		0.026	

Table.2.18.
The result of the Friedman test for medium-size problems.

MEDIUM				
Metaheuristic	RDI-Objective Function	Rank (RDI-OF)	CT	Rank CT
TGA	4.00	4	3.00	3
TS	**1.93**	**1**	**1.00**	**1**
PSO	2.16	3	2.00	2
GAPSO	2.03	2	4.00	4
P-value	0.029		0.002	

Table.2. 19.
The result of the Friedman test for large-size problems.

LARGE				
Metaheuristic	RDI-Objective Function	Rank (RDI-OF)	CT	Rank CT
TGA	3.2	3	3.03	3
TS	1.7	2	**1.46**	**1**
PSO	3.6	4	2.00	2
GAPSO	**1.6**	**1**	3.90	4
P-value	0.019		0.002	

As well as the three groups of test problems, a test with 220 bins and seven trucks is solved by both a static approach and a dynamic framework to demonstrate the advantages of the proposed approach in this paper. To this end, the initial plan for the vehicles is found without the re-routing at the sequential decision epochs, named the base plan. The route of one truck for the base plan and dynamic plan is investigated in Fig. 2.22 and Fig. 2.23, respectively. Each figure is composed of two parts which the road network is visualized in the right while the left just considers the sub-zoning system. The sub-zones 1000126, 1000131, and 1000147 are close to city centers and expected that the travel time of links within these regions would be more affected by traffic conditions during peak hours. As seen in Fig. 2.10, the route is constructed without considering the time the trucks arrive at the mentioned sub-zone near the city center.

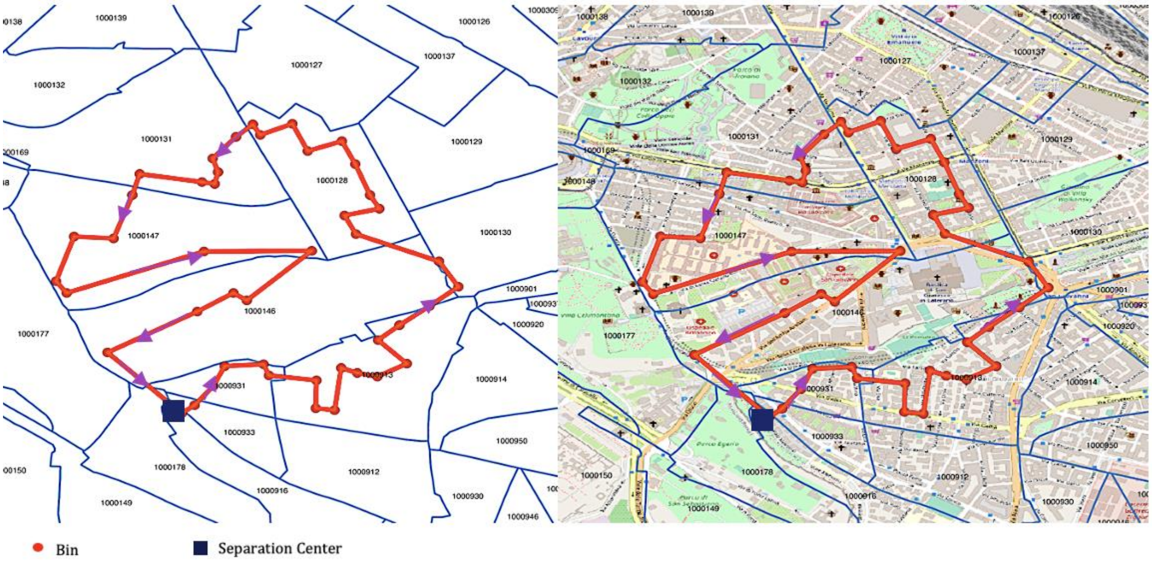


Fig.2. 22. The route of the truck is based on a static approach.
Depot (rectangle), customers (solid red circle).
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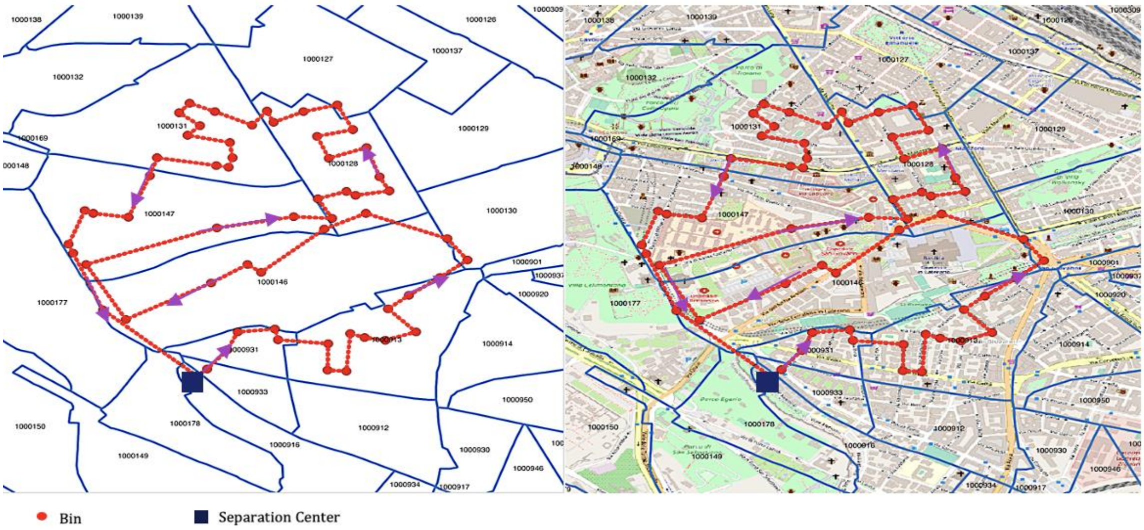

Fig. 23. The route of the truck is based on a dynamic approach.
Depot (rectangle), customers (solid red circle).
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The dynamic framework, however, takes into account the changes in the road network and the waste generation rate to modify the constructed initial routes. Because of performing the service for the last bin in the sub-zone 1000130 around the peak hour, the route is changed to carry out the collection services for other sub-zones and finally sends the truck to the ones near the city center. As a result of postponing waste collection in mentioned sub-zones, TWL has exceeded in more bins. Therefore, the route is changed to improve responsiveness by considering the remaining available capacity to satisfy this constraint.

Moreover, the proposed methodology is validated through a comprehensive case study conducted in an urban area. Real-time data on waste generation rates, travel times, and other parameters of the model are collected from the study area to ensure the realism and accuracy of the test case. The performance of the dynamic routing approach by comparing it to traditional waste collection methods and the effect of considering multi-compartment trucks are evaluated in the case study. Different elements of the designed objective function are used to assess the effectiveness of the proposed methodology, including transportation costs, carbon dioxide emissions, and the number of used vehicles. Waste collection problem is solved considering different combinations of vehicle types (single compartment vs. multi-compartment) and routing strategies (static approach vs. dynamic routing).

The key components of the proposed approach can provide a comprehensive perspective to compare all the combinations. For example, referring to Table 2.20, it can be observed that the implementation of the proposed dynamic routing, considering hourly travel time functions and real-time waste level information to apply DCM, led to a reduction in the number of routes to collect all the generated waste. This reduction resulted in significant cost savings in terms of transportation expenses and a notable decrease in carbon dioxide emissions. Furthermore, the performance of single-compartment vehicles in comparison to multi-compartment vehicles is evaluated to demonstrate its advantages. The results showed that using multi-compartment vehicles enabled the consolidation of different waste types during transportation which results in further cost reductions and a more environmentally friendly waste management process.

Table.2.20.
Comparison of Transportation Costs, Carbon Dioxide Emissions, and Vehicle Deployment.

Method	Total Cost ($)	CO2 (kg)	Vehicles (N)	Reduction (%)*
Static routing with single compartment	61854	68	12	--
Dynamic routing with single compartment	42342	50	9	-32%
Static routing with multi-compartment	49765	59	10	-20%
Dynamic routing with multi-compartment	36139	43	7	-42%

* Compared to Static Approach with Single-Compartment Vehicles

The obtained results showed clear distinctions among the different combinations that in the first case by having static approach for routing with only single-compartment vehicles yielded a total cost of 61854, CO2 emissions of 68, and required 12 vehicles. This combination is used as the baseline for further comparison. The application of dynamic routing in base case demonstrated improvements by reducing total cost 42342. The dynamic approach could reach 32% reduction in objective function compared to the static approach to do routing. While adding multi-compartment vehicles to based case results in the reduction of total cost by 20%, applying both dynamic routing approach and multi-compartment vehicles demonstrated the most significant improvements across all objective functions. It achieved the lowest total cost of 36139, the lowest CO2 emissions of 43, and required the fewest vehicles. The reductions compared to the static approach with single-compartment vehicles were 42%. These results clearly indicate that the dynamic routing approach, particularly when it is combined with multi-compartment vehicles, offers substantial benefits. Accordingly, two obtained dynamic routes for multi-compartment vehicles are illustrated in Fig. 2.24. It results in total transportation cost reduction, carbon footprint reduction, and vehicle deployment optimization.

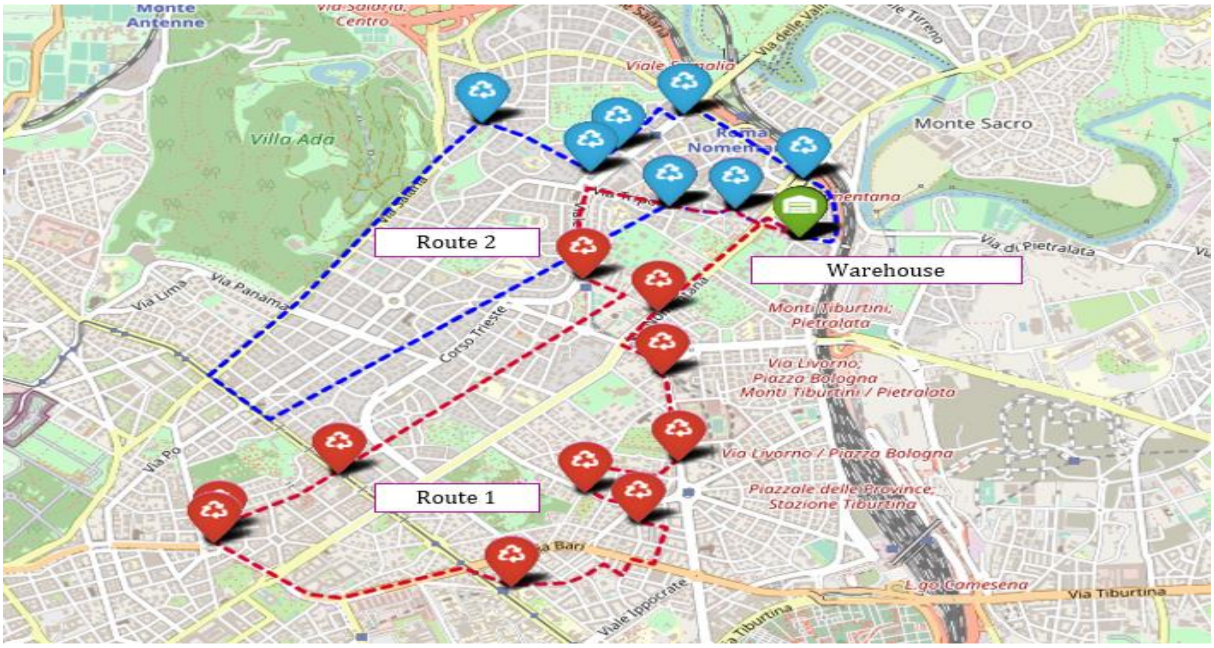


Fig. 24. The obtained route of trucks based on a dynamic approach for multi-compartment vehicle. ©OpenStreetMap contributors—www.openstreetmap.org/copyright.

2.7. CONCLUSION

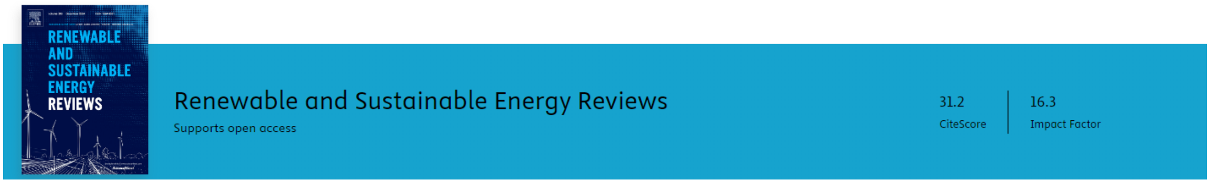
The waste management process consists of several stages, with the collection phase playing a pivotal role due to its interaction with society. Given that a significant portion of waste management costs is typically incurred for collecting phase, its optimization can meet the expectations of various stakeholders. One of the challenges in waste management revolves around determining the optimal timing for visiting each bin to avoid unnecessary trips to empty or overloaded bins. To address this challenge, an efficient and dynamic approach is proposed in this study, aiming to minimize transportation costs and environmental impact by optimizing the collection of garbage across the study area and its subsequent transfer to separation centers. The time windows associated with individual bins are adjusted by integration of an IoT technology for the identification of the threshold waste level (TWL) for each bin. The proposed dynamic approach minimizes transportation costs and environmental impact by optimizing the waste collection and its subsequent transfer to separation centers. This approach becomes even more effective by considering the multi-compartment vehicles, which allow for the simultaneous collection of different waste types while maintaining their segregation during transportation.

A time window capacitated multi-compartment dynamic vehicle routing problem is formulated to minimize transportation costs and CO2 emissions. The initial routes can be adjusted by considering changes in travel time or waste generation rate by calling re-optimization process. A time-dependent travel time function and the use of IoT devices are proposed to specify the decision epoch for re-optimization. The proposed approach divides zones into sub-zones based on local characteristics of the road network and waste generation levels, allowing for efficient re-routing after visiting the last bin in each sub-zone. This practical method, supported by an application of DCM, considers transportation costs and waste quantity to select the next sub-zone. According to the implemented conducted tests the proposed dynamic approach demonstrated the total cost reduction by 32%, a significant improvement. Additionally, incorporating multi-compartment vehicles further reduces total cost by 20%. The combination of both dynamic routing, and multi-compartment vehicles, yielded the most substantial improvements, cutting costs by 42% which clearly highlight the potential benefits of the proposed approach.

Furthermore, the effectiveness of various algorithms can differ depending on specific performance metrics. However, our evaluation, which takes multiple criteria into account, designates the GA-PSO algorithm as the most superior solution. In terms of algorithm performance for addressing the models, it is worth noting that each algorithm may showcase its strengths according to different performance measures. Consequently, the algorithms are ranked using the BWM technique to consider all criteria simultaneously, and the analysis reveals that the GA-PSO algorithm exhibits the highest level of performance. Nonetheless, a key drawback of this technique is the requirement for precise data regarding model parameters, such as the waste fraction in each bin and the estimation of travel time for each road link during specific time intervals. The availability and accuracy of this data can significantly impact the precision and reliability of the proposed model.

Obtaining precise travel time data can be challenging and may introduce uncertainties in the optimization process. Future research could focus on improving data collection methods to address these limitations and further enhance the effectiveness of the waste management optimization framework. To conclude, the main insight for future research is that considering the application of artificial intelligence for routing problems in the context of smart cities to consider a huge amount of data in decision making that are vital in WM system such as technical information, climatic data, environmental, demographic, socio-economic, and legislative parameters. Further inquiry might look into expanding mathematical models to include multi-depot vehicle routing problems, which would permit the sharing of trucks between depots to foster collaboration, if it leads to a reduction in the objective function.

The result is published in Renewable and Sustainable Energy Reviews Journal.



A dynamic approach for the multi-compartment vehicle routing problem in waste management 28 2023
M Mohammadi, G Rahmanifar, M Hajiaghaei-Keshteli, G Fusco, ...
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Date: 28/09/2024

CHAPTER 3

PAPER 2:

An Allocation-Routing Optimization Model for Integrated Solid Waste Management

Integrated smart waste management (ISWM) is an innovative and technologically advanced approach to managing and collecting waste. It is based on the Internet of Things (IoT) technology, a network of interconnected devices that communicate and exchange data. The data collected from IoT devices helps municipalities to optimize their waste management operations. They can use the information to schedule waste collections more efficiently and plan their routes accordingly. In this study, we consider an ISWM framework for the collection, recycling, and recovery steps to improve the performance of the waste system. Since ISWM typically involves the collaboration of various stakeholders and is affected by different sources of uncertainty, a novel multi-objective model is proposed to maximize the probabilistic profit of the network while minimizing the total travel time and transportation costs. In the proposed model, the chance-constrained programming approach is applied to deal with the profit uncertainty gained from waste recycling and recovery activities. Furthermore, some of the most proficient multi-objective meta-heuristic algorithms are applied to address the complexity of the problem. For optimal adjustment of parameter values, the Taguchi parameter design method is utilized to improve the performance of the proposed optimization algorithm. Finally, the most reliable algorithm is determined based on the Best Worst Method (BWM).

Keywords: Waste Management System; Vehicle Routing Problem; Waste to Energy; Best Worst Method; Meta-Heuristic.

3.1. INTRODUCTION

The growing waste generation problem creates severe environmental, economic, and social impacts and because of the fast-increasing rate of the world's population, urbanization, and economic growth, it is expected to have a quick increase in the amount of waste generated worldwide, particularly in urban areas (Akbarpour et al. 2021). Fig 3. 1 indicates an anticipated increase in global waste generation in the next few decades by 2050. The increasing rate of waste is concerning mainly in developing countries, where the infrastructure of waste management systems (WMS) is often insufficient or non-existent, leading to widespread dumping and littering. The cost of waste management is high, particularly in urban areas with dense populations. The improper disposal of waste can also impact property values and the quality of life in affected communities (Tirkolaee et al., 2022). To address the inefficiencies in waste management efforts should focus on reducing waste at the source, promoting recycling and reuse, and developing better waste management infrastructure.

The ISWM is a promising solution for improving the efficiency and effectiveness of waste management (WM) as well as promoting sustainability and reducing costs. The ISWM is a comprehensive approach to managing solid waste that considers the entire waste stream from generation to final disposal. The primary objective of ISWM is to minimize the impact of waste on human health and the environment while maximizing resource efficiency and sustainability (Tsai et al., 2020). This involves a combination of strategies, including source reduction, reuse, recycling, composting, waste-to-energy conversion, and landfilling. ISWM typically involves the collaboration of various stakeholders, such as government agencies, private sector entities, and the public sector to design and implement a waste management system that is economically, socially, and environmentally sustainable.

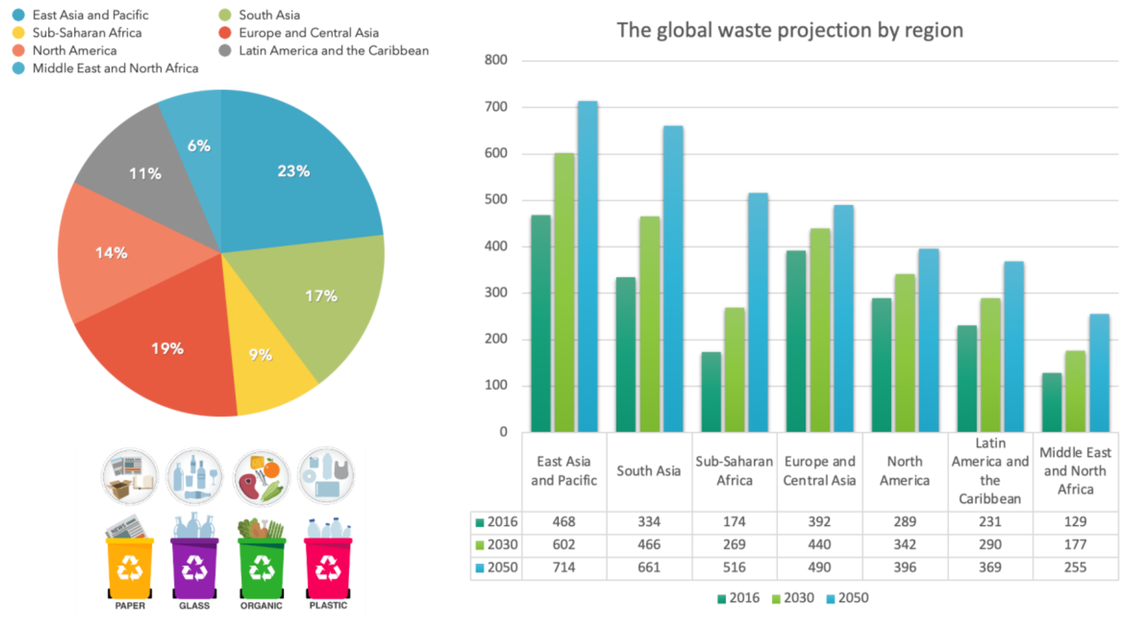

Fig.3.1. The estimation and share of global waste production by region for the years 2016, 2030, and 2050. Source(s): World Bank; ID 233613 (Statista website).

The ISWM offers several benefits for cities, such as the ability to enhance the system's performance and decrease the expenses associated with WM operations. One of the primary advantages of ISWM is the optimization of the waste collection routes using data collected from sensors and other IoT devices, which reduces fuel consumption, time, and costs(Lotfi et al., 2022; Zahedi et al., 2021b). Additionally, a smart WM framework gives this chance for real-time monitoring of waste bins and containers to enable WM firms to swiftly address overflowing or faulty bins. By using smart bins equipped with sensors and cameras, waste can be sorted and separated more effectively, which results in an improved recycling rate and the quantity of waste in landfills. Furthermore, smart waste management can help decrease littering by offering real-time information about the cleanliness of public areas, which can be used to target specific areas for cleaning. Finally, smart waste management can improve environmental sustainability by decreasing waste directed to landfills and increasing the recycling rate(Cheraghalipour et al., 2017).

Generally, waste management encompasses several operations, including the collection and transportation, processing and sorting, recycling, and disposal of waste materials generated by human activity (Abdel-Shafy & Mansour, 2018; Tsai et al., 2020). Among all these steps, collection and transportation activities account for a significant part of the waste management expenses in terms of financial and environmental aspects. In managing solid waste, a major proportion of costs (60 to 80%) is attributed to collection and transportation operations. Therefore, collection and transportation operations play a critical role in enhancing the waste system and urban service management. The importance of an optimal waste collection system cannot be overemphasized due to the necessity for the efficient collection and transportation of waste materials from waste generation locations to disposal sites. Thus, making appropriate waste collection policy decisions can significantly reduce expenses and improve sustainability in the waste system (Tirkolaee et al., 2018).

This study proposed an ISWM optimization model, which is developed based on the following principal contributions:

- Designing an ISWM network for collection, recycling, and recovery of solid waste materials without regionalization of the smart city, which potentially enables the municipality or contractors to collect a waste container in every corner of the city.
- Introducing a solid waste management system for multiple types of wastes and considering a heterogeneous fleet VRP to improve the efficiency and profitability of the recycling and energy recovery activities.
- The processing plants might be served by multiple vehicles from different separation centers. Studying the uncertainty of profits comes from recycling or energy recovery processes.
- Most studies in this field assumed that a particular group of waste has a certain amount of profit or added value which is not a realistic assumption.
- Furthermore, this study contributes to integrating the allocation and routing problems for all levels of the network. Although solving a sub-model for each level of the network can reduce the problem's complexity and provide the optimal routing solution at that level, developing an integrated multi-level model enables the decision-makers to find the optimal VRP decisions between all elements of the network simultaneously.

3.2 Literature review

The local authorities and city administrations have been under pressure to design and implement an efficient system to address different aspects of WM, including transportation and collection of the waste, separating them, treatment, and disposal of waste because of challenging issues of the waste management system (Chand Malav et al., 2020). Different strategies including reducing generated waste, reusing, efficient recycling, disposal, and recovery have been implemented in ISWM. The ISWM provides a comprehensive view to reducing waste, collecting the generated waste, transporting them efficiently with minimum negative impact, and composting, recycling, and disposal system by minimizing negative impacts on the environment and society.

The WM is considered a system composed of interconnected operations and functions by ISWM to provide a holistic approach to address various problems in transportation, processing, recycling, resource and energy recovery, and disposal technologies (McDougall et al. 2008). However, transportation and logistics operations contribute a significant share of the total cost in the WM system (Peng et al., 2023). Hence, the vehicle routing problem (VRP) has received considerable attention to reducing the cost contributing to this step of the waste management system (Rahmanifar et al., 2023b). For example, Mojtahedi et al. (2021) developed a heterogeneous VRP for solid waste management regarding economic, environmental, and social objectives. Liu and Liao (2021) proposed a two-step collaborative waste collection problem by considering optimization in the cost of waste collection and improving sustainable urban development. In another study, Sahib and Hadi (2021) proposed an efficient optimization model for the collection of solid waste to optimize the waste collection cost and time. The proposed collection schedule chose the most efficient path for the collection of waste, resulting in saving electricity and cutting down on working hours and fuel consumption.

Another interesting work refers to Hajar, Btissam, and Mohamed (2018), which focuses on hospital waste for determining optimal routes from the generation point to the storage location, aiming to reduce the overall trip length and disinfection time of vehicles. Given the nature of this problem, it is a special case of VRP with a time window (VRPTW). However, due to having several special characteristics, such as managing vehicle departure times and route sequencing, it is more complicated than the general form of VRPTW. In addition, this problem is a multi-trip VRP, where such transportation is provided by a set of vehicles that travel multiple routes during each shift.

Furthermore, Ghannadpour, Zandieh, and Esmaeili (2021) studied the healthcare waste collection problem considering social, economic, and environmental objectives, aiming to achieve sustainable development. The proposed model defines the economic objective to minimize fixed and variable transportation costs. In this problem, a novel definition of risk in medical waste collection is defined to improve the social objective by reducing waste collection time. In addition, the authors provided a detailed assessment of vehicle fuel consumption that can be decreased by an optimization model and consequently reduce the environmental risks.

However, it is important to mention that two challenges play a key role in designing and implementing an optimal framework to deal with the problems in ISWM. First is that the decision-making process in waste management should involve various objectives which are not coordinated, such as environmental, energy-related objectives, and economic performance indicators. But considering these objectives is necessary to take practical steps toward solving real-world problems while there is a trade-off relationship between these three conflicted dimensions. Mathematical programming can provide a good foundation for achieving stakeholders' consensus in a transparent and scientific way by finding several options and selecting the optimal one (Chen et al. 2022). The multi-objective optimization (MOO) methods have recently gained attention to address the problems of waste management. For example, Ooi, Woon, and Hashim (2021) developed a multi-objective model to optimize an MSW network considering economic and environmental objectives.

Meanwhile, Lin, Ooi, and Woon (2021) presented an integrated life cycle multi-objective model developed for the food waste sector. Ecosystems, Human health, and economic impacts are optimized in the proposed model. In another work, Pourreza Movahed et al. (2020) studied the optimization of the life cycle assessment of integrated waste management using the genetic algorithm to optimize energy consumption and CO2 emission. Rossit, Toutouh, and Nesmachnow (2020) presented an exact multi-objective approach to find the optimal location of bins to increase the efficiency of the reverse logistic system. The author determined the location of bins by considering the accessibility, the fixed cost, and the frequency of visiting a bin for unloading to reduce future routing costs by proposing an exact algorithm as well as a set of heuristic-based approaches. A set of single and multi-objective heuristics were developed by Toutouh, Rossit, and Nesmachnow (2020) to optimize the location of garbage in smart cities to improve accessibility and reduce the fixed cost along with maximizing the coverage of the citizens by installed facilities. In the same field, Mahéo, Rossit, and Kilby (2022) proposed an integrated multi-objective approach to solving two tactical problems in waste management composed of finding the location of the garbage and the route optimizing for unloading the located bins by decomposition-based approach.

The static routing methodologies determine the tours of vehicles to satisfy the demand and implement the routes within the road network, while the uncertainty of information implies updating the decision over time. Hence, it is vital to consider different sources of uncertainties, such as the environment, demand, and resources that are not perfectly known in advance and can strongly affect the optimization problem to develop an efficient and applicable integrated waste management framework in real-world problems. Therefore, the optimization models must consider various uncertain parameters such as travel time, waste generating rate, disposal facility output, treatment cost, and stochastic customers. Different formulation and solution approaches have been explored, including stochastic programming, robust optimization, chance-constrained programming, data forecast, and machine learning-assisted algorithms to address these uncertainties in modeling and in the case of incomplete data. (Hashemi-Amiri, Ghorbani, et al., 2023a; Savku & Weber, 2018; Weber et al., 2009).

The VRP has been modeled with the stochastic programming method in which a specific probability distribution function describes the uncertain parameters of the model(Weber et al., 2013). Neuro-Dynamic Programming, referred to as reinforcement learning in the literature of artificial intelligence, has been utilized to solve the stochastic VRP by the value and policy-function approximation method (Bertsimas et al., 2011; J. Zhang et al., 2023). Although the probability distributions function to describe the unknown parameters must be known in stochastic programming, robust optimization requires the known range for uncertain parameters while the probability distribution function can be unknown(Kara et al., 2019; Khalilpourazari et al., 2019; Özmen et al., 2016). While another approach that has been explored by different research to handle the uncertainty is the chance-constraint programming method. The distinguishing feature of this method is that it satisfies the constraints of the problem to some degree which is different from stochastic programming and robust optimization. in the VRP, the demand of customers is satisfied by each vehicle with a certain (Babaee Tirkolaee et al., 2020a, 2020b; Midya et al., 2021; Tirkolaee et al., 2021). Moreover, machine learning algorithms are employed as a predictive model to predict the problem's parameters which impose uncertainty in different types of the subject(Çevik et al., 2017; Eligüzel et al., 2022; Kilic et al., 2014). Because considering them as deterministic parameters is an over-simplification of the real-world problem(Zantalis et al., 2019).

However, having historical data for uncertain parameters enables decision-makers to probe different approaches. The IoT devices can collect and store massive amounts of data to carry out advanced analysis to capture the uncertainty of the problem (Mosallanezhad, Gholian-Jouybari, et al., 2023). For instance, in addressing the uncertainty of the construction and demolition waste collection problem, Yazdani et al. (2021) developed a novel sim-heuristic-based solution approach by integrating the simulation with a meta-heuristic algorithm. In this solution approach, which belongs to the field of simulation optimization, the simulation considers the related uncertainty of the problem and the meta-heuristic algorithm searches for the near-optimal solution. This method solved the routing problem of transferring construction waste from different projects to recycling facilities by reducing the travel and operational cost under uncertainty. In another related work, Mamashli et al. (2021) concentrated on developing a sustainable–resilient waste management system under hybrid uncertainty by employing a fuzzy robust stochastic optimization model.

Moreover, Asefi et al. (2019) developed a tri-echelon ISWM network considering the uncertainty of waste generation rate. This study proposed a mixed-integer linear programming (MILP) model to formulate the VRPTW, aiming to optimize the logistics network and transportation system. The authors applied a stochastic optimization approach in two steps to optimize the cost of transportation, fleet size, vehicle routes, and capacity allocation. Then the proposed solution method was implemented for a real-world case study in Tehran to verify the effectiveness in reducing the cost of waste collection.

On the other hand, the newly developed technologies, and IoT devices in smart cities are effective tools for managing uncertainties in the MSW. In smart cities, the obtained real-time data from cloud-based IoT devices are employed to assist managers in making better decisions and dealing with the uncertain nature of the problem. The application of tools and technologies that provide real-time data in the infrastructure of cities can significantly reduce related costs, and it is very helpful for achieving sustainable goals such as improving energy distribution, traffic congestion, and air quality to streamlining trash collection (Xiaoyi et al., 2021).

In terms of the importance of IoT technologies in WM, we can point to (Jatinkumar Shah et al. 2018), which focused on addressing the uncertain value of collected waste in a smart city and which can be caused by uncertain conditions and quality of waste materials. The goal of the optimization model is to improve the total transportation costs and the recovery value of collected waste, considering the operational costs, energy consumption, and pollution emissions. Later, Akbarpour et al. (2021) developed a stochastic routing model to optimize waste collection and recovery value operations in smart cities using IoT devices. This research aimed to improve the efficiency of routing and recovery operations considering the uncertain output value of waste in separation centers. To improve this work, Salehi-Amiri et al. (2022) proposed a new multi-objective waste management model to optimize the waste collection decisions, recovery value of waste, and visual pollution in the waste system.

In this section, the literature of previous studies is reviewed to demonstrate the importance of this problem. Most of the works mentioned above are considered the primary strategies to waste management systems. Some studies developed a model to focus on a single-echelon network or examined separately different levels of a multi-level network that could significantly affect the performance of the system in an interconnected network. For instance, in a multi-echelon network, solving the routing problem for each level individually can only obtain the best routing decisions in that level of the network; however, in an integrated MSW network, the decisions of a level might overshadow the optimality of the decisions in other levels. Thus, focusing on a specific level of a network without examining the impact of other-level decisions might not provide an optimal global solution for the problem under study. Although several optimization models have been presented for the MSW system, a very limited number of papers have addressed the resource allocation and routing problems without considering simplifying assumptions. For example, it is not very realistic to divide the smart city or urban area into separate regions and determine the optimal allocation and vehicle routing decisions. Furthermore, little attention has been paid to energy recovery, which is one of the most efficient and robust alternatives for landfilling and traditional incineration. Energy recovery from waste materials enhances the circular economy approach and reduces the harmful environmental impact and natural resource consumption by converting non-recyclable waste materials into electricity, heat, and fuel.

3.3 PROBLEM STATEMENT

Due to the rapid growth of solid waste generation in cities and municipalities, one of the most fundamental elements in the MSW system is the waste collection activity which directly affects the environmental health and visual aspects of urban areas. Likewise, recycling and recovery activities play a key role in conserving natural resources and reducing the waste volume at disposal centers, consequently improving our environment and community. Because of the great importance of these operations, this study develops an integrated waste collection, recycling, and recovery network. The general structure of a closed-loop waste system is shown in Fig 3. 2.

Fig.3.2. The structure of a closed-loop waste system.

In the proposed waste network, each residential area possesses several smart waste disposal bins which are designed for various municipal solid wastes. Each waste bin is equipped with various IoT technologies, such as weight sensors, RFID tags, and GPS, to help decision-makers keep track of waste level information constantly. Mainly, smart sensors enable municipalities or contractors to check the status of the waste handling equipment and determine the optimal policies based on real-time data on the weight, volume, content, or other characteristics of waste bins. This study assumed that the waste management organization utilizes only the weight sensor to monitor the waste levels of bins and considers this information once the integrated mathematical model optimizes the problem in a certain or short period.

The solid waste generated across the city must be collected by separation centers in a predefined time window. To handle the waste collection in the smart city, each separation unit has a set of heterogeneous low-capacity vehicles with different capacities, which can transfer different types of waste directly to the collection center. In the separation center, the collected waste materials are segregated into different categories on a daily basis based on the type and condition of the waste. Each separation center also has a set of heterogeneous high-capacity vehicles to transfer sorted materials to the processing centers. However, there is a capacity limitation for recycling/recovering a specific group of waste in a processing plant, which can potentially limit the amount of waste that can be transferred to the processing plant. The recycling centers purchase a recyclable portion of the waste materials that come in different types. In addition, the non-recyclable solid waste materials will be sold to waste-to-energy (WtE) facilities to produce energy in different forms.

In this optimization problem, the optimal set of low- and high-capacity vehicles in a separation center is determined based on the amount of waste allocated to that center, as well as the available capacity of vehicles. At the end of the planning horizon, some recyclable and non-recyclable waste materials may remain in the separation centers due to the limited capacity of processing plants, which will be transferred to landfills or disposal centers. Finally, recycled or recovered products can be provided to the end customers or other industries that reproduce solid waste at the starting point of the network. The proposed MSW network in this study is schematically represented in Fig3.3. In the next section, the assumptions of the waste management problem under study are presented in detail.

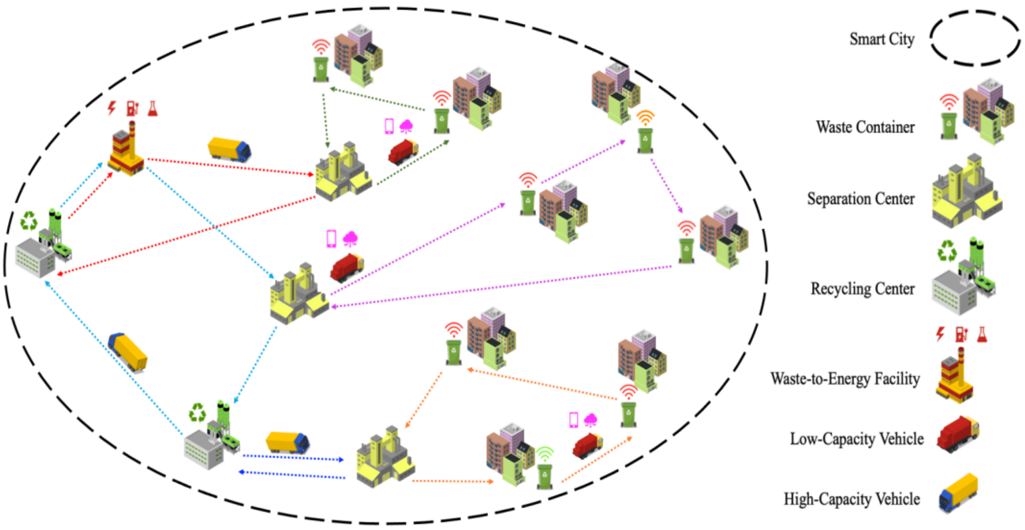

Fig.3.3 The proposed municipal solid waste network.

3.3.1 PROBLEM ASSUMPTIONS

In the proposed ISWM network, it is assumed that the separation and storage operations of the collected wastes are accomplished in the separation center. To collect waste materials from waste bins and transfer them to the processing centers, a heterogeneous fleet VRP with a hard time window is considered, known as HVRPHTW, in which a given set of waste bins must be served within a pre-specified period by determining the optimal set of routes and composition of heterogeneous capacitated vehicles. In this study, we assumed that the waste materials are not separated in different colored waste bins at the point of generation, and truck and vehicle fleets can collect different types of MSW (e.g., plastic, glass, paper, food) at the same time. Furthermore, it is assumed that the recyclable waste materials will be separated into specific types of waste (e.g., plastic, paper, glass, etc.). Besides that, all non-recyclable waste materials are placed in one single group. Therefore, the waste types contain both recyclable and non-recyclable materials.

The profit from recycling/recovering activities is an uncertain parameter that is influenced by different factors, such as condition and combination of waste types, purchasing price of waste materials, and so forth. For example, all types of plastic materials with different components (e.g., Polyethylene Terephthalate (PET), High-Density Polyethylene (HDPE), Polyvinyl Chloride (PVC), etc.) are grouped in one category, and each one of them might have a particular profit margin. Moreover, the non-recyclable waste group may be composed of different types of waste in different separation centers or during different collection periods. Thus, these varying combinations of materials in the non-recyclable waste group could affect the profit of the WtE facilities. Other parameters of the optimization model are considered certain and known. The additional assumptions in developing the MSW network are represented as follows:

- Each waste bin can be served at most once by a separation center. Therefore, the bin collection must be completed on the first visit, and vehicles are not allowed for the partial collection of bins.
- Waste bins can potentially be served by any of the separation centers. Indeed, the integrated model must determine the optimal allocation of waste bins to separation centers considering the waste level of bins and their threshold waste levels, availability and capacity of vehicles, and travel time between waste bins and separation centers.
- The hard time window constraint in the routing problem requires the low-capacity vehicles to collect waste containers within the predefined time window.
- A vehicle must return to its separation center (or origin point) when the vehicle's route is completed.
- A high-capacity vehicle can transfer different types of solid waste in a trip.
- There is no flow of waste between separation centers.
- The separation centers have a limited capacity to collect and separate waste materials.

This study aims to enhance the efficiency of waste management operations by simultaneously optimizing the collection, recycling, and recovery-related decisions. The mathematical formulation of the proposed MSW problem is described in the following section.

3.3.2 THE CHANCE-CONSTRAINED MATHEMATICAL MODEL

This section develops a MOO model for the MSW problem under uncertainty. One of the major purposes of this problem is finding the best waste collection policies to support the citizens of a smart city and decrease the risk of chemical and visual pollution. The other goal is to increase the profitability of the processing activities in the MSW network, which consequently enhances the economic efficiency and the environmental effectiveness of waste management. In the collection phase, the decision-making is conducted from the municipality or waste management organization's point of view. However, the recycling/recovery-related decisions are made directly by processing plants. The sets, parameters, and decision variables of the mathematical model are respectively presented in Tables 3.1 to Table3.3.

Table 3.1.
Sets and indices.

Set	Definition
S	Set of separation centers; s ∈ S.
N	Set of nodes including bins and separation centers. $i,j \in N = \{1,\dots,\mathcal{NS}+\mathcal{NB}\}$; $i,j \in S = \{1,\dots,\mathcal{NS}\}$ represents separation centers; $i,j \in N\backslash S = \{\mathcal{NS}+1,\dots,\mathcal{NS}+\mathcal{NB}\}$ represents bins.
P	Set of nodes including separation centers and processing plants (recycling and waste-to-energy facilities) $e,f \in P = \{1,\dots,\mathcal{NS}+\mathcal{NP}\}$ $e,f \in S = \{1,\dots,\mathcal{NS}\}$ represents separation centers. $e,f \in P\backslash S = \{\mathcal{NS}+1,\dots,\mathcal{NS}+\mathcal{NP}\}$ represents processing plants.
W	Set of waste types; $w \in W$.
VL_s	Set of low-capacity vehicles at separation center s; $l \in VL_s$.
VH_s	Set of high-capacity vehicles at separation center s; $h \in VH_s$.

Table 2.
Sets and indices.

Parameter	Definition
$\mathcal{NB}$	The total number of bins,
$\mathcal{NS}$	The total number of separation centers,
$\mathcal{NP}$	The total number of processing plants,
$CapS_s$	Capacity of separation center s,
$Cap\mathcal{P}_{p,w}$	Capacity of processing plant p to recycle/recover waste type w,
$CapL_{s,l}$	Capacity of vehicle l at separation center s (Low-capacity services),
$CapH_{s,h}$	Capacity of vehicle h at separation center s (High-capacity services),
$Cap\mathcal{B}_b$	Capacity of waste bin b,
Wt_b	The weight of bin b,
$\mathcal{TL}_b$	Threshold waste level for bin b (in percent),
δ_w	The average percentage of waste type w in total generation of municipal solid waste,
Pr_w	The probabilistic profit from recycling/energy recovery of waste type w (per unit waste),
$Tr^N_{i,j}$	Travel time between set of nodes including bins and separation centers,
$Tr^P_{e,f}$	Travel time between set of nodes including separation centers and processing plants,
$Tc^P_{s,h,w}$	Transportation cost for a high-capacity vehicle h to transfer one unit of waste type w from separation center s to processing plants,
$[ET_b, LT_b]$	Time window for collecting waste from bin b,
ScT_b	Service time at bin b,
$\mathcal{M}$	A large number,
ε	A small number,
η	Confidence level.

Table 3.
Variables of the model.

Variable	Definition
$X_{i,j,s,l}$	Binary variable: 1: If route *(i,j)* is selected for low-capacity vehicle *l* at separation center *s*, 0: Otherwise.
$B_{b,s}$	Binary variable: 1: If bin *b* is collected at separation center *s*; 0: Otherwise,
$Y_{e,f,s,h}$	Binary variable: 1: If route *(e,f)* is selected for high-capacity vehicle *h* at separation center s, 0: Otherwise.
$LCV_{s,l}$	Binary variable: 1: If low-capacity vehicle l at separation center s is selected for a route; 0: Otherwise.
$HCV_{s,h}$	Binary variable: 1: If high-capacity vehicle *h* at separation center s is selected for a route; 0: Otherwise.
QS_s	The total quantity of solid wastes collected at separation center s.
$QW_{w,s}$	The total quantity of waste type w collected at separation center s.
$QP_{s,p,h,w}$	The quantity of waste type w transported from separation center s to processing plant p by high-capacity vehicle *h*.
Ar_b	Arrival time to bin *b*.
$\zeta_{p,s,h}$	Auxiliary time variable at which processing plant p is visited by high-capacity vehicle *h* from separation center *s*.

3.3.3 OBJECTION FUNCTIONS

In this section, a stochastic optimization model is proposed comprising three objective functions to optimize the total collection and transportation times, allocation and usage of vehicles, and the overall profit of recycling and recovering activities in the MSW network. Eq. (1) represents the total travel time among all levels of the network. The first term indicates the total collection time of waste containers using low-capacity vehicles of collection centers. Likewise, the second term is associated with the total transportation time of high-capacity vehicles to transfer separated solid waste from separation centers to processing plants. Eq. (2) indicates the total number of low- and high-capacity vehicles that separation centers apply to provide service to citizens, recycling centers, and WtE facilities. The third objective function in Eq. (3) represents the total expected profit that processing plants can achieve by recycling or recovering various types of waste. The first term in this equation indicates the profit that can be achieved from recycling and energy recovery activities considering the potential revenue for selling each unit of a specific type of waste, and also operating expenses imposed on processing plants to recycle/recover the waste material. The second term in Eq. (3) shows the total transportation cost in transferring waste materials to processing plants. In this study, we assumed that each separation center could compute the average cost of transportation to transfer a specific type of waste by a high-capacity vehicle, which can be obtained from preceding service information. In this equation, the Pr_w shows the probabilistic profit of processing plants from waste type w, which is an uncertain parameter. The reformulation of Eq. (3) will be explained in detail in section 3.2.3 to find a deterministic optimization model.

$$\text{Minimize } Z_1 = \sum_{i \in N} \sum_{j \in N} \sum_{s \in S} \sum_{l \in VL_s} X_{i,j,s,l}\, Tr_{i,j}^{N} + \sum_{e \in P} \sum_{f \in P} \sum_{s \in S} \sum_{h \in VH_s} Y_{e,f,s,h}\, Tr_{e,f}^{P} \tag{3.1}$$

$$\text{Minimize } Z_2 = \sum_{s \in S} \left(\sum_{l \in VL_s} LCV_{s,l} + \sum_{h \in VH_s} HCV_{s,h} \right) \tag{3.2}$$

$$\text{Maximize } Z_3 = \sum_{s \in S} \sum_{f \in P \setminus S} \sum_{h \in VH_s} \sum_{w \in W} QP_{s,f,h,w}\, Pr_w - QP_{s,f,h,w}\, Tc_{s,h,w}^{P} \tag{3.3}$$

To ensure the optimality of the system, the optimization model determines the routing decisions at all levels of the network simultaneously, including the optimal number and type of vehicles and the optimal route for each assigned vehicle. To meet the needs of the proposed MSW network, we need to identify some of the system's constraints for the optimization model, which are provided in the next section.

3.3.4 CONSTRAINTS

According to the above-mentioned assumptions and definition of the problem, the constraints of the MSW network are presented in Eqs. (3.4) -(3.30). The general VRP constraints between waste bins and separation centers are shown in Eqs. (3.4) -(3.7). Eq. (3.4) guarantees that at most, one vehicle can serve bin j from starting point i which represents set of nodes including separation centers and other bins. Eq. (3.5) shows that there is no route between separation centers and also ensures that the low-capacity vehicles of a separation center will never visit other separation centers. Eq. (3.6) indicates that there is no path between two identical nodes. This equation ensures that a vehicle cannot start its trip from a separation center and then returns to the separation center without serving at least one bin. In addition, Eqs. (3.4) and (3.6) ensure that each bin can be served at most once and if it will be visited by a low-capacity vehicle its collected waste material will be transported to a separation center. Eq. (3.7) depicts the conservation flow constraint, which means that an entering vehicle to a node must leave it after the completion of the service toward the next destination.

Subject to

$$\sum_{i \in N} \sum_{s \in S} \sum_{l \in VL_s} X_{i,j,s,l} \leq 1 \qquad \forall\, j \in N \setminus S, \tag{3.4}$$

$$\sum_{i \in N} \sum_{j \in S \setminus \{s\}} X_{i,j,s,l} + \sum_{i \in S \setminus \{s\}} \sum_{j \in N} X_{i,j,s,l} = 0, \qquad \forall\; s \in S, l \in VL_{s,} \tag{3.5}$$

$$\sum_{i \in N} \sum_{s \in S} \sum_{l \in VL_s} X_{i,i,s,l} = 0 \tag{3.6}$$

$$\sum_{i \in N} X_{i,j,s,l} = \sum_{i \in N} X_{j,i,s,l} \qquad \forall\; j \in N, s \in S, l \in VL_{s,} \tag{3.7}$$

Eq. (3.8) ensures that a waste bin will surely be served if the fill level of the bin is equal to or greater than the predefined threshold waste level, for instance, 70 percent of the total weight of the bin. Eq. (3.9) ensures that there must be a route for an assigned bin to a separation center, and Eq. (3.10) determines if a low-capacity vehicle at a separation center is selected for a specific route. Eqs. (3.11) and (3.12) compute respectively the total quantity of solid waste and the quantity of a particular type of waste collected at a separation center. Eqs. (3.13) and (3.14) show the capacity constraints for the separation centers and the low-capacity vehicles in collection of waste materials.

$$\frac{Wt_j}{Cap\mathcal{B}_j\ \mathcal{TL}_j} - 1 \leq \mathcal{M}\left(\sum_{i\in N}\sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}\right) - \varepsilon\left(1 - \sum_{i\in N}\sum_{s\in S}\sum_{l\in VL_s} X_i \right. \quad \forall\ j \in N\backslash S, \tag{3.8}$$

$$\sum_{i\in N}\sum_{l\in VL_s} X_{i,j,s,l} \geq B_{j,s} \qquad \forall\ j \in N\backslash S, s \in S, \tag{3.9}$$

$$\sum_{i\in N}\sum_{j\in N} X_{i,j,s,l} \leq \mathcal{M}\ LCV_{s,l} \qquad \forall\ s \in S, l \in VL_s, \tag{3.10}$$

$$\sum_{b\in N\backslash S} B_{b,s} Wt_b = QS_s \qquad \forall\ s \in S, \tag{3.11}$$

$$QW_{w,s} = \delta_w QS_s \qquad \forall\ w \in W, s \in S, \tag{3.12}$$

$$QS_s \leq CapS_s \qquad \forall\ s \in S, \tag{3.13}$$

$$\sum_{i\in N}\sum_{j\in N\backslash S} X_{i,j,s,l}\, Wt_j \leq CapL_{s,l} \qquad \forall\ s \in S, l \in VL_{s,} \tag{3.14}$$

Eqs. (3.15) and (3.16) provide the arrival time of a vehicle at bin j, if path *(i,j)* is dedicated to the vehicle, and Eq.(3.17) indicates that the waste collection from a bin must be accomplished within the predefined time interval. In addition, the subtour-elimination of the routing between the two first levels of the network can be guaranteed by Eq. (3.18).

$$Ar_j - (Ar_i + Tr_{i,j}^N + ScT_i) \leq \mathcal{M}(1 - \sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}) \qquad \forall\ i \in N, j \in N\backslash S, \tag{3.15}$$

$$Ar_j - (Ar_i + Tr_{i,j}^N + ScT_i) \geq \mathcal{M}(1 - \sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}) \qquad \forall\ i \in N, j \in N\backslash S, \tag{3.16}$$

$$ET_j\left(\sum_{i\in N}\sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}\right) \leq Ar_j \leq LT_j\left(\sum_{i\in N}\sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}\right) \qquad \forall\ j \in N\backslash S, \tag{3.17}$$

$$Ar_i - Ar_j \leq \mathcal{M}(1 - \sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}) \qquad \forall\ \mathrm{i} \in \mathrm{N}, \mathrm{j} \in \mathrm{N}\backslash\mathrm{S}, \tag{3.18}$$

Similarly, the routing, conservation flow, and subtour-elimination constraints among separation centers and processing plants are presented in Eqs. (3.19) -(3.23). Eqs. (3.19) and (3.20) denote that a high-capacity vehicle in a separation center can serve a processing plant at most once and that vehicle cannot visit other separation centers. These equations ensure that a high-capacity vehicle can start the trip from its separation center, visit the allocated processing plants only once and then return to the origin point. Eq. (3.21) represents that there is no path between a node and itself, and Eqs. (3.22) and (3.23) show the conservation flow and subtour-elimination constraints, respectively.

$$\sum_{e \in P} Y_{e,f,s,h} \leq 1 \qquad \forall\ f \in P \backslash S\,, s \in S, h \in VH_s, \tag{3.19}$$

$$\sum_{e \in P} \sum_{f \in S \backslash \{s\}} Y_{e,f,s,h} + \sum_{e \in S \backslash \{s\}} \sum_{f \in P} Y_{e,f,s,h} = 0 \qquad \forall\ s \in S, h \in VH_s, \tag{3.20}$$

$$\sum_{e \in P} \sum_{s \in S} \sum_{h \in VH_s} Y_{e,e,s,h} = 0 \tag{3.21}$$

$$\sum_{e \in P} Y_{e,f,s,h} = \sum_{e \in P} Y_{f,e,s,h} \qquad \forall\ f \in P, s \in S, h \in VH_s, \tag{3.22}$$

$$\zeta_{e,s,h} - \zeta_{f,s,h} \leq \mathcal{M}(1 - Y_{e,f,s,h}) \qquad \forall\ e \in P, f \in P \backslash S, s \in S, h \in VH_s, \tag{3.23}$$

Eqs. (3.24) and (3.25) determine if a high-capacity vehicle at a separation center is selected for a specific route and whether there is a flow for a type of waste between a separation center and the processing plants. Eq. (3.26) ensures that the total quantity of a type of waste transported from a separation center to processing plants cannot exceed the total quantity of that type of waste collected at the separation center. The capacity constraint for the high-capacity vehicles and the recycling/recovering capacity of the processing plants are respectively considered in Eqs. (3.27) and (3.28). Finally, the binary and positive integer variables of the proposed model are shown in Eqs. (3.29) and (3.30).

$$\sum_{e \in P} \sum_{f \in P} Y_{e,f,s,h} \leq \mathcal{M}\ HCV_{s,h} \qquad \forall\ s \in S, h \in VH_{s,} \tag{3.24}$$

$$QP_{s,f,h,w} \leq \mathcal{M}(\sum_{e \in P} Y_{e,f,s,h}) \qquad \forall\ f \in P \backslash S, s \in S, h \in VH_s, w \in W, \tag{3.25}$$

$$\sum_{f \in P \backslash S} \sum_{h \in VH_s} QP_{s,f,h,w} \leq QW_{w,s} \qquad \forall\ s \in S, w \in W, \tag{3.26}$$

$$\sum_{f \in P \backslash S} \sum_{w \in W} QP_{s,f,h,w} \leq CapH_{s,h} \qquad \forall\ s \in S, h \in VH_s, \tag{3.27}$$

$$\sum_{s \in S} \sum_{h \in VH_s} QP_{s,f,h,w} \leq Cap\mathcal{P}_{f,w} \qquad \forall\ f \in P \backslash S, w \in W, \tag{3.28}$$

$$X_{i,j,s,l},\ B_{b,s},\ Y_{e,f,s,h},\ LCV_{s,l},\ HCV_{s,h} \in \{0,1\} \qquad \forall\ i \in N,\ j \in N,\ b \in N \backslash S,\ e \in P,\ f \in P,\ s \in S,\ l \in VL_s,\ h \in VH_s, \tag{3.29}$$

$QS_s, QW_{w,s}, QP_{s,p,h,w}, Ar_b, \zeta_{p,s,h} \geq 0$ and integer $\quad \forall\ s \in S,\ p \in P \backslash S,\ h \in VH_s,\ w \in W,\ b \in N \backslash S,$ (3.30)

3.3.5 CHANCE-CONSTRAINED APPROACH

In this study, the profit of the processing plants from recycling/recovering activities is considered uncertain due to some external factors that impact the efficiency and quality of the final products (e.g., recycled plastic materials, electricity and heat energies, renewable liquid, and gaseous fuels). For example, the demographic and socioeconomic factors are one of the most influential elements that can affect the type and combination of the solid wastes in an urban area, thereby directly affecting productivity and the added value of the recycled materials or recovered energy. We can find several research studies in literature assuming that the uncertain parameters follow the normal distribution. For instance, Johansson (2006) considered the waste generation rate to be a stochastic variable, and then assumed that the weight of each waste container follows a normal distribution after a certain time. This assumption was based on the Central Limit Theorem stating that the distribution of the sufficiently large random samples will be approximately normally distributed. This assumption was validated using a Kolgomorov–Smirnov Goodness of Fit test for the normal distribution on the collected empirical data. Correspondingly, we assume that the $\mathrm{Pr_w}$ parameter in the proposed mathematical model follows a normal distribution with mean (μ_w) and standard deviation (σ_w). In this section, to incorporate the normal distribution to the third objective function, the chance-constrained programming (CCP) method is applied to formulate the probabilistic profit from recycling/recovery activities. In the first step, Eq. (3) can be converted to a minimization function, as follows:

$$\text{Maximize} \sum_{s \in S} \sum_{f \in P \backslash S} \sum_{h \in VH_s} \sum_{w \in W} QP_{s,f,h,w}\, Pr_w - QP_{s,f,h,w}\, Tc^P_{s,h,w}$$
$$\Rightarrow \quad \text{Minimize} \quad -\left(\sum_{s \in S} \sum_{f \in P \backslash S} \sum_{h \in VH_s} \sum_{w \in W} QP_{s,f,h,w}\, Pr_w - QP_{s,f,h,w}\, Tc^P_{s,h,w} \right) \tag{3.31}$$

Then, Eq. (3.31) can be reformulated using the chance-constrained approach by defining a new variable (Ψ), a confidence level (η), and a probabilistic constraint, as shown in Eqs. (3.32) -(3.33). These equations ensure that Eq. (3.31) can be satisfied at a given confidence level.

Minimize $\quad \Psi$ (3.32)

Subject to

$$\mathcal{P}rob\left(-\left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s}\sum_{w\in W} QP_{s,f,h,w}\, Pr_w - QP_{s,f,h,w}\, Tc^P_{s,h,w}\right)\leq \Psi\right)\geq \eta, \tag{3.33}$$

Now, let's define a new variable (Υ) to simplify the proposed chance constraint Eq. (3.33) as follows:

$$\Upsilon = -\left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s}\sum_{w\in W} QP_{s,f,h,w}\, Pr_w - QP_{s,f,h,w}\, Tc^P_{s,h,w}\right) - \Psi \tag{3.34}$$

$$\mathcal{P}rob(\Upsilon \leq 0)\geq \eta, \tag{3.35}$$

The only probabilistic variable in Eq. (34) is Pr_w which follows the normal distribution ($Pr_w \sim \mathcal{N}(\mu_w, \sigma_w^2)$). Also, we assumed that the Pr_w is an independent random variable, and the correlation between profits of all types of waste is equal to zero. Therefore, we can conclude that the variable Υ follows a normal distribution with the following mean and variance:

$$E(\Upsilon) = -\left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s}\sum_{w\in W} QP_{s,f,h,w}\, \mu_w - QP_{s,f,h,w}\, Tc^P_{s,h,w}\right) - \Psi, \tag{3.36}$$

$$Var(\Upsilon) = \sum_{w\in W}\sigma_w^2\left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s} QP_{s,f,h,w}\right)^2, \tag{3.37}$$

As shown in Eq. (3.37), the variance of the sum of Pr_wvariables equal the sum of their variances. Since variable Υ follows a normal distribution with mean ($E(\Upsilon)$) and variance ($Var(\Upsilon)$), $\mathcal{Z} = \frac{\Upsilon - E(\Upsilon)}{\sqrt{Var(\Upsilon)}}$ is a standard normal random variable and Eq. (3.35) can be rewritten as follows:

$$\mathcal{P}rob\left(\frac{\Upsilon - E(\Upsilon)}{\sqrt{Var(\Upsilon)}} \leq \frac{-E(\Upsilon)}{\sqrt{Var(\Upsilon)}}\right) = \mathcal{P}rob\left(\mathcal{Z}\leq \frac{-E(\Upsilon)}{\sqrt{Var(\Upsilon)}}\right) = \Phi\left(\frac{-E(\Upsilon)}{\sqrt{Var(\Upsilon)}}\right)\geq \eta, \tag{3.38}$$

where, the cumulative distribution function (CDF) of the standard normal distribution is expressed by the Φ function.

$$\Phi^{-1}(\eta)\sqrt{Var(\Upsilon)} \leq -E(\Upsilon), \tag{3.39}$$

$$\Phi^{-1}(\eta)\sqrt{\sum_{w\in W}\sigma_w^2\left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s}QP_{s,f,h,w}\right)^2} \leq \left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s}\sum_{w\in W}QP_{s,f,h,w}\,\mu_w - QP_{s,f,h,w}\,Tc_{s,h,w}^P\right)+\Psi, \tag{3.40}$$

Hence, Eq. (3.40) provides the deterministic equivalent of the chance constraint proposed in Eq. (3.33). Finally, to transform the stochastic optimization model into a deterministic one, we need to replace the third objective function in the proposed mathematical model Eq. (3.3) with Eq. (3.32) and add Eq. (3.40) to the system constraints.

3.4 SOLUTION APPROACH

In real-world scenarios, optimizing the performance of a system requires dealing with multiple and often conflicting objectives that cannot be optimized together. These problems can be turned into multi-objective programs and addressed by multi-objective optimization techniques to achieve a solution that balances different goals. This paper uses the Goal Programming method to handle multiple objectives simultaneously, which is a widely used multi-objective optimization approach.

In addition, the VRPTW is an NP-hard combinatorial optimization problem that plays a vital role in logistics systems. To address the complexity of the solution process in the problem under study, numerous approximate solution methods have been proposed in the literature (Elgharably et al., 2022). In this study, four multi-objective meta-heuristic algorithms are employed to solve the proposed optimization model, which are illustrated in the next subsections.

3.4.1. GOAL PROGRAMMING APPROACH

The Goal Programming (GP) method was first introduced by Charnes et al., (1955) and has since been improved by other researchers. The basic idea of GP is to consider all objective functions, whether they require maximizing or minimizing, and set a goal value for each objective. GP aims to compare different possible solutions and minimize the total deviation from ideal goals. The mathematical structure of GP is illustrated in Eqs. (3.41) -(3.44). Eq. (3.41) shows the objective function of the GP model which aims to reduce the total amount of positive and negative deviations from the pre-determined goals. The Goal and System constraints of the model are respectively indicated in Eqs. (3.42) and (3.43).

$$\text{Minimize} \quad \sum_{o=1}^{O}\left(\frac{d_o^- + d_o^+}{Goal_o}\right) \tag{3.41}$$

Subject to

$$F_o(x) - d_o^+ + d_o^- = Goal_o \qquad \forall\, o = \{1, \dots, O\}, \tag{3.42}$$

$$S_c(x)\ (\leq or\ = or\ \geq)\ 0 \qquad \forall\, c = \{1, \dots, C\}, \tag{3.43}$$

$$d_o^+,\ d_o^- \geq 0 \qquad \forall\, o = \{1, \dots, O\}, \tag{3.44}$$

Index o represents an objective function within the main problem, index c represents a constraint in the main problem, $F_o(x)$ denotes the *oth* objective, $S_c(x)$ refers to the *cth* constraint in the main problem, $\mathrm{d_o^-}$ and $\mathrm{d_o^+}$ show the negative and positive deviational variables for *oth* objective, respectively. The deviational variables are calculated as follows:

$$d_o^- = \begin{cases} Goal_o - F_o(x) & if\ Goal_o > F_o(x) \\ 0 & otherwise \end{cases} \qquad \forall\, o = \{1, \dots, O\}, \tag{3.45}$$

$$d_o^+ = \begin{cases} F_o(x) - Goal_o & if\ Goal_o < F_o(x) \\ 0 & otherwise \end{cases} \qquad \forall\, o = \{1, \dots, O\}, \tag{3.46}$$

The proposed mathematical model in this study can be reformulated by GP approach, as shown in Eqs. (3.47) -(3.52). All objective functions of the optimization model are in minimization type, and thus, they take only positive deviational variable (d_o^+) in the GP model. In the objective function of the GP model, the deviational variables are divided by their corresponding goals to ensure that all objective components are on the same scale. Furthermore, prior to solving the GP model in each test problem, three separate subproblems are solved as a single-objective optimization problem to determine the goal value for each objective as input value in the proposed model.

$$\text{Minimize} \quad \sum_{o=1}^{3} \left(\frac{d_o^+}{Goal_o} \right) \tag{3.47}$$

Subject to

$$Z_1 - d_1^+ + d_1^- = Goal_1, \tag{3.48}$$

$$Z_2 - d_2^+ + d_2^- = Goal_2, \tag{3.49}$$

$$\Psi - d_3^+ + d_3^- = Goal_3, \tag{3.50}$$

$$\textit{Eqs. (4)−(30), and Eq. (40),} \tag{3.51}$$

$$d_1^+, d_2^+, d_3^+, d_1^-, d_2^-, d_3^- \geq 0\ , \tag{3.52}$$

3.4.2. MULTI-OBJECTIVE META-HEURISTIC ALGORITHMS

Multiple-criteria decision-making (MCDM) problems are referred to a set of planning problems in which multiple conflicting objectives must be considered concurrently. One of the main criteria for classifying such problems is whether a set of discrete predefined alternatives exists or not. A problem with this predefined set of alternatives belongs to multi-attribute decision analysis. However, if the feasible set of problems specified by a set of constraints, like the problem studied in this paper, it is classified in another group of MCDM known as the MOO problem, in which the alternatives are not known in advance(Das et al., 2021). A general formulation of the MOO problem is defined by decision space x, objective space Z, and n objectives, which are in conflict with each other:

$$\text{Minimize / Maximize} \quad Z = \{ f_1(x), f_2(x), \dots \dots, f_n(x) \}, \tag{53}$$

Subject to

$$g(x) \leq 0, \tag{54}$$

$$x \in X, \tag{55}$$

The main characteristic of MOO problem is that instead of a unique solution, there are a set of pareto solutions which are mathematically equally good and known as non-dominated solutions. In recent decades, several methods have been developed that can be categorized in four groups, including no-preference, priori, interactive, and posteriori methods (Hakanen et al., 2022) . In posteriori methods, firstly, a set of non-dominated solutions are generated, and then the decision-maker selects the most preferred solution by having available an overview of different solutions, where a representation of pareto solutions is first generated. Evolutionary MOO algorithms employed in this paper typically belong to this class. The proposed MOO meta-heuristics is described in the following subsections.

3.4.3. MULTI-OBJECTIVE SIMULATING ANNEALING (MOSA)

Multi-objective Simulating Annealing (MOSA) was firstly developed by Kirkpatrick, Gelatt, and Vecchi (1983). The procedure of this algorithm is based on maintaining the highest temperature for the heat bath for solid melts. At this temperature level, the particles are arranged randomly, and then the temperature declines gradually. In the final step, the solid structure is positioned with minimum energy in the optimal structure. In this algorithm, if a selected movement refines the solution, it is always accepted, otherwise, the acceptance of the movement is assessed based on a random probability that is less than one to avoid trapping into the local minima. If a bad movement was taken, the probability continues to decrease exponentially with the amount delta by which the solution worsened. A two-step non-dominated sorting approach is applied to determine the pareto set based on ranking and crowding distance, respectively, in order to select the solution from one iteration and then move forward into the next iteration. The maximum temperature of the heat bath is the Boltzmann constant, and the accepting rule is known as Metropolis criteria (Mosallanezhad, Chouhan, et al., 2021). The pseudo-code of the MOSA is illustrated in Fig.3. 4.

The pseudo-code of the MOSA

Setting the parameters of the algorithm such as temperature, the maximum number of iterations, cooling rate, end temperature t_0,
Initialization of a solution s,
Setting the current temperature as t,
Setting the initial value of the counter at temperature t equal to 1,
Setting s as the best solution,
While ($t > t_0$),
    While (counter is smaller than the maximum number of iterations),
        Add up the counter,
        Do the mutation operator and create a neighbor solution s',
        Calculate the fitness function of the solutions s and s',
        If the new neighbor's solution dominates the current best solution s
            Updating the best solution by s',
        Elseif s'not dominates s and s is not dominates s' ,
            Updating the best solution by s',
        Elseif s not dominates s',
            Δf_i= difference between fitness functions of s and s' in dimension i,
            Generating a random number h between zero and one,
            $P_i = \exp\left(\frac{-\Delta f_i}{T}\right)$
            If $h <= P_i$
                Update the best solution $s = s'$
    Update temperature ($T=\alpha*T$)
    Do non-dominated sorting of the Pareto set,
    Calculating the crowding distance and determine the ranks,
Stop if the termination criteria for the algorithm is met, otherwise do mutation operator s'

Fig.3.4. Pseudo-code of MOSA.

3.4.4. Non-dominated Sorting Genetic Algorithm (II) and Non-dominated Ranked Genetic Algorithm

Non-dominated sorting genetic algorithm II (NSGA-II) and non-dominated ranked genetic algorithm (NRGA) are two extensions of the Genetic Algorithm (GA), which was firstly proposed by Holland (1984). In this study, these two algorithms are employed to evaluate the efficiency and quality of other proposed algorithms. Instead of converting a multi-objective problem to a single-objective one, these evolutionary algorithms try to provide a trade-off between conflicting objectives. NSGA-II and NRGA were introduced respectively by Deb et al. (2002) and Jadaan et al. (2008). The implementation of these algorithms is mainly similar, but the difference between them is related to the parent selection procedure, in which NSGA-II utilizes the Binary Tournament Selection (BTS) and NRGA exploits the Roulette Wheel Selection (RWS) strategy.

However, both algorithms use the crossover and mutation as biological operators to diversify the solution search and avoid trapping in local optima. Pseudo-code of NSGA-II is represented in Figure 5, and readers are referred to Cheraghalipour, Paydar, and Hajiaghaei-Keshteli (2018) for further study.

Pseudocode of NSGA-II

```
Setting the parameters of the algorithm such as number of populations N, crossover rate
Pm, mutation rate Pc, and maximum iteration Im
Initialize the first population randomly,
Evaluating the fitness value,
Pareto based ranking of individuals in population,
Calculation of crowding distance,
Assigning non-dominance ranking,
While i < Im
    For j in [1: (Pc * N)/2]
        Select two solutions randomly,
        Select the crossover operator,
        Apply the crossover operator on the selected individuals,
        Store the new generated solutions,
    EndFor
    For j in [1: (Pm * N)/2]
        Select two solutions randomly,
        Select the mutation operator,
        Apply the mutation operator on the selected individuals,
        Store the new generated solution,
    EndFor
    Combine all new generated and old solutions,
    Evaluating the fitness value,
    Pareto based ranking of individuals in population,
    Calculation of crowding distance of solutions belong to each non-dominated
Pareto front,
    EndFor
    i=i+1,
```

Fig.3.5. Pseudo-code of NSGA-II.

3.4.5. Hybrid Multi-Objective Keshtel Algorithm and Simulating Annealing (MOKASA)

The Multi-objective Keshtel Algorithm (MOKA) is a well-known meta-heuristic developed by Hajiaghaei-Keshteli and Aminnayeri (2014). In this algorithm, randomly generated solutions are referred to as Keshtel, as a type of bird, and the food source and the lake respectively represents solutions and feasible regions. MOKA contains six main steps. The first two steps are the random solution generation and finding the lucky Keshtels (N1) based on the food source. In the third step, the attraction and swirling operators are applied to find a good food supply for attracting neighbors and then swirl around the lucky Keshtels (N2). In the next step, other remaining Keshtels move to the unexplored regions to search for a better food source. Finally, the algorithm has the opportunity to replace the worst solution with a new random solution (N3). The interested readers may refer to the work of Mosallanezhad, Chouhan, et al. (2021). In this algorithm, the merging of the population is based on a sorting technique that employs crowding distance. In this paper, to empower the searching phase of MOKA, it is hybridized with SA algorithm. As mentioned above, the population in MOKA divided into three sub-populations, including N_1, N_2, and N_3. The hybridized strategy is targeted to enrich the exploitation phase in which N_3 (the worst solution) is generated by SA(Rajabi-Kafshgar et al., 2023). The acceptance or rejection of solutions is determined by applying Metropolis criteria. The pseudo-code of MOKASA is shown in Fig.3 6, and the readers are also referred to (Chouhan, Khan, and Hajiaghaei-Keshteli 2021).

The pseudo-code of MOKASA

Landing N Keshtels and do initialization
non-dominate sorting
Sorting the non-dominated Keshtels based on crowding distance and determining(N_1, N_2, N_3).
Set It = 0
while (It < Max_{it})
For each Lucky Keshtel in N_1
Select the nearest Keshtel (N_k) swirling around the Lucky Keshtel
Set Temperature = initial temperature
while (Temperature < final temperature)
Compute the objective function difference Δf1 and Δf2 between the Lucky Keshtel and N_k.
if (Δf_1 <= 0 and Δf_2 >= 0)
Update the best solution
Update the solution
else if ((Δf_1>= 0 and Δf_2 >= 0) or (Δf_1 <= 0 and Δf_2<= 0)) Δf_1.
Keep the current solution in the Pareto set
else
Set P1 = exp (-Δf_1/ T) and P2 = exp (-Δf_2/ T)
Generate a random number h between 0 and 1
if (h < P_1 and h < P_1)
Update the solution
end if
end if
Update temperature using the cooling rate
end while
end for
For each Keshtel in N_2
Explore the unexplored regions by the Lucky Keshtels
end for
For each Keshtel in N_3
Generate a random new Keshtel f_2
Find the Keshtel f1 with the least food in N1 and replace it with f_2
Compute the difference Δf= f_2 - f_1
if (Δf > 0)
Replace $f_1$with f_2
else
Generate a random number r between 0 and 1
if (r < exp(Δf))
Replace f_1 with f_2
end if
end if
end for
Merge the populations N_1, N_2, and N_3
Do non-dominate sorting and crowding distance
Select *N* better Keshtels from the merged population for the next generation
Increment It by 1
end while

Fig.3.6. The pseudo-code of MOKASA.

3.5. SOLUTION REPRESENTATION

To define the decision variables of a problem in the meta-heuristic algorithms, the first step is to determine an appropriate coding and decoding approach for the problem, which is also called solution representation (Mousavi et al., 2021). In this paper, the Random Key (RK) method is applied within a three-step approach to address all decision variables of the mathematical model. In the RK method, a vector is generated randomly by random numbers between zero and one. The length of the vector is the summation of total number of bins and trucks plus one, to have the required number of separators for constructing routes. Then, the vector is sorted and the position of each element in the original vector extracted to have encoding plan. Implementing this technique provides a procedure to change even infeasible solutions to a feasible one (Mosallanezhad, Hajiaghaei-Keshteli, et al., 2021; Sadeghi-Moghaddam et al., 2019). Using this three-step approach, the solution of MSW problem can be obtained from a randomly generated solution through the computation of all decision variables. Firstly, it is required to read the data about the number of bins, separation centers, processing plants, and available vehicles, including both low-capacity and high-capacity trucks in the separation centers. Then the assignment problem is performed in the first step to allocate each bin to a separation center and accordingly to an available vehicle on the selected separation center.

In the assignment problem, two randomly generated vectors should be produced with the length of the number of bins. Each element of the first vector is extracted from the uniform distributed function of *U* (1, number of separation centers). A vector is generated from the uniform distributed function of *U* (1, number of available vehicles at each separation center) for the second assignment, which allocates a waste bin to a vehicle. After performing the assignment problem for the first level of network, the routing decisions can be determined using the RK method to find the routes of selected vehicles and the order of each one.

However, a matrix of the number of high-capacity trucks by the number of processing plants is required to address both assignment and sequencing phases. Each row of this matrix must be filled by the element-wise multiplication of two randomly generated vectors. The first one is a random binary vector that determines the allocation of processing plants to available vehicles and makes it possible that a processing plant can be visited by several trucks. To solve the sequencing problem, the second vector is generated based on a uniform distributed function between zero and one ($\sim U(0,1)$). In this section, an example of a problem is presented composed of ten waste bins, three separation centers, three low-capacity trucks, two high-capacity trucks, and three processing plants.

In Table 3. 4, the structure of the proposed solution representation is composed of 10 bins, 3 separation centers, and 3 low-capacity trucks in each separation center. The first row represents the waste bins. The second and third rows indicate the allocation of bins to the separation centers and to the low-capacity trucks in the first level of the network. For each cell of the second row, the number of a separation center is randomly generated within a range between one and the maximum number of separation centers. Similarly, in each cell of the third row, the number of a truck is randomly generated for the associated separation center. In this example, the applied vehicles at separation centers 1,2, and 3 are respectively vehicle (1), vehicles (1) and (2), and vehicle (1). Then the sequence of visiting bins for a selected truck at a separation center can be determined based on the ascending order of the generated numbers in the fourth row. It means that the fourth row is the sorted vector of the randomly generated numbers between zero and one.

As shown in Table 3.5, bins (3) and (9) are allocated to vehicle (2) at separation center (2), and the visiting sequence of these bins is (3 → 9) based on the ascending order of random numbers. It means that bin (3) must be visited earlier than bin (9) because its corresponding random number is lower. In Table 3.6, the solution representation of the second level is determined. In this example, each cell of the matrix is filled by multiplication of two random numbers in order to determine whether a processing plant is visited or not and which vehicle(s) will serve that processing plant. For instance, in separation center (2), the second high-capacity truck is not utilized and the order of visit for the first truck is processing plants (2), (1), and (3).

Table 4.
The structure of the proposed solution representation.

Bins	1	2	3	4	5	6	7	8	9	10
Allocation of bin to a separation center	1	3	2	1	3	2	3	3	2	2
Allocation of bin to a vehicle at separation center	1	1	2	1	1	1	1	1	2	1
Random Key	0.14	0.15	0.42	0.48	0.79	0.80	0.91	0.95	0.96	0.97

Table 5.
The result of the encoding plan at the first stage.

Separation center	Vehicle	Route from bin to the separation center
1	1	1 → 4
2	1	6 → 10
2	2	3 → 9
3	1	2 → 5 → 7 → 8

Table 6.
The result of the encoding plan at the second level.

Separation center	High-capacity vehicle	Processing plant 1	Processing plant 2	Processing plant 3
1	1	(1×0.98) = 0.98	(0×0.35) =0	(1×0.24) =0.24
1	2	(1×0.93) = 0.93	(1×0.84) =0.84	(0×0.42) =0
2	1	(1×0.26) =0.26	(1×0.19) =0.19	(1×0.75) =0.75
2	2	(0×0.23) =0	(0×0.54) =0	(0×0.84) =0
3	1	(0×0.56) =0	(0×0.27) =0	(1×0.78) = 0.78
3	2	(1×0.64) =0.64	(1×0.81) =0.81	(0×0.25) =0

3.6. DATA GENERATION AND PARAMETER TUNNING

In this section, several numerical experiments are introduced to validate the applicability of the mathematical model and efficiency of the proposed solution approaches. In addition, the parameter tuning of the approximate solution methods are described. For this purpose, a random data set is generated, and then the Taguchi method is applied to determine the parameters of each algorithm. Due to the novelty of the proposed mathematical model, there is insufficient literature to assess the performance of the developed MSW system. Therefore, fifteen numerical examples are randomly generated in three different dimensions (small, medium, and large) to evaluate the efficiency and performance of the proposed mathematical model and solution methods, which are shown in detail in Table 3.7 (Fasihi et al., 2021).

Table 7.
Dimensions of the proposed test problems.

Problem Size	Problem Number	Dimension					
		$\mathcal{NB}$	$\mathcal{NS}$	$\mathcal{NP}$	W	VL_s	VH_s
	P1	7	2	2	1	2	2
	P2	10	2	2	1	2	2
Small	P3	15	3	2	1	2	2
	P4	20	3	2	1	2	2
	P5	25	3	2	1	2	2
	P6	30	4	2	2	2	2
	P7	45	5	2	2	2	2
Medium	P8	60	5	2	2	3	3
	P9	75	6	3	2	3	3
	P10	90	6	3	2	4	4
	P11	110	7	3	3	4	4
	P12	150	8	3	3	5	5
Large	P13	200	8	3	3	6	6
	P14	250	9	3	3	7	7
	P15	300	10	3	3	8	8

To set the parameters of the proposed algorithms, some random values are determined for the parameters of the model. For example, Wt_b displays the weight of bin b which is assumed to have a uniform value between 40 and 50 kg. $CapL_{s,l}$ parameter is the capacity of vehicle l at separation center s that is assumed to be 3 tons. $Tr_{i,j}^{N}$ shows the travel time between a set of nodes, including bins and separation centers which is between 30 and 40 minutes. Then, to determine the parameters of each algorithm, the Taguchi experimental design method is applied. In the following, the tuning of parameters using Taguchi method is explained.

Taguchi method tries to find a maximum number of controllable factors and the minimum level of noise effect based on a "signal to noise ratio" (Gholian-Jouybari et al., 2018a). In this work, the smaller "signal to noise ratio" is better for each algorithm due to the nature of the optimization problem. Eq. (3.56) computes the signal to noise ratio, in which y and n respectively represents the response value and the number of orthogonal arrays. In this study, the response value is calculated based on the division of two separated metrics, namely, the convergence rate of solution ($\mathcal{C}$) and the variety of solution ($\mathcal{V}$) (see Eq. (3.57)) (Colombaroni, Mohammadi, and Rahmanifar 2020).

$$S/N = -10 \times \log\left(\sum (y^2)/n\right) \tag{3.56}$$

$$y = \mathcal{C}/\mathcal{V} \tag{3.57}$$

First, the level of each factor for all proposed algorithms should be identified. MOSA has three parameters with three levels. NSGA-II and NRGA have four parameters with three levels. Finally, MOKASA contains seven parameters with three levels. Other levels of algorithms can be determined in a similar way. Table 3.8 denotes the optimum level (tuned values) of parameters obtained from test problems in 30 different runs.

Table 8.
The parameters of the proposed algorithms and their levels.

Meta-heuristics	Parameter	Parameter Level			Optimum Level
		L1	*L2*	*L3*	
MOSA	Max_{It}	100	200	300	200
	T_0	1000	1500	2000	1000
	T_{damp}	0.88	0.90	0.99	0.90
NSGA-II	Max_{It}	100	200	300	300
	N_{pop}	100	150	200	200
	P_c	0.7	0.75	0.8	0.8
	P_m	0.05	0.10	0.15	0.05
NRGA	Max_{It}	100	200	300	100
	N_{pop}	100	150	200	150
	P_c	0.7	0.75	0.8	0.8
	P_m	0.05	0.10	0.15	0.05
MOKASA	Max_{It}	100	200	300	200
	N-Keshtel	100	150	200	100
	S_{max}	10	15	20	15
	M1	0.05	0.1	0.15	0.15
	M2	0.2	0.25	0.30	0.25
	T_0	1000	1500	2000	1500
	T_{damp}	0.88	0.90	0.99	0.90

3.7 COMPUTATIONAL RESULTS

In this section, an exact solution method (GAMS) and the proposed meta-heuristic algorithms are applied, for solving numerical examples in different scales, to validate the feasibility and performance of the optimization model and investigate the effectiveness of the proposed solution methods. Due to the complexity of the problem under study, it is reasonable to use an exact method to solve only the first two numerical experiments, and the larger examples cannot be solved in a reasonable amount of time. In addition, by changing the dimension and parameters of an algorithm, the scale of the objective function can be changed. Therefore, it is necessary to define appropriate indicators to make an efficient comparison between the performance of the proposed meta-heuristic algorithms. For this purpose, six performance metrics are used to compare the algorithms, including the number of non-dominated pareto solution (NPS), mean ideal distance (MID), maximum spread (MS), the spread of non-dominance Solution (SNS), hypervolume (HV), and CPU time. After setting the tuned values of parameters, each test problem is solved 30 times for each algorithm, and the average of all runs is reported as the final result of that algorithm.

3.7.1. PERFORMANCE METRICS

To compare different multi-objective meta-heuristic algorithms, several studies have been conducted to introduce different performance indicators, which mainly investigated the quality of pareto front. The goal in evolutionary MOO is not only to find a pareto front with an accurate approximation, but also to determine the large number of non-dominated solutions that are uniformly distributed and cover all the regions of pareto front. Accordingly, three main categories can be listed to classify the performance indicators: convergence, coverage, and success metrics. In the first group indicators, the closeness of the final solutions to the true pareto front is measured, while the coverage of a different range of objective functions is considered in the second group. And the third group measures the number of times the pareto optimal solutions are obtained (Mirjalili & Lewis, 2015). The interested readers may also refer to the works of Behnamian, Fatemi Ghomi, and Zandieh (2009) and Gholami et al. (2019). In this section, to compare the performance of multi-objective meta-heuristics, the selected performance metrics are illustrated as follows:

- **Number of pareto solutions (NPS):** This measure represents the number of non-dominated solutions obtained from each algorithm. The greater number of pareto solutions shows the better performance of the algorithm (Gholian-Jouybari et al., 2023a).

- **Spread of non-dominated solution (SNS):** The spread of ideal and non-dominated solutions can be measured by this indicator (see Eq.58), which can be ensured by higher value of SNS:

$$SNS = \sqrt{\frac{\sum_{i=1}^{n}(\bar{c} - c_i)^2}{n-1}} \tag{3.58}$$

$where,\ c_i = \left\|\vec{f_i} - \overrightarrow{f_{Ideal}}\right\|,\ \bar{c} = \frac{c_i}{n},\ \overrightarrow{f_{Ideal}} = \{min(f_1), min(f_2), \ldots, min(f_k)\}$, and n is the number of solutions.

- **Mean ideal distance (MID):** MID measures the performance of algorithms using the minimum gap between the pareto and the ideal solutions (see Eq.59).

$$MID = \frac{\sum_{i=1}^{n}\sqrt{\left(\frac{f_{1i} - f_1^{best}}{f_{1,total}^{max} - f_{1,total}^{min}}\right)^2 + \left(\frac{f_{2i} - f_2^{best}}{f_{2,total}^{max} - f_{2,total}^{min}}\right)^2}}{n} \tag{3.59}$$

- **Maximum Spread (MS):** It is desirable to have a larger area covered with the best pareto front, and the higher value of MS reflects bigger distance between solutions with respect to the best pareto front. The MS indicator can be formulated as (see Eq.3.60):

$$MS = \frac{1}{M}\sum_{m=1}^{M}\left(\frac{\min(F_{i,known}^{max}, F_{i,true}^{max}) - \max\,(F_{i,known}^{min}, F_{i,true}^{min})}{F_{i,true}^{max} - F_{i,true}^{min}}\right)^2 \tag{3.60}$$

Hypervolume (HV): Hypervolume is a performance metric representing how much volume of the objective feasible space is covered by a pareto set. Hypervolume is calculated using Eq. (3.61).

$$HV = \text{volume}\left(\bigcup_{i=1}^{|R|} b_i\right) \tag{3.61}$$

where, R denotes the pareto solutions, and b_i is the volume of the feasible space covered by pareto set R.

CPU time: The speed of running an algorithm to reach the optimal solution(s) is an important factor in evaluating the performance of algorithms. The CPU time for any algorithm is the total computational time.

3.8 ANALYSIS AND DISCUSSION

After setting the tuned values of parameters, each test problem is solved 30 times for each algorithm, and the average of all runs is reported in Tables 3.9−3.12. Accordingly, based on the average result obtained from all test problems, the best algorithm regarding each indicator is determined, as shown in Table 3.13.

Table 3.9.
The obtained results of performance indicators for NSGA-II.

Problem Name	NPS	MID	SM	SNS	CPU Time (Second)	HV
N.1	17.60	6.371	2.95E+07	7.77E+06	108	3.98E+07
N.2	24.20	3.487	5.14E+07	2.33E+07	134	6.01E+07
N.3	11.00	2.348	6.25E+07	2.85E+07	456	7.83E+06
N.4	16.50	2.684	2.36E+08	1.11E+09	412	1.49E+08
N.5	27.50	3.129	2.38E+08	1.47E+07	383	2.71E+08
N.6	28.60	4.821	4.02E+08	1.72E+08	539	3.87E+08
N.7	27.50	1.372	3.16E+08	3.16E+08	986	5.77E+08
N.8	37.40	3.464	6.49E+08	5.62E+08	1145	7.73E+08
N.9	28.60	2.433	9.09E+08	1.04E+09	1150	1.39E+09
N.10	30.80	4.835	1.05E+09	1.17E+09	1677	1.57E+09
N.11	53.90	3.354	5.30E+08	1.70E+09	2511	2.85E+09
N.12	45.10	3.422	2.38E+09	1.27E+09	2610	2.04E+09
N.13	57.20	1.380	2.86E+09	2.83E+09	4019	3.13E+09
N.14	47.30	2.444	3.52E+09	3.44E+09	6916	2.14E+09
N.15	42.90	3.749	3.36E+09	2.04E+09	14266	3.35E+09

Table 3.10.

The obtained results of performance indicators for NRGA.

Problem Name	NPS	MID	SM	SNS	CPU Time (Second)	HV
N.1	24.2	5.75	7.16E+06	4.64E+06	144	1.14E+09
N.2	9.9	2.06	4.00E+07	2.32E+07	198	3.51E+07
N.3	19.8	1.39	3.84E+07	3.19E+07	558	4.18E+07
N.4	17.6	1.98	1.17E+08	8.84E+08	578	1.20E+08
N.5	25.3	2.86	3.22E+08	1.56E+07	620	2.59E+06
N.6	30.8	6.57	2.80E+08	2.16E+08	1073	4.19E+08
N.7	25.3	2.57	5.70E+08	3.26E+08	1524	4.78E+08
N.8	35.2	3.44	3.91E+08	3.39E+08	1704	4.39E+08
N.9	22	1.73	1.06E+09	1.08E+09	3919	1.12E+09
N.10	33	3.46	1.13E+09	8.39E+08	4047	9.13E+08
N.11	47.3	2.59	1.16E+08	1.16E+08	6176	1.73E+09
N.12	55	3.60	1.36E+09	1.36E+09	3303	3.19E+09
N.13	51.7	1.77	2.19E+09	2.19E+09	10763	4.55E+09
N.14	55	1.77	3.01E+09	3.01E+09	10193	4.20E+09
N.15	57.2	2.64	3.10E+09	3.10E+09	32739	4.90E+09

Table 3.11.

The obtained results of performance indicators for MOSA.

Problem Name	NPS	MID	SM	SNS	CPU Time (Second)	HV
N.1	18.7	3.96	2.16E+07	2.10E+06	39	1.69E+08
N.2	16.5	2.55	5.03E+06	1.55E+07	55	5.99E+06
N.3	11	2.16	5.73E+07	4.02E+07	78	7.38E+07
N.4	12.1	1.88	2.53E+08	1.04E+09	80	2.40E+06
N.5	25.3	2.45	2.56E+08	1.81E+07	98	2.88E+08
N.6	29.7	6.93	2.31E+08	1.95E+08	94	3.79E+08
N.7	36.3	2.16	6.59E+08	4.50E+08	319	5.66E+08
N.8	22	3.43	6.22E+08	4.25E+08	432	8.01E+08
N.9	28.6	1.32	8.08E+08	1.26E+09	335	1.00E+09
N.10	26.4	5.23	1.19E+09	1.18E+09	376	1.02E+09
N.11	55	2.89	1.59E+08	1.59E+08	660	2.10E+09
N.12	52.8	2.86	1.84E+09	1.84E+09	496	3.03E+09
N.13	44	1.18	3.43E+09	3.43E+09	1051	3.03E+09
N.14	53.9	1.46	3.81E+09	3.81E+09	2810	3.73E+09
N.15	52.8	2.99	2.19E+09	2.19E+09	2095	5.10E+09

Table 3.12.
The obtained results of performance indicators for MOKASA.

Problem Name	NPS	MID	SM	SNS	CPU Time (Second)	HV
N.1	17.6	4.46	5.36E+06	1.13E+07	320	8.98E+06
N.2	17.6	3.62	4.16E+07	1.70E+07	412	5.13E+08
N.3	19.8	1.75	5.50E+07	4.92E+07	492	5.48E+06
N.4	16.5	1.74	1.91E+06	7.51E+08	416	1.49E+07
N.5	4.9	2.27	2.87E+07	1.77E+07	904	3.47E+07
N.6	2.6	4.82	3.28E+08	1.98E+08	794	4.12E+08
N.7	3.0	1.37	6.78E+08	2.87E+08	1150	4.81E+08
N.8	2.6	3.46	5.17E+08	4.56E+08	2417	7.84E+08
N.9	4.0	2.43	6.07E+08	7.57E+08	3859	6.57E+08
N.10	4.9	4.83	1.07E+09	9.50E+08	3410	1.30E+09
N.11	53.9	2.81	1.70E+09	5.30E+08	2984	2.20E+09
N.12	47.3	4.03	1.27E+09	2.38E+09	3145	2.62E+09
N.13	57.2	1.98	2.83E+09	2.86E+09	18882	3.84E+09
N.14	53.9	2.96	3.44E+09	3.52E+09	17736	2.20E+09
N.15	44	2.75	2.04E+09	3.36E+09	22662	5.10E+09

Table 3.13.
The best algorithms in different problem dimensions are based on each performance indicator.

	NPS	MID	MS	SNS	CPU Time	HV
Small	NSGA-II	MOSA	NSGA-II	MOKASA	MOSA	MOKASA
Medium	MOKASA	MOKASA	MOKASA	MOSA	NSGA-II	NSGA-II
Large	NRGA	MOKASA	MOKASA	MOKASA	MOSA	NRGA

In this study, we conducted a comprehensive comparative analysis of four popular multi-objective optimization algorithms across small, medium, and large-sized problems. Our findings indicate that NSGA-II outperforms the other algorithms with respect to NPS and MS indicators for small-sized problems. Meanwhile, MOSA displays the best performance in terms of CPU Time and MID indicators for the same problem size. The hybridized MOKASA algorithm exhibits superior performance in HV and CPU Time measures for small-sized problems. Moving on to medium-sized problems, MOKASA emerges as the top-performing algorithm across NPS, MID, and MS indicators. However, NSGA-II demonstrates the best performance for HV and CPU Time indicators, while MOSA shows better performance for the SNS indicator. Finally, for large-sized problems, MOKASA leads the pack with excellent performance across three measures, namely MID, MS, and SNS. NRGA, on the other hand, provides better results for HV and NPS indicators, while MOSA remains the leading algorithm in terms of CPU Time. Our study results provide valuable insights into the comparative performance of multi-objective optimization algorithms across different problem sizes and evaluation measures.

Additionally, to facilitate a graphical comparison of our results, we present mean plots and Least Significant Difference (LSD) values for the performance indicators. To obtain these plots and values, we convert the obtained performance metric values to the Relative Deviation Index (RDI) using Eq. (3.62) and apply statistical analysis techniques. This approach allows for a more comprehensive and meaningful comparison of the algorithms' performance across different test problems, while also taking into account the variance and standard deviation of the results. By utilizing mean plots and LSD values, our study presents a clear visualization of the comparative performance of the algorithms, which can aid researchers and practitioners in selecting the most appropriate algorithm for a given optimization problem. (Mosallanezhad, Ali Arjomandi, et al., 2023).

$$RDI = \frac{|S_{Alg} - S_{best}|}{S_{max} - S_{min}} \tag{3.62}$$

In Eq. (3.62), S_{Alg} and S_{best} indicate respectively the calculated value of the performance metric and the best value obtained for that specific metric by each meta-heuristic. S_{max} and S_{min} show the maximum and minimum values of performance metrics. It should be noted that a lower RDI value indicates better algorithm performance, as reported by (Mosallanezhad, Chouhan, et al., 2021). The mean plot and LSD for small, medium, and large-sized problems are shown in Figures 3.7, 3.8, and 3.9, respectively. To provide a more comprehensive comparison of the algorithms' performance, we present mean plots and LSD values for small, medium, and large-sized problems in Figures 7, 8, and 9, respectively. The results show that MOSA outperforms the other algorithms in terms of MID, CPU, and HV indicators for small-sized problems (see Fig 3.7). On the other hand, NSGA-II, NRGA, and MOKASA demonstrate better performance in terms of MS, NPS, and SNS, respectively, for the same problem size.

According to Fig 3. 8, NSGA-II outperforms the other algorithms considering HV, CPU Time, and MID indicators in medium-sized problems. However, MOKASA has shown better performance in MS and NPS indicators, and MOSA provides better RDI results for the SNS indicator. To evaluate the performance of proposed algorithms in large-sized problems, the RDI for different performance indicators is calculated, and then the mean plot and LSD of performance metrics are shown graphically, as illustrated in Fig 3.9. The RDI is utilized to have the same scale for different performance indicator using Eq. (3.62). Fig 3.10 reveals that NRGA overcomes other algorithms in terms of NPS and HV, while MOKASA shows better performance in terms of MS and SNS indicators. Finally, MOSA is the best algorithm for MID and CPU Time metrics. Finally, Fig 3.11-3.14 and Tables 3.14-3.17 describe the statistical description of performance metrics and do compare all algorithms in terms of variance and standard deviation.

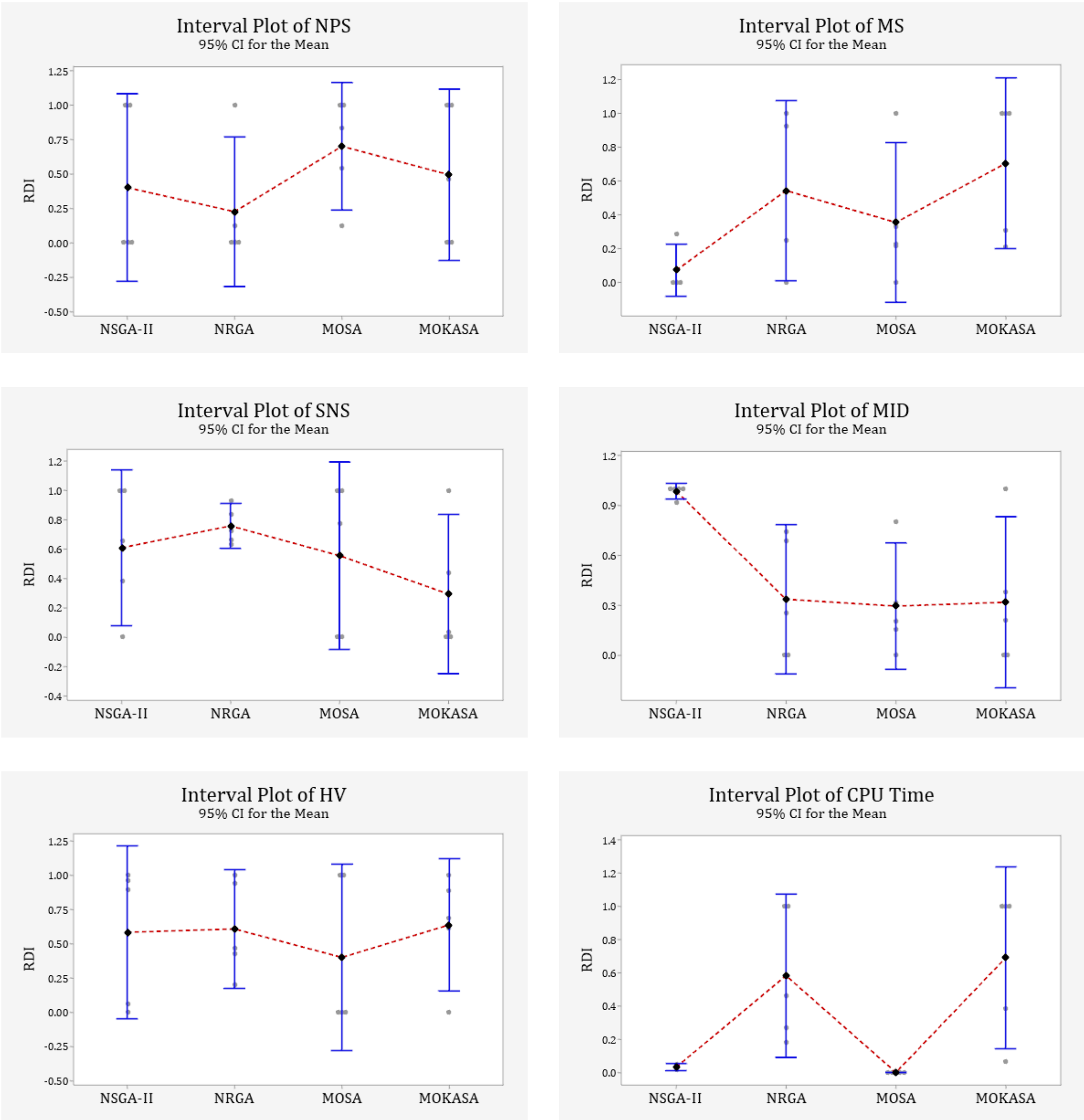

Fig.3.7. Interval Plot of small-sized problems based on performance metrics.

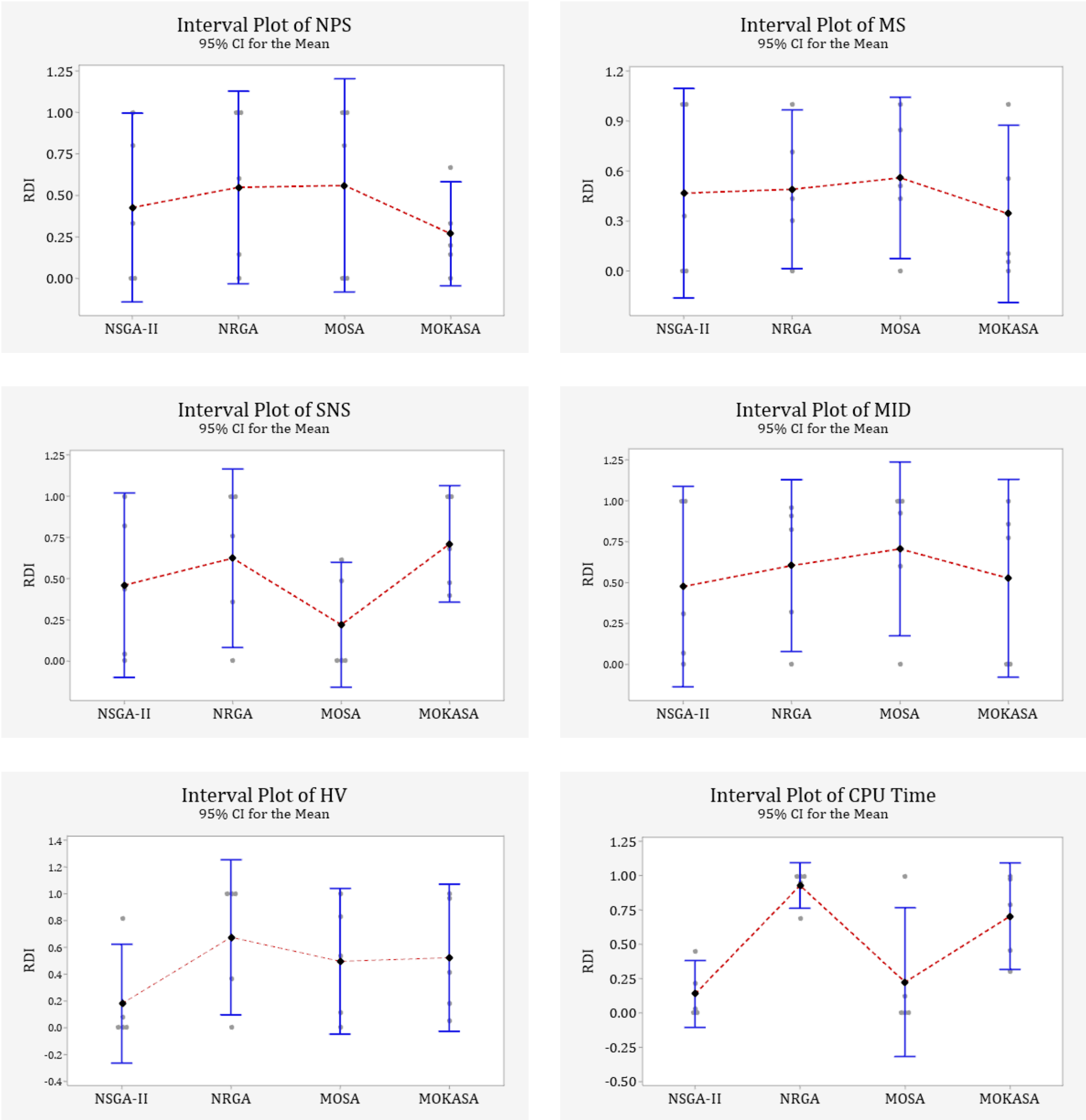

Fig.3.8. Interval Plot of medium-sized problems based on performance metrics.

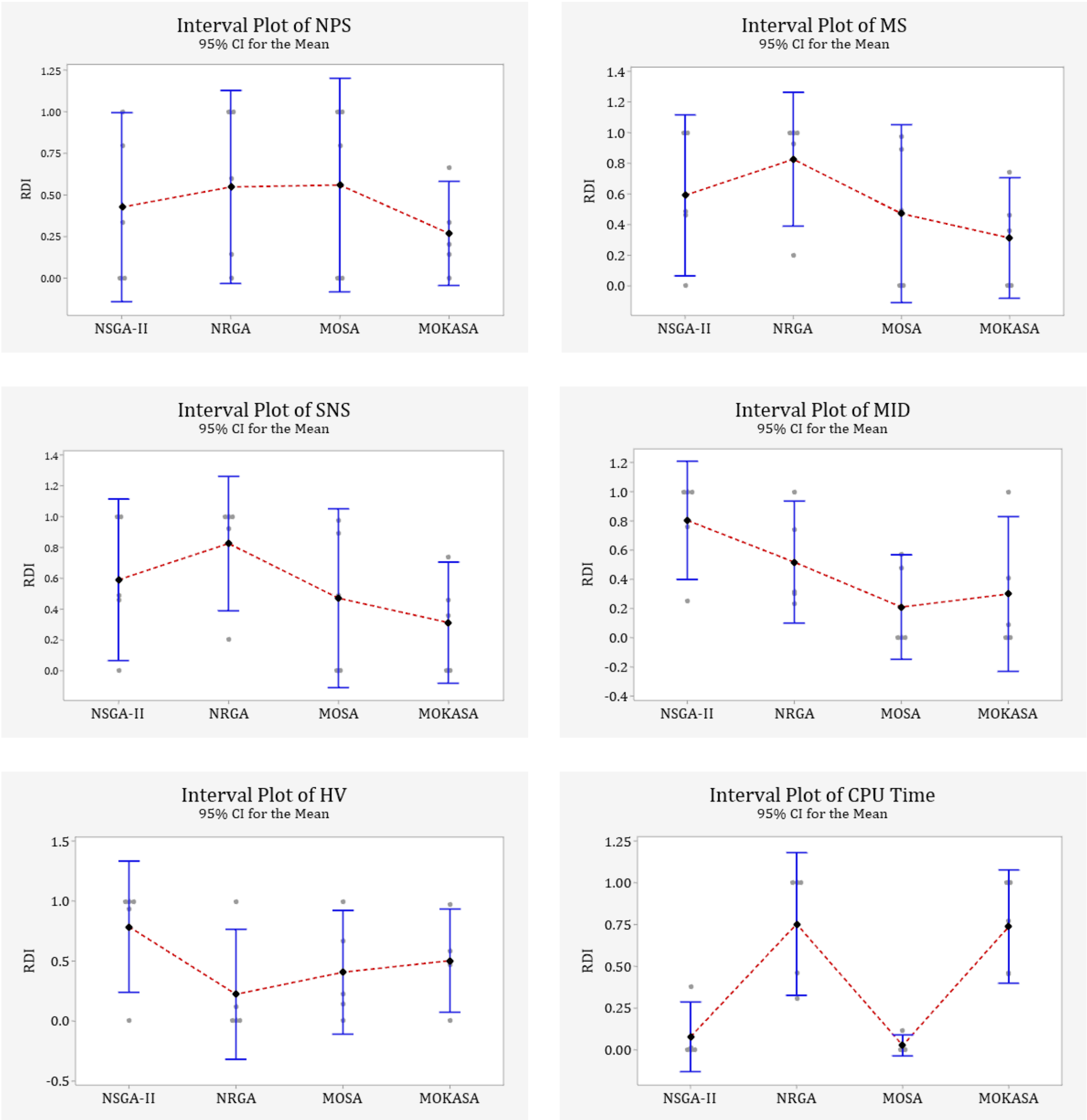

Fig.3.9. Interval Plot of large-sized problems based on performance metrics.

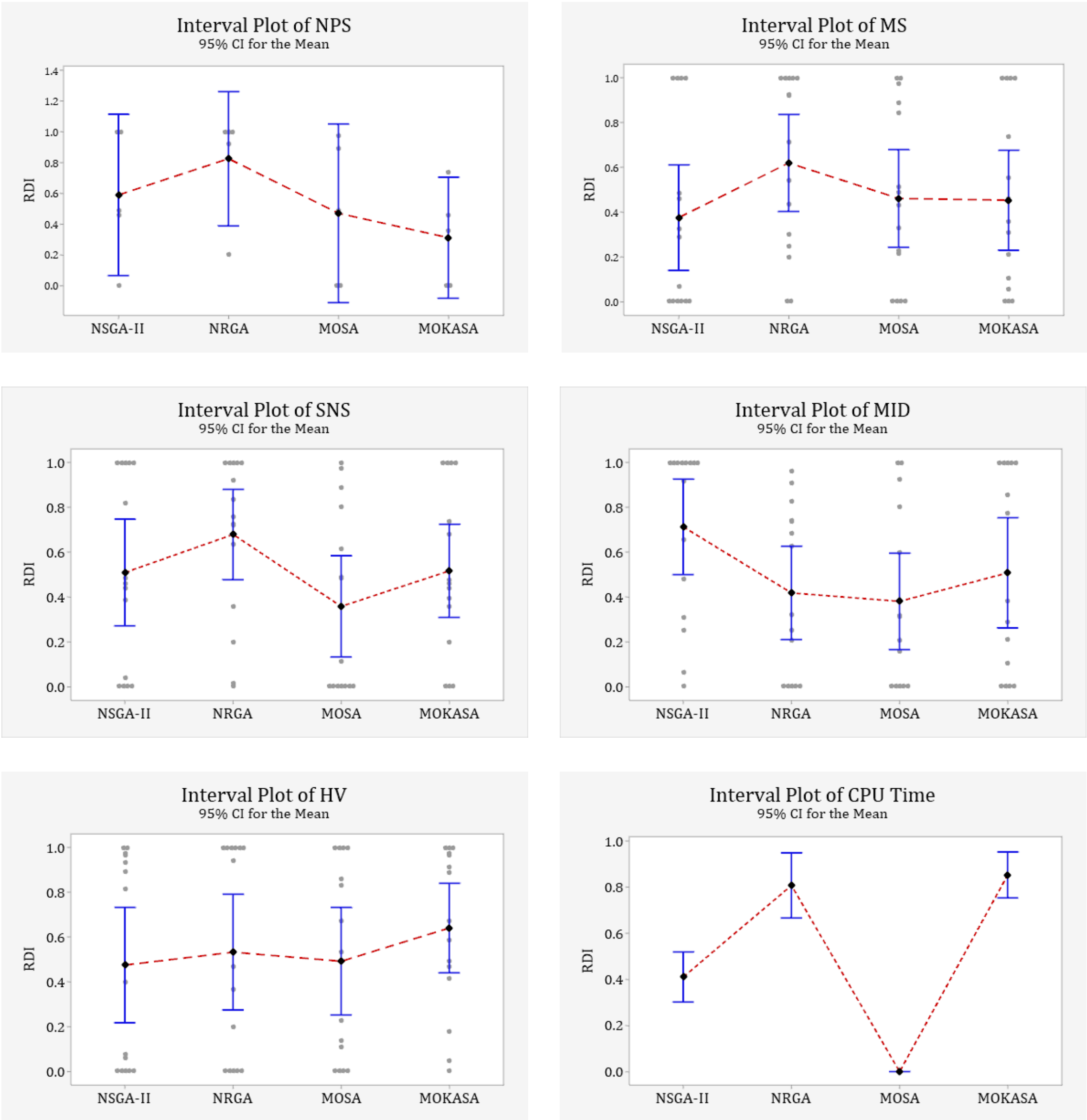

Fig.3.10. Interval Plot of overall performance metrics for all dimensions.

Table 3.14.
Statistical description of SNS.

Algorithm	Mean	SE Mean	StDev	Variance	Sum of Squares	Median
NSGA-II	0.508	0.111	0.429	0.184	6.459	0.459
NRGA	0.6779	0.0938	0.3632	0.1319	8.7397	0.7572
MOSA	0.358	0.105	0.408	0.166	4.245	0.114
MOKASA	0.5159	0.0967	0.3747	0.1404	5.9577	0.4573

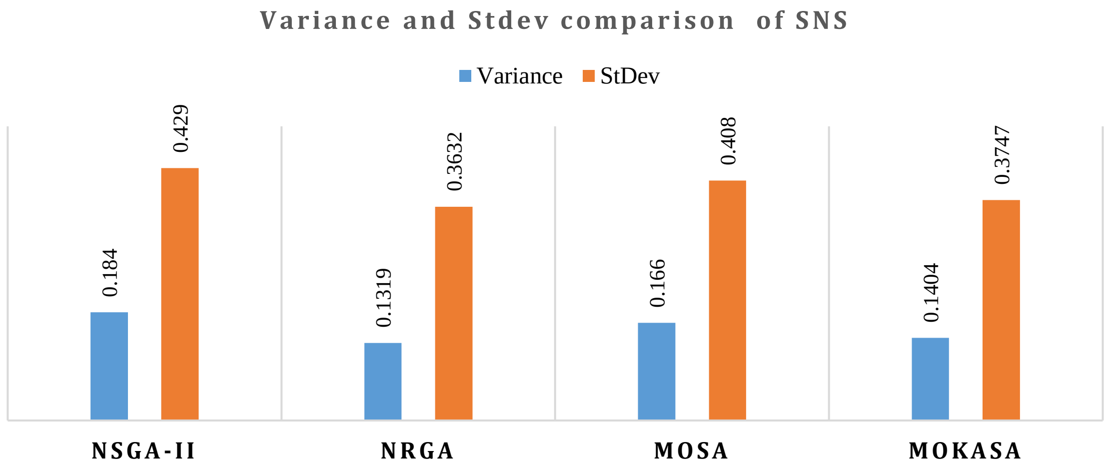

Fig. 3.11. Variance and Stdev comparison of SNS.

Table 15.
Statistical description of NPS.

Algorithm	**Mean**	**SE Mean**	**StDev**	**Variance**	**Sum of Squares**	**Median**
NSGA-II	0.589	0.189	0.422	0.178	2.446	0.485
NRGA	0.824	0.157	0.351	0.123	3.891	1
MOSA	0.47	0.209	0.467	0.218	1.975	0.487
MOKASA	0.311	0.141	0.316	0.1	0.884	0.359

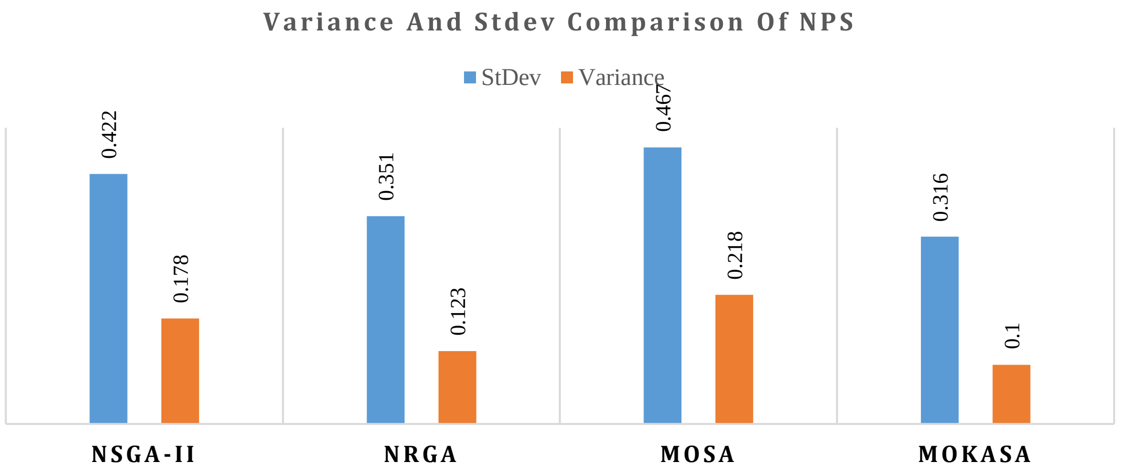

Fig. 12. Variance and Stdev comparison of NPS.

Table 16.
Statistical description of MID.

Algorithm	Mean	SE Mean	StDev	Variance	Sum of Squares	Median
NSGA-II	0.7115	0.0992	0.3841	0.1475	9.6598	1
NRGA	0.4175	0.0971	0.3759	0.1413	4.5937	0.3185
MOSA	0.38	0.1	0.388	0.15	4.27	0.311
MOKASA	0.507	0.114	0.443	0.197	6.609	0.381

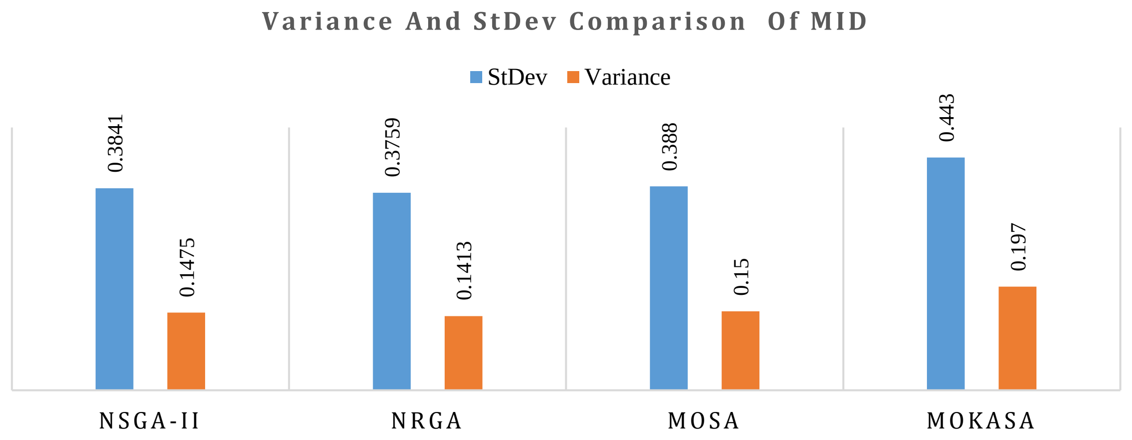

Fig. 13. Variance and Stdev comparison of MID.

Table 17.
Statistical description of HV.

Algorithm	Mean	SE Mean	StDev	Variance	Sum of Squares	Median
NSGA-II	0.474	0.12	0.463	0.215	97.77	0.397
NRGA	0.532	0.12	0.466	0.217	87.67	0.469
MOSA	0.491	0.112	0.433	0.188	88.22	0.533
MOKASA	0.6396	0.0932	0.361	0.1304	56.45	0.6711

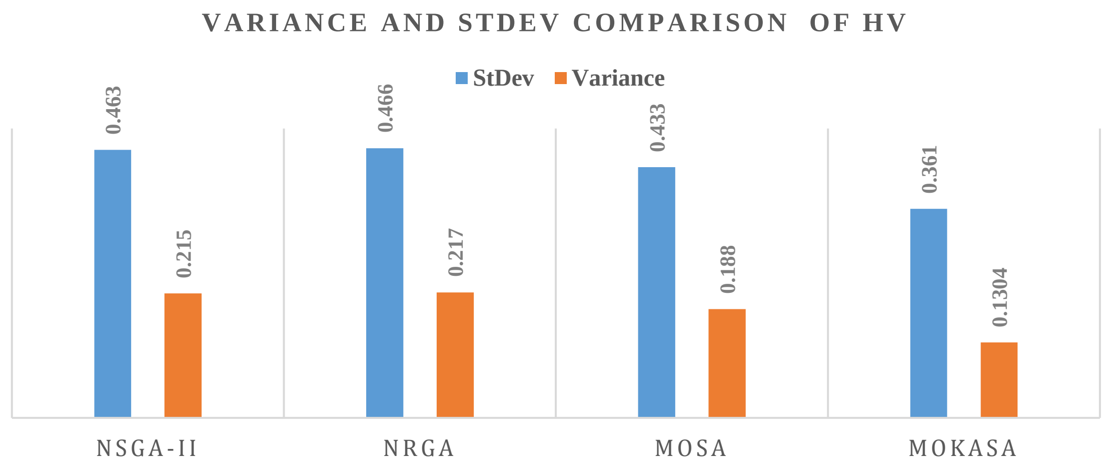

Fig. 14. Variance and Stdev comparison of HV.

The proposed mathematical model in this study is a complex optimization problem, due to being an extension of VRP (Akbarpour et al. 2021). Therefore, it is justifiable to utilize an exact method only in solving the initial two numerical experiments. It is not feasible to solve larger examples using GAMS within a reasonable time frame, because the running time grows exponentially. The graphical representation of the results obtained from the best proposed meta-heuristic algorithm (MOKASA) can be observed in Figures 15 and 16, respectively for the first two numerical experiments. Moreover, the corresponding objective values of the non-dominated solutions obtained from MOKASA are compared with the optimal solutions of GAMS software, as shown in Tables 18 and 19. As mentioned above, the remaining test problems are only solved using the proposed meta-heuristic algorithms, because the processing time increases significantly, making it impractical or unfeasible to use exact methods.

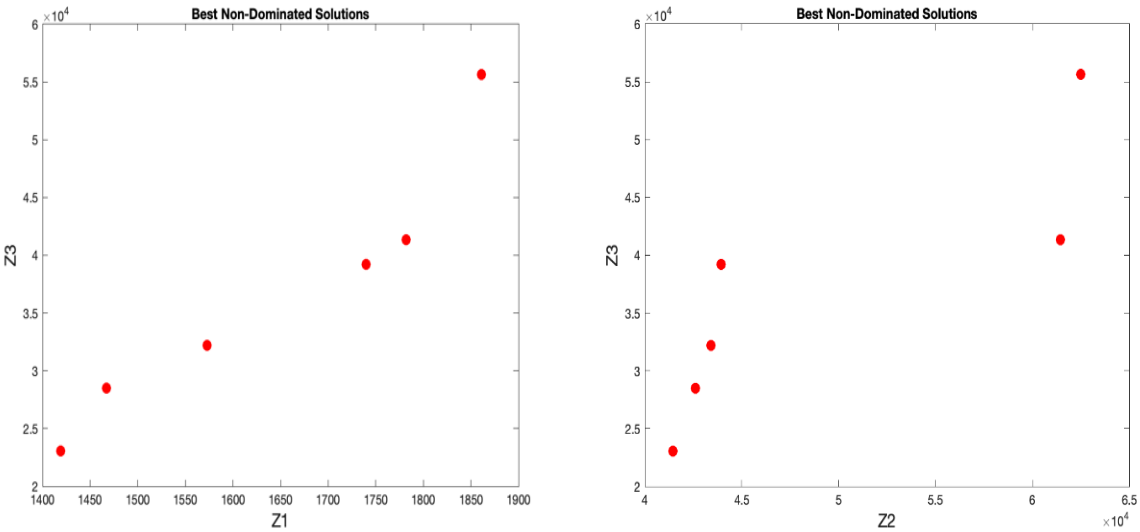

Fig.3.15. Pareto front of MOKASA for test problem 1.

Table3. 18.
A comparison of the outcomes for test problem 1.

	GAMS	Non-dominated solutions of pareto front from MOKASA					
First objective	1370	1419	1467	1573	1740	1782	1861
Second objective	39841	41456	42618	43415	43929	61457	62498
Third objective	23605	23078	28519	32186	39210	41374	55626

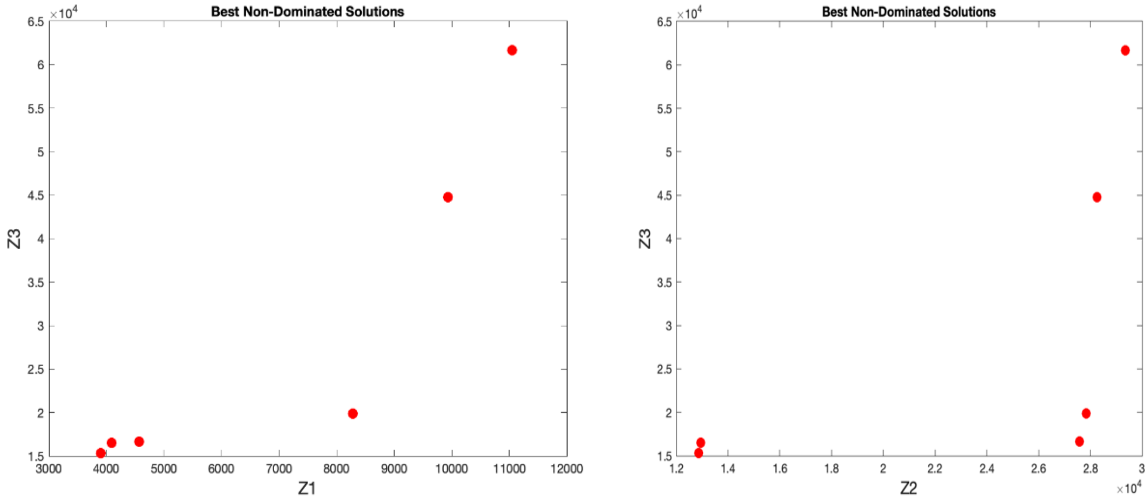

Fig.3.16. Pareto front of MOKASA for test problem 2.

Table 3.19.
A comparison of the outcomes for test problem 2.

	GAMS	Non-dominated solutions of pareto front from MOKASA					
First objective	3790	3900	4091	4573	8282	9937	11051
Second objective	12750	12857	12946	27584	27833	28252	29349
Third objective	15524	15308	16528	16632	19892	44784	61688

In this paper, we utilize BWM developed by Rezaei (2015) to do comparison between algorithms and selecting the best alternative considering the performance metrics provided in Section 6.1. BWM is a Multi-Criteria Decision-Making (MCDM) approach that allows decision-makers to determine the relative importance of criteria and their respective weights. The BWM involves ranking the best and worst criteria in order to identify the most important and least important criteria. By employing the MCDM method, decision-makers can evaluate the performance of different algorithms based on multiple criteria and subsequently rank them according to a weighted sum of all criteria. In this study, the proposed algorithms comprise the set of possible alternatives, and the evaluation criteria consist of NPS, MID, MS, SNS, HV, and CPU Time. Figure 17 illustrates the hierarchical structure of the alternatives and criteria for selecting the optimal MOO method. To determine the value of both the criteria and alternatives, we employed the BWM method, which is a comparison-based approach. For this method, we only conducted pairwise comparisons of the best criterion against other algorithms and then other algorithms against the worst criterion to obtain the weights of all criteria. This approach generally requires less information for pairwise comparisons of different criteria. We used the mathematical model of BWM to specify the weights of the criteria and then calculated them by maximizing the consistency of comparisons. In this study, we identified MID and NPS as the most and least desirable criteria, respectively, in the pairwise comparison matrix.

Ultimately, using the weighted sum of performance metrics, we selected MOKASA as the optimal solution method among the proposed algorithms.

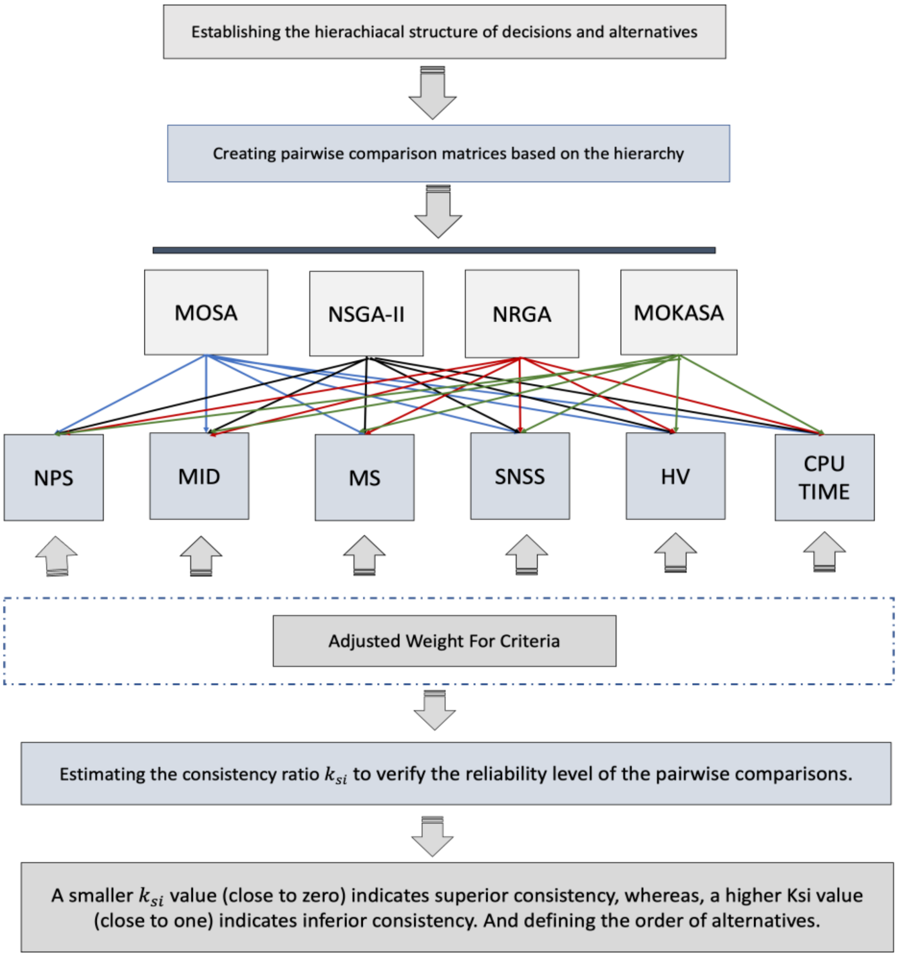

Fig.3.17. The hierarchical representation of alternatives and criteria.

3.9. CONCLUSION

In conclusion, this study proposed an ISWM framework based on the IoT technology to optimize the collection, recycling, and recovery operations in the waste management system. The proposed multi-objective optimization model aimed to maximize the probabilistic profit of the network while minimizing the total travel time and transportation costs. The chance-constrained programming approach dealt with the profit uncertainty gained from waste recycling and recovery activities. Additionally, several meta-heuristic algorithms were applied to address the complexity of the problem. The Taguchi parameter design method was utilized to optimize the parameter values of algorithms, and the BWM was used to identify the most reliable algorithm. The results of the study revealed that the proposed ISWM optimization model was effective in improving the efficiency and effectiveness of waste management while promoting sustainability and reducing costs. The proposed optimization algorithm was capable of finding near-optimal solutions within a reasonable amount of time. The obtained results also showed that considering multiple objectives in the waste management problem is essential to balance economic, social, and environmental goals.

Multi-objective optimization in integrated solid waste management (ISWM) is a crucial area of research that has gained significant attention in recent years. With the growing concerns regarding the impacts of WM practices, there is a need for advanced optimization techniques that assist decision-makers in achieving sustainable, cost-effective, and environmentally friendly solutions. However, due to the inherent uncertainty in the input parameters, optimization in ISWM poses significant challenges. Therefore, there is a need for the development of new techniques for addressing those issues. Here, a few potential research directions can be pursued in this area. Future research may focus on developing new robust optimization methods that are more effective in managing uncertainty in the context of ISWM. The development of powerful optimization techniques can handle uncertainty in the input parameters and ensure the solution remains feasible and acceptable even when input parameters deviate from their expected values. Another approach for modeling uncertainty is stochastic programming, which uses probability distributions to represent input parameters as random variables. Incorporating stochastic programming into multi-objective optimization models for ISWM can be explored in future studies.

Moreover, utilizing Artificial Intelligence (AI) and Machine Learning (ML) techniques is beneficial to analyze data generated by the ISWM system and produce insights that facilitate the decision-making process. Future research can focus on integrating AI and ML techniques with multi-objective optimization models to improve the accuracy and robustness of the models. To ensure that solutions are sustainable and acceptable to all stakeholders, multi-objective optimization models should consider social, environmental, and economic factors. Future studies can focus on developing new models that incorporate more relevant variables into the decision-making process. Overall, the above-mentioned research avenues can potentially improve the multi-objective optimization in ISWM under uncertainty.

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CHAPTER 4

PAPER 3:

Industry 4.0 In Waste Management: An Integrated Iot-Based Approach for Facility Location and Green Vehicle Routing

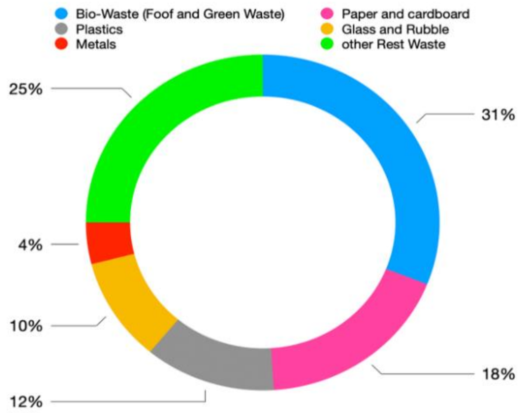
The increasing production of solid waste rate in urban areas plays a critical role in sustainable development. To mitigate the adverse effect of waste and enhance waste management efficiency, this paper introduces a holistic approach that notably reduces the overall cost while mitigating social and environmental impacts. Central to the system's efficacy is the critical process of waste sorting, which enhances the output value of the waste management system. While previous studies have not extensively addressed simultaneous waste collection and sorting, this paper provides an innovative framework. This approach coordinates waste collection from various bins, followed by their transfer to separation centers. At these centers, waste is categorized into organic and non-organic varieties, which are then dispatched to a recovery center at the second level. In the context of optimizing the routes at both levels, this paper presents a green, multi-objective location-allocation model. This model is designed to optimize the number and location of separation center facilities. Since the routing problem is influenced by the facility location model it is addressed as a multi-depot green vehicle routing problem, integrating real-time information from IoT-equipped bins. This paper also proposes the vehicle routing problem with a split pickup, aiming to minimize cost, CO2 emissions, and visual pollution. The mathematical models introduced to formulate the problem are solved using the GAMS optimization software to apply an exact method, while Social Engineering Optimization and Keshtel metaheuristic algorithms are deployed to solve the routing problem. The proposed approach offers a comprehensive and sustainable solution to waste management, filling crucial gaps in current research and practice.

Keywords: Waste Management System; Internet of Things; Facility Location Problem; Dynamic Vehicle Routing Problem; Sustainability.

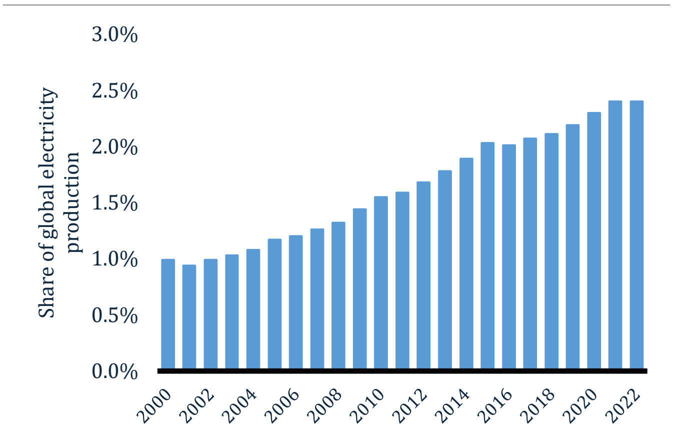
4.1 INTRODUCTION

Due to the rapid rise of world population, urbanization, and growth of industrial production, the amount of waste generated worldwide is projected to surge to 2.2 billion tons over the next thirty years (Saravanan et al., 2023). This substantial increase leads to an approximate cost of $600 billion for managing Municipal Solid Waste (MSW) (Ali et al., 2020). The MSW concept refers to the unwanted remnants originating from households, institutions, industrial establishments, and construction and demolition sites. These wastes can be broadly categorized into six main groups: bio-waste, plastics, paper, glass, metals, and other miscellaneous waste types (Bello et al., 2022). On the other hand, with the continuous reduction in available space for municipal waste in landfills, the spotlight in waste management is progressively shifting toward thermal waste recovery. As illustrated in Fig.1.a, the significant presence of bio-waste (31% contribution) within solid waste streams presents an optimistic potential for energy recovery via the Waste-to-Energy (WTE) technology. This optimistic potential of WTE technology in harnessing energy from bio-waste further emphasizes the importance of exploring and implementing sustainable waste management strategies.

Biowaste, which encompasses all biodegradable organic waste along with fossil fuels like oil, coal, and natural gas, is emerging as a dominant source of renewable energy today (Jiménez-Rosado et al., 2023). As seen in Fig.1.b, there has been a notable increasing trend in biopower generation. In 2019, electricity generated globally from biomass reached a total value of 655 terawatt-hours, underscoring its potential as a significant contributor to meeting worldwide electricity demand. Additionally, the waste-to-energy market, encompassing digestion and thermal power generation techniques, mitigates the risks associated with pollutants emitted from landfills. These pollutants include parasites, volatile organic compounds, carbon dioxide, and methane gas. Therefore, transforming waste into energy not only provides a sustainable energy solution but also plays a crucial role in reducing environmental hazards.



a. Contribution of different MSW categories in European countries



b. Biomass electricity generation worldwide from 2000 to 2022.

Fig.4.1. Biomass contribution and worldwide electricity generation by Biomass (Source: Statista – 2022).

MSW management encompasses a range of activities, including waste generation, monitoring of storage sites, waste collection, transportation, processing, and disposal (Cheraghalipour et al., 2017). In order to effectively address waste-related challenges, municipalities require an efficient mechanism to control waste, monitor the status of waste bins, optimize capacity, and plan collection routes in a sustainable manner. To address these needs, an Internet of Things (IoT)-based smart waste management solution can provide cities with the necessary tools to manage the increasing volume of MSW. The proposed technique relies on data collected from smart bins installed throughout the city to determine the waste level (K. Guo et al., 2022; Zahedi et al., 2021b).

In this study, the filling status of smart IoT-based bins is simulated based on real-time information obtained from the smart bins and through interviews conducted with municipal authorities. The simulation considers two distinct time periods: nighttime collection and daytime collection, with the latter prioritizing areas with higher levels of garbage production, such as those near markets or other high-traffic areas. By incorporating smart waste management practices, the study aims to address the inefficiencies observed in traditional waste management approaches such as unnecessary collection of waste, leading to increased costs and delays in waste collection. These inefficiencies can result in a significant increase of approximately 70% in annual collection costs. Additionally, inefficient route planning leads to congestion, requiring more fuel and trucks to complete the collection process. Therefore, the carbon footprint associated with waste collection is amplified by approximately 50% (Cialani & Mortazavi, 2020).

The proposed smart waste management system aims to mitigate these issues by leveraging real-time data and optimizing waste collection routes. By accurately monitoring the fill levels of bins and implementing efficient collection schedules, unnecessary pick-ups can be minimized, resulting in cost savings and reduced environmental impact. Through the implementation of IoT solutions, garbage vehicles can be equipped with more efficient routes and receive notifications from drivers when emptying is required. By utilizing smart IoT-based bins in both time periods, we gain access to real-time information about the amount of trash in each bin. This allows us to create a list of bins that require emptying, enabling us to optimize routing specifically for this category of bins. This approach eliminates the need to visit all bins, reducing transportation costs and the associated pollution caused by unnecessary travel (Mojtahedi et al., 2021c; W. Wu et al., 2023).

One of the methodological contributions of this proposed study is the development of a three-step framework that considers the following models: facility location for separation centers, vehicle routing optimization from separation centers to bins, and from the recovery center back to the separation centers. The first model focuses on long-term and strategic objectives, while the second model addresses operational objectives in routing optimization, resulting in the minimization of transportation costs and the use of the fewest possible number of vehicles for waste collection. In the proposed waste collection framework, the location of separation centers is of particular importance as it impacts transportation costs and pollutant emissions. Moreover, the location of separation centers influences the determination of their number. Also, the location and number of separation centers play a vital role in determining the routes taken by vehicles for waste collection from bins, delivery to separation centers, and subsequent transfer to recovery centers. Finally, the three-step framework is extended to include the optimization of separation center locations, waste collection from bins to separation centers, and the transfer of waste to recovery centers. This comprehensive approach aims to address real-world waste collection challenges and achieve sustainable waste management practices.

4.2 LITERATURE REVIEW

The management of Municipal Solid Waste (MSW) comprises five critical elements, including source waste handling, collecting and transferring, dumping, processing, and treating (Akbarpour et al., 2021a; Jatinkumar Shah et al., 2018). A significant portion of the resources and cost is dedicated to the collection and transportation of waste, accounting for approximately 80% of the overall MSW expense. This operation is influenced by different factors such as the city's road network, congestion, weather conditions, and citizen interactions (Jorge et al., 2022b; Kang et al., 2020). Concurrently, waste management's hierarchy underlines the importance of source reduction, recycling, and waste transformation in the overall waste management system. Source reduction primarily aims to minimize waste generation; while recycling and waste transformation are significant for reusing materials and have been the focus of considerable research (Szulc et al., 2021). Moreover, it is essential to consider non-decomposable waste since the processing and potential transportation of non-decomposable waste to recycling centers can lead to additional costs. In this regard, the optimization of separation center locations plays a key role in enhancing the overall efficiency and effectiveness of waste management systems, minimizing costs, and maximizing resource utilization.

Hence, it is worth noticing that MSW is a labor-intensive management system which necessitates strategic efficacy due to the significant distances (2 to 50 km for European and Central Asian cities) of bins from separating waste production sites and final destinations such as disposal or recovery facilities (Kaza et al., 2018). Given the transportation expenses for waste, which lie between \$20 to \$50, formulating an efficient and sustainable model to reduce costs while minimizing environmental, social, and economic impacts is necessary (Erdem, 2022). The sustainable development goals outlined by the United Nations offer a framework to balance the mentioned dimensions. Many of these goals can be achieved directly or indirectly through operational improvements and reductions in fleet emissions. Numerous techniques have been explored to optimize collection and transportation costs while minimizing environmental impacts. For instance, the Backtracking Search Algorithm has been developed to address the capacitated vehicle routing problem by optimizing vehicle routes, minimizing distance, fuel consumption, CO_2 emissions, and collected waste. It introduces the concept of threshold waste level (TWL) to reduce the number of bins that need to be visited, with an optimal TWL range of 70% to 75% of total bin capacity (Akhtar et al., 2017). Nesmachnow et al., (2018)proposed two multi-objective evolutionary algorithms to solve the urban waste collection problem considering priorities and the conflicting goals of minimizing the total distance while maximizing the quality of service. The results of their tests showed that the evolutionary algorithms outperformed greedy strategies and the current routing methodology applied in Montevideo. Furthermore, the best results are obtained for a dynamic version of the problem using real time information.

Indeed, the implementation of tracing systems to provide real-time information plays a vital role in sustainable waste management by reducing unnecessary bin visits. As such, the application of IoT technology becomes crucial in the design of sustainable MSW management systems (Bibri, 2018; Fujdiak et al., 2016a). A smart integrated system consisting of four parts based on the application of IoT was presented by Sohag & Podder, (2020). The proposed system measures the garbage level using sensors and displays it on a liquid crystal display, allowing for efficient waste management by reducing manpower, waste spillage, time, and overall costs. The IoT-based waste collection system was evaluated by applying modified Entropy measures and a multi-criteria decision-making method and considering uncertain parameters (Bahadori-Chinibelagh et al., 2022; Seker, 2022).

Also, the use of IoT for real-time information makes it possible to have dynamic routing that is currently underutilized in such systems (Hajiaghaei-Keshteli et al., 2023; Mohammadi et al., 2023; Yang et al., 2022). Expósito-Márquez et al. (2019) designed a greedy adaptive search procedure to determine the routes for visiting the selected bins that minimize the number of visited bins. Only bins with the highest fullness level can be selected to collect because of the maximum shift duration constraints. Jorge et al., (2022) designed a framework to consider dynamic routes for the smart waste collection system using real-time information and developed a hybrid metaheuristic algorithm to determine, firstly, the day of collection and then the bins that must be visited. Moreover, collection of waste in a two-echelon waste collection, leveraging Industry 4.0 concepts and IoT devices is addressed to minimize operational costs and environmental impact. The system focuses on optimizing waste collection from bins to separation centers and the transfer to recycling centers by implementing meta-heuristic algorithms and novel heuristics (Rahmanifar et al., 2023c).

Recently, Salehi-Amiri et al., (2022) proposed WMS in smart cities by incorporating real-time waste bin fill level data obtained through IoT-based devices. Two different sub-models were proposed based on the vehicle routing problem: the first determines the optimal routes to collect waste from bin to separation centers while the second one maximizes the recovery value and minimizes visual pollution by efficiently transporting waste from separation centers to recovery centers. Different threshold waste levels were investigated and a waste level between 70% and 75% was found as the best one to optimize transport efficiency, traveled distance, and collected waste amount. While dynamic routing is crucial, which optimizes the collection of waste from bins to separation centers and further to recovery centers, it's equally important to consider the strategic, tactical, and operational decisions in WMS. These decisions have significant impacts on the environmental, social, and economic aspects of waste management, highlighting their vital role in sustainable development (Hashemi-Amiri, Mohammadi, et al., 2023).

While most of the previous research considered a separate waste management center for each zone of the smart city, the current paper highlights that the location and the number of these centers are crucial elements of the logistic network that directly influence the routing problem solution. However, facility location decisions are long-term and unchangeable, unlike flexible routing decisions which bins location problem, for example, has been investigated in several previous works (Rossit et al., 2019, 2020b; Rossit & Nesmachnow, 2022; Toutouh et al., 2019). As routing problems can be solved using real-time data from sensor-equipped bins, the routes can be updated frequently but the related problem cannot be integrated with static facility location. This paper extends the previous work by Salehi-Amiri, Akbapour et al., (2022). Instead of assuming different zones and one separation center for each one, the proposed model develops a green facility location model that determines the number and location of separation centers and to assign bins to each opened facility. Moreover, the formulated location problem avoids establishing separation centers that are near other opened facilities. Regarding the routing problem, a multi-depot routing problem is suggested, enabling depot resource sharing to cover all bins. Additionally, constraints are implemented to maximize utilized truck capacity, minimize travel distance, ensure maximum load, and reducing energy consumption and pollution.

Moreover, it is important to mention that the sustainability of MSW management practices calls for a shift from incineration towards more environmentally friendly options such as composting, which presents a viable solution for waste transformation (Fogarassy et al., 2022). This context forms the basis of our proposed two-stage mathematical model to address the routing problem. This system facilitates waste movement from bins to separation centers and subsequently to recovery centers separately. Separating them into two distinct models is justified by several motivations. Firstly, the processing time and storage requirements at separation centers, where sorting and pre-processing take place, can extend beyond a day. So, it is more practical to model them separately from collection and transportation processes. Secondly, since separation centers can store collected waste for extended periods, the transportation of waste from these centers to the recovery centers does not need to happen on the same day as the collection. Also, the storage capacity at separation centers provides a buffer that decouples the first and second levels of routing. This buffer allows for differences in the capacity of the vehicles used in the two routing levels. Lastly, dynamic factors such as processing rates, demand, and vehicle availability can vary independently, and separate models provide flexibility to adapt to these changes. These motivations highlight the practicality, flexibility, and efficiency of treating the two routing levels as separate models.

4.3 Problem Statement and Mathematical Formulation

Problem statement and mathematical formulation are discussed in this section. The models introduced here address the following issues: location of waste separation facilities, vehicle routing for urban waste collection, and transfer of waste from separation to recovery centers. Each of them is presented in the subsequent subsections. The initial issue involves identifying the optimal vehicle routing within the city center, whereas the subsequent issue involves mapping the routes between the separation center and the recovery center, both of which are situated on the city's outskirts. Since the routing problem is affected by the location of the separation center, a location facility problem is proposed to find the optimal position of separation centers, which is a long-term decision plan (See Fig. 2).

It is crucial to note that the primary challenge is mainly within the city center, because of some factors such as changes in travel time and other uncertain factors that can affect routing problems. Using IoT devices to collect real-time information is a convenient strategy as it promotes efficient decision-making and manages such uncertainties. By leveraging IoT-based smart waste management systems, municipalities can enhance their waste management practices, improve operational efficiency, and contribute to the overall sustainability of their cities. A key use of IoT devices in waste management systems is the measurement fill-up levels by smart waste bins. In the proposed approach, the system defines three fill-up levels to monitor the status of waste in the bins. This information enables cities to efficiently allocate resources and optimize waste management processes. These three levels are identified as follows:

- **Empty Level:** This is the initial stage of the waste bin, indicating that it has recently been emptied. The empty level serves as a reference point for the system to monitor the bins' status and predict the time it takes to fill up again.
- **Half Level:** The half level is used to check the new status of bins. It allows the system to anticipate the fill-up time of these bins based on historical data and patterns. By predicting the fill-up time, waste collection drivers can incorporate the collection of bins at the half level during their regular visits, further optimizing their routes and reducing operational costs.
- **Full Level:** Upon detecting a full level, the system promptly notifies both the municipal authority and waste collection drivers of the need for a high-priority collection service. This ensures that full bins are promptly addressed and prevents any potential overflow or inconvenience to residents.

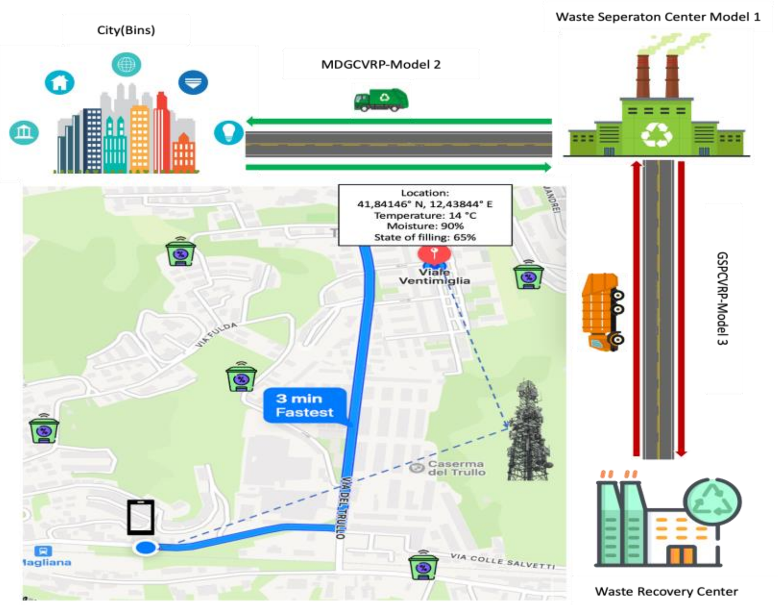


Fig.2. A snapshot of the proposed network.

4.3.1 SEPARATION CENTER LOCATION PROBLEM

The number of optimal facilities is determined based on initial fixed costs, transportation costs, emission costs associated with transportation services, pollution costs for opened facilities, and capacity utilization. Some constraints are introduced to ensure that candidate locations are not opened near other existing facilities and that the total capacity must be able to comply with the total generated demand. The single allocation hub location problem is also considered in this paper, which implies that each demand point must be allocated and served by only one of the opened facilities (Alumur et al., 2021). The costs associated with opening a potential location include the cost of land and the construction of separation centers. Also, the opening costs depend on the different capacities of each candidate location. In addition to opening costs, the objective function also considers transportation costs, carbon emission costs associated with transportation at the first level, and pollution costs related to gas and electricity consumption at separation centers.

However, the carbon emission cost of vehicles from separation centers to recovery centers and the deviation from the minimum required capacity for each opened separation center have been considered separately. These costs are included in a second objective function, which considers the opening of facilities with the required capacity and incentives for larger capacity to minimize operational costs. The model is encouraged to open facilities with a capacity closer to the required value by penalizing the deviation from the minimum required capacity. The trade-off between minimizing carbon emissions and maximizing capacity utilization is made by defining a weighting factor that gives more importance to maximizing capacity utilization. The value of this factor can be adjusted using information integration methods by leveraging real-time or historical data. This process involves identifying the relevant data sources for the decision-making and setting criteria to adjust the weighting factor considering various factors such as fluctuations in energy prices and changes in waste generation rates (Hajiaghaei-Keshteli & Sajadifar, 2010).

The location problem is solved when the emission costs of transporting waste are minimized at both levels, from bins to separate centers and from separate centers to recovery centers. The two goals are conflicting because minimizing the emission costs of the first level forces the model to open candidate locations near bins while minimizing the emission costs of the second level aims to close separation centers to recovery centers. The model also considers a minimum distance between every two locations before opening a new location, which can result in a wider coverage area. The main assumptions are reported in the following.

- The amount of waste generated in each bin is deterministic.
- Only one recovery center is assumed.
- Different construction costs are assumed to open candidate locations.
- The land price is fixed and equal for all locations.
- The candidate locations are assumed to have different capacities.

The sets of variables, the model parameters, and the decision variables of the model are reported in Tables 4.1 to 4.3. Equations 1 to 10 provide the formulation of the optimization problem.

Table 4.1

Set of proposed models.

Sets	Description
I	Set of bins,
J, W	Set of candidate locations for separation centers,
RE	Set for recovery centers,
i	Index of demand points,
j, w	Index of candidate locations for separation centers,
Re	Index of recovery centers.

Table 4.2

Parameters.

Parameters	Explanation
f_j	Land price of separation center *j*,
q_i	The amount of generated waste in bin *i* (kg),
d_{ij}	The distance between *jth* separation center and *ith* bin,
dm_{jw}	The distance between two separation centers,
$e_{t_{ij}}$	Cost of carbon emission associated with transportation between separation centers and bins,
$e_{tr_{Rej}}$	Cost of carbon emission associated with transportation between separation centers and recovery centers,
N_j	The construction cost of separation centers,
v_j	Capacity of *jth* separation center,
v_{min}	Minimum required capacity if a facility location is opened,
e_{g_j}	Cost of carbon emission associated with gas consumption at separation center,
e_{e_j}	Cost of carbon emission associated with electricity consumption at separation center,
md	Minimum allowed distance between two opened separation centers,
γ	The minimum level of using an opened facility,
δ	The maximum level of using an opened facility,
K	The minimum number of required facilities,
C	Unitary transportation cost per kilometer.

Table 4.3

Decision variables.

Variables	Description
x_{ij}	A binary variable and it equals to one if bin number *i* is assigned to separation center *j*,
y_j	Equals to 1 if jth potential location is opened, otherwise it is 0,
$u_{R_{Rej}}$	Equal to 1 if separation center *j* is allocated to recovery center *Re* and 0, otherwise.

$$\text{minimize } z_{cost} = \sum_{j\in J} f_j * y_j + \sum_{j\in J} N_j * y_j + C * \sum_{i\in I}\sum_{j\in J} d_{ij} * x_{ij} + \sum_{i\in I}\sum_{j\in J} e_{t_{ij}} * x_{ij} + \sum_{j\in J}\left(e_{g_j} + e_{e_j}\right) * v_j * y_j \qquad \text{Eq. (4.1)}$$

$$\text{minimize } z_{CO2emission} = \sum_{Re\in RE}\sum_{j\in J} e_{tr_{Rej}} * u_{R_{Rej}} + B * (v_j - v_{min}) * y_j \qquad \text{Eq. (4.2)}$$

subject to:

$$\sum_{i\in I} q_i * x_{ij} \le v_j * y_j \qquad \forall j \in J \qquad \text{Eq. (4.3)}$$

$$\sum_{j\in J} x_{ij} = 1 \qquad \forall i \in I \qquad \text{Eq. (4.4)}$$

$$y_j \le 1 \qquad \forall j \in J \qquad \text{Eq. (4.5)}$$

$$\sum_{Re\in RE} u_{R_{Rej}} = y_j \qquad \forall j \in J \qquad \text{Eq. (4.6)}$$

$$dm_{jw} < md \rightarrow y_j + y_w \le 1 \qquad \forall j \in J, w \in J, j \ne w \qquad \text{Eq. (4.7)}$$

$$\sum_{i\in I} q_i * x_{ij} \le \gamma * v_j * y_j \qquad \forall j \in J \qquad \text{Eq. (4.8)}$$

$$\sum_{i\in I} q_i * x_{ij} \le \delta * v_j * y_j \qquad \forall j \in J \qquad \text{Eq. (4.9)}$$

$$\sum_{j\in J} y_j \le K \qquad \text{Eq. (4.10)}$$

Eq. (4.1) represents the first objective, which is composed of land and construction costs, transportation costs of the first level, carbon emission costs associated with transportation between separation centers and bins, and pollution costs related to gas and electricity consumption at separation centers. Eq. (4.2) considers the carbon emission costs of vehicles from separation centers to recovery centers. Hence, the locations must be selected by trading off these two conflicting objectives, with the aim of minimizing environmental impact of transportation at both levels and opening facilities with a capacity closer to the required value. The conflicting objectives force the model to balance the need for meeting demand with the goal of minimizing operational costs through the utilization of larger capacity separation centers. Eq. (4.3) ensures the capacity constraints of the opened separation centers. Eq. (4.4) guarantees the assignment of each bin to only one separation center. Eq. (4.5) indicates that one potential location can be opened or not, and all locations should not be necessarily opened. Eq. (4.6) assigns all established separation centers to the recovery centers to calculate the last part of the first objective function. Eq. (4.7) represents that a candidate location can be opened if it is not near other opened facilities. Eq. (4.8) ensures that the total waste assigned to each separation center is at least a certain percentage of its capacity and encourages so a minimum level of capacity utilization to optimize operational costs. The maximum capacity utilization is satisfied by Eq. (4.9) and prevents excessive capacity utilization that may lead to operational inefficiencies or reduced service quality. The number of opened facilities is controlled by Eq. (4.10) to balance operational costs and overall system efficiency.

4.3.2 MATHEMATICAL FORMULATION OF THE ROUTING MODEL FROM BINS TO SEPARATION CENTERS

The second model implemented is the Multi-Depot Green Capacitated Vehicle Routing Problem (MDGCVRP), predominantly employed within urban settings due to environmental considerations. This model employs the use of Low-Capacity Vehicles (LCVs). In this routing model, the sequence of bin collection is determined along with the optimal number of vehicles required, leading to the minimization of the fixed vehicle cost. Moreover, bins are equipped with IoT devices and should be emptied during two distinct periods, maintaining a 70% threshold level (Braekers, Ramaekers, & Van Nieuwenhuyse, 2016; Rahmanifar et al., 2023c). In the current model, bins are classified based on two visitation periods (day and night). The main assumptions are reported in the following.

- The amount of waste generated in each bin is deterministic.
- There is no direct trip between the separation centers.
- The travel time between the nodes is pre-defined.
- The amount of waste in the bins is certain.
- The transportation cost per kilometer is the same for all vehicles.
- The carbon dioxide emission penalty is not the same for all vehicles.
- The social impact cost is not the same for all vehicles and it is the summation of the weighted impact costs of all the contributed factors which is represented in monetary terms (e.g., dollars or euros) for ease of comparison and aggregation with other objective function elements.

The elements of the model are described in Tables 4.4-4.6, while the mathematical formulation is provided by equations (11)-(30).

Table 4.4
Set of proposed models.

Sets	Description
I, J	Set of all nodes including separation centers, Dummy waste separation centers, and garbage bins $\in \{1, \dots, \mathrm{N} + \mathrm{M}\}$,
M	Set for separation centers,
N	Set for bins,
K	Set of low capacitated vehicles,
j, i	Index of nodes,
k	Index of nodes.

Table 4.5
Parameters.

Parameters	Description
FC_k	Fixed cost of low capacitated vehicle *k*,
GA_k	Carbon dioxide emission penalty for each vehicle per kilometer,
SI_k	Social impact cost associated with each vehicle *k*,
c_j	The amount of waste in the *jth* bin (kg),
Cap_k	Vehicle capacity k (kg),
d_{ij}	Distance between two nodes *i* and *j*,
td_{ij}	travel time between two nodes *i* and *j*,
tl_i	Time to load waste from the *ith* bins,
$LimTime_k$	Maximum time available to collect waste and transport it to waste separation centers,
CT_k	Maximum time available for garbage collection,
Lim_{GA}	Maximum allowed emission amount,
Lim_{SI}	Maximum social impact allowed,
n	scalar for the sub-tour deletion constraint,
M	A big number,
Tc	Transportation cost per unit kilometer,
p_j	Priority of bin j which higher value indicates a higher priority,
ths	Threshold to determine the high priority bins if the waste exceeds a predefined value,
Lim_{tran}	maximum allowed transportation cost,
Pen	Penalty for violation of collection hours limit.

Table 4.6
Decision variables.

Variables	Description
x_{ijk}	It is equal to 1 if the vehicle *k* moves between two nodes *i* and *j*, otherwise is equal 0,
y_{ik}	It is equal to 1 if the *ith* bin is assigned to the *k*, otherwise is equal 0,
q_{ijk}	The amount of waste collected between two nodes *i* and *j* by the vehicle *k*,
A_{jk}	The time of the *kth* truck arriving at the node *j*,
α_j	It is equal to 1 if the arrival time of the *kth* vehicle to the *jth* garbage bin is greater than the maximum time available for garbage collection otherwise 0,
z_{ijk}	It is equal to 1 if the *ith* bin with priority j is assigned to the *kth* vehicle, otherwise is equal 0.
u_i	Variable for sub-tour elimination constraint,
AOW_k	Total waste collected by vehicles with low-capacity *k*.

$$\text{minimize } z = \sum_{i=1}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K}(GA_k + SI_k) * d_{ij} * x_{ijk} + \sum_{i=1}^{M}\sum_{j=M+1}^{n}\sum_{k=1}^{K} FC_k * x_{ijk}$$
$$+ p_j \sum_{i=1}^{M}\sum_{j=M+1}^{n}\sum_{k=1}^{K} FC_k * z_{ijk} + Tc \sum_{i=1}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K} d_{ij} * x_{ijk}$$
$$+ \sum_{i=1}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K} d_{ij} * q_{ijk} + \sum_{j=M+1}^{n} \alpha_j * Pen - \sum_{k=1}^{K} AOW_k / Cap_k \qquad \text{Eq. (4.11)}$$

subject to:

$$\sum_{\substack{i=M+1 \\ i \neq j}}^{n}\sum_{k=1}^{K} x_{ijk} + \sum_{i=1}^{M}\sum_{k=1}^{K} x_{ijk} = 1 \qquad \forall\, j = M+1, \dots, n \qquad \text{Eq. (4.12)}$$

$$\sum_{\substack{j=M+1 \\ i \neq j}}^{n}\sum_{k=1}^{K} x_{ijk} + \sum_{j=n+1}^{n+M}\sum_{k=1}^{K} x_{ijk} = 1 \qquad \forall\, i = M+1, \dots, n \qquad \text{Eq. (4.13)}$$

$$\sum_{k=1}^{K}\sum_{i=1}^{M} x_{ijk} \leq 1 \qquad \forall\, j = M+1, \dots, n \qquad \text{Eq. (4.14)}$$

$$\sum_{\substack{j=M+1 \\ j \neq i}}^{n} x_{ijk} + \sum_{j=n+1}^{n+M} x_{ijk} + \sum_{\substack{j=M+1 \\ j \neq i}}^{n} x_{jik} + \sum_{j=1}^{M} x_{jik} = 2 * y_{ik} \qquad \forall\, i = M+1, \dots, n;\, k = 1, \dots, K \qquad \text{Eq. (4.15)}$$

$$\sum_{i=1}^{M}\sum_{j=M+1}^{n} x_{ijk} \leq 1 \qquad \forall\, k = 1, \dots, K \qquad \text{Eq. (4.16)}$$

$$\sum_{i=M+1}^{n}\sum_{j=n+1}^{n+M} x_{ijk} \leq 1 \qquad \forall\, k = 1, \dots, K \qquad \text{Eq. (4.17)}$$

$$u_i - u_j + n * x_{ijk} \leq n - 1 \qquad \forall\, i, j = M+1, \dots, n;\, i \neq j;\; k = 1, \dots, K \qquad \text{Eq. (4.18)}$$

$$\sum_{j=M+1}^{n} q_{ijk} = 0 \qquad \forall\, k = 1, \dots, K;\, i = 1, \dots, M \qquad \text{Eq. (4.19)}$$

$$c_i * x_{ijk} = q_{ijk} \qquad \forall\, i, j = 1, \dots, n+M;\, k = 1, \dots, K \qquad \text{Eq. (4.20)}$$

$$\sum_{i=1}^{n+M}\sum_{j=1}^{n+M} q_{ijk} = AOW_k \qquad \forall\, k = 1, \dots, K \qquad \text{Eq. (4.18)}$$

$$\left(\sum_{\substack{i=M+1 \\ i \neq j}}^{n}\sum_{j=M+1}^{n} c_i * x_{ijk} + \sum_{i=M+1}^{n}\sum_{j=n+1}^{n+M} c_i * x_{ijk}\right) \leq \mathrm{Cap}_k \qquad \forall\, k = 1, \dots, K \qquad \text{Eq. (4.21)}$$

$$A_{jk} \geq A_{ik} + (tl_i + td_{ij}) - M(1 - x_{ijk}) \qquad \forall\, i, j = 1, \dots, \mathrm{n} + \mathrm{M};\, i \neq j;\, k = 1, \dots, k \qquad \text{Eq. (4.22)}$$

$$\mathrm{A}_{jk} \leq A_{ik} + (tl_i + td_{ij}) + M(1 - x_{ijk}) \qquad \forall\, i, j = 1, \dots, \mathrm{n} + \mathrm{M};\, i \neq j;\, k = 1, \dots, k \qquad \text{Eq. (4.23)}$$

$$A_{jk} > CT_k \rightarrow \alpha_j = 1 \qquad \forall\, j = M+1, \dots, \mathrm{n};\, k = 1, \dots, K \qquad \text{Eq. (4.24)}$$

$$\sum_{\substack{i=1\\i\neq j}}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K} GA_k * d_{ij} * x_{ijk} \leq Lim_{GA} \qquad \text{Eq. (4.25)}$$

$$\sum_{\substack{i=1\\i\neq j}}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K} SI_k * d_{ij} * x_{ijk} \leq Lim_{SI} \qquad \text{Eq. (4.26)}$$

$$\sum_{\substack{i=1\\i\neq j}}^{n+M}\sum_{j=1}^{n+M} td_{ij} * x_{ijk} + \sum_{i=M+1}^{n} tl_i * y_{ik} \leq LimTime_k \qquad \forall\, k = 1, \dots, K \qquad \text{Eq. (4.28)}$$

$$Tc * \sum_{\substack{i=1\\i\neq j}}^{n+M}\sum_{j=1}^{n+M}\sum_{k=1}^{K} d_{ij} * x_{ijk} \leq Lim_{tran} \qquad \text{Eq. (4.29)}$$

$$\sum_{j=M+1}^{n} p_j * z_{ijk} \leq ths \qquad \forall\, i = 1, \dots, n + M; k = 1, \dots, k \qquad \text{Eq. (4.30)}$$

In Eq. (4.11), minimization of the total cost composed of carbon dioxide emission, social impact, cost of utilizing vehicles, transportation cost, cost of exceeding the maximum available time to collect, and finally, total transported load by vehicles is minimized by the last element of the objective function. Vehicles are forced to collect waste from the farthest bins because of this part of the objective function. In this way, vehicles can travel longer distances with a lower load, thereby minimizing the amount of fuel consumed based on the load of vehicles. Moreover, the last element of the objective function rewards higher vehicle utilizations. Thus, the optimization model is incentivized to use vehicles at their maximum capacity. Eq. (4.12) and Eq. (4.13) ensure that each bin must be visited one time. Eq. (4.14) guarantees that each bin must be assigned to one separation center. Eq. (4.15) provides the continuity of flow. Eq. (4.16) and Eq. (4.17) force vehicles to start and finish their trips at separation centers. The elimination of sub-tour is guaranteed by Eq. (4.18). Eq. (4.19) determines that the loads of vehicles are zero when they are departing from separation centers. Eq. (4.20) and Eq. (4.21) add the quantity of the waste in a visited bin to the vehicle's load and update the total weight of collected waste by each vehicle. The capacity constraint of the vehicles is satisfied by Eq. (4.22). Eq. (23) and Eq. (4.24) specify that the arrival time of the vehicle to a bin is the summation of visiting time at the previous bin and the travel time between them. The violation of the maximum available time for each vehicle is monitored by Eq. (4.25). Eq. (4.26) and Eq. (4.27) ensure the maximum allowable carbon dioxide emission and social impact, respectively. Accordingly, the maximum available time of each vehicle and total costs of utilizing vehicles are met by Eq. (4.28) and Eq. (4.29). Eq. (4.30) ensures that each vehicle is assigned to bins with a total priority exceeding a predefined threshold. The highest priority bins are selected first by this constraint.

4. 3. 3 MATHEMATICAL FORMULATIONS OF THE ROUTING MODEL FROM THE SEPARATION CENTER TO RECOVERY CENTER

A mix-integer linear model of the Green Split Pick-up Capacitated Vehicle Routing Problem (GSPCVRP) is applied in this layer, in which the demand of a node can be divided among multiple vehicles assuming a homogeneous fixed fleet. High-capacity Vehicles (HCVs) are considered in this model. To pursue sustainable goals with respect to social and environmental impacts, the objective is to minimize fleet costs and total distance traveled. Split pickup services can be beneficial in reducing the number of vehicles used by improving capacity utilization. In addition, the model minimizes the variance of loads between vehicles to create load balancing among vehicles. Following the main assumptions are described in the following while the corresponding elements of the model are defined in Tables 4.7-4.9.

- The amount of waste from separation centers is deterministic.
- There is no direct trip between the separation centers.
- The travel time between the nodes is pre-defined and deterministic.
- The recovery center is considered in this model.
- The transportation cost per kilometer is the same for all vehicles.

Table 4.7
Set of proposed models.

Sets	Description
I, J	Set of all nodes including separation centers and recovery centers,
K	Set of high capacitated vehicles,
P	Set for recovery center,
N	Set of separation centers,
j, i	Index of nodes,
k	Index of nodes,

Table 4.8
Parameters.

Parameters	Description
FC_k	Fixed cost of high capacitated vehicle *k*,
GA_k	Carbon dioxide emission penalty for each vehicle per kilometer,
Vp_k	Maximum allowable visual pollution,
AOW_i:	Amount of waste in the *ith* separation canter (kg),
Cap_k	Vehicle capacity *k (kg),*
d_{ij}	Distance between two nodes *i* and *j*,
td_{ij}	Travel time between two nodes *i* and *j*,
tl_i	Time to load waste from the *ith* separation centers,
$LimTime_k$	Maximum time available for waste collection,
CT_k	Maximum time available for waste collection,
Lim_{GA}	Maximum amount of allowed emission,
Lim_{VP}	Maximum social impact allowed,
Lim_{tran}	Maximum allowable transportation cost,
n	Scalar for the sub-tour deletion constraint,
Tc	Transportation cost per unit kilometer.

Table 4.9
Decision variables.

Variables	Description
x_{ijk}	It is equal to 1 if the vehicle *k* moves between two nodes *i* and *j*, otherwise is equal 0,
y_{ik}	It is equal to 1 if the *ith* bin is assigned to the *k*, otherwise is equal 0,
q_{ijk}	The amount of waste collected between two nodes *i* and *j* by the vehicle *k*,
u_i	variable for sub-tour elimination constraint,
Tw_k	The total amount of waste collected by the *kth* high-capacitated vehicle,
Avg	Average load of vehicles which can be calculated by division of Tw_k to number of vehicles,
Twc_i	Total amount of waste collected by all high capacitated vehicles at the recovery center.

The mathematical formulation of the model is provided by equations from (4.31) to (4.46).

$$\text{minimize } z = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{K}(GA_k + Vp_k) * d_{ij} * x_{ijk} + Tc * \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{K} d_{ij} * x_{ijk} + \sum_{i=0}^{p}\sum_{j=P+1}^{n}\sum_{k=1}^{K} Fc_k * x_{ijk} + \sum_{k=1}^{K} Tw_k - Avg \qquad \text{Eq. (4.31)}$$

subject to:

$$\sum_{\substack{i=P+1 \\ i\neq j}}^{n} \sum_{k=1}^{K} x_{ijk} + \sum_{i=0}^{P} \sum_{k=1}^{K} x_{ijk} \geq 1 \qquad \forall\, j = P+1, \dots, n \qquad \text{Eq. (4.32)}$$

$$\sum_{\substack{j=P+1 \\ i\neq j}}^{n} \sum_{k=1}^{K} x_{ijk} + \sum_{j=0}^{P} \sum_{k=1}^{K} x_{ijk} \geq 1 \qquad \forall\, i = P+1, \dots, n \qquad \text{Eq. (4.33)}$$

$$\sum_{\substack{j=P+1 \\ j\neq i}}^{n} x_{ijk} + \sum_{j=0}^{P} x_{ijk} + \sum_{\substack{j=P+1 \\ j\neq i}}^{n} x_{jik} + \sum_{j=0}^{P} x_{jik} = 2 * y_{ik} \quad \forall\, i = P+1, \dots, n; k = 1, \dots, K \qquad \text{Eq. (4.34)}$$

$$\sum_{\substack{i=0 \\ i\neq j}}^{n} x_{ijk} - \sum_{\substack{i=0 \\ i\neq j}}^{n} x_{jik} = 0 \qquad \forall\, k = 1, \dots, K;\ j = 0, \dots, n \qquad \text{Eq. (4.35)}$$

$$u_i - u_j + n * x_{ijk} \leq n - 1 \qquad \forall\, i,j = P+1, \dots, n; i \neq j;\ k = 1, \dots, K \qquad \text{Eq. (4.36)}$$

$$\sum_{j=P+1}^{n} q_{ijk} = 0 \qquad \forall\, k = 1, \dots, K; i = 0, \dots, P \qquad \text{Eq. (4.37)}$$

$$q_{ijk} \leq AOW_i * x_{ijk} \qquad \forall\, i,j = 0, \dots, n; k = 1, \dots, K \qquad \text{Eq. (4.38)}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} q_{ijk} = Tw_k \qquad \forall\, k = 1, \dots, K \qquad \text{Eq. (4.39)}$$

$$\sum_{k=1}^{K} TW_k = TWC_i \qquad \forall\, i = 0, \dots, P \qquad \text{Eq. (4.40)}$$

$$\left(\sum_{\substack{i=0 \\ i\neq j}}^{n} \sum_{j=0}^{n} q_{ijk} \right) \leq \mathrm{Cap}_k \qquad \forall\, k = 1, \dots, K \qquad \text{Eq. (4.41)}$$

$$\sum_{j=0}^{n} \sum_{k=1}^{K} q_{ijk} = AOW_i \qquad \forall\ i = P+1, \dots, n \qquad \text{Eq. (4.42)}$$

$$\sum_{\substack{i=0 \\ i\neq j}}^{n} \sum_{j=0}^{n} \sum_{k=1}^{K} GA_k * d_{ij} * x_{ijk} \leq Lim_{GA} \qquad \text{Eq. (4.43)}$$

$$\sum_{\substack{i=0 \\ i\neq j}}^{n} \sum_{j=0}^{n} \sum_{k=1}^{K} Vp_k * d_{ij} * x_{ijk} \leq Lim_{VP} \qquad \text{Eq. (4.44)}$$

$$\sum_{\substack{i=0 \\ i\neq j}}^{n} \sum_{j=0}^{n} td_{ij} * x_{ijk} + \sum_{i=P+1}^{n} tl_i * y_{ik} \leq LimTime_k \qquad \forall\, k = 1, \dots, K \qquad \text{Eq. (4.45)}$$

$$Tc * \sum_{\substack{i=0 \\ i \neq j}}^{n} \sum_{j=0}^{n} \sum_{k=1}^{K} d_{ij} * x_{ijk} \leq Lim_{tran} \qquad \text{Eq. (4.46)}$$

The environmental and social dimensions of sustainable goals are minimized in Eq. (4.31), as well as total transportation costs and fixed costs of utilizing vehicles. Moreover, the last element of the objective function provides a load balancing among vehicles by minimizing the deviation of loads between vehicles. In this context, the variance is considered as the sum of the difference between each vehicle's load and the average load. Eq. (4.32) and Eq. (4.33) ensure that each separation center must be visited at least once to provide split collection. It is possible to visit a separation center following a visit to another separation center or a recovery center due to the constraints. The constraint in Eq. (4.34) is defined to assure the conservation of flow, and each separation center can be visited once by each specific vehicle but can be visited more than once by different vehicles. The constraint in Eq. (4.35) guarantees that all tours must be ended at the recovery center. The elimination of the sub-tour is provided by Eq. (4.36). The constraint in Eq. (4.37) is defined to ensure each vehicle is empty at the departure time from the recovery center. Eq. (38) coordinates the route construction, transported load, and split collection decision variables. Constraints in Eq. (4.39) and Eq. (4.40) calculate the total weight of collected waste by each vehicle and then determine the total collected waste at the recovery center. The constraint in Eq. (4.41) ensures that the total collected waste by each vehicle does not exceed its capacity. Eq. (4.42) is designed to ensure the collection of all the waste in each separation center by different vehicles. Having a split collection without defining this constraint may result in a portion of the waste being left in the separation center. Constraints in Eq. (4.43), Eq. (4.44), Eq. (4.45), and Eq. (4.46) are defined to set the maximum limit for carbon dioxide emission, visual pollution, available time, and maximum possible transportation costs. A user may use this set of constraints as an option, for instance, if financial resources are limited.

4.4. SOLUTION APPROACH

The complexities of urban waste management necessitate creative and systematic approaches. This section elaborates on the solution methodology behind our proposed three-step waste management system designed to balance economic efficiency, environmental sustainability, and societal considerations. The proposed methodology is grounded in three main components: the Facility Location Problem (FLP), the first-level routing problem, and the second-level routing problem. The FLP is vital in determining the optimal locations for waste separation centers, a task complicated by various factors like cost, service quality, and meeting customer demands. To tackle this issue, our study employs a combination of mathematical models and numerical methods, providing solutions for both small-scale and large-scale instances of FLP. The Simplex Method and Newton-Raphson iterations form the backbone of our approach to smaller instances, whereas heuristic or approximation algorithms come into play for larger-scale problems. Next, the First-Level Routing Problem addresses the crucial task of waste collection(Golshahi-Roudbaneh et al., 2017). It involves the strategic planning of vehicle routing to ensure efficient waste collection from various points within specific timeframes. Due to its dynamic nature and inherent complexities, this routing problem requires the use of powerful metaheuristic algorithms, like the Social Engineering Optimization (SEO) and Keshtel Algorithm (KA). These algorithms have proven to be effective in tackling the dynamic VRP that characterizes waste collection. The Second-Level Routing Problem focuses on the routing model from the recovery center to the separation centers. Here, we use the linear programming Simplex method, combined with the GAMS optimization software, to deliver an efficient and optimal solution. This combination allows for the accurate determination of optimal routes, hence enhancing the transportation and logistical aspects of the waste management system. Incorporating these three components, the proposed methodology offers a resilient and adaptable solution to waste management. To demonstrate the practicality and applicability of this methodology, we apply it to a case study of a small city in Iran.

4.4.1. FACILITY LOCATION PROBLEM – SEPARATION CENTER LOCATION PROBLEM SOLUTION METHODOLOGY

Facility Location Problem (FLP) is a crucial optimization challenge within the field of supply chain management and logistics. Its objective is to determine the optimal location of facilities, such as warehouses or factories, considering factors like cost, service quality, and meeting customer demands. FLP is formulated as a Multi-Objective Optimization (MOO) that searches for the optimal facility locations that balance between minimizing transportation costs and reducing environmental impact. MOO seeks to find a set of solutions that account for conflicting objectives, rather than a single optimal solution. To tackle this challenge, the epsilon-constraint method is a widely adopted approach that is formulated in Eq. (4.47). It transforms conflicting objectives into constraints, designating one objective as the primary optimization goal while treating the others as constraints with an upper limit (epsilon). By varying the value of epsilon, a range of solutions along the Pareto frontier, representing optimal trade-offs between objectives, can be generated.

In the presented problem, the epsilon-constraint method can be employed to navigate the trade-off between transportation costs and environmental impact. By setting an upper limit (epsilon) for the carbon emission costs and treating it as a constraint, a diverse set of solutions that offer various compromises between transportation costs and environmental sustainability can be obtained. Utilizing the epsilon-constraint method empowers decision-makers to thoroughly analyze and select solutions from the Pareto frontier that align with their specific preferences and priorities. It offers a comprehensive perspective on optimal trade-offs, facilitating an informed decision-making process within the context of FLP with multiple conflicting objectives.

$$\text{minimize } f_l(x) \qquad \text{Eq. (4.47)}$$

$$\text{subject to } f_j(x) \leq \varepsilon_j \text{ for all } j=1,\dots,k, \quad j\neq l,$$

$$x \in S,$$

Where $l \in \{1,\dots,k\}$ *and* ε_j are upper bounds for the objective, *(j≠ l).*

4.4.2. SOLUTION APPROACH OF ROUTING MODEL FROM BINS TO SEPARATION CENTERS SOLUTION APPROACH

The first-level routing problem addresses the waste collection of waste from bins to separation centers. It involves the strategic planning of vehicle routing to ensure efficient waste collection from various points within specific timeframes. Due to the inherent complexity of VRP –recognized as NP-Hard combinational optimization problems– these exact methods prove insufficient for real-sized scenarios, as they fail to provide solutions in a reasonable timeframe. Consequently, heuristic and meta-heuristic approaches have become increasingly preferred (Bahadori-Chinibelagh et al., 2022; Nezhadroshan et al., 2021). So, to address the proposed problem, two suitable metaheuristic algorithms, Social Engineering Optimization (SEO) and Keshtel Algorithm (KA), are applied from both categories.

The SEO algorithm, a single-based solution metaheuristic, has recently emerged as a successful approach to solving various combinatorial optimization problems, including VRP, supply chain network design, and scheduling problems. The algorithm starts with the generation of two randomly generated solutions, known as the attacker and defender, based on their fitness function values. Inspired by the training and retraining activities observed in the human behavior, the algorithm designs random experiments for each characteristic of the defender. The attacker then assesses the defender based on these extracted characteristics and traits. During this process, some features of the attacker are converted to match those of the defender in the search space, while simultaneously computing the retraining rate of the attacker based on the defender. In the subsequent phase, a Social Engineering (SE) attack procedure is detected as an effective method to alter the defender's position within the feasible space. To respond to a SE attack, the fitness value of the new defender's position is calculated, and a comparison is made between the old and new position. The best position is then selected based on these comparisons. If the fitness value of the defender surpasses that of the attacker, a change in position occurs between the attacker and defender. Finally, to maintain the effectiveness of the attacker, the defender is replaced by a new random solution within the search space (Fathollahi-Fard et al., 2018).

In recent years, a population-based metaheuristic algorithm inspired by the feeding behavior of Keshtel birds has been developed by Hajiaghaei-Keshteli (2014). The algorithm draws its core concept from the natural process in which Keshtel birds search for valuable food sources in lakes and engage in a swirl and circling procedure until the food is depleted. At the start of the algorithm, a population of initial solutions, represented as Keshtel birds, is randomly generated to address an optimization problem. The population is then divided into three distinct groups: *N1*, *N2*, and *N3*. *N1* comprises the "lucky" Keshtels that have successfully located a good food source, while N3 consists of the poorest solutions in the population. The algorithm calculates the nearest neighbors around these lucky Keshtels, which is an essential step in the process. The swirling procedure continues around the current food source until a better source is found, and the population belonging to *N2* moves between the other two groups. In this way, *N1* is responsible for the intensification phase of the algorithm, focusing on exploiting the promising solutions; however, *N2* and *N3* contribute to the diversification phase, ensuring the exploration of the search space. To enhance the computational efficiency of the algorithm, researchers have focused on developing solution representations that reduce the running cost. The specific procedure used to represent the solutions of the proposed problem is described in detail in the subsequent section.

4.4.3. SOLUTION APPROACH OF ROUTING MODEL FROM SEPARATION CENTERS TO WASTE BINS

To address the routing model from the recovery center to the separation centers a simplex method is applied. This method systematically explores the feasible solution space, iteratively improving the objective function to determine the optimal solution. Given the presence of linear constraints and objectives in the routing model, the simplex method is well-suited for efficiently obtaining an exact solution. To accomplish this, we employed the GAMS optimization software, which seamlessly integrates the simplex method into its framework. By leveraging GAMS alongside the simplex method, we were able to effectively solve the routing model, optimizing the routes from the recovery center to the separation centers. This approach successfully addresses the transportation and logistical intricacies associated with waste management. These findings emphasize the suitability and effectiveness of utilizing the simplex method within GAMS to solve routing models in waste management scenarios. The accurate determination of optimal routes contributes to the efficient operation of the system, enhancing sustainability and resource allocation within the waste management process.

4.5 COMPUTATIONAL RESULTS

The applicability of a proposed solution is assessed through its outcomes. This section, therefore, explores the computational results derived from implementing the three-step waste management system and applies a sensitivity analysis to them. These analyses offer insight into the system's performance and aim at highlighting its adaptability and efficiency. The computational results are analyzed in two ways: the primary results are the immediate outcomes from deploying the proposed methodology; the sensitivity analysis investigates the models' responses to variations in key parameters. This comprehensive exploration provides a thorough understanding of the model's capabilities and potential improvement areas.

4.5.1. MODEL I – SOLUTION METHODOLOGY OF THE SEPARATION CENTER LOCATION PROBLEM

A significant aspect of waste management involves the strategic placement of separation centers. Determining the location of these centers involves considering multiple factors, including population density, waste generation rates, proximity to waste sources, existing transportation infrastructure, and potential environmental impacts particularly carbon dioxide (CO_2) emission. The objective is not just to minimize transportation costs but also to reduce environmental impacts, specifically CO_2 emissions. This emphasis on CO_2 emissions is of critical importance, because transportation is a relevant contributor to greenhouse gas emissions and thereby climate change. To integrate this important environmental consideration, our model incorporates a penalty factor for CO_2 emissions. This emission penalty is applied to waste transportation between separation centers and waste bins as well as between recovery centers and separation centers. The penalty is calculated based on the distance of transportation and the CO_2 emission penalty per kilometer (TE), as described in Eq. (4.44) and Eq. (4.45) respectively.

Additionally, the proposed model considers CO_2 emissions from gas and electricity consumption at each separation center. It is well-known that energy consumption for operations at these centers contributes significantly to the total emissions footprint. The CO_2 emission penalty due to gas consumption at each separation center is determined using Eq. (4.46), which follows from the method described by Harris et al., (2011). Similarly, the CO_2 emission penalty attributable to electricity consumption at each separation center is calculated using Eq. (4.48). The corresponding steps are outlined in Fig.4.3. By integrating these emission penalties, our model offers a holistic approach to urban waste management that accounts for both economic and environmental aspects, encouraging more sustainable practices. This comprehensive strategy ensures that the various sources of emissions in the waste management process, from transportation to operational energy consumption, are addressed effectively.

$$\mathrm{e\_t}_{ij} = d_{ij} * TE \qquad \text{Eq. (4.49)}$$

$$\mathrm{e\_tr}_{Rej} = \mathrm{d\_Re}_{Rej} * TE \qquad \text{Eq. (4.50)}$$

$$e\_g_j = \left(\frac{G_c * v_j * G_{cf}}{B_{tu}}\right) * c_f \qquad \text{Eq. (4.51)}$$

$$\mathrm{e\_e}_j = \left(\mathrm{E}_c * \mathrm{v}_j * \mathrm{E}_{cf}\right) * \mathrm{c}_f \qquad \text{Eq. (4.52)}$$

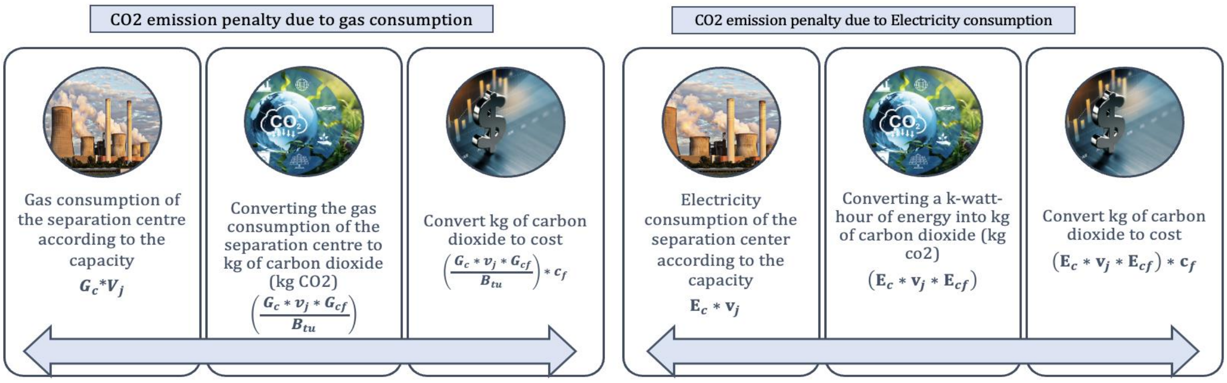


Fig.4.3. The CO_2 emission penalty is attributable to electricity and gas consumption.

Table 4.10
Data related to the location-allocation model.

Parameter	Values	Unit
i	1000	-
j, w	6	-
Re	1	-
F_j	[1.764e+11, 2.06e+11, 2.1e+11, 3.68e+11, 1.842e+11, 1.276e+11, 1.83e+11]	IRR
q_i	Uniform ~ [362, 394, 418, 449, 480]	Kilogram (Kg)
d_{ij}	Uniform ~ [1.1672, 23,1432]	km
dm_{jw}	Uniform ~ [0.0012, 26.57]	km
d_Re_j	[12.2162, 24.8776, 29.6532, 31.7656, 23.8765, 10.9845, 9.1021]	km
TE	6000	CO_2 emission per Km
CF	400	Kg CO_2 to cost
V_j	Uniform ~ [300000, 365159, 456280, 834470, 417690, 289340, 414970]	Kilogram (Kg)
N_j	Uniform ~ [7e+11, 8.1746e+11, 8.33332e+11, 1.46032e+12, 7.20458e+11, 6.6235e+11, 7.26198e+11]	IRR
Gcf	64	Gas conversion factor
Ecf	0.64	KWh to kg CO_2
G_c	1000	The British thermal unit (Btu) per kg
E_c	0.15	KWh per kg
C	1200	Transportation cost per Km
md	4	Kilogram (Kg)
B_{tu}	1000000	Btu factor

Moreover, this model is designed to find the best location of the separation centers. In designing this model, two main points were considered: the ability of proposed locations to effectively handle the task of waste separation, and their potential to reduce overall costs. A mathematical model was developed to optimize the selection process in small size problems. The model is solved for a test problem obtained from a real case in Iran whose corresponding data are reported in Table 4.10. The result of the model strongly suggested that separation centers number one y (1) and number six y (6) are the best options for setting up these facilities (See Fig. 4.4 and Table 4.11). The proposed model ensures the capacity of potential locations that effectively handle waste separation, considering also the costs associated with these locations. For instance, in a specific solution given by the model, separation center number 1 is given 932 waste bins and separation center number 6 is assigned 352 waste bins. This unequal distribution is designed to favor the first separation center. The reasons for this are several, but include its strategic location and increased capacity, which leads to lower transportation costs. The main goal of this model is to figure out the best way to distribute separation centers. It accomplishes this task by finding the best spots for these centers in areas that have enough room for waste separation, while also trying to keep the overall costs as low as possible. Deciding how many waste bins to assign to each center is a complex task that involves balancing many factors. These include the costs to transport waste to each center and the amount of waste each center can handle. Thus, the model provides a strong plan to manage different separation centers improving efficiency and reducing costs.

Fig. 4.4. The optimal location for separation centers.
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Table 4.11.
Optimization Results of the Separation Center Location Problem.

Dimension	Number of bins	1000
	Candidate Location	6
	Recycling center number	1
Objective elements	Optimal Location for separation center	1 and 3
	Optimal number of assigned bins to separation center number 1	400
	Optimal number of assigned bins to separation center number 6	600
	Land cost	2,404,000,000,000 IRR
	Capacity cost	2,110,000,000,000 IRR
	Transportation cost	34,600,000,000 IRR
	Pollution penalty from bin and separation center cost	44,300,000,000 IRR
	Separation center pollution penalty cost	27,400,000,000 IRR
	Pollution cost penalty from separation center and recycling center	84,600,000 IRR
	Value of the first objective function	1,730,000,000,000 IRR
	Value of the second objective function	83,600,000 IRR
	Value of the total objective function	1,730,083,600,000 IRR

4.5.2. ROUTING MODEL FROM SEPARATION CENTERS TO WASTE BINS

This section gives detailed computational results of the routing problem associated with waste collection from bins to separation centers. The data related to the problem are outlined in Table 4.14. The structured design of the waste management network required an initial solution to the location-allocation model. This crucial first step determines the count of operational separation centers, setting the stage for the subsequent processes in the waste management system. In addition to the transportation and environmental costs, the social impact cost is considered in this step. Measurement of social impact cost can indeed be a difficult task due to the multifaceted nature of the factors involved. However, relevant social and environmental impact is achievable based on several studies, and they are generally represented in monetary terms for ease of comparison and aggregation with other objective function elements. After identifying these factors and their relevance to the specific situation, data related to these factors need to be collected; for instance, measurements of noise levels or air pollution caused by waste collection vehicles, or data regarding additional travel time caused by these vehicles when inducing traffic congestion. The following stage, as the most challenging one, involves quantifying these impacts, which requires determining their social cost. Once the impact of each factor is quantified, it may need to be weighted based on its perceived significance or severity. Then, the total social impact costs can be determined by the summation of the weighted impact costs of all the factors (Akbarpour et al., 2021a; Bektaş & Laporte, 2011; C. Lin et al., 2014). Optimization results of the routing model from bins to separation center for the first and second periods are reported in Table 4.12-4.16 and the patterns of the resulting routes are illustrated in Fig 4.5.

Table 4.12.
The data related to routing problem to collect waste from bins to separation centers.

Parameter	Values	Unit
i, j	1000	-
k	120	-
FC_k	293499996	The cost of utilizing vehicles
S	[1,2]	Time interval
GA_k	1100	CO2 penalty per unit distance and vehicle
SI_k	Uniform ~ $[10, 10 \times 10^6]$	Social penalty per unit distance and vehicle (dollars)
c_j	Uniform ~ [350, 500]	Kg
Cap_k	[2500,6000]	Kg
d_{ij}	Uniform ~ [0.0096, 8.0603]	km
td_{ij}	With respect to distance	Time in minutes
tl_i	2	Time in minutes
$LimTime_k$	320	Time in minutes
CT_k	250	Maximum time available
Lim_{GA}	400000000	Maximum pollution (IRR)
Lim_{SI}	400000000	Maximum social impact (IRR)
n	2	-
Tc	1500	Cost per Km
Lim_{tran}	400000000	Maximum cost (IRR)
Pen	900000	Penalty for violation of available time

Table 4.13

Optimization Results of the routing model from bins to separation center (First period).

Dimension	Number of bins	600
	number of separation center	2
	Total travel time	4678.2689 min
	Total distance	1732 km
Objective elements	maximum traveled distance	45.6732 km
	Waste quantity in separation center number 1	274266 kg
	Waste quantity in separation center number 3	0 kg
	Number of vehicles	56
	Number of assigned bins to separation center number 1	667
	Number of assigned bins to separation center number 6	0
	Sustainability goal	16143426.6 IRR
	Vehicle fixed cost	12450400 IRR
	Transportation cost	10865000 IRR
	Cost of capacity	457210 IRR
	Penalty of time window	0 IRR
	Total cost	37637036.7 IRR

Table 4.14

Optimization Results of the routing model from bins to separation center (second period).

Dimension	Number of bins	400
	Number of separation center	2
	Total travel time	4448.9614 min
	Total distance	1568 km
Objective elements	Maximum traveled distance	41 km
	Waste quantity in separation center number 1	114230 kg
	Waste quantity in separation center number 6	109103 kg
	Number of vehicles	53
	Number of assigned bins to separation center number 1	271
	Number of assigned bins to separation center number 6	256
	Sustainability goal	15445985 IRR
	Vehicle fixed cost	38429000 IRR
	Transportation cost	10976000 IRR
	Cost of capacity	402280 IRR
	Penalty of time window	0.00 IRR
	Total cost	65253447 IRR

Table. 15

The pattern of routes in the routing model from bins to separation center (First period).

Vehicle	Operational time (hours)	Amount of collected waste	Vehicle capacity	Goods quantity/capacity	number of visited bin to empty	Routes
1	102.256495	5761.5	6000	0.835	12	D1 – 100 - 195 - 112 - 20 - 277 - 278 - 10 - 15 - 181 - 161 - 620 - 750 – D1
2	67.059168	3466.1	6000	0.502	7	D1 – 550 - 280 - 451 - 550 - 650 - 452 - 707 – D1
3	98.722327	6518.2	6000	0.944	13	D1 – 625 - 212 - 222 - 635 - 202 - 222 - 427 - 224 - 325 - 250 - 352 - 228 - 268 – D1
4	101.142327	6591.8	6000	0.955	14	D1- 589 - 220 - 520 - 35 - 85 - 77 - 12 - 20 - 42 - 32 - 45 - 44 - 49 - 245 – D1
5	102.848185	6575.7	6000	0.953	13	D1 –125 – 325 - 258 - 652 - 265 - 125 - 265 - 254 - 452 - 185 - 249 - 513 - 582 – D1

Table 16

The pattern of routes in the routing model from bins to separation center (Second period).

Vehicle	Operational time (hours)	Amount of collected waste	Vehicle capacity	Goods quantity/capacity	number of visited bin to empty	Routes
1	100.437792	3378.7	6000	0.563	7	D1 - 359 - 339 - 337 - 248 - 466 - 348 - 362 - 328 - 226 - 405 - 202 - 102 – D1
2	89.269264	4671.3	6000	0.778	10	D1 – 48 - 10 - 11 - 62 - 127 - 26 - 129 - 164 - 132 - 180 – D1
3	112.725312	6551.55	6000	1.091	14	D1 - 89 - 90 - 49 - 402 - 12 - 54 – 41 - 40 - 68 - 482 - 70 - 39 - 141 - 347 – D1
4	88.631984	4774.8	6000	0.795	10	D1 – 12 - 13 - 11 - 52 - 227 - 27 - 135 - 251 - 235 - 280 – D1
5	86.92824	5868.45	6000	0.978	12	D1 - 359 - 354 - 337 - 348 - 166 - 148 - 162 - 202 - 205 - 257 - 215 - 405 - D1

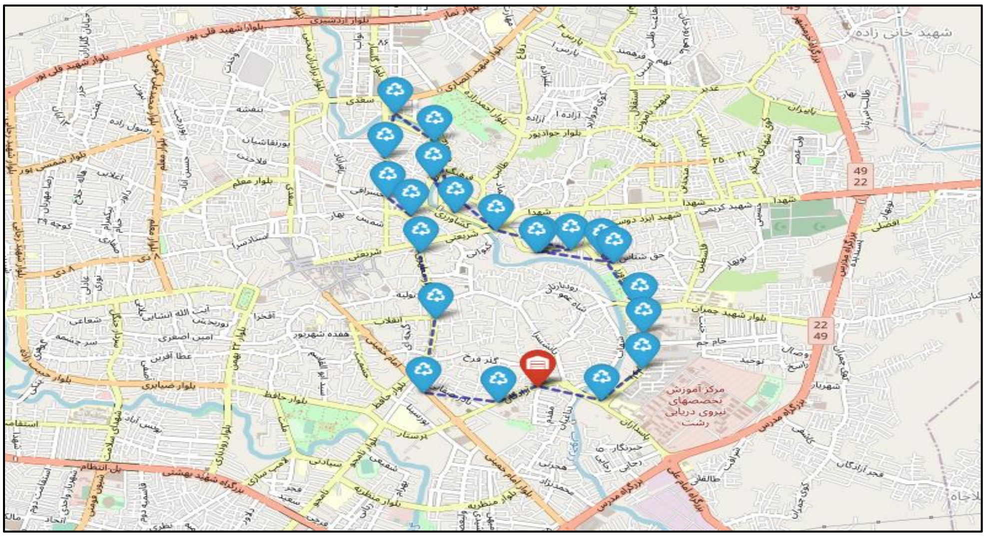


Fig. 5. An example of route in in the routing model from bins to separation center.

4.5.2.1 SOLUTION REPRESENTATION

Solution representation is integral to the functionality of the meta-heuristic algorithm employed: a matrix consisting of three rows, corresponding to bins, separation centers, and vehicles are utilized for the proposed problem (Fathollahi Fard & Hajiaghaei-Keshteli, 2018; Hajiaghaei-Keshteli et al., 2011; Mosallanezhad et al., 2021). Let us consider the first row of the matrix which is related to the bins of the proposed problem. This matrix length depends on the number of bins. The first row gives the sequence of visiting bins based on a random permutation of the number of bins, while the second row indicates which bin is assigned to each separation center. The last row in the matrix represents the assignment of the vehicles in each separation center to visit the assigned bins. Fig. 6 is the pseudocode of explained solution representation.

Solution representation Pseudocode
*Create empty matrix with size (3*number of bin)*
Filling first row by random permutation of number of bins
Filling each element of the second row with a random number between (1 to the number of opened separation centers)
To assign bins to vehicles in each separation center:
Determine the number of separation centers
Determine the unique number of vehicles at each separation center
    for *i=1: number of columns of the proposed matrix*
        S $\ll=$ *Finding the corresponding separation center at the location of* i^{th} *in the second row*
        V $\ll=$ *Generate a random number between (1 to the number of vehicles belonging to S)*
    end

Fig.4.6. Pseudocode of explained solution representation.

Fig. 7 gives an illustrative example of the solution representation that contains a randomly generated matrix as a possible solution and the corresponding routes. In this example, the numbers of objects that define the problem are generated randomly to take a generic possible solution. This example contains 10 bins, 2 separation centers, and 3 vehicles. The first row of the matrix [1, 3, 2, 4, 7, 5, 8, 6, 10, 9] indicates the sequence of bin visits; the second row [1, 1, 2, 1, 2, 2, 1, 1, 1, 2] assigns each bin to a separation center; and the third row [1, 1, 1, 2, 1, 1, 1, 1, 2, 1] designates the vehicle for each bin. In this case, bins 4 and 10 are assigned to the truck LCV02 of the separation center number 1 (S_01). Bins 1, 3, 8, and 6 are assigned to the truck LCV01 of the first separation center, while bins 2, 7, 5, 9 are assigned to a single vehicle LCV03 that visits the second separation center (S_02).

Bin	1	3	2	4	7	5	8	6	10	9
Separation center	1	1	2	1	2	2	1	1	1	2
Vehicle	1	1	3	2	3	3	1	1	2	3

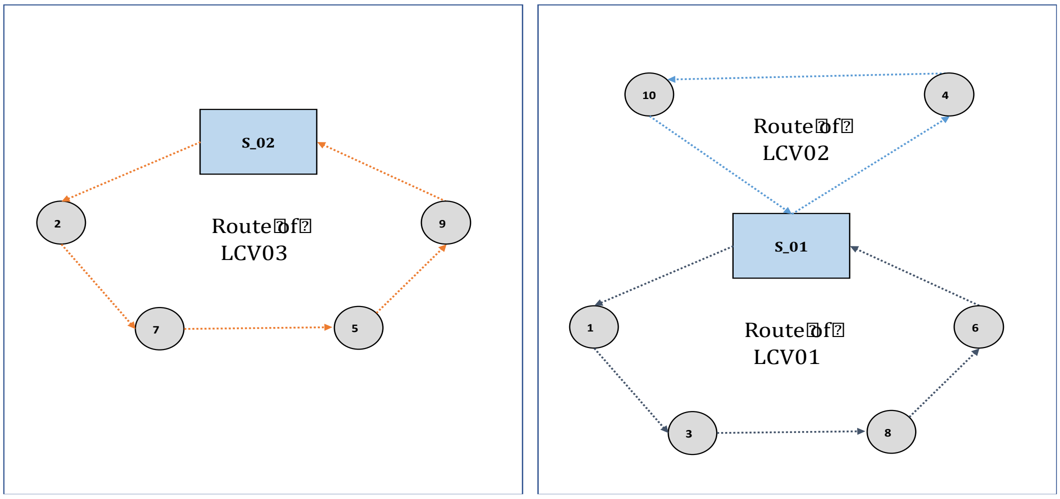


Fig. 4.7. An illustrative example of the solution representation.

4.5.2.2. PARAMETER LEVEL OF THE PROPOSED METAHEURISTIC ALGORITHM

Since the parameters of a metaheuristic algorithm directly affect its performance, a fine tuning is necessary to get the desired performance. In this paper, the Taguchi method is applied to fix the values of each parameter of the metaheuristic algorithms (Chouhan et al., 2021b; Gholian-Jouybari et al., 2018b; Liao et al., 2020). Generally, the Taguchi method is a robust problem-solving method to improve the process performance and productivity of algorithms. This method ensures the quality of a process by a reasonable test number (Abdi et al., 2019; Mosallanezhad, Ali Arjomandi, et al., 2023; Valentini et al., 2023). The variation of each parameter and its optimal level is determined according to the signal-to-noise (S/N) ratio. Two equations for standard ratios are defined in Eq. (53) and Eq. (54). The parameters Y_i and n represent the response value and the number of observations, respectively. If the response is maximum, the "Larger is better" state is considered by Eq. (53) to optimize the process. Otherwise, the "Smaller is a better" state is considered when the response is a minimum and is calculated by Eq. (54) (Bavar et al., 2023; Gholian Jouybari et al., 2016; Pal et al., 2023). Accordingly, the proposed levels of parameters for each algorithm are listed in Table 17 and one of them, determined as L^*, is selected as the best one. Testing all combinations of parameters for each algorithm is time-demanding because of the Taguchi orthogonal array. A proportion of these tests should be investigated instead to find the minimum *S/N* to select the best levels of parameters (Colombaroni et al., 2020; Sahebjamnia et al., 2020).

$$S/N\ ratio\ =\ -10\log\left(\frac{1}{n}\sum_{i=1}^{n} {y_i}^2\right) \qquad \text{Eq. (4.53)}$$

$$S/N\ ratio\ =\ -10\log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{{y_i}^2}\right) \qquad \text{Eq. (4.54)}$$

To ensure comparability of the objective function across different trials, the relative percentage deviation (RPD) method is employed. This method normalizes the objective function values, allowing for a consistent scale of comparison. To calculate the RPD the objective function values in the algorithm (Alg_{sol}) and the best solution for the trial (Min_{sol}) are utilized. The RPD is then computed, and the average RPD is determined for each trial. The Taguchi approach develops orthogonal arrays according to the mean signal-to-noise ratio estimated by RPD in Eq. (4.55).

(Eq. 4.55)

$$RPD = \frac{|Alg_{sol} - Min_{sol}|}{Min_{sol}}$$

Table 4.17
The proposed levels for the parameters of the meta-heuristic algorithms

Algorithm	Factor	Levels			
		L1	**L2**	**L3**	**L^***
KA	A: Population size (n-pop)	750	950	1250	**950**
	B: Percentage of the population of Lucky Keshtel (P_{N1})	0.5	0.6	0.7	**0.7**
	C: percentage of N_2 Keshtel (P_{N2})	0.25	0.3	0.35	**0.3**
SEO	A: Collecting data rate(α)	0. 15	0. 2	0. 25	**0.25**
	B: Connecting attacker rate(β)	0. 03	0. 05	0. 07	**0.05**
	C: Number of connections (N)	40	60	80	**80**

4.5.2.3. COMPUTATIONAL RESULTS OF THE PROPOSED ALGORITHMS

This section presents a computational study to test the performances of the proposed metaheuristic algorithms to solve generated random instances, which are classified into three groups: small, medium, and large size problems. These test problems are solved by each algorithm thirty times to consider the approximate nature of the metaheuristic algorithms. For each run, three indicators are calculated to evaluate algorithms and finally the average value of each indicator is computed for each algorithm. Detailed results of the minimum values of the objective function for each algorithm and other indicators are reported in Table.4.18 for each instance.

Table 4.18.
Detail objective function, RPD, HT results for each algorithm.

		SEO			KA		
		OF	RPD	HT	OF	RPD	HT
Small-Size	1	970.587294	0.26	14.60	786.025810	0.00	35.45
	2	623.369167	0.10	18.15	607.491547	0.07	46.44
	3	1571.770609	0.48	21.08	1095.075226	0.00	73.47
	4	1443.326234	0.12	34.71	1628.976513	0.28	94.31
	5	2512.425661	0.38	41.17	2172.225297	0.18	100.09
Medium-Size	6	1313.652181	0.00	71.44	1590.557534	0.23	167.17
	7	2233.581490	0.07	65.45	2104.471854	0.00	244.63
	8	2406.191218	0.15	111.80	2635.945074	0.27	287.82
	9	3598.036100	0.35	158.50	3164.251401	0.18	374.98
	10	4516.893992	0.29	198.55	4230.561568	0.20	494.12
Large-Size	11	5255.841734	0.31	981.02	5091.592361	0.27	2062.62
	12	5473.837033	0.18	1237.40	4827.620163	0.03	2998.55
	13	5773.298732	0.20	1681.40	5352.035797	0.10	3518.63
	14	5931.818440	0.07	1952.02	6193.835699	0.12	4752.89
	15	7741.404196	0.14	3152.20	8562.998426	0.27	7029.60

Note:
HT: The first-time algorithm that can find the best solution (HT).

As depicted in Fig.4.8, in small-sized test problems, SEO exhibits a greater variation in RPD values compared to KA, indicating that SEO's response time might fluctuate more widely for this set of instances. This could potentially affect the efficiency of SEO in small-sized problem sets. For medium-sized test problems, the deviation in RPD values for SEO increases compared to the small-sized problems, suggesting less consistency in response times. On the other hand, KA exhibits a tighter range of RPD values and is a more consistent performer in terms of response time for medium-sized test problems. However, the scenario changes for large-sized problems. Here, the KA algorithm shows a higher variation in RPD values than SEO, implying that the former's efficiency may drop with the increase of the problem size. SEO performs more consistently in these instances, highlighting its robustness to problem size in terms of response time. Fig. 4.9 and Fig. 4.10 illustrate the behavior of hitting time and objective function, respectively. Across all problem sizes, SEO consistently outperforms KA in terms of hitting time. This suggests that SEO, irrespective of the problem size, is more likely to arrive at a solution faster than KA. This robust performance of SEO across different problem sizes underscores its superior efficiency. The comparison in terms of the objective function highlights that in larger test problems both algorithms show considerable deviations in their solutions. However, SEO exhibits a more tightly clustered set of outputs, implying better precision and reliability than KA in larger problem contexts. To summarize, while both algorithms show strengths in different areas: SEO demonstrates more robust and consistent performances across different problem sizes, especially in terms of response time and hitting time. However, it is important to consider the specific context and requirements when choosing an algorithm, as KA also shows potential advantages, particularly in the response time when handling medium-sized test problems.

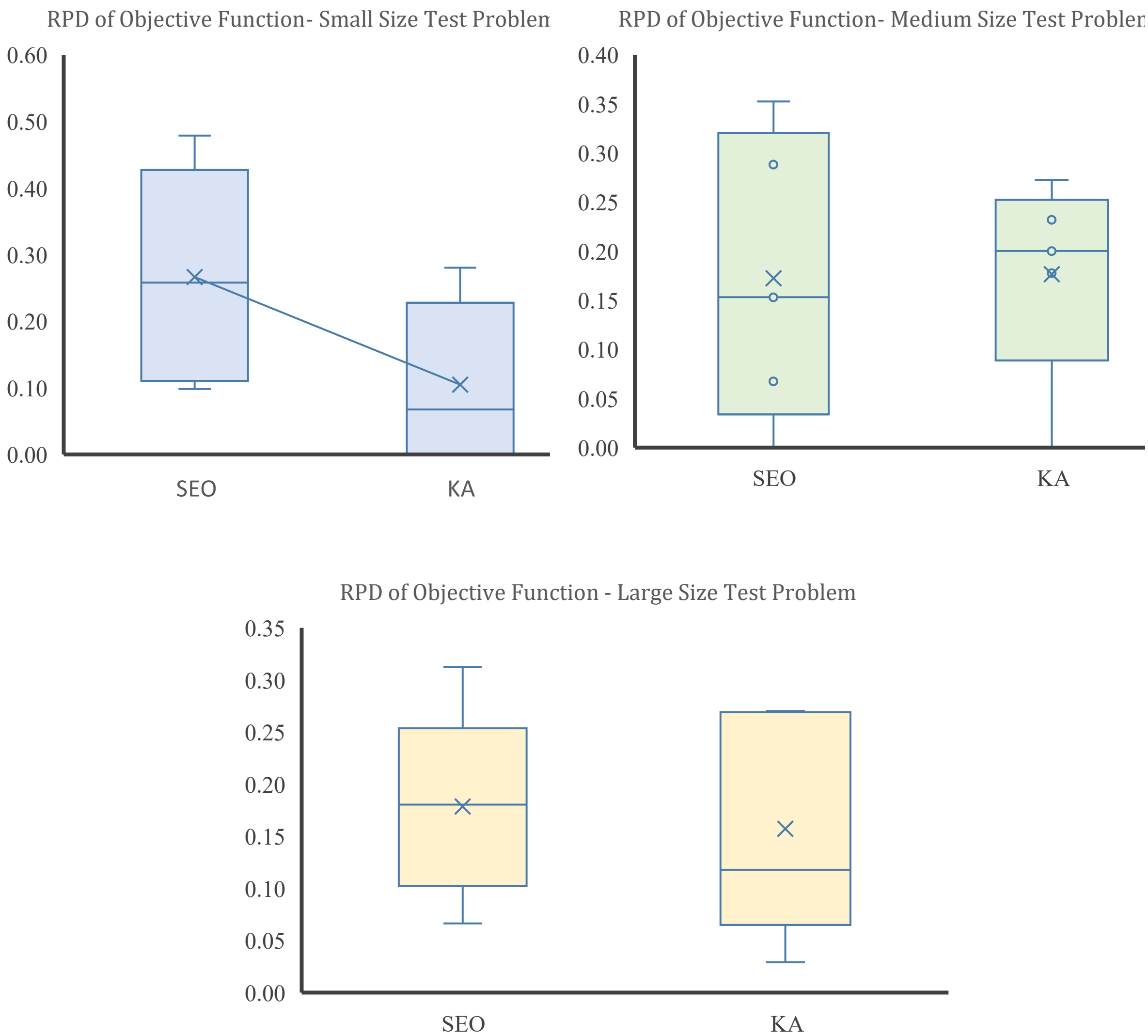


Fig. 4.8. The comparison of algorithms behavior concerning RPD in small, medium, and large size.

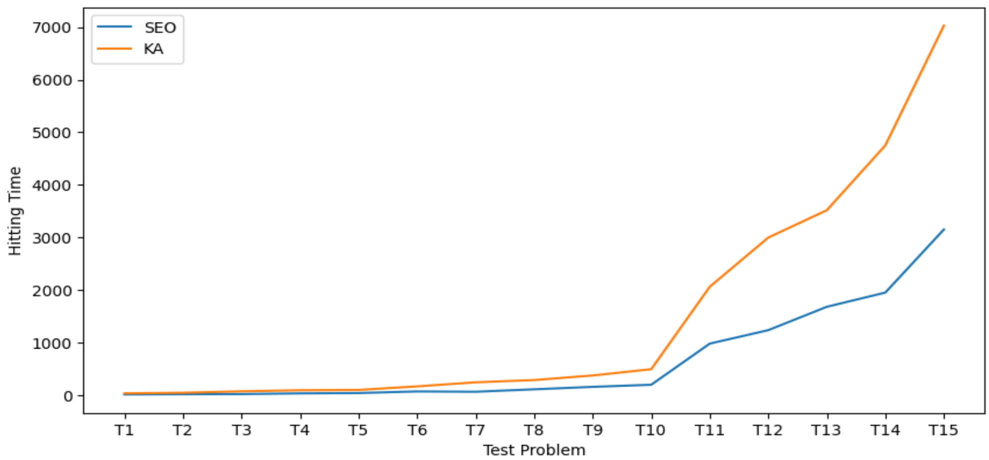


Fig. 9. Hitting Time values for all test beds.

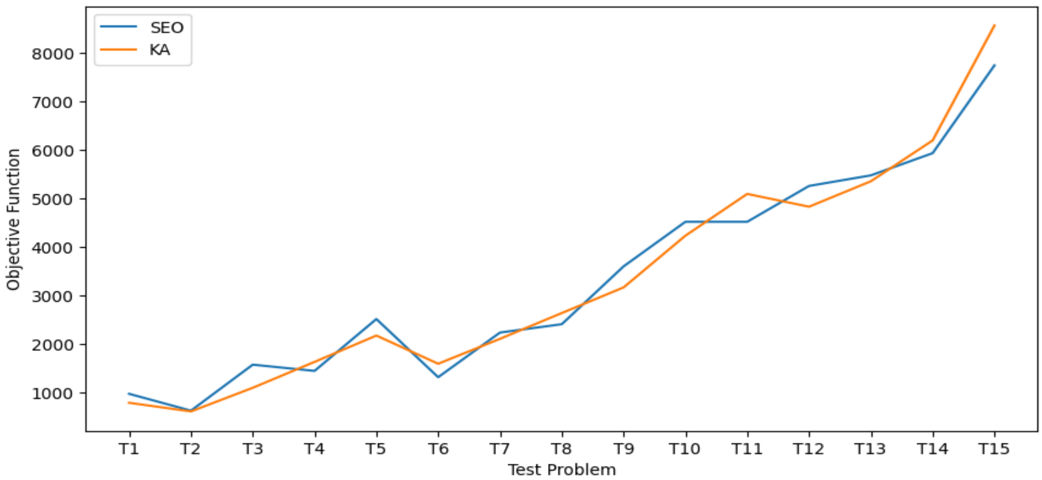


Fig. 10. Objective values for all test beds.

4.6. Routing Model from Separation centers to Waste Bins

The second level of the routing problem involves the collection of sorted waste from various separation centers and its transfer to recovery centers. The volume of waste at each separation center can potentially exceed the capacity of each vehicle, thereby necessitating the concept of split pickups. Despite the potential requirement for multiple vehicles to gather all waste from a single separation center, the relatively small number of such centers, as determined by the facility location model, allows the efficient use of exact methods to solve the problem within a reasonable timeframe. This problem has been encoded and resolved using GAMS/CPLEX. The data pertaining to the second-level routing problem are also influenced by the output of the facility location model. These data are reported in Table 4.19. It is important to mention that the distance between every two nodes is calculated based on the Haversine formula. The optimization results of the second-level routing problem from separation centers to waste bins is summarized in Tables 4.20 and 4.21.

Table 19

The parameters of the routing model from separation centers to recovery center.

Parameter	Values	Unit
i,j	0, 1, 6	-
FC_k	296599992	-
k	[1,32]	-
GA_k	1500	CO2 penalty per unit distance and vehicle
Vp_k	1200	Visual pollution per HCV k
AOW_i	[0, 171253, 71988.5]	Kg
Cap_k	10000	Kg
d_{ij}	Uniform ~ [7.4226, 13.2284]	km
td_{ij}	Uniform ~ [8.9072, 15.8741]	Time in minutes
tl_i	[0, 10, 10]	Time in minutes
$LimTime_k$	480	Time in minutes
Tc	1500	Cost per Km
Lim_{GA}	800000000	Gas conversion factor
Lim_{VP}	800000000	KWh to kg CO_2
n	2	-

Table 20

Optimization Results of Second-Level Routing Problem - Routing model from separation centers to waste bins.

Dimension	Number of separation center	2
	Number of recycling center	2
	Total travel time	803.445
Objective elements	maximum traveled distance	41
	Waste quantity in separation center	508699.00
	Waste quantity in recycling center	254349.50
	Number of vehicles	26
	Number of assigned vehicles to separation center number 1	26
	Number of assigned vehicles to separation center number 6	6
	Sustainability goal	6695372.02
	Vehicle fixed cost	21127670.00
	Transportation cost	4686760.42
	Total cost	32509802.44

Table 21

List of Routes in the routing model from the recovery center to the separation centers.

Vehicle	Operational time (hours)	Traveled distance	Amount of collected waste	Vehicle capacity	Goods quantity/capacity	Routes
1	31.74	26.44	9798	10000	0.9798	Re – 1 – Re
2	31.74	26.44	9848	10000	0.9848	Re – 1 – Re
3	31.74	26.44	9998	10000	0.9998	Re – 1 – Re

4.7. SENSITIVITY ANALYSIS

Sensitivity analysis is a method that measures how the impact of uncertainties of one or more input variables can lead to uncertainties in the output variables and investigates how small changes in inputs affect the outcomes. This analysis is useful because it allows to improve the predictions produced by the model and to reduce it by studying qualitatively and/or quantitatively the model response to changes in input variables. In this section, the capacity of the separation centers *v*(*j*) and the minimum distance *md* between two separation centers are analyzed through the sensitivity analysis. The corresponding results are reported in Tables 4.22-4.24. Moreover, the impact of significant parameters on the total cost for each model is illustrated in Fig 4.11, 4.12, 4.13, and 4.14.

Table 22

The impact of the parameters of the model for the separation center location on the total cost.

Parameters	parameter Change (%)	Total Cost	Change in total cost (%)
Land purchase cost	50%	1,781,754,628,000	9.30%
	%25	1,705,754,628,000	4.60%
	0%	1,629,754,628,000	0.00%
	-25%	1,553,754,628,000	-4.60%
	-50%	1,477,754,628,000	-9.30%
Cost of creating capacity	50%	2,232,924,628,000	37.00%
	25%	1,931,344,628,000	18.50%
	0%	1,629,754,628,000	0.00%
	-25%	1,328,174,628,000	-18.50%
	-50%	1,026,584,628,000	-37.00%
Transportation cost	50%	1,648,044,628,000	1.12%
	25%	1,638,904,628,000	0.56%
	0%	1,629,754,628,000	0.00%
	-25%	1,620,614,628,000	-0.56%
	-50%	1,611,464,628,000	-1.12%
CO_2 Emission Cost	50%	1,500,837,933,800	1.12%
	25%	1,593,068,933,800	0.56%
	0%	1,585,291,433,800	0.00%
	-25%	1,577,522,433,800	-0.56%
	-50%	1,569,744,933,800	-1.12%

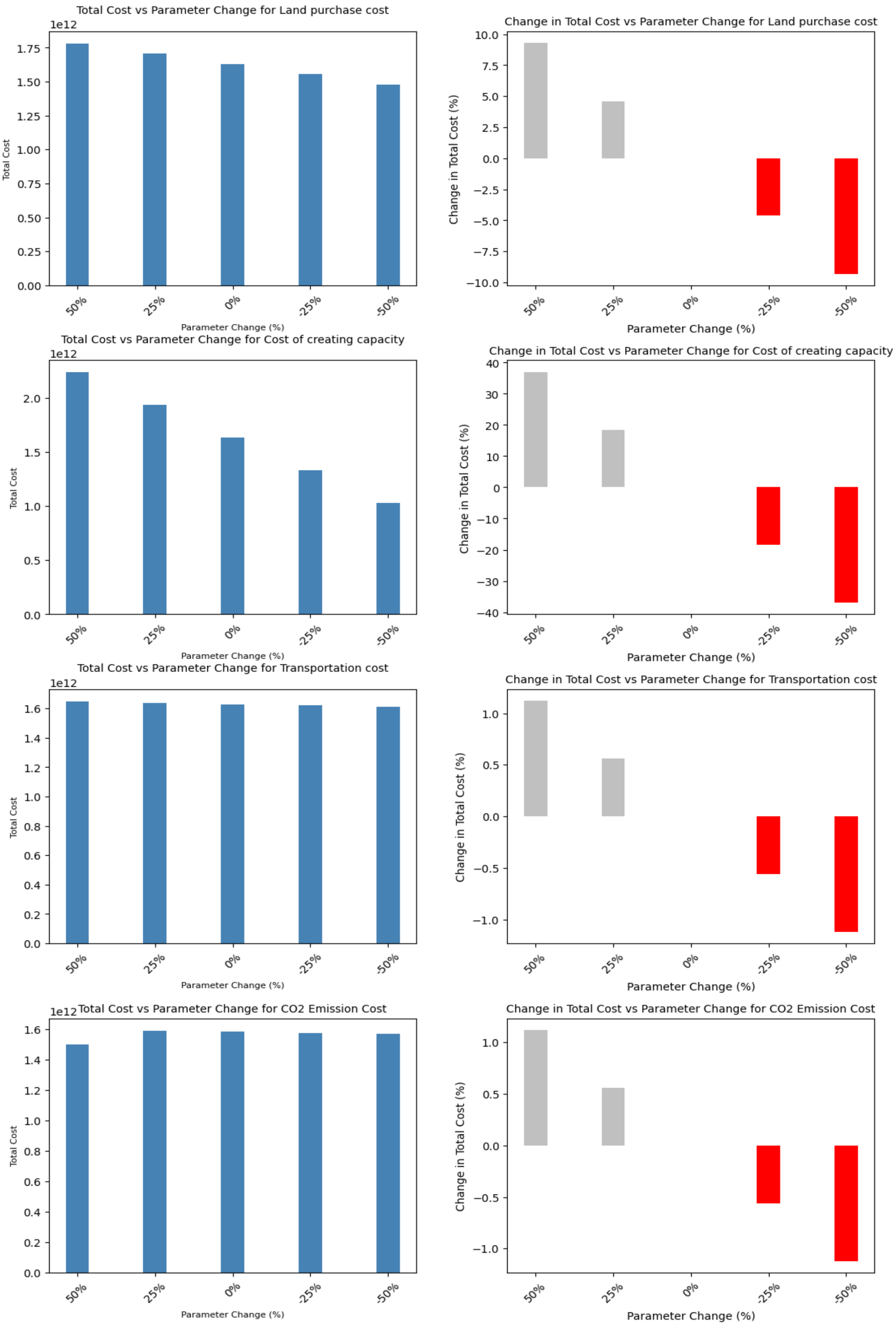


Fig.4.11. The impact of the significant parameters of the model for the separation center location on the total cost.

Table 4.23

The impact of the significant parameters of the first routing model on the total cost.

Parameters	parameter Change (%)	Total Cost	Change in total cost (%)
	50%	78,622,392	10.80%
	%25	74,611,103	5.20%
Co2 Emission Cost	0%	70,905,850	0.00%
	-25%	66,750,236	-5.80%
	-50%	62,403,445	-11.90%
	50%	93,510,204	31.80%
	25%	82,300,076	16.06%
Fixed Cost of vehicle	0%	70,905,850	0.00%
	-25%	60,107,942	-15.20%
	-50%	49,773,095	-29.80%
	50%	75,468,867	6.40%
	25%	74,285,974	4.70%
Transportation cost	0%	70,905,850	0.00%
	-25%	66,641,174	-6.10%
	-50%	64,256,676	-9.30%

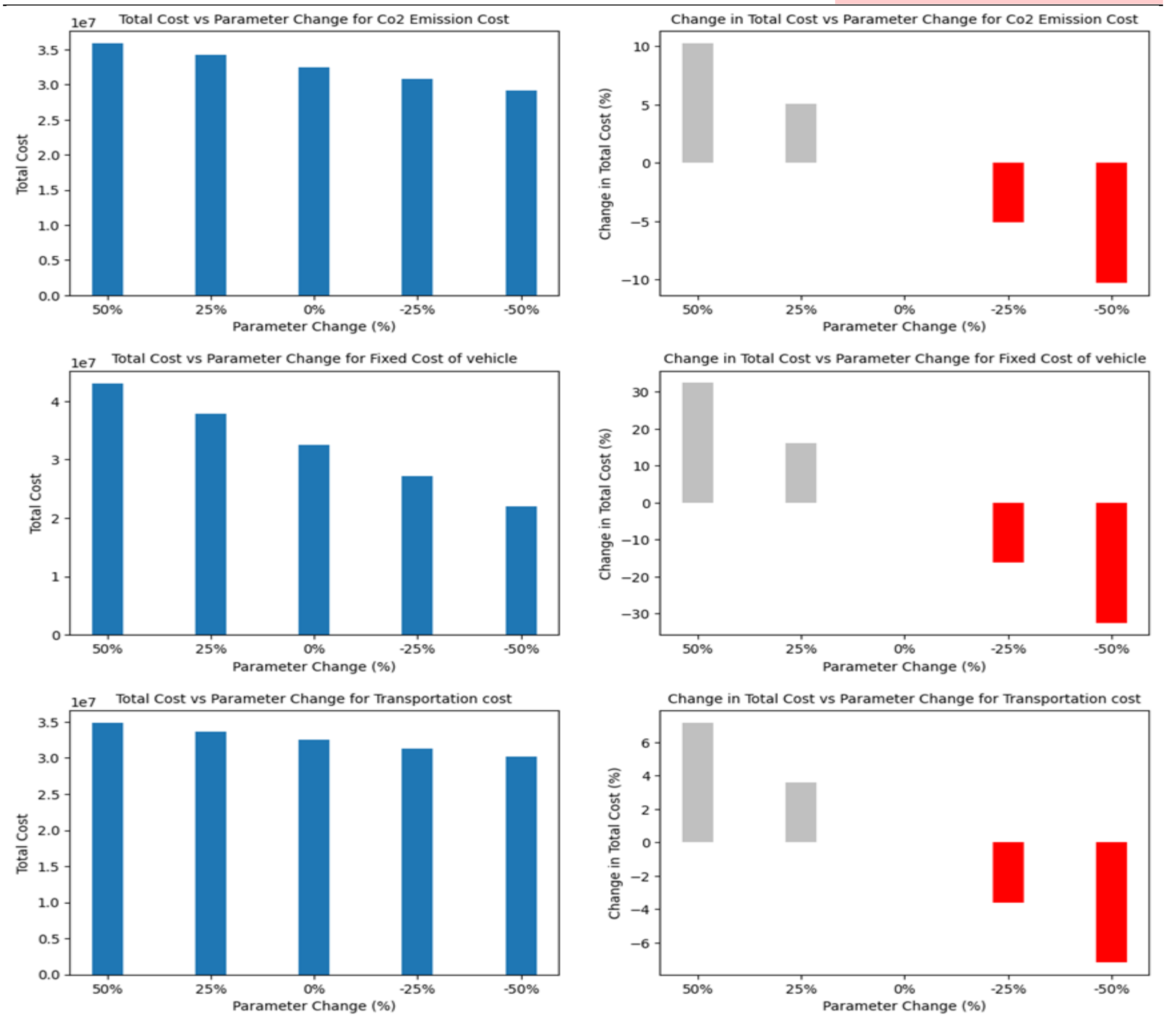


Fig.4.12. The impact of the significant parameters of the first routing model on the total cost.

Table 4.24

The impact of the significant parameters of the second routing model on the total cost.

Parameters	parameter Change (%)	Total Cost	Change in total cost (%)
	50%	35,857,490	10.30%
	25%	34,183,650	5.10%
Co2 Emission Cost	0%	32,509,800	0.00%
	-25%	30,835,960	-5.10%
	-50%	29,162,120	-10.30%
	50%	43,073,640	32.50%
	25%	37,791,720	16.20%
Fixed Cost of vehicle	0%	32,509,800	0.00%
	-25%	27,227,890	-16.20%
	-50%	21,945,970	-32.50%
	50%	34,853,180	7.20%
	25%	33,681,490	3.60%
Transportation cost	0%	32,509,800	0.00%
	-25%	31,338,110	-3.60%
	-50%	30,166,420	-7.20%

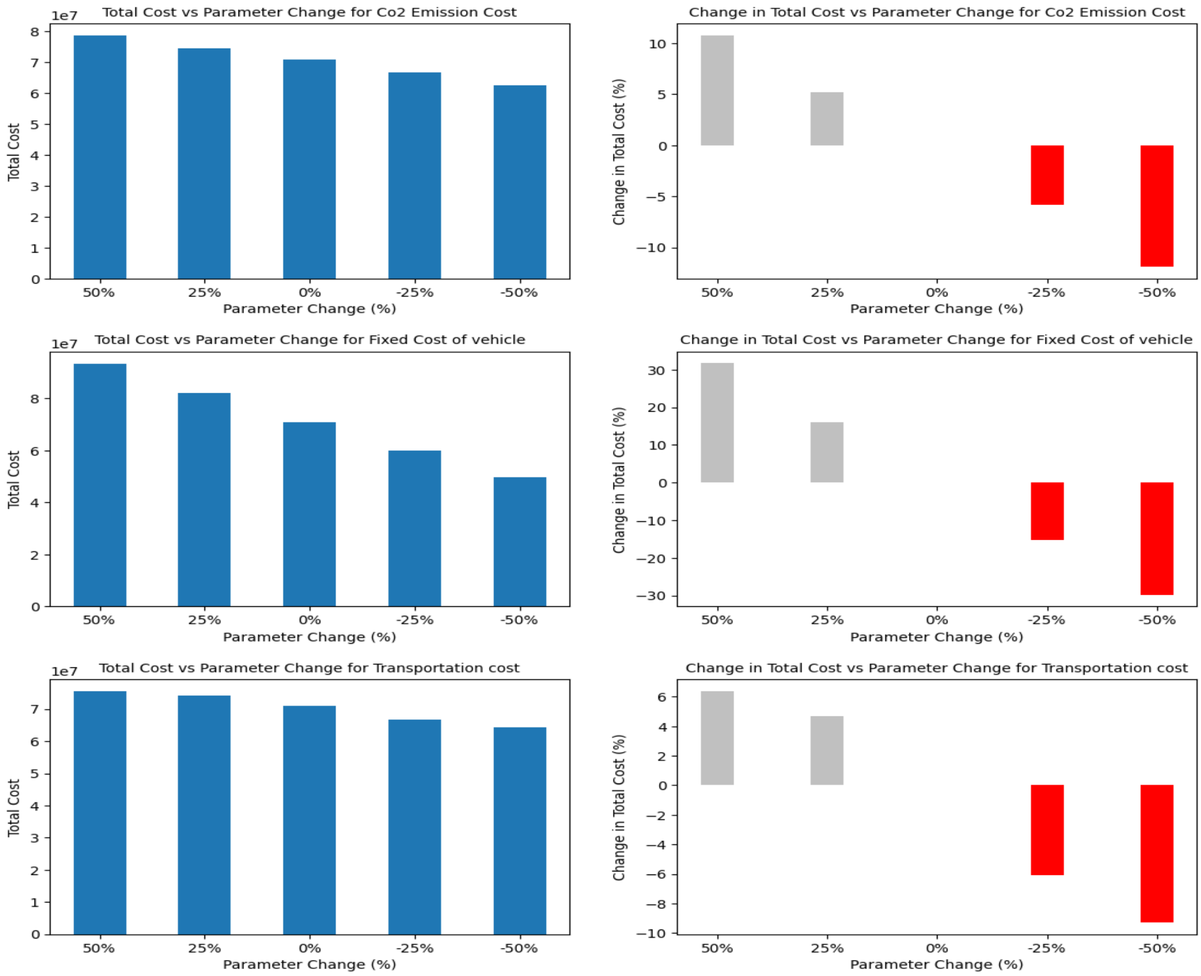


Fig.13. The impact of the significant parameters of the second routing model on the total cost.

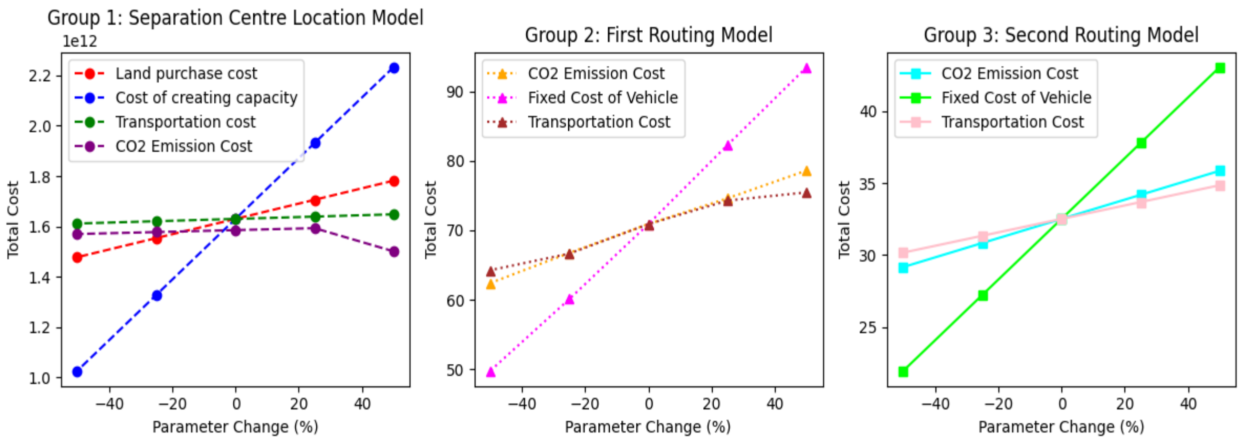


Fig.4.14. The impact of the significant parameters of all models on the total cost.

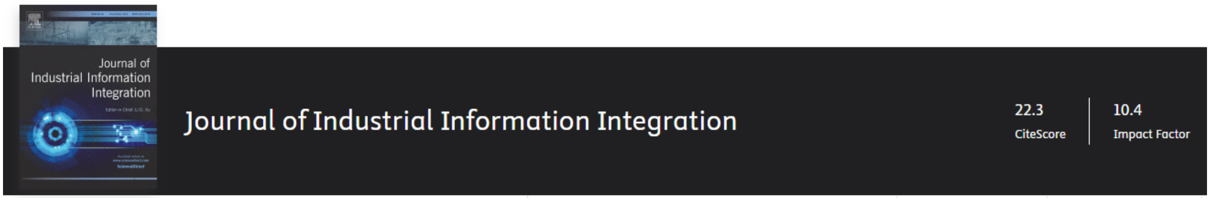
4.8. CONCLUSIONS

Waste collection is a critical step in waste management with significant economic, societal, and environmental impacts. This study focuses on enhancing the efficiency of this crucial component, focusing on the challenge of insufficient land in urban areas for separation center facilities. Since the usual assumption of one separation center per zone presents a barrier to progress, incorporating both the facility location and routing problems within our management system is the goal of this study. Hence, a location-allocation model is proposed followed by the formulation of two sustainable routing problems to enable an efficient collection of waste from bins to separation centers and then to recovery centers. This novel approach brings a new perspective to the logistics of waste management and has the potential to significantly improve system efficiency.

The facility location model proposes an innovative method to locate and distribute waste separation centers. Through optimization, optimal locations such as are proposed based on strategic location, increased capacity, and overall cost-efficiency. By considering the capacity and costs associated with potential locations, we offered a strategy to manage waste more effectively and economically. Determining the number and location of facilities is a long-term decision that is made at the strategic level. So, instead of assuming a predefined number of separation centers, a multi-objective location-allocation model is presented to determine the opened facility with sustainable goals in this paper and solved by the epsilon constraints method in GAMS. Then, the first-level routing problem was addressed using low capacitated vehicles for the day and night intervals integrating real-time data from sensor-equipped bins. The Social Engineering Optimizer and the Keshtel Algorithm were tested and compared to select the most suitable method to solve the problem. The former showed the smallest variation in objective function for small test instances in comparison to the latter, while the opposite conclusion was achieved for larger instances. For the second-level routing problem, a split pickup approach was utilized because of the larger amounts of waste to handle in each separation center. The optimization of the route was performed in GAMS/CPLEX with considerations for sustainable goals such as CO_2 emissions, social impact, and economic factors. The results highlight the potential benefits of leveraging real-time data, mathematical modeling, and strategic allocation to improve waste management systems. Further work could be conducted to refine the model and test its performance in larger-scale applications.

Future research should consider incorporating transshipment points into the waste management network, where vehicles can exchange loads without requiring additional storage capacity. This is particularly applicable to crowded urban areas, where the use of even low-capacity vehicles can exacerbate traffic and environmental issues. Therefore, a practical solution would involve a three-tier routing system, where waste is collected at these transshipment points before being transported to separation centers. This approach would require an integrated solution, where the first and second routing levels are solved simultaneously, allowing efficient waste collection. Future work should not only investigate optimal locations for separation centers but also analyze the optimal number and locations for these transshipment points within the facility location model. Moreover, future studies should consider more specific characteristics of real-world scenarios, such as the handling of hazardous waste, the weight of waste, and the use of historical data on each bin's filling rate. This would allow for different thresholds for different bins in various zones, leading to more accurate waste collection schedules. Furthermore, the incorporation of socioeconomic factors of the zones in dynamic routing could significantly improve the quality of routes provided by the optimization approach, making the waste management system even more efficient and effective.

The Result is Published in Journal of Industrial Information Integration.



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CHAPTER 5

PAPER 4:

Designing A Multi-Period Dynamic Electric Vehicle Production-Routing Problem in A Supply Chain Considering Energy Consumption

The coordinated decision-making approach for considering sequential activities of the supply chain results in additional benefits by optimizing production, inventory, and distribution operations. Accordingly, this paper proposes a mixed integer linear mathematical model to optimize a multi-period production routing problem utilizing electric vehicles. The proposed model optimizes the total cost associated with fixed and variable production, holding inventory, and routing, including the fixed cost of utilizing electric vehicles and travel time. However, mileage limitation is one of the main restrictions of utilizing electric vehicles in performing deliveries which is strongly affected by the consumed energy. Although optimization of the routes of vehicles can facilitate using them, considering the variation of travel speed network links during different times of the day because of traffic conditions can obviously affect the required energy to perform the assigned deliveries. To the best of our knowledge, this paper is the first to study simultaneous multi-period dynamic production routing problems using a set of heterogenous electric vehicles whose travel time of links can vary by dividing each production period into several hourly time intervals to capture different traffic conditions. Finally, a series of capable and hybrid metaheuristic algorithms are designed and implemented to solve this problem in a real-case dimension, and all proposed algorithms are compared.
Keywords: Integrated Production, Vehicle Routing, Electric Vehicles, Dynamic Routing, Metaheuristics.

5.1. INTRODUCTION

The continuous rise in global temperatures is a direct result of the rapid increase in greenhouse gas (GHG) emissions over the past century. Among various sectors, the transportation industry stands out as a significant contributor, accounting for more than 23% of global GHG emissions (Xiao et al., 2021). Numerous governments across the globe have established targets to decrease their GHG emissions to mitigate the negative environmental impact. Electric Vehicles (EVs) present a promising opportunity to address this problem by their eco-friendly characteristics, including low GHG emissions, high energy efficiency, and minimal noise pollution. By leveraging these features, EVs present an excellent opportunity to tackle the problem effectively (Fateme Attar et al., 2022).

However, a significant limitation in fully achieving the potential of EVs is their limited battery capacity (Feng & Figliozzi, 2013). In addition, EVs often face limitations in terms of their travel capacity, with a shorter range compared to traditional internal combustion engine vehicles as well as a lack of sufficient infrastructure for battery recharging (Young et al., 2013). Consequently, the Electric Vehicle Routing Problem (EVRP) has emerged, as a crucial area of research, to optimize EV routing and ensure timely access to recharging stations (Y. J. Kim & Chung, 2023; Y. Wang et al., 2023). The recent advancements in technology and battery power, combined with the increasing cost of fossil fuels, have made EVs more cost-effective and competitive. EVs offer several advantages, including zero exhaust emissions during operation, lower air and noise pollution, and lower long-term maintenance costs due to their fewer moving parts.

Given the increasing importance of sustainable transportation and logistics, in recent years, researchers have devoted significant attention to EVRPs. EVs are practical solutions for small package delivery, food and beverage distribution, and other transportation tasks (Pelletier et al., 2016). However, to date, there has been little research exploring the use of EVs in a dynamic multi-period supply chain context. This study proposes a new integrated approach for making the decision for production, inventory, and distribution level of a multi-period supply chain with time-dependent travel time by utilizing the EVs at the distribution level. The resulting Production Routing Problem (PRP) can lead to significant cost savings and productivity gains compared to independent decision-making. The PRP has far-reaching implications for businesses seeking to reduce their carbon footprint and increase efficiency while maintaining high-quality product distribution services. As a result, this study contributes to the emerging field of sustainable logistics and supply chain management.

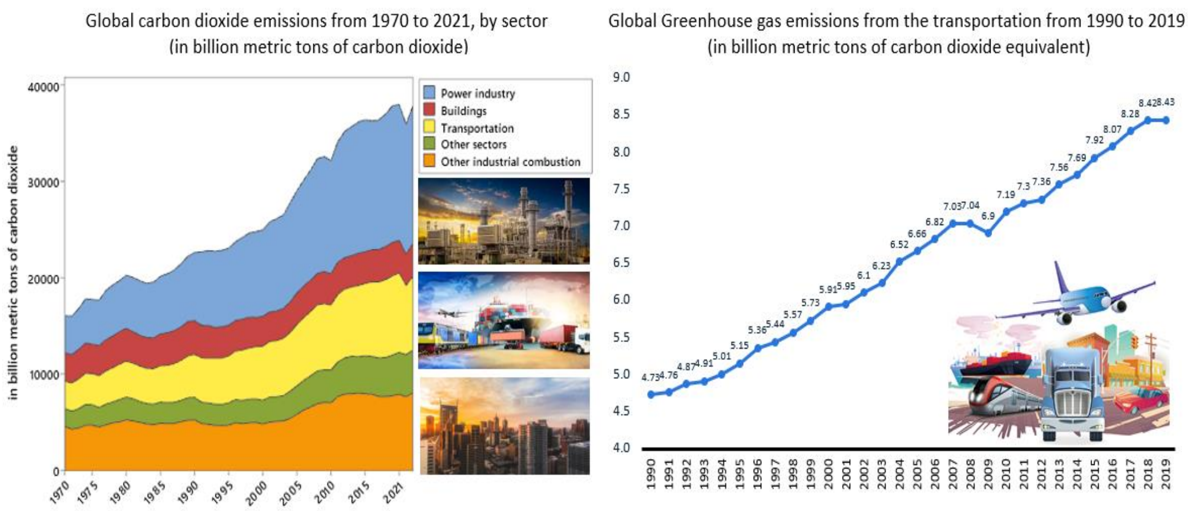


Fig.5.1. Global Carbon dioxide emission with a focus on transportation.

Source(s): www.Statista.com, ID 276480 and ID 1084096.

The PRP is a complex issue that arises in supply chain management by combining the Lot-Sizing Problem (LSP) and the Vehicle Routing Problem (VRP) (Gutierrez-Alcoba et al., 2023). Logistics plays a vital role in determining the performance and cost of the PRP. The PRP involves two replenishment policies: the maximum level (ML) policy and the order-up-to (OU) policy. Under the ML policy, the quantity of products to be delivered to customers is determined by the plant. However, it is crucial to ensure that the inventory capacity is not exceeded. In contrast, the OU policy ensures that the customer's inventory capacity is fully replenished with each delivery. The transportation of products from plants to end nodes is done through available fleets with corresponding transportation costs. Furthermore, inventory holding costs are incurred when products are stored in plant and customer sites. Firstly, Chandra (1993) has demonstrated the benefits of PRP and has shown that a simple heuristic approach can lead to considerable cost saving for a PRP compared to a sequential approach to address the problem. To sum up, the PRP holds significant importance in supply chain management as it encompasses the integration of LSP and VRP. The PRP considers a range of factors, including different replenishment policies, setup costs, transportation, and inventory holding costs. Its comprehensive nature makes it a vital aspect to be addressed for efficient supply chain operations.

Integrating routing and production planning is crucial to have cost reduction of supply chains across diverse sectors, including electronics, food, fuel, pharmaceuticals, and medical distribution networks. With this motivation, this paper investigates the integration of EVs in transportation fleets for the PRP to address the growing global concern for environmental pollution.

However, one of the central limitations of deploying EVs in transportation fleets is their dependency on recharging operations. Hence, route optimization plays a critical role in utilizing these vehicles to take their potential capacity to reduce the costs and negative environmental impact (Cheraghalipour et al., 2017). Nevertheless, factors like traffic congestion and accidents can lead to fluctuations in travel time, which in turn directly impact the optimized routes based on the time of day. So, to effectively tackle a significant challenge in utilizing EVs for freight transport, it is imperative to consider the different traffic conditions during different time periods in the production routing problem. So, with the aim of facilitating the utilization of EVs in PRP, the different traffic conditions during different time periods are considered for the first time in this context.

Fig.5.2. The different types of EVs charging stations.

So, a novel formulation of the multi-period dynamic electric vehicle production routing problem is proposed in this paper to consider not only the traffic conditions at different times within a day but also considers different traffic characteristics that vary depending on the day of the week. This is due to the fact that traffic conditions can vary on different days of the week, even at the same time of day. The main contributions of this study are listed as follows:

- Proposing a mixed integer linear programming to model the DEVPRP model that addresses the production routing problem by minimizing the total cost, which is composed of the fixed and variable costs of production, holding costs, fixed cost of utilizing EVs, and total traveled time.
- Considering stepwise travel time function to capture different behaviors of traffic conditions not only within a day but also on different days.
- Proposing a hybrid metaheuristic approach to address the complexity of the problem and implementing several numerical experiments on different generated test beds.

To the best of our knowledge, although there are a few studies to investigate the electric vehicle production routing problem, still the dynamic travel time in different periods has not been investigated (DEVPRP). The objective of the DEVPRP is to determine the most efficient and feasible set of production and delivery schedules for a production system using a fleet of EVs. The proposed model incorporates at the same time multiple recharge options, heterogeneous EVs, a full recharge policy, varying holding costs in different periods, time windows for deliveries, and stepwise travel time functions to account for different traffic conditions of multiple periods. It is important to mention that vehicles are heterogeneous in terms of consumption rate, maximum battery energy, loading capacity, and recharging time. Since the inherent limitations of EVs make the PRP more challenging compared to traditional internal combustion vehicles, the considered assumptions and conditions for this problem aim to closely resemble real-world scenarios. To address this complexity, a series of capable and hybrid metaheuristic algorithms are employed to solve this problem in a real-case dimension.

5.2 LITERATURE REVIEW

Recently, the PRP has been investigated by researchers to model the problem with different assumptions to improve the decision made by decision-makers for the whole supply chain instead of considering the supply chain as a sequence of activities such as production, storage, and distribution (Berghman et al., 2023). While optimization of each step, which is according to decisions made for preceding activities, can lead to a sub-optimal solution without exploiting the benefits of coordination in the planning (Hashemi-Amiri, Ghorbani, et al., 2023b). Not only these sub-optimal solutions can result in higher costs but also can increase the negative impact on the environment. Hence in this paper, the application of EVs in PRP has been proposed, and in this section, the relevant recent work has been investigated.

The PRP has been modeled by considering various assumptions, including single multiple products, single or multiple plants, single or multiple vehicles for the distribution phase, and a two-echelon network under different replenishment policies to perform the deliveries to customers (Fateme Attar et al., 2022). Boudia et al., (2007)investigated a multi-period integrated production distribution problem with minimization of production, inventory, and distribution costs by extending an integer linear mathematical model. The proposed model was solved by a greedy randomized adaptive search metaheuristic for problems in big dimensions. The multi-period problem of considering one product was addressed by (Boudia et al., 2008) by proposing two greedy heuristics combined with local search procedures to minimize the total cost of producing and distributing them. While two tabu search metaheuristic algorithms were developed by Armentano et al., (2011) to minimize the total production, inventory at plant and customers location, and distribution costs. The first proposed algorithm was constructive and based on a short-term memory, while the second one was based on a longer-term memory to involve path relinking procedure in the first algorithm.

More recently, a multi-objective mathematical formulation of multiple-vehicle PRP was developed to minimize the total cost of operations and pollution using a set of homogenous vehicles. The developed problem was addressed by a hybrid Self-Learning Particle Swarm Optimization metaheuristic algorithm (R. S. Kumar et al., 2016). The integrated PRP was addressed by designing two heuristics based on mathematical programming by relaxing a mixed integer model to determine an initial solution. The concept of set partitioning and seed routes were employed to determine an approximate solution (Russell, 2017). The problem of production routing was investigated for the perishable products in which maintaining temperature over the whole chain plays a critical role (Manouchehri et al., 2020). Due to the high complexity of the proposed problem, a combined variable neighborhood search with a simulated annealing algorithm was developed to address the problem. Zhang et al., (2020) proposed a benders decomposition approach to address the PRP with multiple vehicles to determine the production day and consequently the amount of product each day and the customers visiting in different periods.

On the other hand, several authors have also investigated the PRP problem under multiple products assumption by Lagrangian relaxation and tabu search metaheuristic algorithm with the limited available fleet (Fumero & Vercellis, 1999). Li et al., (2019) modeled a PRP by considering multiple products and outsourcing possibilities as a mixed integer linear programming and solved by a three-level heuristic. The production, inventory, and routing problems were modeled to investigate the impact of short-term decisions on carbon emissions (Darvish et al., 2019). Moreover, the PRP with multiple plants has been investigated by several authors (Y. Li et al., 2020; Schenekemberg et al., 2021).

However, due to the negative environmental impact of transportation services, the application of EVs in supply chain management problems has been investigated by several papers (Schenekemberg et al., 2021). Since 1959 when Dantzig and Ramser introduced this problem for the first time, different variants of the problem have been extended to take practical steps toward solving real-world problems such as vehicle routing problems with pickup and delivery. Interested readers can refer to (Vidal et al., 2020) for reviews of different existing structures and their emerging variants. However, one of the variants of the vehicle routing problem, EVRP is proposed by (Conrad & Figliozzi, 2011). Because of the maximum mileage limitation of EVs, the recharging strategy plays a key role in the previous works of the EVRP, which have resulted in the investigation of various strategies. Mao et al., (2020) introduced a full charging strategy for the EVRP with backhauls, while (Y. Zhou et al., 2021) presented a partial recharging strategy for EVs and solved the problem by proposing a hybrid metaheuristic combining a greedy algorithm with the variable neighborhood search. However, the idea of exploiting the charging time to deliver the demand of customers near the charging station by walking was proposed by (Cortés-Murcia et al., 2019).

The EVRP was mathematically formulated with multiple charging types, including slow, regular, and fast charging to minimize the total cost (Yindong et al., 2021). The strategy of battery swapping has been investigated by (Zhou & Zhao, 2022) and (Karakatič, 2021) and the later study proposed a two-layer genetic algorithm to address a multi-depot EVRP with nonlinear recharging times and the possibility of battery swapping. Raeesi & Zografos, (2020) designed a framework to synchronize the EVs and a battery swapping van which provide the possibility of changing the utilized battery with a fully recharged battery. The time and location of meeting the EVs and battery swapping van must be synchronized. However, the speed of vehicles on the different links of the road network can vary during different times of the day which obviously affects the required energy to traverse that link. Hence, considering the time-varying characteristics of the traffic condition seems to be necessary to optimize the routes of EVs which strongly depends on the recharging operation. The time-dependent variant of the vehicle routing problem has been introduced to consider traffic congestion in the road network. The mathematical formulation of the time-dependent routing was developed by (Malandraki & Daskin, 1992) in which the travel time of each link was determined based on the departure time of the vehicle from the start node of that link. (Fleischmann et al., 2004) modeled the travel time has been modeled with the smoothed travel time function.

Ichoua et al., (2003) presented a model where travel time becomes a piecewise linear function based on a stepwise function of speed. These two methods respect the FIFO property to be sure that first vehicles traversing specific links must leave it earlier. On the other hand, the underlying shortest paths problem has been investigated by (Eglese et al., 2006) to create a timetable of time-dependent shortest paths utilizing the floating car data in England. Kok et al., (2012) addressed the problem of the computational time of calculating the time-dependent shortest paths by dynamic programming heuristic. Although extensive research has been carried out on the time-dependent vehicle routing problem, few research has been conducted to address the variant of the time-dependent electric vehicle routing problem. The time dependent EVRP was modeled by considering the energy consumption constraint of EVs and the time window (Lu et al., 2020). To address the proposed problem, an iterated variable neighborhood search algorithm was designed. Li et al., (2020) developed a mathematical formulation to minimize the cost and consumed energy of the time dependent EVRP under path flexibility.

5.3PROBLEM STATEMENT

The main aim of this work is developing an optimization procedure in both planning and operation steps in freight distribution within an urban network, utilizing EVs from a unique depot center. The electric fleet are heterogeneous and composed of various load capacity range and operational unit costs. Deliveries are linked to a set of delivery points, each of them has a specific time window within the fleet operation hours. A set of fast recharge stations is available across the delivering area to be used if the energy level goes under a predefined threshold. The considered problem and the developed mathematical formulation are described in this section. A set of delivery points must be served by a set of EVs. The vehicles are assumed to be used only once, which implies that each electric vehicle can depart from the distribution center once, and its tour must be finished at the distribution center, and all vehicles are in only one depot at the beginning of the planning horizon. There is a time window for each delivery point which must be served within the assumed time window. However, the possibility of visiting a charging station makes it feasible for EVs to have longer routes by even having multiple recharges during the operational day.

The service time of the vehicles at each delivery point is determined in advance, which depends on the amount of demand. However, if the visited node is a recharging station, the required time depends on the current state of the charge and the amount of needed energy to be fully recharged, and the power of recharging stations. Regarding the time of traversing links, it is modeled based on the departure time of the vehicle from the starting node of that link. Hence, travel speed and, consequently travel time of traversing a link is determined based on the time of the day and traffic congestion. Since capturing the traffic characteristics of the road network is a difficult task, the floating car data of the road network of Rome city has been utilized to specify the travel speed of each link every hour. So, the travel time of a link depends on the hourly time slice that an electric vehicle wants to use it. Fig. 03 represents the graph of Rome, and then the mathematical formulation of the problem is explained.

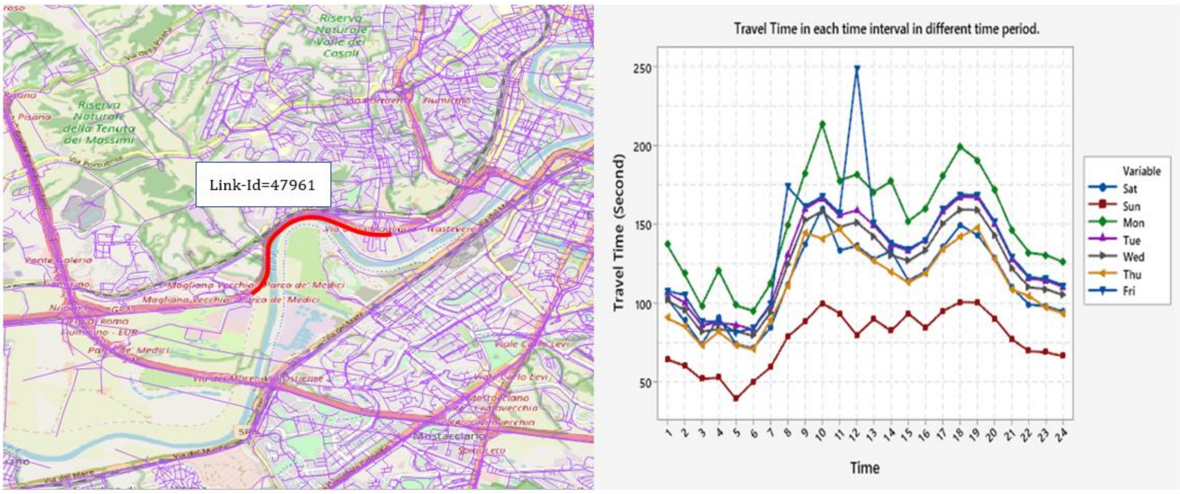


Fig.5.3. Travel time in each time interval in different periods.

5.3.1. MATHEMATICAL MODEL

The mixed integer linear programming is used to develop a DEVPRP model that addresses the production routing problem by minimizing the total cost, which is composed of the fixed and variable costs of production, holding costs, fixed cost of utilizing EVs, and total traveled time. Table 5.1, Table 5.2, and Table 5.3 represent the set of models, parameters of the model Decision variables, respectively.

Table 5.1
Model's sets.

Sets	Description
U_0	Manufacturer,
N	Set of customers,
N_0	Set of nodes including customers and manufacturer,
F	Set of recharging stations,
F'	A dummy set of recharging stations to make multiple recharging possible for each electric vehicle,
F'_0	Set of recharging station with multiple dummy vertices and manufacturer,
N'	Set of recharging stations and customers,
N'_0	Set of recharging stations, customers, and manufacturer,
T	Set of the time period for production and distribution,
M	Set of time intervals at each time period to represent different traffic condition,
V	Set of EVs available at plant.

Table 5.2
Model's parameters.

Parameters	Description
FP	Fixed setup cost for producing product at each time period,
VP	Unitary production cost,
h_{jt}	Unitary holding cost at node j in time period t,
dis_{ij}	The distance between node i and node j,
t_{ijtm}	The travel time between node i and node j in time period t and time interval m,
d_{it}	The demand of customer i in time period t,
s_i	The service time of node i,
Q_v	The maximum capacity of the vehicle v,
I_j^{max}	The maximum inventory level at node j,
I_j^0	The initial inventory level at node j,
Cap^p	The maximum production capacity at each time period,
Y_v	The maximum battery capacity v (KWh),
r_v	The unitary energy consumption rate of vehicle v (KWh),
g_v	The unitary recharging time of electric vehicle v,
TC	The volume-to-weight conversion factor,
$[ST_i, FT_i]$	The opening and closing time window of the node i,
T_{mt}	The upper bound of time interval m in time period t,
FC_v	The fixed cost of using electric vehicle v,
L	A large number.

Table 5.3

Decision variables.

Variables	Description
p_t	The amount of produced goods in time period t,
I_{jt}	The level of inventory at node j by the end of period t,
q_{ijvt}	The load of vehicle v when traversing arc (i,j) in time period t,
y_{jvt}	The current energy level of vehicle v at node j in time period t,
dt_{it}	The departure time from node i in time period t,
w_t	A binary variable equal to 1 if the plant is used to produce in time period t, and 0 otherwise,
z_{vjlt}	A binary variable equal to 1 if vehicle v delivers the demand of period l for node j in period t, and 0 otherwise,
x_{ijvtm}	A binary variable equal to 1 if the arc (i,j) is traversed by electric vehicle v in time interval m of time period t, and 0 otherwise,

$$\text{Minimize} \sum_{t\in T} FP\, w_t + \sum_{t\in T} VP\, p_t + \sum_{j\in N_0}\sum_{t\in T} h_{jt}\, I_{jt} + \sum_{j\in N'}\sum_{v\in V}\sum_{t\in T}\sum_{m\in M} FC_v\, x_{U_0 jvtm} + \sum_{\substack{i,j\in N_0',\\ i\neq j}}\sum_{v\in V}\sum_{t\in T}\sum_{m\in M} t_{ijtm}\, x_{ijvtm} \qquad \text{Eq. (5.1)}$$

Subject to:

$$I_{U_0 t} = I_{U_0 t-1} + p_t - \sum_{v\in V}\sum_{j\in N}\sum_{t\in T} d_{it}\, z_{vjlt} \quad \forall t\in T, \qquad \text{Eq. (5.2)}$$

$$I_{it} = I_{it-1} - d_{it} - \sum_{v\in V}\sum_{l\in T} z_{vjlt} \quad \forall t\in T, \forall j\in N, \qquad \text{Eq. (5.3)}$$

$$0 \le I_{it} \le I_i^{max} \quad \forall i\in N_0, \forall t\in T, \qquad \text{Eq. (5.4)}$$

$$p_t \le Cap^p w_t \quad \forall t\in T, \qquad \text{Eq. (5.5)}$$

$$\sum_{\substack{i,j\in N_0',\\ i\neq j}}\sum_{m\in M} x_{ijvtm} - \sum_{\substack{k\in N_0',\\ j\neq k}}\sum_{m\in M} x_{jkvtm} = 0 \quad \forall j\in N_0', \forall t\in T, \forall v\in V, \qquad \text{Eq. (5.6)}$$

$$\sum_{i\in N'}\sum_{m\in M} x_{U_0 jvtm} \le 1 \quad \forall t\in T, \forall v\in V, \qquad \text{Eq. (5.7)}$$

$$\sum_{i\in N_0'}\sum_{v\in V}\sum_{m\in M} x_{ijvtm} \le 1 \quad \forall t\in T, \forall \text{j}\in N, \qquad \text{Eq. (5.8)}$$

$$\sum_{i\in N_0'}\sum_{m\in M} x_{ijvtm} \le 1 \quad \forall t\in T, \forall \text{j}\in F', \forall v\in V, \qquad \text{Eq. (5.9)}$$

$$dt_{it} + \left(t_{ijtm} + s_j\right)x_{ijvtm} - L\left(1 - x_{ijvtm}\right) \le dt_{jt} \qquad \text{Eq. (5.10)}$$
$$\forall i\in N_0, \forall j\in N_0', i\neq j, \forall t\in T, \forall v\in V, \forall m\in M,$$

$$dt_{it} + t_{ijtm}\, x_{ijvtm} + g_v\left(Y_v - y_{jvt}\right) - \left(L - g_v Y_v\right)\left(1 - x_{ijvtm}\right) \leq dt_{jt}$$ Eq. (5.11)

$\forall i \in N_0', \forall \mathrm{j} \in F', i \neq j, \forall t \in T, \forall v \in V, \forall m \in M,$

$$dt_{it} + L\, x_{ijvtm} \leq T_{mt} + L \qquad \forall i,j \in N_0', i \neq j, \forall t \in T, \forall v \in V, \forall m \in M,$$ Eq. (5.12)

$$dt_{it} + T_{m-1\,t}\, x_{ijvtm} \geq 0 \qquad \forall i,j \in N_0', i \neq j, \forall t \in T, \forall v \in V, \forall m \in M,$$ Eq. (5.13)

$$dt_{U_0 t} = ST_{U_0} \quad \forall t \in T,$$ Eq. (5.14)

$$ST_i + s_i \leq dt_{it} \leq FT_i + s_i \qquad \forall i \in N_0', \forall t \in T, \forall v \in V, \forall m \in M,$$ Eq. (5.15)

$$\sum_{\substack{i \in N_0', \\ i \neq j}} q_{ijvt} - \sum_{\substack{k \in N_0', \\ j \neq k}} q_{jkvt} = \sum_{l \in T} z_{vjlt} \qquad \forall \mathrm{j} \in N, \forall t \in T, \forall v \in V,$$ Eq. (5.16)

$$\sum_{j \in N'} q_{jU_0 vt} - \sum_{k \in N'} q_{U_0 kvt} = -\sum_{j \in N'} \sum_{l \in T} z_{vjtm}$$ Eq. (5.17)

$\forall t \in T, \forall v \in V,$

$$q_{ijvt} \leq Q_v\, x_{ijvtm} \qquad \forall i,j \in N_0', i \neq j, \forall t \in T, \forall v \in V, \forall m \in M,$$ Eq. (5.18)

$$0 \leq y_{jvt} \leq y_{ivt} - \left(r_v\, dis_{ij}\right) x_{ijvtm} + Y_v\left(1 - x_{ijvtm}\right)$$ Eq. (5.19)

$\forall i,j \in N_0', i \neq j, \forall t \in T, \forall v \in V, \forall m \in M,$

$$0 \leq y_{ivt} \leq Y_v - \left(r_v\, dis_{ij}\right) x_{ijvtm}$$ Eq. (5.20)

$\forall i,j \in N_0', i \neq j, \forall t \in T, \forall v \in V, \forall m \in M,$

$$y_{U_0 vt} \leq Y_v \qquad \forall t \in T, \forall v \in V,$$ Eq. (5.21)

$$q_{iU_0 vt} = 0\ \forall t \in T, \forall j \in N', \forall v \in V,$$ Eq. (5.22)

$$z_{vjjt} = 0 \qquad \forall j \in N_0', \forall t \in T, \forall v \in V$$ Eq. (5.23)

$$z_{vjkt} - z_{vjkt} \leq 1 \qquad \forall \mathrm{k}, j \in N', k \neq j, \forall t \in T, \forall v \in V$$ Eq. (5.24)

The objective function Eq. (5.1) minimizes the total cost which is composed of the fixed and variable costs of production, holding costs, fixed cost of utilizing EVs, and total traveled time. The inventory balance of customers and plants is guaranteed by equations Eq. (5.2) and Eq. (5.3). Accordingly, the upper bound and lower bound inventory level at all nodes is satisfied by Eq. (5.4). Constraint Eq. (5.5) ensures the maximum production capacity of the plant if it is utilized to produce in a specific time period. The continuity of the flow of each tour is ensured by constraints Eq. (5.6) while Eq. (5.7) limits the use of an electric vehicle for at most one tour. Eq. (5.8) guarantees that each customer must be visited at most once in each time period and Constraint Eq. (5.9) limits visiting each dummy recharging station for one time. Eq. (5.10) calculates the departure time of the vehicle from a node by summation of the departure time of the vehicle from the previous customer and the link's travel time associated with the correct time interval and service time of the vehicle in the current node. However, the departure time of a vehicle from the recharging station is according to Eq. (5.11), which is the summation of travel time between two consecutive nodes and the time required for full recharging of the vehicle considering the current state of the charge and unitary recharging time. The choice of the correct time interval of traffic conditions based on the departure time from a link is guaranteed by Eq. (5.12) and Eq. (5.13) while Eq. (5.14) sets the departure time of all as the opening time of the plant. Eq. (5.15) ensures that the delivery to each customer must be performed within the time window on a corresponding day. Eq. (5.16) ensures that the remaining load of the vehicle must be reduced by the demand of the currently visited customer. The load of vehicles when departing from the plant is calculated according to the demand of all assigned customers by Eq. (5.17). The maximum capacity of each electric vehicle is ensured by Eq. (5.18). Eq. (5.19) represents that a vehicle's current state of charge is calculated based on the vehicle's energy in the previous node subtracting the required energy to traverse the distance between two consecutive nodes. Eq. (5.20) ensures the current state of the charge if the previously visited node is the recharging station, and Eq. (5.21) sets the charging level of all vehicles to be full while they depart from the depot. The valid inequalities are defined by Eq. (5.22)- Eq. (5.24) which makes the solving process faster.

5.4 SOLUTION APPROACH

This study addresses a complex, multi-dimensional problem: the optimization of multi-period dynamic production-routing problem within a supply chain context. The integration of routing and production planning presents a challenging issue in SCM which entails the simultaneous consideration of LSP and the VRP, both of which are classified as NP-Hard combinatorial (Hashemi-Amiri, Mohammadi, et al., 2023). Consequently, the complex nature of this task requires a robust and time-efficient solution methodology. Various methodologies have been proposed to tackle such problems. For example, exact algorithms, which involve techniques such as Mixed Integer Linear Programming (MILP) and Branch and Bound, strive for optimal solutions(J. Wang et al., 2021). While these offer a guarantee of optimality, they are often limited by the computational intensity and can be infeasible for large-scale problems. Contrarily, meta-heuristics offer several benefits over these approaches. They excel at handling complicated, non-linear, and large-scale problems. Moreover, the integration of multiple algorithms allows for the capitalization of their synergistic strengths and mitigation of their weaknesses, which boosts overall performance and solution robustness.

Metaheuristic approaches have proven particularly valuable in solving NP-hard combinatorial optimization problems, which involve searching for an optimal solution in a problem space where the number of possible solutions grows exponentially with the size of the problem. One primary advantage of using metaheuristics is their ability to provide near-optimal solutions in a relatively short computation time. While exact methods may struggle with large problem sizes due to their time complexity, metaheuristics offer scalability and efficiency, making them particularly suited for handling real-world problems that often involve large datasets and complex decision variables. Moreover, metaheuristics are flexible and adaptable, capable of addressing a broad range of optimization problems without the need for problem-specific adaptations. These methods typically operate on a population of solutions, not just a single one, and allow exploration of the solution space through iterations. By incorporating mechanisms of intensification (exploiting promising areas) and diversification (exploring new areas), they effectively avoid premature convergence to local optima, a common pitfall for greedy algorithms. These characteristics make metaheuristics a powerful tool when tackling NP-hard combinatorial optimization problems, where the optimal solution is not directly attainable (Rahmanifar et al., 2023b).

Since, no single algorithm can address all optimization problems effectively, this work proposed several meta-heuristics algorithms to solve the problem including simulated annealing (SA), Genetic algorithm (GA), keshtel Algorithm (KA), Particle swarm optimization algorithm (PSO), The Grey wolf optimizer (GWO). On the other hand, each algorithm has its strengths and weaknesses, and the performance of an algorithm can vary significantly depending on the problem at hand. For instance, Simulated Annealing is great at escaping local optima but can be slow to converge. Genetic algorithms, on the other hand, are efficient at exploring the solution space but can prematurely converge to suboptimal solutions. This is where hybridization comes in. In hybrid meta-heuristics, two or more algorithms are combined, aiming to produce a new algorithm that performs better than its components. The rationale is that the strengths of one algorithm can compensate for the weaknesses of the other (Gholian-Jouybari et al., 2023b). In this research, the authors propose the hybridization of Genetic Algorithm with Simulated Annealing (HGASA), and the hybrid of Keshtel Algorithm with Simulated Annealing (HKASA). By doing so, the authors intend to take advantage of the efficient exploration capabilities of Genetic Algorithms and Keshtel Algorithm and pair it with the excellent exploitation abilities of SA algorithm to escape local optima. The hybrids are designed to be more robust and versatile, providing superior performance on a wider range of problems. Hybrid algorithms can share information, learn from each other, and adjust their strategies based on the problem's characteristics and the current state of the search.

5.4.1 ENCODING AND DECODING PLAN

The problem under investigation, DEVPRP, is a complex optimization problem that involves determining whether the production facilities should be used or not in a period and the amount of production, the optimal routes for a fleet of EVs to deliver products from a production facility to customers over a multi-period time horizon. Moreover, the time for recharging procedure and selecting the Meta-heuristic algorithms have been widely used to solve it due to their ability to provide good-quality solutions in reasonable time frames. The first and crucial step in implementing a meta-heuristic algorithm is solutions representation as chromosomes to derive the decisions. This step also can significantly affect the algorithm's performance, and a two-step procedure is proposed to represent the solution in this paper. The first step is dedicated to the production level by determining a random number for the number of production days and the amount of production on each day. By following the equation, the minimum number of production days is determined to satisfy the demand of all customers over the whole period. Then the number of production days, p_d, is determined by a randomly generated number between the minimum required production day, which is calculated based on Eq. (5.26), and the number of periods available T. After extracting the number of production days randomly, a valid range is required to extract the amount of production on each day. It is generated randomly between $[\frac{Total\ demand}{p_d}, production\ capacity]$.

$$\text{Minimum required production day} = \frac{\text{Total demand}}{(\text{production capacity}) * \text{production availability rate}} \qquad \text{Eq. (5. 26)}$$

The second step deals with the routing problem to represent the routes of EVs in different periods. As it can be seen in Fig.5.4. firstly, the delivery points of each period must be determined by a $number\ of\ period * number\ of\ customers$ matrix with zero and one elements representing that whether a customer has a demand for a specific day or not. Then, a $[2 * \ number\ of\ customer]$ matrix is generated for each period to determine the routes of vehicles. For each time period, the elements of the first row are filled based on the random key method, and each element of the second row is generated randomly between $[1, numberof\ available\ electric\ vehilce]$. The assignment of the customers to vehicles has been done with this two rows matrix for each day and all periods. However, the scheduling problem of vehicles has remained to determine the visiting order of vehicles. The scheduling problem of each vehicle is based on the random key method and is defined after extracting the original position of each random number between zero and one after sorting. For example, for the first vehicle in the first period, it is obvious that two first customers are assigned to it. However, the sorted corresponding random numbers are 0.45,0.68. Since the index of these two numbers are 1 and 2 in the original random key vector, the schedule of the first vehicle to visit customers is represented in Fig.5.4.

An important part of utilizing metaheuristic algorithms is Constraints handling. Although several approaches were introduced to handle the constraint of a problem by (Talbi, 2009) such as penalizing the violated constraint or repairing strategy, we applied two approaches in this paper to handle the problem's constraints to be sure about the feasibility of the final solution. Assigning a penalty to the violated constraints is the first used approach and implemented for constraints such as the capacity of vehicles and time window to direct the search procedure toward the final solution, which is also feasible. However, another posterior method is applied to tackle the energy constraint after having the result of the algorithms by defining an insertion strategy to add recharging stations to a tour based on the state of the charge of an electric vehicle. As it is illustrated in Fig. 5.5, the state of the charge is negative which violates the energy constraint of the model. To make the solution feasible, we must insert one or more recharging stations into the tour according to the state of charge. Since the recharging station theoretically can be added between every two nodes before negative energy, many possible solutions exist.

Demand Matrix

	C=1	C=2	C=3	C=4	C=5	C=6	C=7
T=1	1	1	1	0	1	0	1
T=2	0	0	1	1	0	1	0
T=3	1	1	0	1	0	1	1
T=4	1	0	1	0	1	0	0
T=5	0	1	1	0	0	0	1
T=6	1	0	1	1	0	1	0

The assignment of the customer to vehicles

	C=1	C=2	C=3	C=4	C=5	C=6	C=7
T=1	0.45	0.68	0.89	0	0.78	0	0.56
	1	1	2	0	2	0	3
T=2	0	0	0.45	0.38	0	0.27	0
	0	0	1	3	0	2	0
T=3	0.29	0.46		0.45	0	0.91	0.61
	1	1		2	0	3	3
T=4	0.36	0	0.13	0	0.64	0	0
	2	0	1	0	3	0	0
T=5	0	0.34	0.64	0	0	0	0.57
	0	1	2	0	0	0	3
T=6	0.12	0	0.89	0.95	0	0.44	0
	1	0	3	3	0	2	0

vehicle 1		
T=1	C=1	C=2
T=2	C=3	
T=3	C=1	C=2
T=4	C=3	
T=5	C=2	
T=6	C=1	

vehicle 2		
T=1	C=3	
T=2	C=6	
T=3	C=4	
T=4	C=1	
T=5	C=1	
T=6	C=2	

vehicle 3		
T=1	C=7	
T=2	C=4	
T=3	C=6	C=7
T=4	C=5	
T=5	C=7	
T=6	C=3	C=4

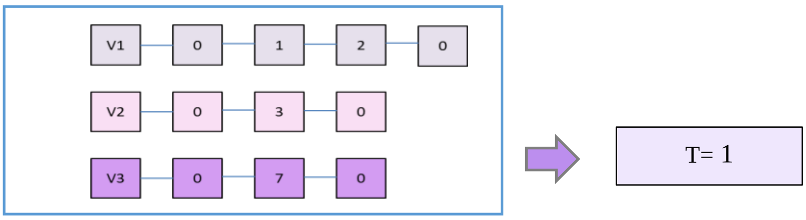


Fig. 5.4. Representation of random key method.

The motivation for exploring all these cases is that although it is required to add the recharging station after customer five in the represented example, the state of the charge is only considered to add the recharging station. However, a recharging station may exist near the previous tour nodes, for example, close to customer number eight, resulting in a lower objective function and feasible solution. Hence, an upper and lower threshold of the state of the charge is defined in this paper between 70% and 20% of remained energy level to check the best position to insert the recharging station. For the illustrated example, there are five possible positions to add a recharging station between the upper and lower threshold. All these five scenarios must be checked, and the best position will be selected based on the minimum objective function provided.

SOC	100	90.549	79.955	66.892	57.022	42.011	24.513	4.1761	-15.076	-23.145
Tour Visit	0	C=1	C=4	C=6	C=8	C=3	C=5	C=7	C=2	0

Fig. 5.5. Representation of random key method.

5.4.2.1. SIMULATED ANNEALING

SA algorithm has become a popular stochastic optimization method to solve complex problems inspired by the annealing process of metals, which involves gradually decreasing the temperature to reach a low-energy state. SA algorithm iteratively examines the solution space by allowing uphill moves, which could result in a solution that is worse than the current one or not. The likelihood of accepting these uphill moves decreases as the algorithm progresses, mimicking the cooling process in annealing. This allows the algorithm to escape local optima and, with a certain probability, find the global optimum (Kirkpatrick & Swendsen, 1985).

SA algorithm comprises several steps, including initialization, temperature initialization, iteration, temperature update, and stopping criterion. In the first step, the algorithm generates an initial solution and sets the initial temperature to a high value. In the next step, the algorithm iteratively perturbs the current solution, evaluates the candidate solution, and decides whether to accept or reject the solution based on the Metropolis criterion, which compares the energy difference between the current and candidate solutions and the current temperature. The temperature is then updated according to a cooling schedule, which gradually reduces the temperature over time. The algorithm terminates when a stopping criterion is met, such as a maximum number of iterations or a minimum temperature (Gholian-Jouybari et al., 2023; Mosallanezhad et al., 2021).

5.4.2.2. KESHTEL ALGORITHM (KA)

KA algorithm as a recent population-based metaheuristic algorithm is inspired by the feeding behavior of the dabbling duck Keshtel as it searches for food in shallow lakes which is invented by (Hajiaghaei-Keshteli & Aminnayeri, 2014b). This algorithm mimics the movement of Keshtel in a lake as it searches for a valuable food source, and other ducks approach the found source and swirl in a circle together until the food is finished. The algorithm starts with generating initial solutions that called Keshtels to solve a specific optimization problem. Then the initial solutions are divided into three groups: *N1* (lucky Keshtels), N2, which includes the solutions that can find the best food source and *N3* as the worst solutions in the population. The algorithm also finds the nearest neighbors around the lucky Keshtels, and the distance from each lucky Keshtel to all others must be calculated. Swirling continues around the current food source until a better food source is found. The population belonging to *N2* moves between the other two groups. It is important to note that *N1* is responsible for the intensification phase of the algorithm, while *N2* and *N3* are considered for the diversification phase. The pseudo-code for the KA algorithm is shown in Fig. 5.6. This algorithm has shown promising results in solving various optimization problems and has the potential for further development in different research (Salehi-Amiri, Akbapour, et al., 2022)

Keshtel Algorithm (KA)

```
Initialize Keshtel population.
Calculate the fitness and sort them in three types: N1, N2 and N3
X*=the best solution.
while (t< maximum number of iteration)
        for each N1 (lucky keshtel)
              Measure the distance between lucky Keshtel and other Keshtels.
               Compare all distance and choose the closest neighbor.
                 S=0;
        while (S< maximum number of swirling)
            Apply swirling.
 if the fitness of this new position is better than prior Update this lucky Keshtel.
             break
endif
            S=S+1
        end while
          end for
      for each N2 (the possible solution that can find the best food resources)
        Move the Keshtel between the two Keshtels.
      end for
      for each N3 (worst solution)
        generate a random solution.
      end for
      Merge all population of  N1, N2 and N3
      Sort the Keshtels and form N1, N2 and N3 for next iteration.
      Do update the X*  as the best solution if algorithm sound  a better solution.
       t=t+1;
 end
return X*
```

Fig. 5.6. The pseudo-code of KA.

5.4.2.3. PARTICLE SWARM OPTIMIZATION ALGORITHM

The PSO algorithm was originally developed by Kennedy and Eberhart by simulating social behavior. It is a swarm-based stochastic procedure which is imitated social animals such as fish schooling and bird flocking. To solve an optimization problem with this algorithm, each possible solution is represented as a particle with a certain characteristic such as flying velocity, through the solution space of the problem (Marinakis et al., 2019). The problem is solved by generating a set of initial solutions, as a set of initial particles, and then several new solutions are constructed by the current ones according to some exploration and exploitation operators dubbing particles and moving them around in the solution space of the problem. However, the particle velocity and position are under the control of the algorithm's operator. Through each iteration, all particles are moved with some disturbance and after moving all of them and their combination, the next iteration will be run. The whole particles are more likely to approach the near or optimal solution gradually by remembering the best position of each particle and the global best positions (Iswari & Asih, 2018).

According to the personal and global position of particles, the velocity is updated. it is affected by inertia, cognitive learning, and social learning terms. Inertia plays the exploitation phase of the algorithm by directing toward the previously obtained solutions to search based on the product of current velocity and inertia rate *(w)*. The cognitive term keeps the particle returning to its best position by multiplying a random number *(u)* and the difference of the current position with the individual best position considering the individual best acceleration constant *(c_1)*. Whereas by multiplying a random number *(u)* and the global best acceleration constant *(c_2)*, and the difference of the current position with the global best position, the social term is applied for directing particles towards the global optimal (Geetha et al., 2013; Salehi-Amiri, Jabbarzadeh, et al., 2022). The main steps of the proposed algorithm are elaborated in Fig.5.7.

Particle Swarm Optimization Algorithm

1. Initialization of problem solution with several particles, c_1, c_2, and termination condition
2. **for** each particle
3. Generating the routes, initial position, and velocity of t=each particle with proposed encoding plan
4. **end**
5. **while** termination condition is not valid
6. **for**
7. fitness function evaluation
8. **If** fitness function of particle < c_1
9. setting c_1 with the current objective value
10. **endif**
11. **end for**
12. selecting best objective value and set it as c_2
13. **for** each particle
14. updating velocity based on
$$w_i(t) = w_i(t-1) + c_1 r_1 (Pbest_i - x_i(t-1)) + c_2 r_2 (Gbest_i - x_i(t-1))$$
15. updating position based on
$$x_i(t) = x_i(t-1) + w_i(t)$$
16. **End**

Fig.5.7. The PSO pseudo-code.

5.4.2.4. THE GENETIC ALGORITHM

GA algorithm represents an influential class of evolutionary optimization algorithms that have demonstrated impressive efficacy in finding near-optimal solutions to a diverse range of optimization problems (Baker & Ayechew, 2003). The GA algorithm operates by emulating the natural process of evolution, involving the iterative selection, breeding, and mutation of candidate solutions and utilizes a population of individuals which can represent the candidate solutions to the optimization problem. Each individual is represented as a chromosome or genotype, consisting of a string of binary, integer, or real-valued values. The fitness of each individual is evaluated based on a user-defined objective function, and the selection of individuals for breeding and mutation is based on their fitness values.

The GA algorithm employs three key operators: selection, crossover, and mutation. The selection operator determines a subset of individuals from the population based on their fitness values, with individuals possessing a higher fitness value being more likely to be selected. The crossover operator merges the chromosomes of two selected individuals to generate one or more offspring, while the mutation operator randomly modifies the chromosomes of the offspring. The GA algorithm repeats the selection, crossover, and mutation operators for a defined number of iterations or until a stopping criterion is met. The algorithm's output is the best individual found in the population. The versatility and robustness of the GA algorithm have led to its application in various optimization problems, including engineering design, scheduling, financial modeling, and machine learning. (Fujdiak et al., 2016b).

5.4.2.5. The Grey wolf optimizer (GWO)

GWO algorithm is a population-based meta-heuristic optimization algorithm that is inspired by the social hierarchy and hunting behavior of grey wolves. The algorithm was first introduced by Mirjalili in 2014 and has been applied for addressing a wide range of optimization problems. The GWO algorithm begins by initializing a population of grey wolves, with each wolf having a position in the search space. The wolves are classified into four groups based on their fitness level and position, and the pack's hierarchy governs their movements. In each iteration, the algorithm updates the position of each wolf based on the movement of the alpha, beta, and delta wolves, with the position of the omega wolf being updated randomly. The position update is controlled by the scaling factor and distance factor, which are randomly generated values that control the step size and direction of the position update. The algorithm continues until a convergence criterion is met, and the solution with the best fitness value is returned as the output. (Mirjalili et al., 2014). The pseudo-code for the GWO algorithm is summarized in Fig.5.8.

Pseudo code for the grey wolf optimizer algorithm

1. **Initialize** a population of N grey wolves randomly in the search space
2. **Define the fitness function** f(x) for each wolf x in the population
3. **Assign the** α, B, δ, and ω wolves based on their fitness values
4. **Set** the initial size of wolf pop and max iteration
5. **Count=0**
6. **Repeat** until stopping criterion is met:
7. **Update** scale factor “a” and distance factor “A” based on “t” and maximum iterations “T”.
8. **For** each wolf x in the population:
9. **If** x is an α wolf:
10. Update the position of x using Eq. (5.27) with p = X_α
11. **If** x is a B wolf:
12. Update the position of x using Eq (5.27) with p = X_B
13. **If** x is a δ wolf:
14. Update the position of x using Eq (5.27) with p = X_δ
15. **If** x is an ω wolf:
16. Update the position of x randomly in the search space.
17. Evaluate the fitness function for each wolf in the population.
18. Assign the α, B, δ, and ω wolves based on their fitness values.
19. **Count=Count+1**
20. **Return** the best solution found in the population as the output

$$\mathrm{x_i i}^{t+1} = \mathrm{x_i}^{t} + \mathrm{a} * \mathrm{A} * (\mathrm{x}^{p} - \mathrm{x_i}^{t}). \qquad \text{Eq. (5.27)}$$

where:

[$\mathrm{x_i}^{t}$ is the position of the i-th wolf at iteration t,
$\mathrm{x}^{p}$is the position of the p-th wolf (p = α, B, δ),
a and A are the scaling factor and distance factor, respectively].

Fig.5.8. Pseudo code for the grey wolf optimizer algorithm.

5.4.2.6. Hybrid Metaheuristic

Metaheuristics algorithms have different capabilities in the exploration and exploitation steps. Using a hybrid optimizer is essential because no single optimization algorithm can be universally effective in solving all optimization problems (Mosallanezhad, Gholian-Jouybari, et al., 2023). So, hybridizing different algorithms integrates the positive aspects of multiple optimization algorithms to form a more effective and robust optimization process that can provide improved solutions to complex problems. In this way, the hybridization of algorithms can offer a better balance between exploration and exploitation capabilities and faster convergence to the global optimum. By leveraging the strengths of multiple algorithms, the hybrid approach can overcome the limitations of individual algorithms and achieve superior performance in terms of solution quality, speed of convergence, and robustness.

Moreover, using hybrid algorithms can improve flexibility in optimization problem-solving, allowing for incorporating various optimization techniques and algorithms in a single framework. This flexibility can be advantageous when dealing with complex optimization problems requiring different strategies and techniques at different stages of the search process. This study intends to combine the SA algorithm as one of the qualified single-solution optimizers due to its local search and kA and GA as an efficient population-based optimizers. In this regard, HKASA and HGASA proposed hybrid algorithms to solve the problem.

5.4.3. PARAMETER TUNING

Parameter tuning is a responsible element for the efficiency of a meta-heuristic algorithm. Properly tuned algorithm parameters make it swift to achieve the global optimum, which can lead to algorithm improvement. Various strategies have been utilized in the literature for tuning the meta-heuristic algorithms' parameters. Smit & Eiben, (2009) employed a "relevance estimation and Value Calibration Method" to find tuned parameters of an algorithm. Bartz-Beielstein & Markon (2004) introduced a method based on regression analysis and statistical design of experiments. The balance of an algorithm's exploitation and exploration phase depends directly on the parameter tunning. One approach is that each parameter of an algorithm can be specified individually but the interchange among them cannot be investigated. So, the optimal output of parameters value cannot be guaranteed by tuning them one-by-one (Colombaroni et al., 2020). Other approach is to exploit an experimental design which requires to define different level for each factor that can have impact on the performance of algorithm. Different levels for the parameters of an algorithm are defined as quantitative. The levels of algorithm's parameters are proposed and reported in Table. 5.4 and Fig.5.9.

Table.5.4.

The proposed level for parameters.

Algorithm	Parameters	L1	L2	L3	**L***
PSO	A: Population size (n-pop)	35	45	55	**45**
	B: Weight of particles (W)	0. 55	0. 65	0. 85	**0.55**
	C: Coefficient related to the speed of moving toward personal best (C1)	1. 2	1. 3	1. 4	**1.2**
	D: Coefficient related to the speed of moving toward personal best (C2)	1. 3	1. 4	1. 5	**1.3**
	E: Maximum iteration (Max_{it})	150	250	350	**350**
SA	L: (Sub-it)	400	500	600	**600**
	T0:(initial temperature)	1	10	100	**10**
	T_{end}:(Final temperature)	0.001	0. 010	1.00	**1**
	Q: (cooling rate)	0.95	0.98	0.99	**0.98**
GA	A: Max-Iteration	150	250	350	**250**
	B: Npop (Population size)	35	45	55	**55**
	C: Pc (Cross over percentage)	0.85	0.9	0.95	**0.85**
	D: Pm (mutation percentage)	0.15	0.20	0.25	**0.15**
KA	A: Population size (n-pop)	25	30	35	**25**
	B: Percentage of the population of Lucky Keshtel (P_{N1})	0.5	0.6	0.7	**0.5**
	C: percentage of N_2 Keshtel (P_{N2})	0.25	0.3	0.35	**0.25**
WOA	A: Maximum iteration (Max_{it})	500	600	700	**500**
	B: Number of search agents (N_s)	50	100	150	**100**
	C: choosing probability (P_e)	0.1	0.2	0.4	**0.1**
H-GASA	A: Max-Iteration	300	450	600	**450**
	B: Npop (Population size)	60	75	80	**60**
	C: Pc (Cross over percentage)	0.75	0.85	0.95	**0.75**
	D: Pm (mutation percentage)	0.10	0.15	0.20	**0.10**
	E: L=(Sub-it)	450	600	700	**450**
	F=T0:(initial temperature)	1	10	100	**1**
	G:Final temperature)	0.001	0. 010	1.00	**0. 010**
	H: cooling rate	0.95	0.98	0.99	**0.99**
HKASA	A: Population size (n-pop)	25	30	35	**30**
	B: Percentage of the population of Lucky Keshtel (P_{N1})	0.55	0.65	0.85	**0.55**
	C: percentage of N_2 Keshtel (P_{N2})	0.30	0.35	0.40	**0.30**
	D: Population size (n-pop)	40	45	50	**40**
	E: (Sub-it)	550	600	700	**550**
	F:(initial temperature)	1	10	100	**1**
	G: (Final temperature)	0.001	0. 010	1.00	**0.010**
	H: (cooling rate)	0.95	0.98	0.99	**0.99**

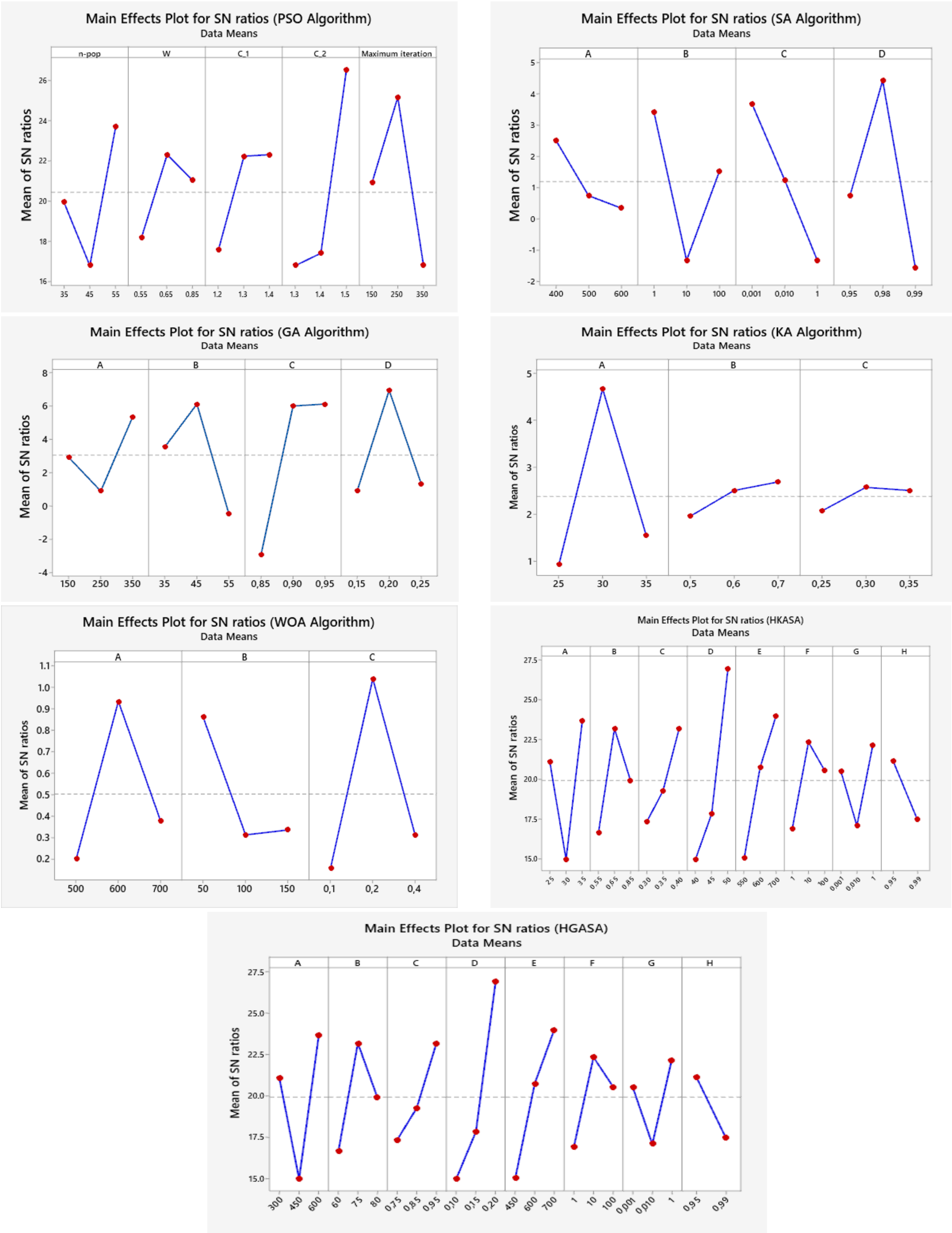
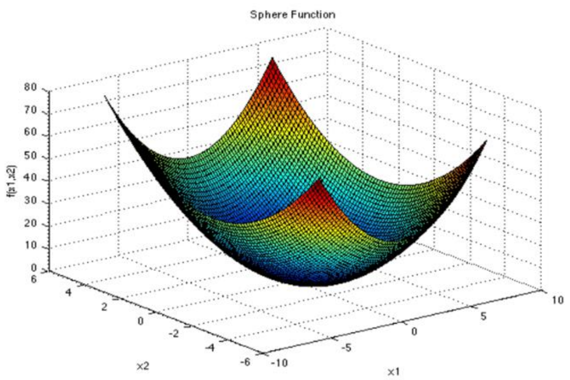


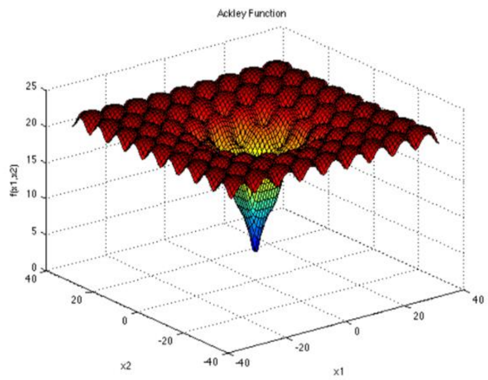
Fig.5.9. The main effects plot for S/N ratios of all proposed algorithm.

5.4.4. EVALUATION OF HYBRID METAHEURISTICS

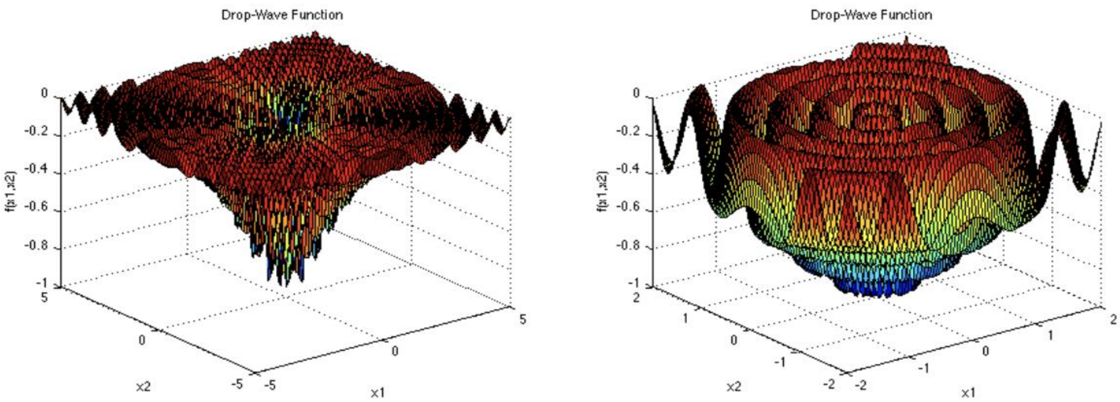
This section provides a framework for evaluating the effectiveness of new modified metaheuristics HGASA and HKASA utilized a different benchmark function which is presented by (Plevris & Solorzano, 2022). These benchmark functions are utilized for unconstrained multidimensional single-objective optimization problems. We analyze the performance of HGASA and HKASA algorithms by using Sphere in the bowl-Shaped group, Ackley and Drop-Wave in the benchmark group of Many Local Minima. The applied benchmark functions are listed in Fig.5.10. and Table 5.5. The implementations of all used benchmarks are run in MATLAB, focusing on objective functions(Chouhan et al., 2021c, 2022). The selected metaheuristics are run thirty times based on the proposed parameter level reported in Table 5.4. Four dimensions of benchmark function, D= [5, 10, 15, 20], are supposed to have an extensive evaluation on a different problem scale per metaheuristic. The benchmark average objective function and standard deviation results are reported in Tables 5.6, 5.7, 5.8, and 5.9.



Sphere Function



Ackley Function



Drop-Wave

Fig. 10. The shape of sphere, Ackley and Drop-Wave Function.

Table. 5.5

The list of utilized Function type and formulation.

Function Name	Type	Equation
Sphere	Bowl-Shaped	$f(\mathbf{x}) = \sum_{i=1}^{d} x_i^2$
Ackley	Many Local Minima	$f(\mathbf{x}) = -a\exp\left(-b\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - \exp\left(\frac{1}{d}\sum_{i=1}^{d}\cos(cx_i)\right) + a + \exp(1)$
Drop-Wave	Many Local Minima	$f(\mathbf{x}) = -\frac{1+\cos\left(12\sqrt{x_1^2+x_2^2}\right)}{0.5(x_1^2+x_2^2)+2}$

Table.5.6.

The result of metaheuristic algorithms for benchmark problem with dimension d=5.

	Average of Objective Function		**Standard Deviation of Objective Function**	
Function name	HKASA	HGASA	HKASA	HGASA
Sphere	1.14E-36	1.34E-37	3.35E-17	1.28E-17
Ackley	2.55E-15	2.34E-15	1.16E-14	4.02E-25
Drop-Wave	0.0545327	0.0646326	7.68E-11	0

Table.5.7.

The result of metaheuristic algorithms for benchmark problem with dimension d=10.

	Average of Objective Function		**Standard Deviation of Objective Function**	
Function name	HKASA	HGASA	HKASA	HGASA
Sphere	1.70E-14	1.92E-19	3.678E-14	3.745E-23
Ackley	8.021E-09	2.122E-10	1.117E-08	5.557E-13
Drop-Wave	0.0654547	0.0637547	7.075E-10	0

Table.5.8.

The result of metaheuristic algorithms for benchmark problem with dimension d=15.

	Average of Objective Function		**Standard Deviation of Objective Function**	
Function name	HKASA	HGASA	HKASA	HGASA
Sphere	2.056E-05	4.167E-13	7.333E-28	1.004E-19
Ackley	6.628E-06	1.201E-07	1.257E-14	1.592E-11
Drop-Wave	0.0567547	0.0938535	0.0941967	0

Table.5.9.
The result of metaheuristic algorithms for benchmark problem with dimension d=15.

	Average of Objective Function		**Standard Deviation of Objective Function**	
Function name	HKASA	HGASA	HKASA	HGASA
Sphere	5.432E-04	1.196E-15	2.909E-09	1.471E-16
Ackley	0.0002044	1.175E-08	2.881E-06	2.268E-09
Drop-Wave	0.0852866	0.0637547	0.0665499	0

5.5.COMPUTATIONAL RESULTS

As stated earlier, the proposed EVPRP model in this study considers not only daily varying traffic conditions, but also the distinct traffic characteristics that can fluctuate depending on the day of the week. Since this aspect of traffic variability is rarely addressed in existing studies, it implies that generating new test problems compatible with the designed model is a crucial step to analyze the proposed algorithms. In the broader context of the application of EVs to the PRP there exist research that considers multiple period horizons. However, one critical overlooked aspect in these studies is the incorporation of both intra-day and inter-day traffic variabilities into their models (Fateme Attar et al., 2022). Their study focused primarily on the impact of multiple periods on parameters like customer demand for each period while the distance between every two demand points considered to optimize the objective function. The travel time was substituted with distance in their proposed mathematical model which overlooks the dynamic nature of travel time. In contrast, the proposed model in this study effectively addresses the complexity of travel time by representing it as a four-index parameter, taking into account both intra-day and inter-day traffic variabilities, as explained in section 3. By incorporating these factors into the proposed model, more efficient and robust decision-making framework is proposed which could potentially lead to significant improvements in the context. Hence, new test problems are generated in difference dimensions to investigate the performance of the proposed algorithms. Moreover, it is essential to have some evaluation criteria to compare the performance of different proposed algorithms. Common evaluation metrics include solution quality, convergence speed, computational time, robustness, and scalability (Gholian-Jouybari et al., 2023b).

Evaluation of metaheuristic algorithms is a crucial step in algorithmic research and practice. This process of evaluation is necessary to determine the effectiveness and efficiency of an algorithm, its applicability to certain types of problems, and to compare its performance with other algorithms. This is where indicators such as hitting time (HT), objective function, and to do comparison in same scale the relative percentage deviation (RPD) of objective function come into play. HT is an essential indicator in evaluating the efficiency of an algorithm. It measures the amount of time taken for the algorithm to find the optimal or best-known solution. The importance of HT lies in its ability to demonstrate the algorithm's speed, especially when solving complex problems. Lower HT values typically signify more efficient algorithms as they are able to achieve satisfactory solutions faster. As a result, this indicator helps researchers and practitioners to choose an algorithm that provides a balance between solution quality and computational speed, which can be especially critical in time-sensitive applications(Abdi et al., 2019).

Objective function plays a key role in defining the optimization problem itself. The goal of a metaheuristic algorithm is to optimize this function, either through minimization or maximization, depending on the problem at hand. By evaluating changes in the value of the objective function, we can monitor the progress of the optimization process and assess how well the algorithm is improving solutions over iterations. Objective function, allowing us to quantify the quality of solutions generated by an algorithm, thereby making it a fundamental component of algorithm evaluation. On the other hand, assessing the performance of different algorithms or various instances of the same algorithm can be challenging, particularly when the problems differ significantly in scale. This is why the RPD of objective function comes into play to this research. RPD offers a valuable means of measuring the performance of an algorithm by comparing its solution with the optimal or best-known solution. The importance of using RPD stems from its ability to provide a standardized measure of deviation across different problem scales. RPD also provides a straightforward and easily understandable way to express this difference. It enables a clear understanding and effective communication of how much the obtained solutions deviate from the optimal or best-known solutions, providing a sense of the magnitude of error.

Furthermore, the use of RPD can assist in identifying whether specific algorithms or configurations consistently produce solutions that are closer to or further from the optimal solutions. This information is invaluable for algorithm selection and fine-tuning purposes. By using these three indicators together - HT, objective function, and RPD - we can achieve a comprehensive evaluation of metaheuristic algorithms. This combination allows us to consider both the quality of solutions (as measured by the objective function and RPD) and the efficiency of the algorithm (as indicated by HT), providing a holistic view of the algorithm's performance.

To calculate these indicators three size problems are developed in small , medium, and large scales in which each algorithm is run thirty times (see Table.5.10). Detailed outcomes, including objective function, RPD, and HT, are reported in Table.5.10-5.17 for each instance. The objective function essentially reflects the cost or the fitness of the solution the algorithm produces. This value is calculated by applying the function to the solution produced by the algorithm in each iteration. The HT is measured as the algorithm runs. This is typically the computational time it takes for the algorithm to find the optimal or best-known solution. This can be achieved by recording the iteration number at which the final solution is obtained, and the steps are clearly defined in following pseudocode in Fig. 5.11. This indicator is valuable in assessing the performance of metaheuristic algorithms and selecting the most suitable one for solving optimization problems.

Pseudo code for calculating the HT

1. **Initialize** hitting_time as -1
2. **Initialize** best solution as null
3. **Initialize** objective_function_vector as empty
4. **Run** the algorithm for a fixed number of iterations:
4.1 **Execute** one iteration of the algorithm.
4.2 **Store** the current objective function value in objective_function_vector.
4.3 **If** the algorithm has reached the final iteration:
4.3.1 **Store** the final solution in best_solution
4.3.2 Check if best_solution is present in objective_function_vector:
4.3.2.1 Find the index of the first occurrence of best_solution in objective_function_vector
4.3.2.2 Set hitting_time as the index found in step 4.3.2.1
4.3.2.3 Exit the loop.
5. Output hitting time as the iteration at which the final solution was found

Fig.5.11. Pseudo code for computation of hitting time.

RPD is estimated post algorithmic computation, taking the solution generated by the algorithm Alg_{sol} and the known minimum solution Min_{sol}. By utilizing Eq.5.28, the absolute difference between these two values is computed and divide it by the minimum solution, thereby getting a percentage value that represents the RPD. By expressing the deviation as a percentage, we can effectively compare the performance of an algorithm across problems of varying sizes and complexities. This helps to ensure fairness when comparing different algorithms or the same algorithm on different problems. The use of RPD allows us to understand how close the solution provided by the algorithm is to the best possible solution and thus gauge the accuracy of the algorithm.

$$RPD = \frac{|Alg_{sol} - Min_{sol}|}{Min_{sol}} \quad \text{(Eq.5.28)}$$

Table .5.10.
The generated test beds.

Class	Description	Problem size			
		N	*S*	*T*	V
Small	TP1	5	3	1	1
	TP2	10	3	1	2
	TP3	15	4	3	2
	TP4	20	4	3	3
	TP5	20	4	5	4
Medium	TP6	30	5	3	3
	TP7	40	5	3	4
	TP8	50	6	4	4
	TP9	50	7	4	5
	TP10	100	8	5	5
Large	TP11	150	10	2	7
	TP12	150	10	3	10
	TP13	200	13	4	10
	TP14	300	13	5	12
	TP15	350	15	6	15

* TP=Test Problem

Table. 5.11.
Detail objective function, RPD, HT results for GA algorithm.

Problem-Size		GA		
		OF	RPD	HT
Small-Size	1	819.4302567	0.23	13.77
	2	526.287084	0.09	17.12
	3	1326.986657	0.44	19.89
	4	1218.545919	0.11	32.75
	5	2121.146259	0.36	38.84
Medium-Size	6	1109.067002	0.00	67.39
	7	1885.728635	0.06	61.75
	8	2031.456516	0.16	105.47
	9	3037.686218	0.32	149.53
	10	3813.443284	0.26	187.31
Large-Size	11	4437.30901	0.28	925.50
	12	4621.35422	0.16	1167.36
	13	4874.178442	0.18	1586.22
	14	5008.010648	0.06	1841.53
	15	6535.775678	0.13	2973.78

Table. 5.12.
Detail objective function, RPD, HT results for SA algorithm.

Problem-Size		SA		
		OF	RPD	HT
Small-Size	1	790.955846	0.19	41.65
	2	582.820691	0.21	38.74
	3	1117.93316	0.21	123.70
	4	1178.47767	0.08	105.38
	5	1940.66446	0.24	166.90
Medium-Size	6	1391.55207	0.25	282.79
	7	2142.87345	0.21	312.45
	8	2423.01418	0.39	571.33
	9	2508.41141	0.09	531.40
	10	3021.74587	0.00	868.54
Large-Size	11	4331.65601	0.25	2302.04
	12	4810.87825	0.21	2972.10
	13	5021.74246	0.21	3229.72
	14	5315.70454	0.13	3979.47
	15	6361.95159	0.10	6689.80

Table. 5.13.
Detail objective function, RPD, HT results for PSO algorithm.

Problem-Size		PSO		
		OF	RPD	HT
Small-Size	1	745.871363	0.12	14.02
	2	652.176353	0.35	17.99
	3	1192.83468	0.29	27.54
	4	1330.50129	0.21	41.43
	5	1643.74279	0.05	50.11
Medium-Size	6	1251.00532	0.15	54.02
	7	1827.87105	0.03	98.59
	8	1805.14557	0.12	110.69
	9	2809.42078	0.22	112.24
	10	3278.17893	0.08	634.57
Large-Size	11	3456.71717	0.00	1018.77
	12	4153.10349	0.05	1292.63
	13	4139.56738	0.00	1426.86
	14	4723.03389	0.00	2114.08
	15	6877.77924	0.19	3118.74

Table. 5.14.
Detail objective function, RPD, HT results for KA algorithm.

Problem-Size		KA		
		OF	**RPD**	**HT**
Small-Size	1	663.611955	0.00	33.44
	2	512.882208	0.06	43.81
	3	924.530723	0.00	69.31
	4	1375.28345	0.25	88.97
	5	1833.92792	0.17	94.42
Medium-Size	6	1342.84775	0.21	157.71
	7	1776.72624	0.00	230.78
	8	2225.42904	0.27	271.53
	9	2671.45815	0.16	353.75
	10	3571.70362	0.18	466.15
Large-Size	11	4298.63945	0.24	1945.87
	12	4075.77768	0.03	2828.82
	13	4518.52203	0.09	3319.46
	14	5229.22195	0.11	4483.86
	15	7229.41671	0.25	6631.70

Table. 5.15.
Detail objective function, RPD, HT results for WOA algorithm.

Problem-Size		WOA		
		OF	**RPD**	**HT**
Small-Size	1	733.715216	0.11	44.40
	2	504.066338	0.04	58.00
	3	1181.73133	0.28	103.10
	4	1155.59461	0.05	115.76
	5	1562.34794	0.00	135.68
Medium-Size	6	1350.88633	0.22	219.48
	7	1773.74566	0.00	376.74
	8	1748.71051	0.00	407.95
	9	2297.3639	0.00	395.38
	10	3499.38708	0.16	636.89
Large-Size	11	4179.67213	0.21	1774.16
	12	4089.31055	0.03	2019.43
	13	4912.49021	0.19	2411.17
	14	5000.1739	0.06	3403.46
	15	6695.3728	0.15	5874.17

Table. 5.16.
Detail objective function, RPD, HT results for HGASA algorithm.

Problem-Size		HGASA		
		OF	RPD	HT
Small-Size	1	671.521513	0.01	59.11
	2	553.096836	0.14	87.25
	3	980.427381	0.06	145.87
	4	1095.98424	0.00	180.47
	5	2165.78154	0.39	211.51
Medium-Size	6	1383.20277	0.25	315.49
	7	1834.29967	0.03	528.89
	8	1866.64776	0.08	577.09
	9	2862.09742	0.12	811.59
	10	3284.63776	0.09	913.81
Large-Size	11	3664.7215	0.06	2139.02
	12	3977.98326	0.00	2388.58
	13	4366.05051	0.05	5796.85
	14	5068.81024	0.07	8127.05
	15	5803.59904	0.00	9253.90

Table. 5.17.
Detail objective function, RPD, HT results for HKASA algorithm.

Problem-Size		HKASA		
		OF	RPD	HT
Small-Size	1	875.588122	0.32	63.36
	2	595.642746	0.23	78.13
	3	1281.1514	0.39	129.34
	4	1272.75589	0.16	156.19
	5	1604.92951	0.03	186.82
Medium-Size	6	1348.31337	0.13	307.12
	7	2071.59032	0.17	414.96
	8	1912.77262	0.09	481.74
	9	2300.21326	0.00	584.13
	10	3589.83409	0.12	723.28
Large-Size	11	3829.21397	0.11	1911.65
	12	4565.91211	0.15	2226.55
	13	5308.16695	0.16	4593.82
	14	5253.2224	0.11	7635.54
	15	6863.0271	0.18	9008.35

It can be seen from Table.5.10-5.17, for small-sized problems, the KA algorithm delivers the best performance in terms of the OF, presenting the lowest values. This suggests it efficiently solves the problem with a smaller objective function result (see Fig.5.12) . However, in terms of HT, the GA algorithm takes the lead, providing the quickest solutions. This is a critical factor in time-sensitive computations (see Fig.5.13). It's also important to notice that despite the relatively larger OF values, the HKASA presents an impressively low RPD, showcasing the quality of its solutions. As the problem size elevates to medium, the WOA algorithm exhibits the lowest OF values, making it efficient for this category of problem size. The GA algorithm continues to stand out with the lowest HT values, maintaining its speedy performance despite the increasing problem complexity. Just as with the small-sized problems, HKASA retains a low RPD value, reinforcing its consistency in solution quality. When it comes to large-sized problems, the PSO algorithm emerges as the most efficient, evidenced by the lowest OF values. However, the GA algorithm doesn't maintain its time efficiency in this category, with the PSO algorithm now demonstrating the lowest HT values. This indicates that the PSO algorithm can handle large-sized problems efficiently and quickly. The HKASA, on the other hand, keeps its RPD values consistently low, further solidifying its position as a reliable provider of high-quality solutions, irrespective of the problem size (see Fig.5.12 and Fig.5.13).

Comparing all algorithms across all problem sizes, the HKASA algorithm shows a unique consistency in maintaining the quality of solutions, as indicated by the consistently low RPD values. This is an essential feature for an algorithm, demonstrating its robustness and reliability in producing quality solutions. In terms of objective function values, different algorithms take the lead for different problem sizes. This suggests that the choice of algorithm may need to be tailored to the size of the problem for optimum efficiency. The GA algorithm shows the fastest performance for small and medium-sized problems, while the PSO algorithm performs the quickest for large-sized problems. In conclusion, each algorithm presents its strengths and performs differently under various problem sizes. GA and PSO shine in terms of speed for smaller and larger problem sizes, respectively. KA and WOA algorithms prove to be more efficient with smaller and medium problem sizes, respectively, while PSO handles large-sized problems most efficiently. Meanwhile, HKASA demonstrates a remarkable consistency in delivering high-quality solutions across all problem sizes, making it a reliable choice regardless of the problem's complexity (see Fig.5.12 and Fig.5.13).

The primary statistics used to compare the performance of these algorithms in addressing small, medium, and large-sized problems include the Mean, Standard Error of the Mean (SE Mean), Standard Deviation (StDev), first quartile (Q1), median, and third quartile (Q3). These statistical measures, used in conjunction, provide a comprehensive view of each algorithm's performance, allowing us to assess central tendency, dispersion, and distribution characteristics. The Mean, or average, is a primary measure of central tendency that gives a snapshot of the 'typical' performance. The advantage of using the Mean lies in its simplicity and direct interpretability. It provides an aggregated summary of all performance scores, making it valuable for comparisons. However, the Mean can be sensitive to extreme values or outliers. If an algorithm's performance varies widely across different runs, the Mean might provide an oversimplified view. This sensitivity to the data's range is a notable limitation. To address this limitation, measures of variability, like SE Mean and Standard Deviation (StDev), are considered. These measures provide insights into the dispersion or spread of performance scores. The SE Mean, an estimate of the standard deviation of the Mean, reflects the precision of the Mean. A smaller SE Mean suggests a more reliable Mean estimate. The StDev provides information about the distribution of individual performance scores around the Mean. A smaller StDev indicates that the results are tightly clustered around the Mean, suggesting consistency in the algorithm's performance. The quartiles (Q1, Median, Q3), on the other hand, offer insight into the data distribution, showing us where the majority of performance results lie.

A detailed examination of these statistical measurements is reported in Table 18-20 which indicates that there is a noticeable difference in the performance of these algorithms across small, medium, and large-sized problems. For small-sized problems (see Table 5.18), GA shows the highest mean, suggesting that it performs better on average. However, it also has a higher standard deviation and SE mean, implying higher variability in its results. WOA Algorithm and KA algorithm show the lowest mean values, indicating poorer average performance, but also demonstrate low variability, suggesting consistent results. Moving to medium-sized problems (see Table 5.19), SA Algorithm has the highest mean, but again, it is important to notice that it also has a relatively high standard deviation. PSO algorithm has the lowest mean and high standard deviation, indicating lower average performance and higher variability. For large-sized problems (see Table 5.20), SA algorithm once again shows the highest mean performance, but it has the highest variability among the algorithms. WOA algorithm shows the lowest mean, thus suggesting a less robust average performance. However, similar to the scenario with small-sized problems, it delivers consistent results. In summary, the differential efficiency of these algorithms across varying problem sizes warrants a judicious choice when selecting an algorithm for specific problem dimensions.

Table.5.18.
Statistical Description for small size problem.

Algorithm	Mean	Standard Error of the Mean	Standard Deviation	first quartile Q1	Median	Third quartile Q3
SA	0.2026	0.0345	0.0772	0.1408	0.2092	0.2611
GA	0.2679	0.0575	0.1286	0.1559	0.2348	0.3965
KA	0.098	0.0504	0.1128	0	0.0615	0.2143
PSO	0.206	0.054	0.1207	0.088	0.214	0.32
WOA	0.0963	0.0485	0.1084	0.0216	0.0544	0.1919
HGASA	0.109	0.0341	0.0762	0.03	0.1448	0.17
HKASA	0.2087	0.037	0.0827	0.1306	0.23	0.2761

Table.5.19.
Statistical Description for medium size problem.

Algorithm	Mean	Standard Error of the Mean	Standard Deviation	first quartile Q1	Median	Third quartile Q3
SA	0.18	0.0295	0.066	0.1108	0.2118	0.2331
GA	0.1623	0.0365	0.0817	0.0932	0.1641	0.2306
KA	0.1429	0.0437	0.0976	0.0591	0.1072	0.2446
PSO	0.0462	0.0358	0.0801	0	0	0.1156
WOA	0.1277	0.0354	0.0792	0.0444	0.1537	0.1979
HGASA	0.038	0.0154	0.0345	0.001	0.0547	0.0667
HKASA	0.1425	0.0143	0.032	0.11	0.1501	0.1713

Table.5.20.
Statistical Description for Large size problem.

Algorithm	Mean	Standard Error of the Mean	Standard Deviation	first quartile Q1	Median	Third quartile Q3
SA	0.1881	0.0665	0.1487	0.0459	0.2081	0.3202
GA	0.1618	0.0599	0.1339	0.0316	0.1617	0.2921
KA	0.1660	0.0451	0.1008	0.0823	0.1820	0.2417
PSO	0.1301	0.0513	0.1147	0.0314	0.0849	0.2514
WOA	0.0752	0.0470	0.1052	0.0000	0.0000	0.1881
HGASA	0.1254	0.0350	0.0783	0.0606	0.1200	0.1929
HKASA	0.0906	0.0379	0.0848	0.0056	0.0938	0.1740

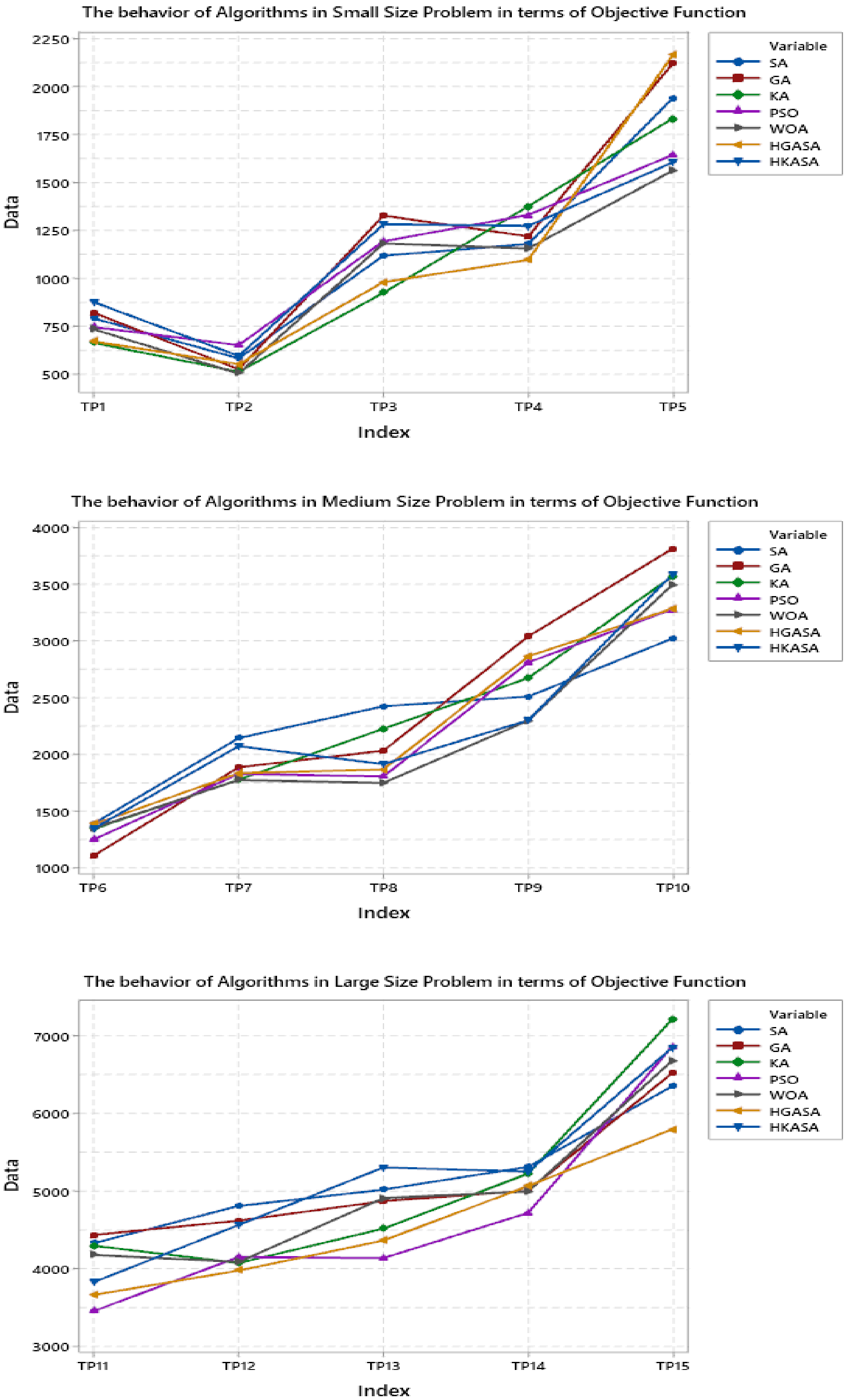
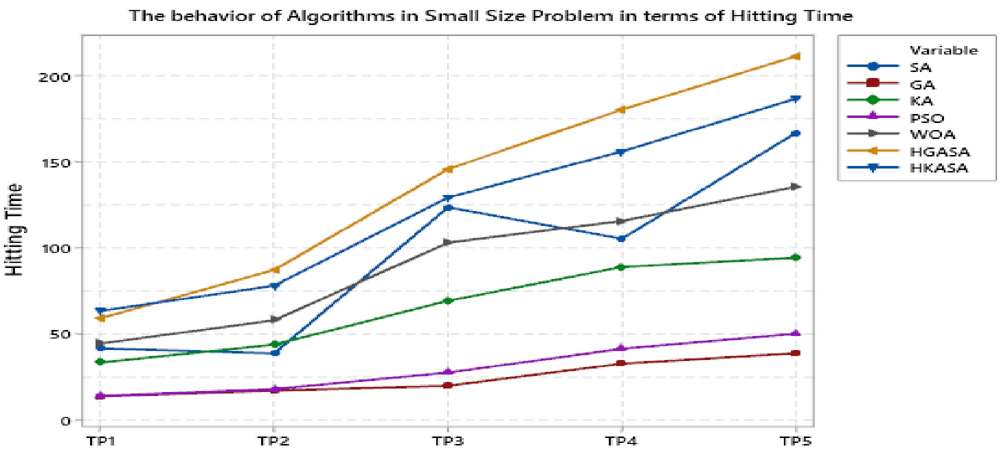
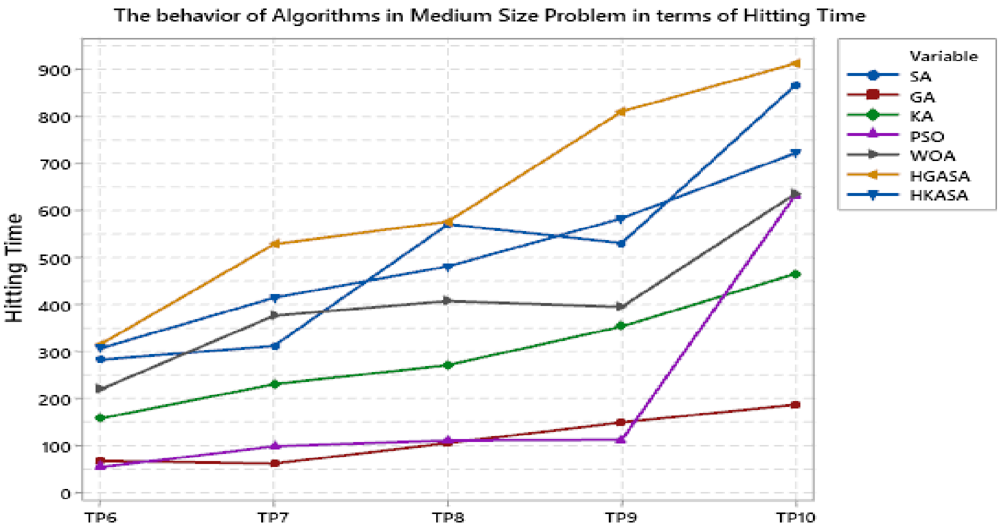


Fig. 5.12. The behavior of algorithm in terms of objective function in small-medium and Large Size.





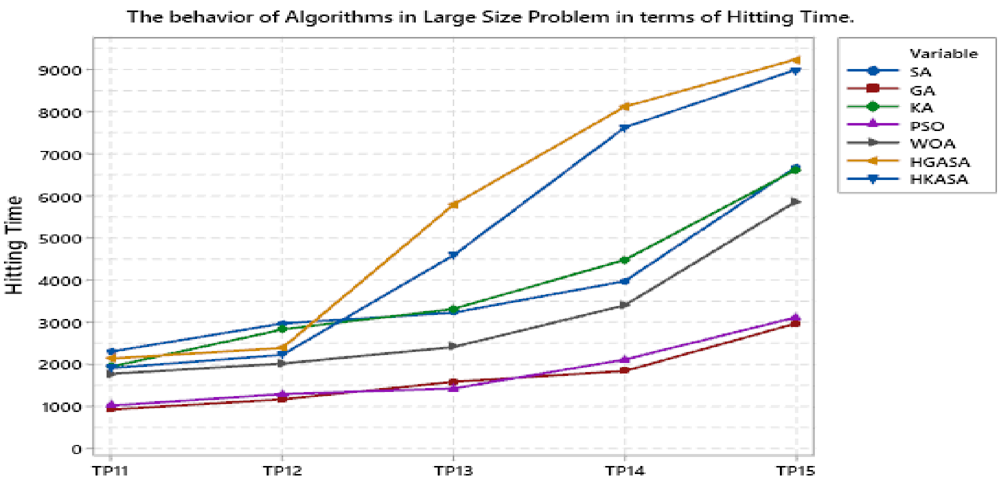


Fig. 5.13. The behavior of algorithm in terms of objective function in small-medium and large size.

As it investigated, solutions of proposed metaheuristics algorithms are very similar to each other based on different criteria. Hence, different statistical tests are applied to have more precise comparisons among them. Wilcoxon signed-rank test and Friedman test are utilized as the pairwise comparison and multiple comparison tests, respectively. The definition of required terms and elements to perform mentioned statistical tests are provided in Table 5.21. Fig.5.14 represent the comparison of algorithm in term of objective function and hitting time based on one-way ANOVA test. Before making a comparison by the mentioned tests, we convert all the performance values to the Relative Deviation Index (RDI) by applying Eq. (5.29). RDI is a statistical analysis that makes it possible to find the standard deviation of algorithms for each problem by converting the results into a reliable metric to have another indicator for comparison. The objective values (Alg_{sol}), the maximum objective value among all trails (Max_{sol}) and the best solution of algorithms among all trails (Min_{sol}) are used to calculate the RDI (see Eq.5.29).

$$RDI = \frac{|Alg_{sol} - Min_{sol}|}{Max_{sol} - Min_{sol}} \qquad \text{(Eq.5.29)}$$

Table.5.21.
Definition of Null hypothesis (H_0), Alternative hypothesis (H_1) and significance level (α).

Term	Definition
Null hypothesis (H_0)	Declares that two metaheuristics have no difference.
Alternative hypothesis (H_1)	Declares that two metaheuristics have differences.
Statistical significance level (α)	The probability of mistakenly rejecting H_0. For P-value, less than α H_0 is rejected

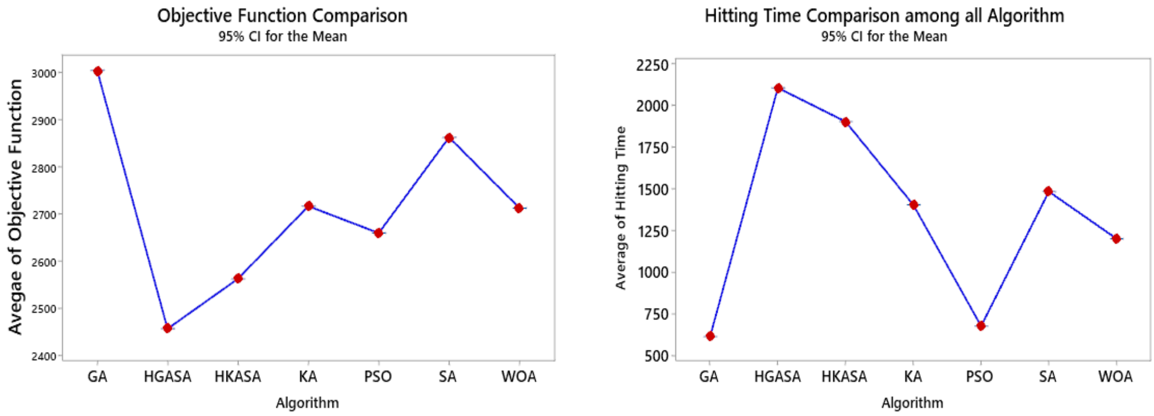


Fig. 5.14. Hitting Time and Objective Function comparison between algorithms.

It is essential to note that the null hypothesis in statistical tests describes that the two studied algorithms are extremely similar. If the P-value of a test to compare two alternatives is lower than 0.05, the null hypothesis is rejected. In other terms, it will be approved that the two metaheuristics are significantly distinguishable (Mosallanezhad, Gholian-Jouybari, et al., 2023). To do so, Wilcoxon signed ranked test is used for the RDI value of objective functions for all pairs of options. The Wilcoxon signed-rank test was employed to assess the performance of proposed optimization algorithms. This assessment was conducted over small, medium, and large problem sizes using Objective Function (OF) values as a metric. The results and P-value of these comparisons are summarized in Table 5.22. The outcomes are obtained by executing the tests with a statistical significance level (α) of 0.05 utilizing SPSS software. Although we have some values near to α, P-values are still less than the significance level (α) of 0.05 for different categories of problems, implying that all algorithms are not significantly similar. As it can be seen in Table 22, the p-values generated by the Wilcoxon signed-rank tests were all below the 0.05 threshold for SA algorithm, indicating statistically significant differences between the SA and all other algorithms across all problem sizes. This suggests that the SA algorithm consistently performs differently than the other algorithms, though these results do not reveal whether SA is superior or inferior to them. In contrast, the results from comparing PSO to other algorithms were more varied. The test results indicated significant differences between PSO and HGASA on small problems, as well as between PSO, HKASA, and WOA on medium-sized problems. However, the tests found no significant difference between the performances of PSO and GA across all problem sizes. For the WOA algorithm, the tests detected a statistically significant difference between WOA and all other algorithms for all problem sizes, except when it was compared to HKASA for medium and large problems. Finally, the comparison of HGASA vs. HKASA yielded p-values below the 0.05 threshold, suggesting statistically significant differences in their performances across all problem sizes.

Table.5. 22.
Wilcoxon signed the ranked test according to OF values for all test problems.

Comparison	P-value (Wilcoxon test)		
	SMALL	MEDIUM	LARGE
SA versus GA	0.008	0.008	0.002
SA versus PSO	0.039	0.012	0.001
SA versus WOA	0.016	0.031	0.011
SA versus HKASA	0.014	0.062	0.017
SA versus HGASA	0.026	0.043	0.040
PSO versus HKASA	0.065	0.012	0.048
PSO versus HGASA	0.007	0.044	0.038
PSO versus GA	0.065	0.056	0.078
PSO versus WOA	0.022	0.016	0.045
WOA versus GA	0.019	0.021	0.015
WOA versus HKASA	0.040	0.074	0.065
WOA versus HGASA	0.042	0.024	0.020
HGASA versus HKASA	0.027	0.064	0.038

As multiple statistical comparisons, the Friedman test is applied using SPSS software for each category of test problems with a significance level of 0.05. The Friedman test is a non-parametric statistical test primarily utilized for the comparison of multiple paired samples or treatments, particularly in scenarios where the assumptions of a parametric one-way ANOVA are not met. This includes cases where the data do not demonstrate normal distribution or when the variances across groups are unequal. The test operates under the assumption that the observations are independent, and that the data's ordinal nature enables them to be ranked.

Table 5.23 presents a comprehensive comparative analysis of proposed metaheuristics, evaluated using the Friedman test. The analysis revolves around two key parameters: the RDI-Objective Function (RDI-OF) and HT. From the perspective of the RDI-Objective Function (RDI-OF), a substantial variance in performance is observable across the different methods. The HGASA method is the most efficient, with a minimum score of 1.21, closely followed by the HKASA. This suggests that these two techniques exhibit significant efficacy in optimizing the RDI-OF. Conversely, despite its wide usage, the SA algorithm method displayed a comparatively poor performance, evidenced by a score of 3.56. This result indicates that the SA method could be more proficient at this task. However, the result will be shifted when considering the HT parameter. In this regard, the GA algorithm indicated superior performance with a score of 1.04, implying its potential to be the fastest and most efficient in pinpointing the optimal solution. However, HGASA and HKASA, which demonstrated excellent performances on the RDI-OF, need to be more competent when dealing with the HT parameter. This indicates that these methods may require longer to arrive at their respective solutions.

Taken as a whole, the results suggest that there is only one universally superior method. The HGASA and HKASA techniques excel in optimizing the RDI-OF but may require more time. In contrast, while the GA technique is swift and efficient concerning the HT parameter, its performance on the RDI-OF is less impressive. The calculated p-values for both parameters fall below the 0.01 threshold, confirming that the observed disparities in performance across these methods are statistically significant. This underlines the necessity of detailed consideration of the unique requirements of each problem when selecting the most appropriate optimization method.

Table.5.23.

The result of the Friedman test.

Metaheuristic	RDI-Objective Function	Rank (RDI-OF)	HT	Rank HT
SA	3.56	7	1.73	3
GA	2.41	5	1.04	**1**
KA	2.56	6	1.42	2
PSO	1.98	4	1.97	5
WOA	1.83	3	1.83	4
HGASA	1.21	**1**	2.63	7
HKASA	1.64	2	2.65	6
P-value	0.007		0.008	

5.6. CONCLUSION

This study presents a mixed integer linear mathematical formulation for managing an integrated multi-period production routing problem using EVs. The proposed integrated approach to deal with production, inventory, and distribution problems at the operational level simultaneously can result in additional benefits. While the mentioned benefits can be left behind by optimization of the different processes of the supply chain individually. Hence the proposed model jointly optimizes the three mentioned processes by determining the number of production days and the amount of production at each period. Moreover, the inventory at the plant and all customers, and the assignment of customers to vehicles in each period are made by the proposed model. The use of EVs is probed to reduce the negative environmental impact of transportation services.

However, the application of EVs has faced several challenges because of battery capacity, long recharging time, lower capacity, and mileage limitations. Although some of these limitations have been addressed by the advance of technology such as having faster recharging time, optimizing routes can significantly facilitate the application of EVs for performing deliveries in freight transport. On the other hand, the travel time of each link plays a key role in route construction, and optimization is highly affected by the different times of day and different traffic conditions because the travel time of a link in the city center during the peak hour and off-peak hour can be substantially different. Hence, a dynamic electric vehicle production routing model is developed in this paper for the first time to address the real-world problem under realistic assumptions such as the time window of customers to perform deliveries and heterogenous EVs.

Therefore, the dynamic multi-period production routing problem considers the production and inventory-related costs for different production days and the travel time variation of the links within a day to distribute the produced goods. The traffic condition such as congestion or accident may result in changes in traveling speed and consequently, travel time of the links. So, it is important to capture these variations and define them in the modeling process to be able to construct the routes of the electric vehicle accurately to make the application of EVs possible while they have a limited loading capacity. So, a travel time matrix is defined to determine the travel time of each link based on the production day and the specific time interval of each day. In this way, not only it is possible to consider the traffic behavior of different time intervals of a day, but also the speed profile of each link for different days can be considered in the integrated production and distribution decisions.

A comparative analysis was conducted on several metaheuristic algorithms to assess their suitability for addressing the proposed problem. The choice of the algorithm should be made based on the problem size, the specific performance measures. Hence, based on each performance measure the best algorithm is introduced. Looking at the RDI of objective function values, the HGASA algorithm had the lowest value, indicating that it performed the best in terms of the objective function. However, it ranked 7th in hitting time, implying that it wasn't the fastest algorithm. In contrast, the GA Algorithm presented the fastest solutions for small and medium-sized problems, as indicated by the lowest HT rank. However, its performance in terms of the objective function was only average (rank 5 in RDI of objective function values). The HKASA algorithm, while not topping either of these categories, was consistently high performing across all problem sizes. This is particularly demonstrated by its consistently low RPD values in the objective function and its second-best performance in terms of the objective function value (RDI-OF). The HKASA algorithm's relative deviation index for the objective function and hitting time (HT) was 1.64 and 2.65 respectively, meaning it balanced both quality of solutions and speed fairly well. HKASA algorithm demonstrates a good balance between solution quality and speed across different problem sizes. Therefore, the decision on the best-performing algorithm would ultimately depend on the priority of the optimization criteria for a specific problem.

To conclude, other practical issues of integrated supply chain planning are discussed as a direction of further studies in this discipline. As stated, due to the inherent characteristics of the most production line, it is reasonable to consider multiple products and the demand of each customer which can consist of different types of products. Moreover, the detailed decisions for the considered problem can be investigated such as considering decision variables related to the scheduling of products and determining the departure time of vehicles according to the completion time of the product at the plant instead of assuming that all the productions are available at the beginning of the production day. Furthermore, a different source of stochasticity can affect the problem and reduce the quality of decisions such as the source of uncertainty related to production lines and the road network. Different approaches are suggested to handle the uncertainty to improve the applicability of the solution provided by decision making approach.

ACKNOWLEDGMENT

Professor Jiří Jaromír Klemeš has worked on the manuscript. Sadly, he passed away before its submission. However, the authors would like to show their appreciation for his leadership and scientific excellence and would like to keep him in the list of authors.

FUND

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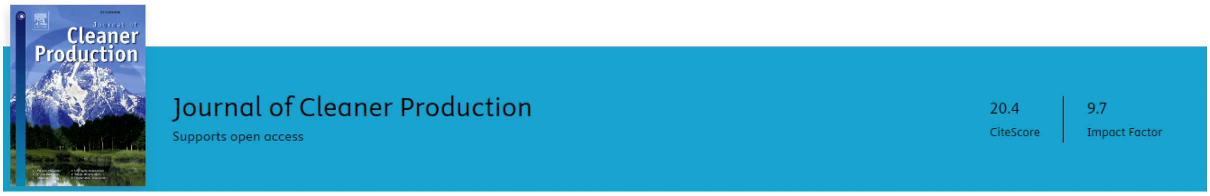

Designing a multi-period dynamic electric vehicle production-routing problem in a supply chain considering energy consumption 22 2023
M Hajiaghaei-Keshteli, G Rahmanifar, M Mohammadi, F Gholian-Jouybari, ...
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CHAPTER 6

PAPER 5:

A platform to optimize urban deliveries with e-vans

The paper reports the results of a research targeted to develop a Decision Support System (DSS) for planning and operation of urban deliveries carried out with electric vans. The research was included within the 2019-21 Research Program for the Electric System, coordinated by the Italian Ministry for the Ecological Transition, and has been performed by ENEA, the Italian Agency for Energy, New Technologies and Sustainable Development, and "La Sapienza" University of Rome. The new DSS is based on meta-heuristics algorithms capable to manage a generic set of goods to be delivered by means of a generic fleet of electric vans, with the objective of minimizing the overall cost of the daily operation. The algorithm considers all the physical constraints, including vehicles batteries capacity. It is assumed that fast recharges can be performed during the delivery tours. For the real-time operation, a monitoring system of the vehicle fleet, road network and recharge stations are assumed, based on IoT technologies, to detect possible unexpected events and manage them in the best way, according to the available resources time by time. The paper describes the DSS general architecture, the optimization algorithms and the recovery procedures and shows results for two testbeds.
Keywords: Urban deliveries; Electric Vans; Decision Support System.

6.1.INTRODUCTION

The paper describes the results of a three-year research carried out within the 2019-21 Research Program for the Electric System, coordinated by the Italian Ministry for the Ecological Transition (formerly by the Italian Ministry of the Economic Development). The research has been performed jointly by ENEA, the Italian Agency for Energy, New Technologies and Sustainable Development, and "La Sapienza" University of Rome.The research goal consists in a software tool aimed at optimizing, day by day, the delivery tours within an urban network, when transport is carried out with Battery Electric Vans (BEVs). The software is designed to manage supply and demand data of urban deliveries in order to make the logistic process more efficient, reducing both operational costs and energy and environmental impacts, but also allowing a better management of public and private facilities such as vehicles unloading areas and charging stations for electric vans. In this sense the tool is targeted not only to logistic operators but also to local public administrators.

The vehicles routing optimization for goods delivering is a topic of vast operational interest, just thinking of the thousands of deliveries that are handled every day in the context of e-commerce. Systems of optimization and management of delivery operation are already adopted by many commercial carriers involved in the deliveries of goods.

However, the use of electric vehicles is a relatively recent topic of research. When considering electric traction, the usual constraints related to vehicle routing problems, like time-windows at delivery points or vehicles load capacity, need to be considered jointly with the vehicles range limits linked to its battery energy capacity. This means that the daily vehicles activity program must also consider the possibility to perform suitable electric recharges during the delivery tours, using the recharge infrastructure spread in the urban area, either public or private. This leads to an increase in computational criticalities, which has been faced during the research.

Apart from this planning functionalities, the project was directed to manage, during vehicle operation, the most common unforeseen events, deriving, for instance, from anomalous traffic conditions or battery defaults, that can require real-time changes to the original schedule, rising new routes and / or recharging operations. From this perspective, the information to be acquired in real time both from the vehicles and the territory in which they operate is crucial.

In recent years, the development of the Information Technologies opened new horizons in the management of Transport and Mobility. Big amounts of data on demand behavior as well as infrastructures and vehicles status can be continuously acquired from the field much easier than in the past. At the same time, communication among users, administrators and operators can take place widely and fast, allowing both off-line analyses and on-line interventions that were unimaginable just few decades ago. In this framework, many sectoral studies and research have focused on the design of modern decision support platforms for local administrators and stakeholders, aimed at identifying, through analytical processes, policies and actions to facilitate the transition to a more efficient planning and management. This is part of a more general attempt to reinvent cities to optimize energy consumption, and quality of life.

In this paper we propose an application of IoT specifically focused on urban delivery electric fleets management. A monitoring system capable to collect data from in-motion electric vehicles, unloading and recharge facilities and transfer them to a Control Center has been designed and tested. For the objectives of the research, this information must be updated at regular and short intervals, in order to allow the algorithms residing on the platform, in case of unexpected events, to rearrange the remaining vehicles tasks, taking into account new operation conditions as well as physical and commercial constraints.

The following figure illustrates the functions to support the urban distribution of goods and the expected results for the two categories of users of the platform.

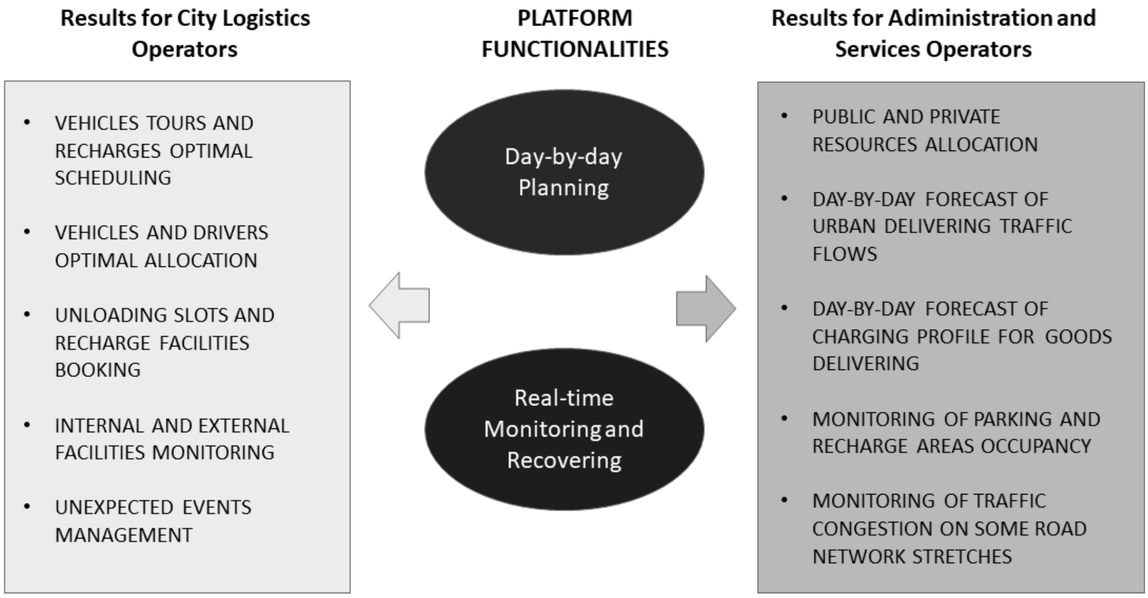

Fig.6.1. Functionalities of the platform for planning and operation of urban deliveries with batteries electric vans

6.2. STATE OF ART OF TECHNOLOGIES

Urban areas are the hub of last mile deliveries, which to date represent the least efficient link in the entire logistics chain in terms of generating costs and negative externalities. According to recent estimates, last mile deliveries account for up to 40% of the total cost of the supply chain [11] and are responsible for 30% of CO2 emissions and about 20% of traffic. About 80% of deliveries take place in the urban areas, 20-25% of them, in terms of travelled kms, concerns outgoing goods, 40-50% are for incoming goods, the remainder relates to goods with both origin and destination within the urban perimeter. In the absence of ad hoc interventions, the number of light commercial vehicles for urban delivery of goods will increase by 36% by 2030.

The renewal of fleets with clean or low-emission vehicles represents an indispensable opportunity towards a substantial reduction in urban negative emissions (GHG, air pollution, noise). Operators and builders consider various sustainable transport solutions, such as cargo bikes (which might contribute to the reduction of road congestion and the risk of accidents) and electric vans. The former, characterized by modest costs, are severely limited in terms of range and load capacity; electric vans on the other hand have higher costs of investment, also for the re-charging equipment.

In Italy, the light commercial vehicles market in the first semester of 2022 was of 86.700 units, decreasing by 11.6% compared to the same period of 2021, due to economic uncertainty. The national van market remains dominated by IC engines and, although in the past few years the sales of electric vans are increasing, in 2021 remaining limited to 2% as for purely electrics and to 7% as for the hybrid ones.

Fig. 2 shows the technology split of vans in Italy in 2021, when the national LCV fleet counted about 4.34 million units, 23% of which were Euro 6. BEVs represent only 0.24% while the hybrids 0.43%.

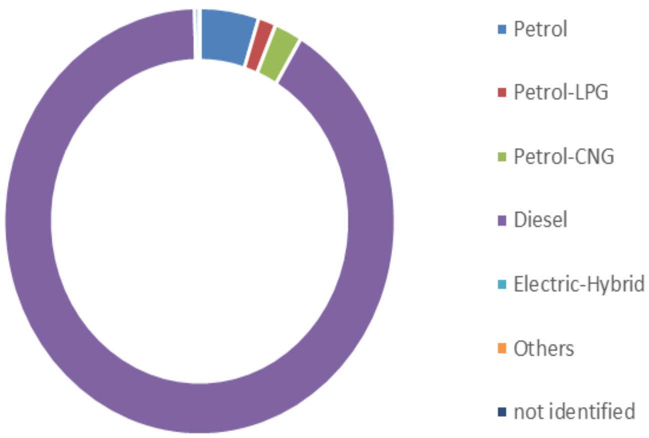

Fig.6.2 . Light Commercial Vehicle fleet in Italy by technology, 2021 (%) – Data source ANFIA

Industrial policies are presently strongly influenced by increasingly stringent environmental regulations, as well as by energetic concerns, so that the electric gamma is rapidly enlarging. In 2022, some automakers even sell only electric van models.

Currently, battery packs guarantee an average of 100-200 km daily mileage, with an energy capacity ranging from 37 up to 70 kWh. Batteries can generally be recharged either with an AC wall-box, requiring several hours, and therefore suitable for an overnight charging, or with more powerful DC charging stations that allows for shorter charging times.

The rise of e-commerce is influencing the evolution of urban logistics so much that the use of goods transport vehicles of limited size and load capacity, such as bicycles and tricycles, drones and robots, have been introduced to carry out small deliveries within narrow areas such as urban ones. In an even more innovative scenario, the 3D printing directly at the buyer's premises can become a widespread mode of goods delivery, making it possible to virtualize freight transport on a par with what teleworking and teleservices are doing with passenger mobility.

The modern cargo bicycles, even trikes (tricycles), can be electrified and modular, this facilitates the carrying out of deliveries and, considering that e-bikes have already been successfully utilized for providing postal deliveries, it can be said that the two / three wheels are back in vogue again. Velove’s Armadillo, for example, is used by numerous delivery operators, including DHL, DB Schenker, Deutsche Post, DPD, Hermes and Swiss Post. Centaur Cargo has developed a modular cargo bike for Royal PostNL and AN Post while Coolblue and Truck Trike partner with Urban Arrow and a Portland-based company is working with UPS

Cargo bicycles might also be used in other services, in addition to the distribution of small packages, such as the Cyclo Plombier, a hydraulic company that travels around Paris on cargo bikes. This allows operators to carry all of their work tools, eliminating the costs of fuel, parking, repairs and all the associated stress.

In Groningen, non-electric trikes were present long before “Mobility-As-A-Service” or “sharing economy” were coined. These very distinctive trikes have become a city institution, rent for half a day at a cost of 12 euros, still not competitive for the delivery of goods, compared to the prices charged by traditional couriers.

Numerous companies are developing drone delivery services for small loads, including Matternet (2 kg for 20 km), ZipLine (1.8 kg for 80 km), Flirtey. The DPDgroup subsidiary of the French group La Poste recently opened its second commercial line to deliver packages at medium altitude, using a drone capable of carrying 2 kg up to 15 km. The Swiss Post teamed up with Matternet to provide medical supplies, although they stopped after two incidents. Alphabet (Google’s parent company) and Amazon have received clearance from the US Federal Aviation Administration to operate their drones and have started delivering via their subsidiaries, with PrimeAir (2.5kg over 25km) and Wing Aviation (2.5 kg over 25 km).
According to the European Energy Agency – EEA [15], in urban area bikes and e-vans can operate better than drones. In any case, all the studies recognize that the environmental benefit of using drones is limited to a small segment of the market (i.e. last mile deliveries to a single or a few recipients with a low payload).

Several players are also evaluating pilot studies for the use of autonomous electric vehicles for last mile delivery, among these: Nuro is planning to build a special vehicle that, for the first time, can keep a speed of 40 km / h. The start-up has already made several food deliveries. Two other operators are Gatik and Udelv, the former intends to specialize in the “middle mile” delivery from warehouses to stores, and has pioneered its solution with Walmart, while the latter has made test deliveries to retail stores. Amazon also aims at autonomous driving with Aurora Innovation; the company is developing a complete software package and hardware components, to allow autonomous vehicles at level 4. More recently, Amazon has also collaborated with the start-up Embark autonomous trucking company to test autonomous driving in the United States attempting to tackle the “middle mile”.

In China, Alibaba is testing low-speed (15km / h) driverless delivery robots and sidewalk delivery robots, these are smaller vehicles with the aim of allowing deliveries in areas where other types of vehicles, more traditional, are not allowed (e.g. pedestrian streets, campuses) and short deliveries in dense urban centres. This initiative is the focus for a number of start-up, including Dispatch, Marble, Robby, Starship or Kiwi Campus. These little robots are also an integral part of Amazon’s multimodal delivery strategy. The company also developed its own delivery robot, a small six-wheeled electric vehicle, and tested it on a new service called Scout. Likewise, FedEx developed Roxo, a four-wheeled robot with the ability to climb a few stairs and aim for same-day delivery, and PostMates was authorised to test their vehicle on the San Francisco sidewalks.

The Ez-Pro solution proposed by Renault consists of a fleet of autonomous electric capsules, capable of transporting up to 2 tons of goods and coordinated by a leading vehicle, on which the “messenger of the future” travels, a single operator whose function it is no longer that of driving the vehicle, but of supervising the route and delivery of goods.

Both vehicle and telematics innovation can be of great importance in the re-thinking logistics systems for last mile distribution and freight transport more generally; as the connection of things (Internet of Things – IoT) grows, the possibilities of managing processes in a more informed and efficient way grow and the overview of telematic solutions aimed at last-mile services is already very wide.

Pending the marketing of autonomous vehicles, connected vehicles are already a reality: complex systems consisting of a set of Electronic Control Units (ECU) connected to each other. The technologies underlying these systems are protocols that allow different types of communication: vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-everything (V2X). The "connected vehicles" therefore process a lot of information: from technical data on the condition of the vehicle or related to its use (speed, seat occupancy or maintenance status), to those on the road surface and weather conditions, or on the presence of pedestrians or other vehicles; or information relating to the location, owner or user. Some advanced features could allow the processing of biometric data, both for the authentication of the driver or user of the vehicle and for the monitoring of some of its psychophysiological parameters. These strategies will save energy, better divide the work between the various carriers and offer a higher quality service, creating the conditions for the cost-effectiveness of last-mile delivery.

6.3. THEORETICAL HINTS

Researchers and practitioners have been studying the Vehicle Routing Problem (VRP) for more than 60 years. It has been now declined in the problem of designing least-cost delivery routes from a depot to a set of geographically scattered customers, subject to side constraints. With the introduction of Electric Vehicles (EVs) for urban freight transport, the limited driving range represents a significant additional constraint, also due to the large time difference between refueling and recharging. Therefore, in literature, many works are addressing the Electric Vehicle Routing Problem (E-VRP), each considering different constraints and approximations.

E-VRP's goal is to design low-cost BEV (Battery Electric Vehicles) routes to serve a number of customers considering the usual constraints: vehicle load capacity, customer location and time windows, working hours, fleet size and characteristics, time-dependent travel time; moreover, vehicles range limits and re-charging possibilities must be considered, either schematically or more realistically. In a review from Erdelic et al, 80 articles regarding E-VRP have been analyzed to determine the frequency of appearance of variants and constraints, including those specific for electric vehicles, as shown in Fig. 3.

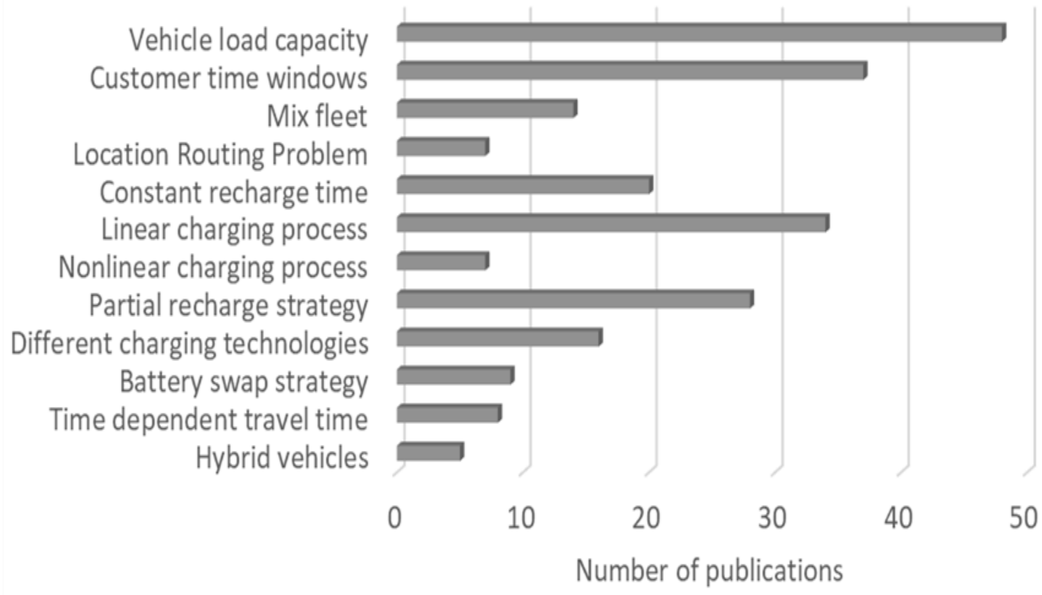

Fig.6.3. Frequency of Variants and Constraints in EVRP papers

The figure highlights that, as for recharging time, a linear process is considered, rather than a fixed or, on the opposite, non-linear one.

Numerous resolution procedures have been proposed to solve the VRP, and many of them, with appropriate adaptations, are also applicable to solve the problem of vehicle routing with electric vehicles (E-VRP). For small-size problems, several exact procedures have been proposed, but since this is an NP-hard problem with a large number of deliveries to be made in real scenarios, most of the procedures used in practice are heuristics, metaheuristics or hybrid combinations.

Heuristics are generally classifiable in two main families: Constructive Heuristics and Local Search Algorithms. The former iteratively inserts customers to the available routes, constructing solutions in what is commonly defined a “greedy” way, that cannot be reversed afterwards. At each step of the algorithm, an unserved customer is added to the route, along with its position in the route, according to the objective function. Two pioneering contributions are the savings method [18] and the sweep algorithm [19]. On the other hand, Local Search algorithms, or Improvement Heuristics, start from a feasible solution and iteratively try to improve it by exploring the current solution in its neighbourhood, by applying perturbation moves. When it is not possible to find an improvement of the solution in its neighbourhood, a local optimum is reached and the search stops.

Metaheuristics, more complex frameworks of heuristics, are employed to allow the algorithm to escape from these local optima to find a better solution. Population metaheuristics are based on the definition of a population of individuals, which represent possible solutions of the VRP and go through the process of evolution. Many applications to E-VRP can be found in literature, including genetic algorithms, ant colony and particle swarm optimization. Otherwise, metaheuristics can be neighbourhood-oriented, directly addressing the problem of falling into repetition patterns, since by allowing a decrease of the objective function the risk of going back to the previous current solution must be prevented. Among this last family, the Simulated Annealing (SA) algorithm modifies the local search algorithm by introducing a randomized criterion for the selection of the new point in the current neighbourhood and for accepting the next step of the local heuristic. It is inspired by the physical cooling process of glass materials, controlling the search process through a parameter that is called temperature. The basic idea of the algorithm is to allow significant worsening of the value of the objective function in the initial stages of execution, to avoid being trapped in local optimum far from the global optimum. After a sufficient number of iterations, the algorithm is supposed to reach a part of the solution space close to the global optimum: at that point the temperature is decreased to refine the search. For a detailed explanation of the heuristics and algorithms for vehicle routing problems the readers are referred to the works of (Mohammadi et al., 2023; Rahmanifar et al., 2023c)

6.4. SOLUTION APPROACH

As already stated, this work is aimed at developing a procedure to optimize, both in planning and operation phases, the tours for delivering goods within an urban network, when transport is carried out only with Battery Electric Vans (BEVs), by a unique carrier, from a unique sorting center. The electric fleet can be heterogeneous, composed by vehicles of various load capacity, range and operational unit costs. Deliveries are linked to a set of delivery points, each of them characterized by a double time window within the fleet operation hours. A set of fast recharge stations is available across the delivering area, to be used if the battery State of Charge (SOC) goes under a certain lower threshold (20% of battery capacity), and a constant recharge time of 30 minutes for any considered type of vehicle.

The procedure is composed of four modules, two of which working off-line, before vehicles operation is started. A first algorithm allocates the deliveries to a subset of vehicles, optimizing the overall delivery time and cost, by matching vehicles load capacity and deliveries time-windows. A second algorithm determines the position of the vehicles on the graph and estimates energy consumption, verifying if and when the battery energy is almost down; in such a case, one (or multiple) recharge(s) is(are) inserted along the vehicle route, selecting the more suitable recharge station(s) among those available. Both these modules work without particular pressing from the time processing point of view. In fact, generally, goods to be delivered in a certain day are known at least the evening before so that more than few hours are available to search for the best solution. This is a crucial factor to set out the optimization methodology to be adopted. In our case a metaheuristic algorithm has been chosen, in the family of Simulated Annealing. The objective function minimizes the number of vehicles used, the total mileage and the total travel time, while penalizing time-window violations.

The other two codes work in real-time, during vehicles operation, in case of anomalies respect to the original schedule. The 'Recovery' code manages any default of battery State of Charge, suggesting additional or alternative recharges to those scheduled. Finally, the 'Update' code manages vehicle delays, not necessarily leading to an alert on the remaining battery range.

The flow diagram presented in **Error! Reference source not found.**Fig. 4 illustrates the w hole software procedure, starting from the acquisition of the characteristics of the road network, which must be schematized with an appropriately graph. The data of the specific case study are then acquired, relating to the composition and characteristics of the electric fleet as well as the attributes of the goods to be delivered, in terms of quantity, delivery points and related time constraints. In this phase, information relating to the charging infrastructure located in the area and the consumption functions of the electric vans are also collected. On the basis of these data, the two modules responsible for the off-line planning of delivery tours (Optimization and Simulation) return a sub-optimal solution. This solution is defined in terms of allocation of the goods to the vehicles, timing of the deliveries and possible recharge, as well as road routes from one delivery/recharge point to another. In addition, the vehicles positions and battery SOCs are provided at time intervals of 10 seconds.

The modules for the recovery of anomalies are launched only in a phase in which the vehicles have already begun their tours and only if, through data acquisitions from the field, there is an excessive misalignment with respect to the planned tour. This misalignment can be due to the battery's state of charge, too low than expected, or the vehicle's position, too far back. In the absence of a real monitoring system, which would have involved costly instrumentation of a real fleet and a real territory, the vehicle anomalies to test the recovery procedures are simulated randomly. Planning and recovery codes were developed in MATLAB and made available as executables compiled for the Linux operating system, while the accessory procedures for creating the work environment and the input files were developed in Python language. The entire procedure (Fig. 4) was planned and implemented to avoid any operator intervention once the suite has been launched. The whole procedure has been integrated in eMU; a multifunctional web-based platform developed in ENEA to ease the diffusion of electric mobility in urban areas.

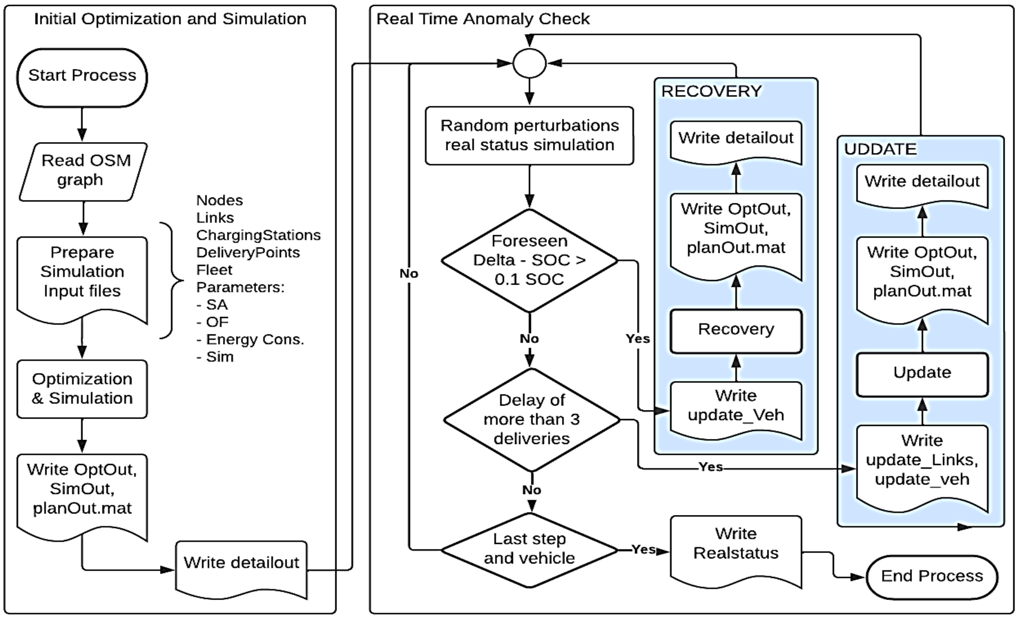

Fig.6.4. Optimal planning and real-time operation procedures

6.5. ALGORITHMS FOR OPTIMAL SCHEDULING

The vehicle routing problem (VRP) is a complex optimization problem that is typically classified as an NP-hard problem. This means that finding the optimal solution to a VRP may require an exhaustive search of all possible solutions, which is computationally infeasible for large-scale problems. To address this challenge, various algorithms and optimization techniques have been developed to find near-optimal solutions within a reasonable amount of time. These include heuristics, metaheuristics, and mathematical programming methods such as linear programming, mixed-integer programming, and dynamic programming. In this work, the proposed routing problem is solved with the use of a Simulated Annealing algorithm, which searches for the most efficient lap itinerary. SA is utilized by many scholars to solve different optimization problems and specifically, this algorithm is among one the most preferred used algorithms to address VRP. The algorithm works according to the cooling physics process which is also called the annealing process. This is the procedure of low energy-state crystallization of molecular metal arrangements by slowing down of the temperature after being subjected to high heat. The optimization process takes place as follows:

- An initial solution (S1) is created (see Fig.6.5).
- The solution is perturbed.
- The cost of the new solution is evaluated.
- A probabilistic function compares the cost of the new and previous solutions and decides which one to keep.
- The procedure of perturbation, evaluation and comparison is iterated for L times.
- The parameter of the probabilistic function (temperature) is decreased, and the best solution of the L iterations is chosen to restart in the next cycle.

This process continues until the temperature drops below a final temperature value, and the found solution is the result of the optimization. This process is explained in Fig. 5.

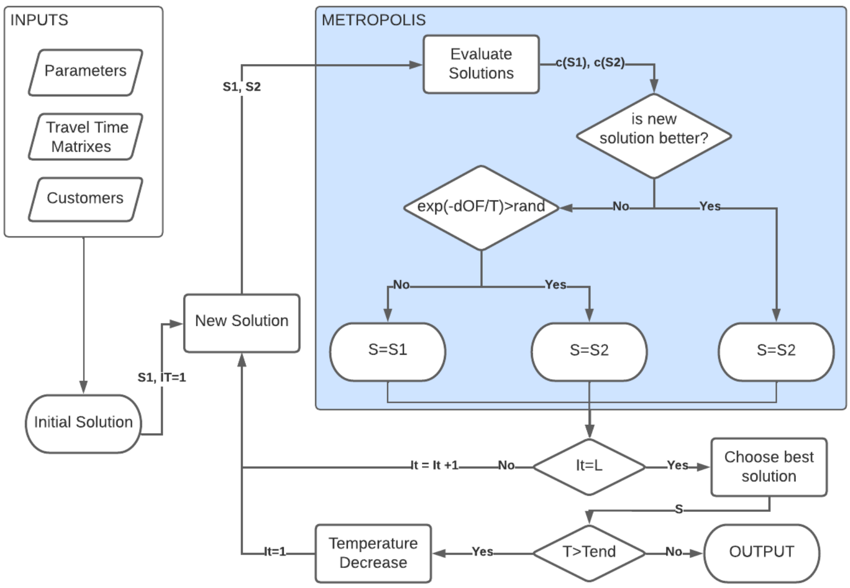

Fig.6.5 Optimization procedure with Simulated Annealing algorithm.

The initial solution (S1) is created starting at the depot and selecting the closest delivery point. The second delivery is determined by searching for the delivery point closest to the first one, and iteratively for the following deliveries. Time windows are not considered since they are used as a soft constraint. Once the distance of the tour overcomes the driving range of the vehicle, the itinerary of that vehicle is terminated adding a stop at the depot. The procedure of assigning deliveries to vehicles starts again with the remaining deliveries using the following available vehicle.

The perturbation of the solution can follow three different strategies: Swap, where two deliveries are randomly selected and their order is switched, Reversion, where a random set of successive deliveries is selected and their order is reversed, or Insertion, where two deliveries are selected, and the first one is moved right after the second one.

The new solution is then evaluated determining its associated cost and it is verified that no autonomy or load constraints are exceeded. The cost is calculated through a linear combination of travelled distance, travel time and number of vehicles, in addition to the time windows violation penalties. The weights used to define the objective function are:

- Operating cost of the vehicle per km travelled (oc).
- Hourly operating cost (including driver cost - tc).
- Additional cost for each vehicle used (use and depreciation - vc).
- Additional cost for every time window violation (wc).

The Objective Function is therefore defined as:

$$OF = oc * dist + tc * time + vc * n\_veh + wc * twviolation \qquad \text{(Eq. 6.1)}$$

Where *dist* is the distance run in km, time is the time required to run the distance in seconds, n_veh is the number of vehicles used for the deliveries and *twviolation* is the total time of the time window violations. The "Metropolis" function then compares the current solution (S1) with the new one (S2) according to the values of the objective function and the current value of the temperature parameter. The choice is not deterministic but is subject to a probabilistic assessment: the new solution can be accepted even though the cost is higher than the previous solution. If the analyzed itinerary is the best choice, the new solution is automatically accepted, but if the value of the objective function is lower than that of the previous solution, the solution can still be approved with a probability expressed as a function of the difference between the two values. The new solution is accepted if:

$$\Delta\text{OF}=e^{\left(-\frac{\Delta OF}{T}\right)} > p \qquad \text{(Eq. 6.2)}$$

Where ΔOF is the difference between the objective function of the two solutions, T is the temperature, and p is a real number extracted from a uniform distribution in the interval [0,1].

6.6. MONITORING AND RECOVERY PROCEDURE: RECOVERY AND UPDATE PROCESSES

When considering electric vehicles, additional issues related to vehicle battery and charging stations defaults may occur in addition to the ordinary problematics related to traffic or mishaps at delivery destinations. This causes an increase of possible critical events, in particular associated to the need to suddenly include a charging event within the planned trip. Our system is designed to face such operational issues in real time. This is performed by two distinct procedures that are activated depending on the kind of problem the vehicle is dealing with. The Recovery procedure is activated in case of an unexpected discharge of the vehicle battery, while the Update process handles any delay of the vehicle, recomputing the optimal path and adding or rescheduling new recharging stops if required. The recovery function allows to consider the need of sending a vehicle to a charging station, which was not initially foreseen in the plan, in case the power reserve is not sufficient to complete the round of deliveries due to unpredicted events that have reduced the charge compared to planning. The module calculates the current position of the vehicle and, from that position, selects the closest charging station. The schedule is then updated according to the new itinerary.

The update function offers the possibility to re-optimize the order of the remaining deliveries of a vehicle if during the monitoring operations a significant deviation of the travel times or the position of the vehicle with respect to the planning is received from the platform. The characteristics of the road network and the performance of the routes can undergo changes during daily operations. As a result, the travel time of electric vehicles may vary, and it is reasonable to re-optimize the remaining part of the journey in case of significant changes in travel times. Also, the current position of the vehicle itself may be different from the plan and in this case a re-optimization for the rest of the lap may be required.

Both Recovery and Update modules act during the operational phase of the whole process. Once the Optimization module has identified a good vehicle routing, including the required stops at charging stations, all involved vehicles start their trip following the planned routes, being continuously monitored in real time.

In fact, the real vehicles operation is always affected by a misalignment respect to the planned one, due to unavoidable approximation of theoretical values (trip time, energy consumption, battery capacity) and unexpected events (traffic conditions, time waste, technical defaults, …). Thus, a proper recovery procedure must be capable to tolerate a certain amount of error, up to not overtake physical or operational constraints, such as vehicles battery capacity or deliveries time windows. In our system Recovery and Update procedure are launched when either real battery State of Charge or real vehicle position differ from the planned ones more than pre-specified threshold values.

The following Fig. 6.6 shows a schematic example of route rearrangement when a “battery alarm” is acquired by the monitoring system from a vehicle during its delivering operation: the nearest available recharging point is immediately identified, and a new recharge is inserted in the tour before next deliveries. Possible recharges previously planned are automatically deleted and other recharges are planned to permit the end of the tour, if necessary. No changes in the deliveries sequence are provided but only recharge rescheduling.

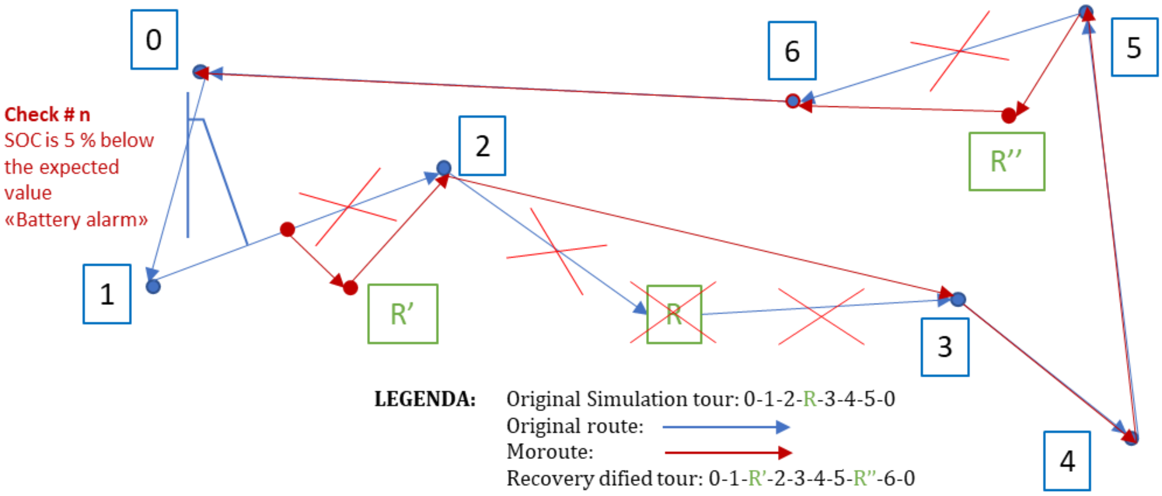

Fig.6.6 Recovery rationale.

Vice versa, when a delay is registered respect to the schedule, a total rearrangement of the remaining deliveries is carried out, considering both destinations time-windows and remaining vehicle range, as well as available recharge opportunities, as schematically shown in the subsequent Fig. 6.7.

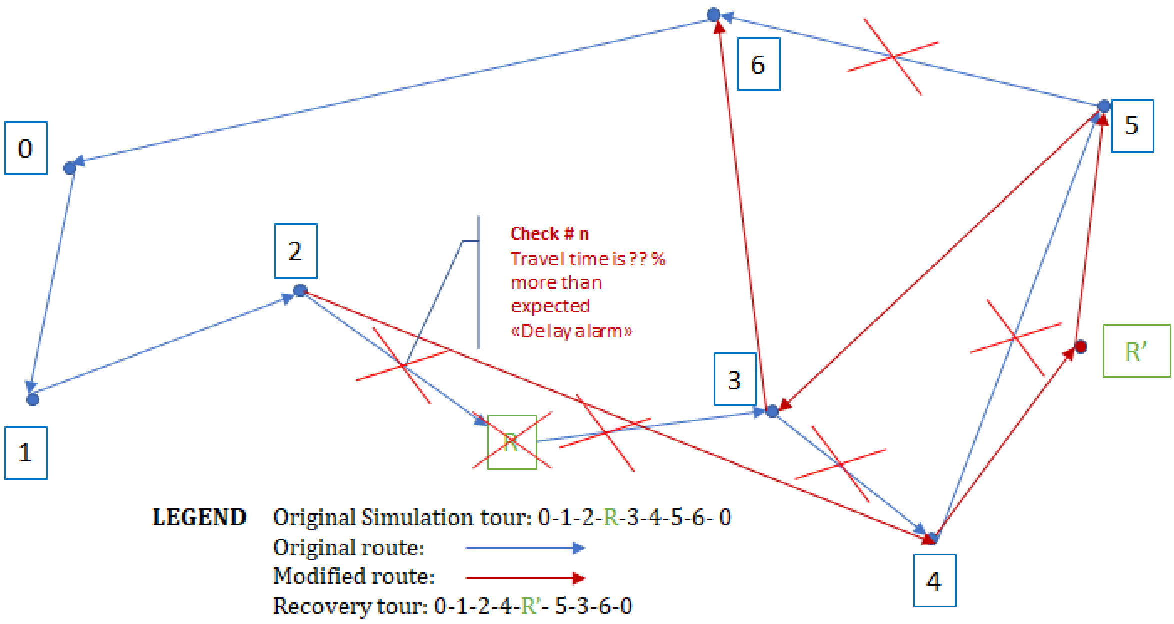

Fig.6.7 Update rationale.

The check frequency has been set to 10 seconds. This requires simulating the battery charge and vehicle position along the planned tour with a very high time resolution, at least less than 10 seconds, in order to determine expected values when a check respect to real conditions is carried out.

Periodically the distance between the real status and the planned status of the vehicle is computed for a set of parameters and compared with predetermined thresholds. If the distance between one of the considered parameters becomes larger than the corresponding threshold, the system automatically generates the files containing the required information to start a recovery or update for the vehicle. These processes can be repeated several times during the day to correct the path and the delivery process as many times as required by the forcing of the external conditions. Moreover, the recovery or update processes are run only for one vehicle per time, to allow to modify only the required paths and deliveries, without disturbing the other vehicles, on schedule at the time of launching, and therefore optimizing the time of recovery and update for each vehicle.

The system is built to acquire information from sensors onboard of vehicles. Yet, in our study the real status of the vehicles is simulated by adding a set of random perturbations to the planned delivery trips: every 10 seconds a delay of 10 seconds and an 0.01 kWh increase in battery discharge is randomly added with 20% probability to the actual status of the vehicle. Contrary to the real case, when both increments and decrements in the delay are possible, in this configuration only a monotonic increase is allowed, to test the system under an over-realistic stress.

Separate checks are carried on for discharge and delay in deliveries, to activate separate recovery processes. Battery status is checked every 5 minutes. Both absolute SOC value and deviation from expected discharge are monitored, to avoid unnecessary recharges when a vehicle is about to conclude its delivery trip. The chosen thresholds, that can be changed by the operator, imply to send a vehicle to a recharging station if its SOC is lower than 20% of its total capacity and if at the same time its value is 5% lower respect to the foreseen one. This is handled by the Recovery process, described above. The Recovery resets all future planned recharging stops and plans an immediate new recharge as well as any other further recharge required up to the end of the delivery trip.

The second check is related to the Update process, and to the delay of the vehicle respect to the expected position and performed deliveries. If the difference between the expected and performed deliveries at the time of check is larger than 3 (operator chosen parameter), the Update process is launched. As described in the case of the Recovery process, also in the Update process the planned path is reset and is recomputed to optimize the remaining deliveries by considering the updated status of traffic, using real time velocities associated to the arcs of the graph. Moreover, if required, new stops for recharging are planned up to the end of the delivery tour.

6.7. THE MONITORING SYSTEM

To allow for the comparison between planned and real status of critical variables, a monitoring system from the field has been designed and partially tested, as described hereby.

6.7.1. GETTING VEHICLE DATA

An embedded system has been developed, which is able to interface with the CAN BUS of the vehicle and transmit the collected data to a remote controller for subsequent processing.

The information of interest of the vehicle concerns the instantaneous position and speed and the state of charge (SoC) of the battery. The issue of capturing data from a moving vehicle in real time has been addressed in the past to pursue a variety of goals. Often, for example, the primary objective has been to study vehicle emissions and fuel consumption. Over time, different technologies aimed at capturing real-time data from the vehicle have been developed. In any case, to achieve this goal it is necessary that an "Onboard Unit" (OBD), a tool aimed at data acquisition, is installed on the vehicle, It is therefore necessary to identify a so-called embedded system, able to connect to the standard OBD port of the vehicle, to acquire the data of interest, process them and transmit them to a monitoring and remote control platform (Fig. 6.8).

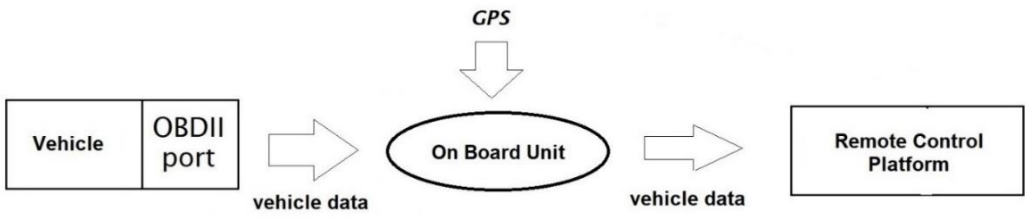

Fig.6.8. On-board unit information exchange.

The system embedded on board the vehicle is complex, composed of several units, each with specific and well-defined tasks (Fig.6.8). To connect to the standard OBD port, capture the information and interpret it correctly, we used a CAN USB interface device. It can read the messages exchanged on the CAN BUS of the vehicle and interpret them thanks to the use of special APIs usually written in a widespread programming language, such as C or Python. For this purpose, it is equipped with a DB9 serial port to connect to the vehicle’s OBD port, and a USB output port to connect to the control device. The control device we used is a Raspberry PI 4 with a Broadcom BCM2711, Quad core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz processor, and 8GB LPDDR4-3200 SDRAM. The Raspberry PI device is equipped with the native Raspbian operating system based on the Debian Linux distribution. The acquisition software developed by ENEA Researchers and based on the API provided by the CAN USB device has been installed over the Raspbian operating system.

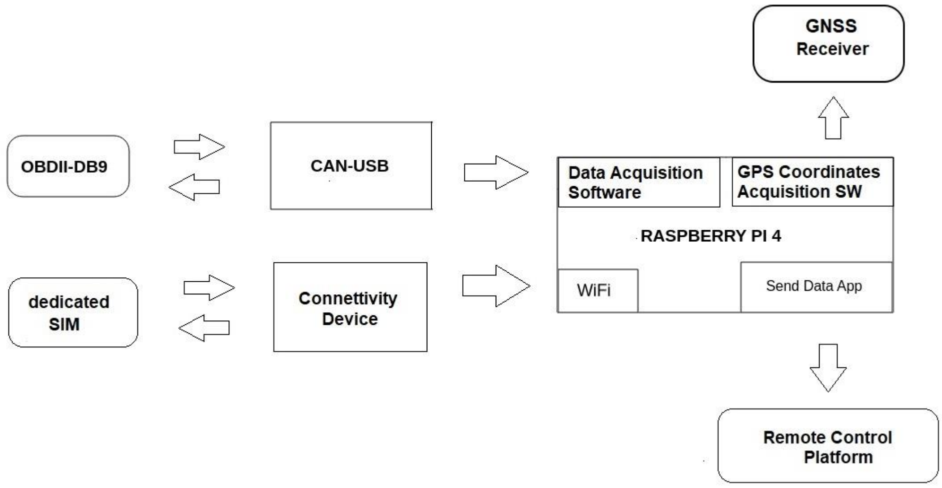

Fig.6.9 .On-board unit architecture.

These three processes are activated at regular intervals in time, to be synchronized with each other. The main process that manages the timing and synchronization of all other processes is the Scheduler process, based on the Linux crontab daemon on the Raspberry PI. The scheduler, at fixed time intervals, activates the three other processes, with a delay from each other, so that the results of the processing can be collected and packaged in the form useful for transmission, and sent to the remote controller for further processing. In the following Fig. 6.10 the most relevant data that can be acquired from the vehicle are shown.

FIELD	DESCRIPTION
DATA	Date (YYYYMMDD)
ORA	Time (hhnmmss)
SOC	Battery State of Charge (%)
MOTORRPM	Angular rate (rpm)
BATTA	Battery charge current (A)
BATTV	Battery charge voltage (V)
AVBATTERY	Available Battery Power (W)
VVEHICLE	Vehicle speed
QCVOLTAGE	Quick Charge Voltage
QCCOMM	Quick Charge Comm Ampere
CHARGEREM	Time to get battery full charge (minutes)

Fig.6. 10. Data acquired from vehicles

6.7.2. GETTING SURROUNDING INFORMATION

Since electric vehicles often have a limited range, to real-time optimize travels in the urban area, it is necessary to acquire the location of charging stations, to identify the unoccupied and available ones, closest to the vehicle when the battery needs to be recharged. This information must be sent to the remote-control platform and must also be updated at regular intervals, to have a constant full knowledge of the (mapped) location of available charging stations, to be used when needed. To acquire the free/busy status from the charging station, local magnetic field sensors are installed on the ground. The sensor measures the change in the Earth's natural (ambient) magnetic field caused by the presence of vehicles or other ferromagnetic objects close to it. The information about the free/busy status of the charging station is sent by the sensor to a Local Gateway, which can communicate with the Remote-Control Platform (Fig. 6.11). At regular intervals during the day, the Remote Controller interrogates the Local Gateway to get information about all monitored charging seats, as listed above:

- Position, expressed in terms of latitude and longitude coordinates
- Date and time of the detection
- Binary information about the occupation or not of the parking space.

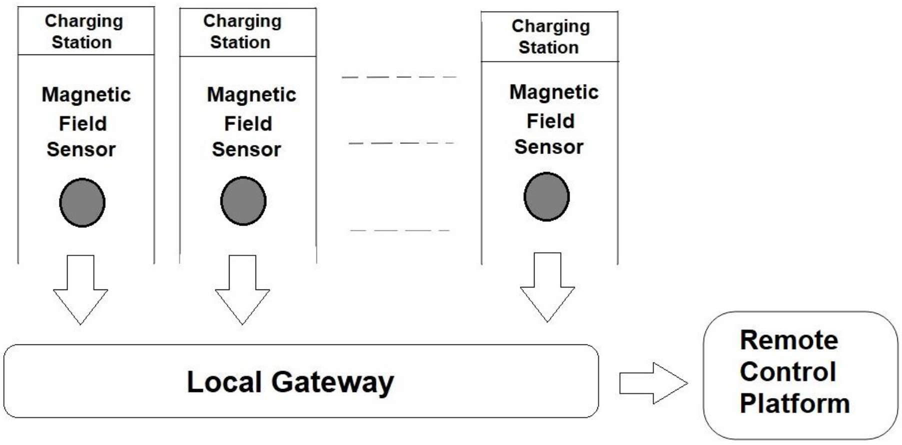

Fig.6.11. Architecture for acquisition of information from recharge and unloading stalls

6.8.THE TEST CASE

Performance and effectiveness of the proposed system have been verified by implementing two real size testbeds containing 209 delivery points through the city of Rome, as shown in the following map.

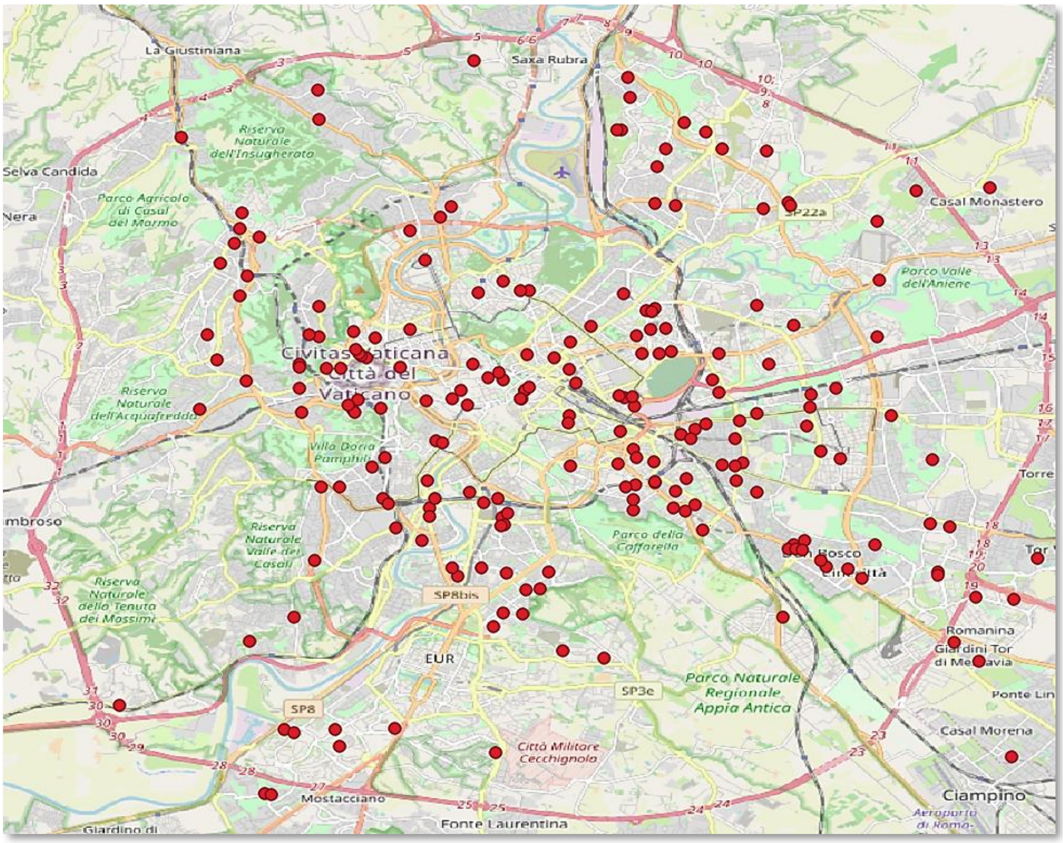

Fig.6.12 Testbeds' delivery points map.

The differences between testbeds are related to the demand for each delivery point and the time-windows scattering, so that the second case results more challenging than the first one.

Table 6.1.
Main testbeds' characteristics.

Test	N° of Delivery Points	Time Windows ranges [minutes from 00:00]	Total Demand [kg]	Total fleet capacity [kg]	Numbers of vehicles
1	209	(480-780), (520-780)	12370	18400	10
2	209	(480-780), (520-780) (500-650), (550-750)	18362	18400	10

The available vehicle fleet is the same for the two testbeds: two mini vans (450 kg capacity), two medium vans (1100 kg capacity) and six small trucks (2550 kg capacity). A set of KPI has then been chosen in order to evaluate the quality of optimization performed in the two cases. Results are shown in the following table.

Table 6.2.

Overall performance indicators of planning results

Performance Indicators	1	2
Total distance Traveled by all vehicles	610.3 km	1137.4 km
Total time traveled by all vehicles	717.6 min	1288 min
Objective function value	1789.3	2701.1
Capacity violation	0	0
Earliness	0	0
Tardiness	0	0
Travel constraint violation	0	0
Unit energy consumption	31.6 Wh/kg	29.7 Wh/kg
Number of used vehicles	7	10
Number of recharging by all vehicles	4	5
Running Time	274.3 seconds	271.4 seconds

Results show that an increasing number of vehicles is needed as the demand gets larger, with consequent larger total travel times and distances. Algorithm running times are similar since they mainly depend on the optimization parameters and not on demand characteristics such as time windows or total demand. For test #1, where seven vehicles are used for deliveries, four of which with scheduled recharges during their trips, vehicles performance indicators are reported in Table.6.3.

Table.6.3.

Detail performance indicators of #1 testbed' planning results.

Vehicle	Distance Traveled to Last Delivery (Km)	Time Traveled (Min)	Capacity (Kg)	Utilized Capacity (Kg)	Number Of Deliveries	Consumed Energy (Kwh)	Number Of Recharging
1654	64.93382	647.4999	1100	826	13	18.78975	0
5381	101.9029	817.1348	2550	2264	38	64.38861	1
2843	89.43698	748.6876	2550	1777	29	53.44788	1
8464	76.37869	775.3624	2550	1772	30	43.4429	1
6184	125.9067	774.0042	2550	1500	29	71.56418	1
6185	66.24281	745.3154	2550	2162	37	42.2879	0
6188	72.68141	755.093	2550	2069	33	46.00743	0

A recovery procedure has been launched, when the real battery SOC of vehicle #2843 detected by the monitoring system was lower than expected, not allowing to perform all the remaining deliveries before the scheduled recharge. With the information on the current position of the vehicle, the last delivery point and the battery state of charge, the Recovery function found the nearest recharging station and, after adding this charging point to the trip, updated the tour for the remaining deliveries.

The following strings in Tab. 4 represent the sequence of delivery and recharge points of the tour based on the result of the planning (P) and after the application of a Recovery (R). The points indicated with code zero (highlighted in red) within the tour represent the charging station. Delivery points in green represent the last delivery before applying the recovery procedure. The original recharge provided by the end of the planned tour is replaced with an earlier one and a second recharge is inserted at the very end of the updated tour, after all deliveries are carried out.

P	28	99	41	51	61	61	28	81	-	94	71	34	66	93	49	51	55	100	72	24	30	66	51	91	57	77	0	25	48	90	83	-
R	28	99	41	51	61	61	28	81	0	94	71	34	66	93	49	51	55	100	72	24	30	66	51	91	57	77	-	25	48	90	83	0

Table.6.4. Vehicle #2483 Original (P) and updated (R) sequence of delivery and recharge points.

The following figures show the rendering of original and updated tours by the User Graphic Interface of the ENEA platform that integrates the Optimal Deliveries modules described in this paper. Original tours are plotted with a semi-transparent line while the updated ones are marked with bold lines. Large part of the new paths is often over imposed to the old ones. In Fig 13 an example of a Recovery result is shown on map. The process is activated just after the delivery at point 11 has been carried out, so that the vehicle is diverted toward the closest recharging station. The vehicle is then sent back on the original path in order to restart the delivery sequence from delivery number 12.

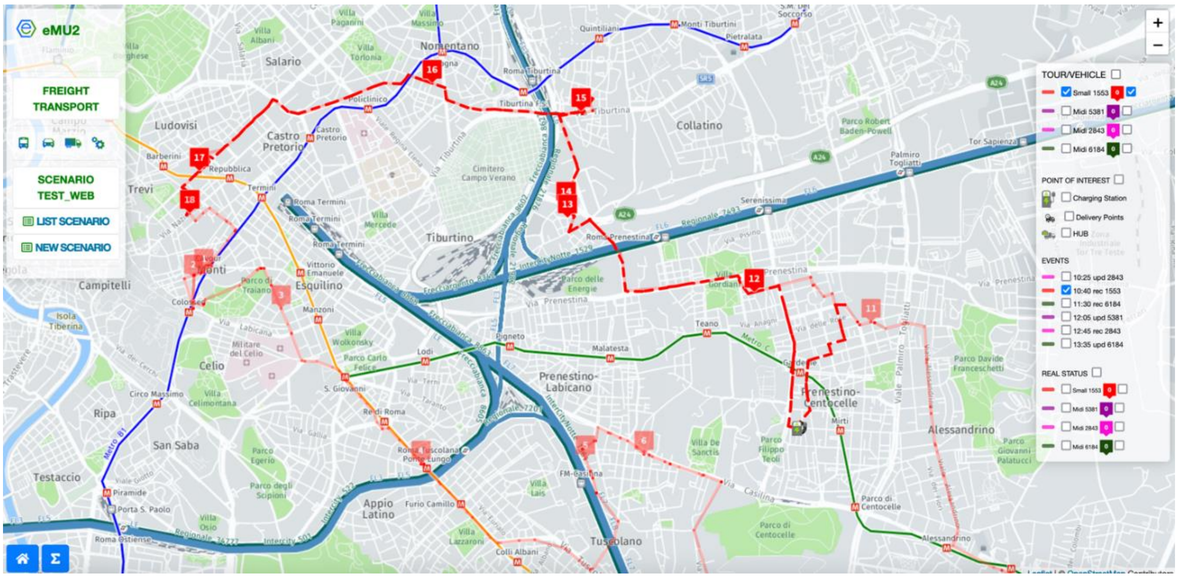

Fig.6.13 Graphical rendering of a Recovery' results, when a default in battery SOC is detected.

In Fig. 6.14 an example of Update is shown for another vehicle. The Update starts from the delivery number 18, due to an excess of delay respect to scheduled time; the path is deeply modified due to the updated speeds associated to the arcs of the graph.

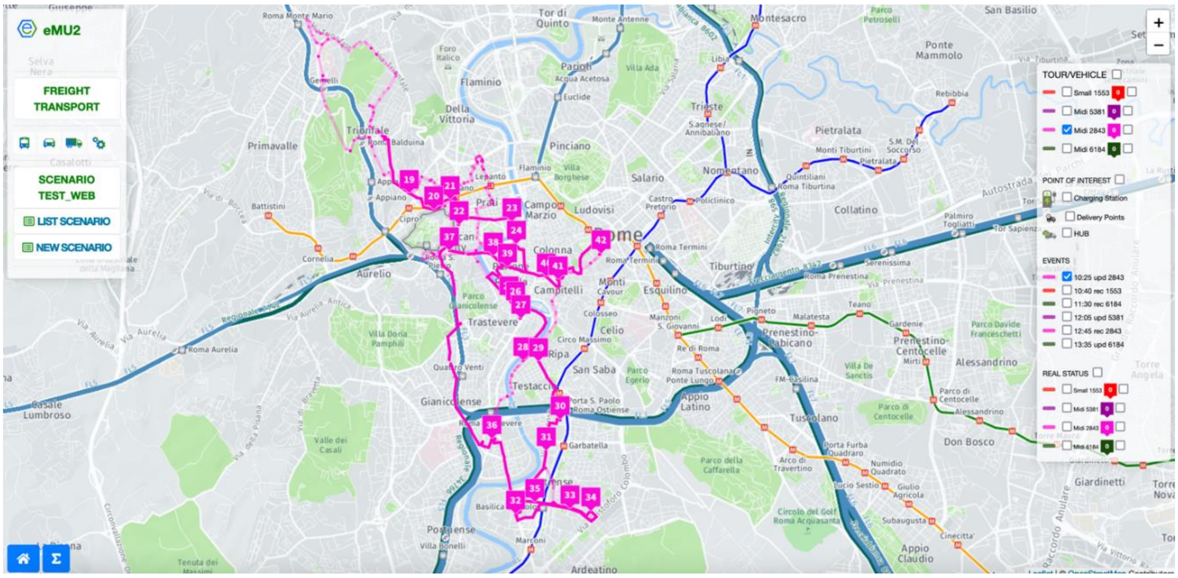

Fig.6.14 Graphical rendering of an Update' results, when a default in battery SOC is detected.

6.9. REMARKS

This paper proposes a general methodology to optimize BEVs operation in city logistics, taking into account possible recharge needs. Energy refuels are considered since the off-line delivery planning, adding a new complexity to the classic VRP with Time-Windows. Moreover, the research proposes the possibility of activating a recovery process if unexpected events, such as battery defaults or delays due to traffic congestion or other inconveniences occur, to be monitored on-field. The performance of the proposed tool has been investigated by implementing two real-size tests consisting of many delivery points and vehicles. Through the tests, different performance indicators of the initial optimization procedure have been calculated, showing a good level of results, as well as of the real-time rearrangement, both in case of additional recharge needs and delays, corresponding to the expected results.

The system is aimed at building an integrated facility to plan and handle deliveries using electric vehicles, including online monitoring of each vehicle status and of the available charging stations. All available information is handled by a central monitoring station, capable to prepare the initial planning, receive information from the field, and react to unexpected events, in order to rearrange the delivery plan to correctly fulfill the complete delivery plan.

More work needs to be performed in order to integrate the system with real acquisition of the traffic status, needed for a better evaluation of the update processes. Though, the described platform can be a good candidate for both city administrations and delivery operators. The formers in order to better plan ordinary traffic conditions and optimal handling of unexpected events, the latter to better plan and handle delivery schedules with the additional constraints related to electric vehicles and their limited autonomy.

CHAPTER 7

CONCLUSION AND SYNTHESIS CHAPTER OUTLINE

7.1. SUMMARY OF RESEARCH CONTRIBUTIONS:

The five papers in this dissertation collectively contribute to the advancement of sustainable urban logistics and waste management, employing a range of innovative methodologies and technologies to address dynamic and complex challenges. Here is a summary of the key findings and contributions from each paper:

Paper 1: Dynamic Routing in Waste Management Using Discrete Choice Modeling (DCM) And Multi-Compartment Vehicles

The first paper contributes to the optimization of waste collection through the development of a dynamic vehicle routing approach that leverages real-time data. A key innovation is the application of Discrete Choice Modeling (DCM) within the context of dynamic vehicle routing, which optimizes waste collection by responding to fluctuations in waste generation levels and transportation conditions. The introduction of multi-compartment vehicles enables efficient waste segregation during collection, reducing the need for multiple trips and enhancing compliance with waste management regulations. Additionally, the hybrid Genetic and Particle Swarm Optimization (GA-PSO) algorithm is applied to solve this complex routing problem, significantly improving operational efficiency and reducing emissions.

Paper 2: Allocation-Routing Optimization with Uncertainty Handling in Integrated Solid Waste Management (ISWM)

The second paper builds on the first by expanding the focus from dynamic routing to an integrated framework for waste collection, recycling, and recovery. The main contribution is the development of an allocation-routing optimization model that incorporates uncertainties in recycling and recovery processes, such as fluctuating market prices for recyclable materials and variable waste generation rates. Chance-constrained programming is employed to address these uncertainties, ensuring that the model produces robust and feasible solutions under different scenarios. IoT technologies enhance data collection and real-time decision-making, while facility location decisions are optimized to improve overall system efficiency. The use of advanced multi-objective metaheuristic algorithms ensures that both economic and environmental objectives are balanced.

Paper 3: Integrated IoT-Based Facility Location and Green Vehicle Routing

The third paper introduces an integrated IoT-based framework that addresses the strategic placement of waste management facilities alongside green vehicle routing optimization. It combines real-time data from IoT-equipped waste bins with strategic infrastructural decisions, such as the optimal location of separation centers for waste sorting. The study develops a multi-objective location-allocation model that minimizes costs, CO_2 emissions, and visual pollution, while improving operational efficiency through the use of green vehicles. By adopting environmentally conscious routing strategies and integrating real-time information, the paper contributes to the sustainability of urban logistics and offers a scalable solution for waste management systems.

Paper 4: Dynamic Production-Routing Optimization with Electric Vehicles and Energy Considerations

This paper shifts the focus from waste management to supply chain logistics, where it addresses the dynamic integration of production planning, inventory management, and electric vehicle routing. The mixed-integer linear programming model developed in this study synchronizes production and routing decisions, considering time-dependent traffic conditions and the limited range of electric vehicles (EVs). By incorporating energy consumption and traffic variations into the decision-making process, the model ensures that production schedules and delivery routes are optimized to reduce costs, minimize emissions, and improve supply chain efficiency. The study's use of advanced metaheuristic algorithms enhances the practical applicability of the model for large-scale, real-world scenarios.

Paper 5: Decision Support System (DSS) for Urban Deliveries with Electric Vans

The fifth paper focuses on the practical implementation of urban logistics through the development of a Decision Support System (DSS) for routing electric vans in urban delivery operations. The DSS employs an optimization simulation framework to address challenges specific to electric vehicles, such as limited range and the need for recharging. It also includes a dynamic recovery and update function that responds to real-time disruptions like traffic delays or unexpected changes in delivery schedules. By simulating urban delivery operations and incorporating real-time data through IoT technologies, the DSS ensures efficient, reliable, and sustainable delivery routes. This paper bridges the gap between theoretical models and their practical application, providing valuable tools for logistics operators and urban planners.

Together, these papers offer a comprehensive approach to sustainable urban logistics and supply chain optimization, making significant contributions in the fields of waste management, production-routing, and urban delivery with electric vehicles. Through the integration of advanced optimization techniques, IoT technology, and multi-objective decision-making frameworks, the research provides actionable insights for improving the efficiency and sustainability of urban systems.

7.2 INTEGRATION AND COHERENCE OF FINDINGS

The collection of five papers in this dissertation forms a cohesive and comprehensive body of work that advances the fields of urban logistics, waste management, and sustainable supply chains. These papers, while each addressing distinct challenges, are united by common themes such as optimization, sustainability, and technological innovation. Together, they lay the foundation for a more integrated, efficient, and sustainable approach to urban logistics.

THEMATIC CONNECTIONS

Optimization: One of the overarching themes across all five papers is optimization—whether it is optimizing waste collection routes, facility locations, production schedules, or electric vehicle routing. Optimization models and algorithms form the backbone of each study, guiding the decision-making process to achieve the most efficient and effective outcomes. In Paper 1, the dynamic routing of waste collection vehicles using a Discrete Choice Model (DCM) significantly enhances the responsiveness of logistics systems to real-time conditions. Similarly, Paper 4 integrates production planning with routing decisions to optimize supply chains, considering energy consumption and traffic-induced variations. This focus on optimization across various urban logistics applications underscores the importance of creating adaptable systems that respond to fluctuating real-world conditions.

Sustainability: Sustainability is another key theme that runs through all the studies. From waste management to urban delivery systems, each paper contributes to minimizing the environmental impact of urban logistics. Paper 3's focus on green vehicle routing and strategic facility location is a prime example of embedding environmental objectives into logistical decisions. Paper 4 addresses sustainability by integrating electric vehicles (EVs) into production-routing decisions, considering both energy consumption and traffic conditions. The use of electric vans in urban deliveries (Paper 5) further illustrates the shift toward greener logistics. Collectively, these papers emphasize the role of sustainable transportation methods, advanced waste management techniques, and energy-efficient routing strategies in reducing emissions and environmental degradation.

Technological Innovation: The papers also emphasize the role of emerging technologies in transforming urban logistics. The integration of IoT technology in Papers 2 and 3 allows for real-time data collection and decision-making, enhancing the ability to respond dynamically to urban logistics challenges. Paper 3's use of IoT-equipped bins to inform both routing and facility location decisions shows how these technologies can be applied to optimize operational and strategic processes simultaneously. Additionally, Papers 4 and 5 leverage electric vehicles, modeling their unique constraints and opportunities within urban logistics systems. Through the use of advanced algorithms, such as hybrid metaheuristics (Papers 1 and 4), and decision support systems (Paper 5), these studies showcase how technological innovation can drive efficiency and sustainability in urban logistics.

METHODOLOGICAL ADVANCES

The methodologies employed in each of the five papers complement each other, collectively contributing to the advancement of the field in several ways.

Advanced Optimization Algorithms: Across the papers, a variety of optimization methods are employed to solve complex problems involving numerous constraints and variables. Paper 1 introduces a hybrid Genetic and Particle Swarm Optimization (GA-PSO) algorithm for waste collection routing, which strikes a balance between exploration and exploitation to generate high-quality solutions. Similarly, Paper 2 introduces multi-objective metaheuristic algorithms to address uncertainty in recycling and recovery, while Paper 3 employs both exact methods and proficient metaheuristics like Social Engineering Optimization (SEO) and Keshtel algorithms to tackle the multi-objective location-allocation problem. These advanced optimization techniques, tailored to handle large-scale and NP-hard problems, reflect the cutting-edge of methodological approaches in logistics and waste management.

Handling Uncertainty: A significant methodological contribution is the handling of uncertainty, particularly in Papers 2 and 3. Paper 2 introduces chance-constrained programming to address the probabilistic nature of recycling and recovery processes, ensuring robust decision-making even under uncertain conditions. This model's capacity to handle uncertainty provides a realistic framework for dealing with fluctuating market conditions and variable waste generation rates. Paper 3 extends this approach by incorporating IoT technology, which provides real-time data to inform dynamic decisions in waste management. By embedding uncertainty into the decision-making process, these papers enhance the robustness of their proposed models and make them more applicable to real-world scenarios.

Integration of IoT and Real-Time Data: Another significant methodological advancement is the integration of IoT and real-time data into the decision-making frameworks. Papers 2, 3, and 5 emphasize the use of IoT technology to monitor waste levels, track vehicle locations, and assess facility operations in real time. This ability to react dynamically to changing conditions enhances the flexibility and responsiveness of urban logistics systems. Furthermore, the real-time recovery and update function in Paper 5's Decision Support System (DSS) exemplifies how IoT data can be used to optimize delivery routes continuously, even as disruptions occur. This approach represents a paradigm shift in logistics, from static, pre-planned operations to more fluid, data-driven decision-making processes.

TOWARD A COMPREHENSIVE FRAMEWORK FOR URBAN LOGISTICS

The collective findings of these five papers suggest a comprehensive framework for sustainable urban logistics that integrates optimization, sustainability, and technological innovation. This integrated framework can be visualized as a dynamic and adaptive system, consisting of several key components that work in synergy:

- **Dynamic Routing Optimization**: Leveraging real-time data to adjust vehicle routes based on current conditions (traffic, waste levels, energy consumption) is essential. The framework would utilize advanced algorithms, such as those introduced in Papers 1, 4, and 5, to ensure efficient and sustainable operations across urban waste management, production-routing, and delivery systems.

- **IoT-Enhanced Decision Making**: The integration of IoT technology, as demonstrated in Papers 2, 3, and 5, is crucial for providing real-time visibility and control over urban logistics. IoT-enabled waste bins, delivery vehicles, and charging stations can continuously feed data into optimization algorithms, allowing for dynamic adjustments to routes, schedules, and facility allocations.

- **Sustainable Facility Location and Allocation**: The strategic placement of facilities, such as recycling centers or distribution hubs, significantly impacts the efficiency of logistics systems. Papers 2 and 3 highlight the importance of incorporating environmental and social factors (such as CO_2 emissions and visual pollution) into facility location decisions. This integrated framework would propose multi-objective models that optimize facility placement based on real-time operational needs and sustainability goals.

- **Electric Vehicle Integration and Energy Management**: Electric vehicles are a key component of sustainable urban logistics, and their integration into routing and delivery decisions is critical, as highlighted in Papers 4 and 5. The proposed framework would optimize EV routing by considering time-dependent traffic conditions, energy consumption, and recharging logistics, ensuring that EVs are used within their operational constraints while minimizing emissions.

- **Handling Uncertainty and Flexibility**: A comprehensive urban logistics system must be resilient in the face of uncertainty. Papers 2 and 3 demonstrate robust methodologies for handling uncertain conditions, particularly in recycling and waste management operations. By incorporating chance-constrained programming and real-time data, the framework ensures that logistical decisions remain robust and adaptable under fluctuating conditions.

In conclusion, the integration of these components into a unified framework provides a holistic approach to urban logistics that addresses the critical challenges of efficiency, sustainability, and technological advancement. This framework not only enhances operational performance but also aligns with broader environmental and social objectives, contributing to the development of smarter, cleaner, and more livable cities.

7.3 LIMITATIONS OF THE RESEARCH

While this dissertation makes significant contributions to the fields of urban logistics, waste management, and sustainable supply chains, there are several limitations that should be acknowledged to provide a balanced perspective on the research findings.

SCOPE LIMITATIONS

One of the primary limitations of this research relates to the scope of the case studies and datasets used in the various papers. The models and algorithms developed throughout the research were primarily tested using specific datasets that may not fully represent the diversity of real-world urban logistics environments. For example, the models for waste collection and production-routing were validated using synthetic or limited real-world data, which may not account for the full range of variations that can occur in different geographic regions or logistical scenarios. Additionally, while the studies introduce IoT-based solutions and electric vehicles, the infrastructure for deploying such technologies is not universally available, potentially limiting the generalizability of the proposed frameworks in regions where such technological adoption is low.

Another scope limitation lies in the narrow focus on specific urban logistics applications. The research focuses predominantly on waste management and urban deliveries, leaving out other critical areas of urban logistics, such as public transportation or emergency services logistics, which could benefit from similar optimization and technological integration. While the proposed methodologies can likely be adapted to other domains, this dissertation does not explicitly explore those applications.

TECHNICAL CHALLENGES

Throughout the research, significant technical challenges were encountered, particularly in the areas of computational complexity and algorithm scalability. The optimization problems addressed in this research, such as the dynamic vehicle routing problem (Papers 1 and 5) and the multi-period production-routing problem with electric vehicles (Paper 4), are NP-hard problems, meaning that they become computationally intractable as the problem size increases. While hybrid metaheuristic algorithms, such as Genetic and Particle Swarm Optimization (GA-PSO) and Social Engineering Optimization (SEO), were developed to provide high-quality solutions within reasonable timeframes, these algorithms still face limitations when applied to large-scale, real-world scenarios. The trade-offs between solution accuracy and computational time pose challenges for real-time applications, particularly in dynamic urban environments where conditions change rapidly.

Another technical challenge involves the data integration needed for real-time decision-making. In Papers 2 and 3, IoT technology plays a critical role in collecting real-time data to inform facility location decisions and dynamic routing. However, the seamless integration of real-time data from various sources (such as waste bins, vehicles, and traffic systems) into optimization algorithms remains a challenge, especially in environments with incomplete or unreliable data streams. Ensuring that the data are accurate, timely, and relevant is essential for maintaining the efficacy of the proposed models, and any gaps in data collection could affect the robustness of the solutions.

GENERALIZABILITY

The generalizability of the research findings is another area of potential limitation. Although the models and algorithms developed in this dissertation provide valuable insights for urban logistics, their effectiveness may vary depending on local conditions, such as infrastructure availability, regulatory environments, and economic factors. For example, the electric vehicle (EV)-based solutions proposed in Papers 4 and 5 may not be as feasible in regions where EV infrastructure, such as charging stations, is underdeveloped. Similarly, the waste management models may need to be adapted to local waste generation patterns and recycling capabilities, which differ significantly across cities and countries. The adaptability of these models to different urban contexts warrants further investigation and testing. In summary, while the research offers innovative solutions and makes substantial contributions to the fields of urban logistics and waste management, it is important to recognize the limitations related to scope, computational complexity, data integration, and generalizability. Addressing these limitations in future research will be critical to expanding the practical application of these findings across diverse urban environments.

7.4 FUTURE RESEARCH DIRECTIONS

The research presented in this dissertation offers substantial advancements in the fields of urban logistics, waste management, and sustainable supply chains. However, there remain several opportunities for further research, particularly in stochastic dynamic problems and the exploration of sequential decision-making approaches. These directions can help address some of the limitations and open new avenues for improving the adaptability and robustness of the models and solutions proposed in this dissertation. This section outlines potential areas for future research related to each of the five papers and overall extensions that can enhance the research framework.

- **Stochastic Dynamic Optimization for Waste Management (Papers 1 and 2)**

In Papers 1 and 2, dynamic routing and allocation-routing models were proposed for waste management. Both studies incorporate optimization under fluctuating conditions, but further research is needed to extend these models to fully account for stochastic dynamics. Currently, the models consider real-time data to adapt routes and facility allocations. However, they do not fully integrate the inherent randomness in variables such as waste generation rates, transportation conditions, and recycling market prices.

Future research could focus on the development of stochastic dynamic programming models that explicitly capture uncertainties over time. This would enable the system to make more adaptive decisions as new information becomes available. For example, a waste collection model could use real-time IoT data to continuously update the probability distributions of waste levels and adjust routing decisions dynamically. Stochastic models that allow for continuous re-optimization could be designed using sequential decision-making frameworks, such as Markov Decision Processes (MDPs) or Partially Observable Markov Decision Processes (POMDPs), to better handle the uncertainty in urban environments.

Moreover, introducing reinforcement learning (RL) techniques could provide new pathways for optimizing the routing of waste collection vehicles over time. RL could be particularly useful in environments where the state of the system (e.g., waste levels or traffic conditions) evolves stochastically, and decisions must be adjusted in real time to improve overall performance. In these scenarios, the system could learn from past experiences and improve its routing and allocation decisions over time, even in the face of uncertain and changing conditions.

- **Sequential Decision Making in Facility Location and Routing (Paper 3)**

Paper 3 addresses the strategic placement of waste management facilities in combination with green vehicle routing, leveraging real-time IoT data. While the study proposes a robust facility location-allocation model, future research should explore stochastic facility location models that account for uncertainties in demand, waste generation, and transportation conditions.

A promising direction would be to integrate sequential decision-making into the facility location process. Instead of making all facility location decisions upfront, future models could adopt a multi-stage approach, where decisions are revisited periodically as new data are collected. This dynamic approach could allow for the expansion, closure, or relocation of facilities based on changing urban conditions or shifts in demand. Such a model could be formulated using stochastic programming or dynamic facility location models, where the placement of facilities evolves in response to uncertain future conditions. Additionally, introducing real options analysis could provide a framework for making flexible decisions regarding facility investments under uncertainty.

Moreover, the integration of vehicle routing with facility location under a stochastic dynamic framework presents a compelling research challenge. Future research could focus on the joint optimization of facility location and vehicle routing under stochastic demand and uncertain travel times, extending beyond the deterministic models currently employed. This would involve continuously updating both the routing strategies and the locations of key facilities in response to evolving urban logistics demands and real-time data streams.

- **Stochastic Production-Routing Models with Electric Vehicles (Paper 4)**

In Paper 4, a multi-period dynamic production-routing problem is presented, integrating production planning with electric vehicle routing while considering energy constraints and traffic conditions. While the model incorporates traffic fluctuations and electric vehicle limitations, it does not fully address the stochastic nature of demand, production capacities, or energy consumption.

Future research could focus on stochastic dynamic production-routing models where demand and production schedules are uncertain. Such models would allow decision-makers to adjust production and routing plans over time, based on real-time updates about customer demand, vehicle battery levels, and traffic conditions. Sequential decision-making models, such as those based on multi-stage stochastic programming, could enable the integration of uncertain future outcomes into today's decisions. This would ensure that production and delivery schedules are optimized not just for the current state but also for anticipated future states.

Incorporating stochastic energy consumption models is another potential direction. Given that electric vehicles are highly sensitive to factors like traffic congestion, vehicle load, and route distance, future research could develop stochastic models that predict energy consumption under various scenarios. This would allow for more precise planning of recharging schedules and routing decisions, reducing the risk of vehicles running out of battery during deliveries.

Another promising area is dynamic pricing and incentive mechanisms for electric vehicle routing. Stochastic models could explore how variable pricing for electricity (based on time-of-use rates) and incentive mechanisms (like rewards for charging during off-peak hours) could be integrated into production-routing decisions to further optimize cost and energy efficiency.

- **Real-Time Urban Delivery Optimization with Electric Vans (Paper 5)**

Paper 5 focuses on a Decision Support System (DSS) for optimizing urban deliveries using electric vans, with particular attention to real-time updates and recovery mechanisms. While the current model addresses dynamic routing, further research could explore stochastic routing under uncertain delivery demand and battery performance.

Future studies could investigate stochastic vehicle routing problems (SVRP) that explicitly model uncertain factors such as delivery demand variations, customer availability, and recharging station occupancy. A sequential decision-making approach could enable the system to continuously update delivery routes based on the latest information. This could be achieved through dynamic programming or approximate dynamic programming (ADP) methods, which offer more efficient solutions to large-scale, real-time decision-making problems in urban delivery contexts.

Another future direction is the integration of predictive analytics into the DSS. By predicting potential disruptions—such as traffic congestion, road closures, or charging station unavailability—the DSS could proactively adjust routes and recharging schedules in real time. Predictive models using machine learning techniques could be incorporated into the DSS to anticipate future conditions and optimize routes accordingly. Coupling these predictions with stochastic models would allow the system to not only react to current conditions but also plan for anticipated changes in the urban environment.

- **General Future Directions: Stochastic Models and Sequential Decision Making**

Across all the studies, the incorporation of stochastic modeling and sequential decision-making approaches represents a critical future direction. As urban logistics systems become more complex and dynamic, decision-makers must be equipped to handle uncertainties in demand, supply, energy usage, and environmental conditions. By adopting sequential decision-making frameworks, such as Markov Decision Processes (MDPs), stochastic dynamic programming, or reinforcement learning (RL), future research can create models that evolve and learn over time. These models would provide more adaptive and resilient solutions, allowing urban logistics systems to respond proactively to unforeseen events and uncertainties. Another key future direction involves expanding the focus to include multi-agent systems and collaborative logistics. Given the increasing complexity of urban systems, future research could explore cooperative game theory or agent-based modeling approaches, where multiple stakeholders—such as municipal authorities, private companies, and logistics providers—collaborate to achieve common sustainability and efficiency goals in a stochastic dynamic environment.

In summary, while this dissertation makes significant contributions to sustainable urban logistics, further research into stochastic dynamic problems and sequential decision-making approaches is essential to fully realize the potential of the proposed models and frameworks. These future research directions will help enhance the adaptability, robustness, and scalability of urban logistics systems, enabling them to respond more effectively to the uncertainties inherent in real-world applications.

7.5 CONCLUDING

This dissertation has explored the intricate challenges and opportunities in optimizing urban logistics, with a focus on sustainability, waste management, and the integration of advanced technologies. The research has demonstrated that using dynamic routing models, IoT technology, electric vehicles, and sophisticated optimization algorithms, significant improvements can be made in the efficiency, environmental impact, and overall performance of urban logistics systems.

At the core of this research lies the critical importance of optimizing urban logistics in the face of rapid urbanization, environmental degradation, and increasing demand for efficient supply chains. Urban logistics systems are vital to the functioning of modern cities, influencing everything from the delivery of goods and services to the management of waste. However, traditional models and systems are no longer sufficient to address the complexity and dynamism of modern urban environments. The increasing emphasis on sustainability—driven by both environmental regulations and public expectations—requires innovative approaches that reduce emissions, minimize energy consumption, and optimize resource use. By optimizing urban logistics through data-driven, technology-enhanced models, cities can achieve a more sustainable balance between economic growth and environmental stewardship.

This dissertation underscores the value of advanced optimization techniques in addressing these challenges. Whether it is the dynamic routing of waste collection vehicles, the integration of facility location decisions with green logistics, or the synchronization of production schedules with electric vehicle routing, optimization plays a central role in ensuring that urban systems operate efficiently and sustainably. Furthermore, the inclusion of stochastic models and uncertainty handling enhances the robustness of these solutions, making them more adaptable to the unpredictable nature of real-world logistics operations.

Looking forward, this research offers a vision of smarter, greener cities where urban logistics systems are fully integrated with the latest technological advancements. The use of IoT technology and real-time data to inform logistics decisions will be pivotal in creating adaptive, responsive systems that can react dynamically to fluctuations in demand, traffic, and environmental conditions. Smart cities will leverage this data to optimize not only the flow of goods and services but also the management of resources, waste, and energy.

Electric vehicles (EVs) will continue to play a crucial role in this transformation, offering a cleaner, more energy-efficient alternative to traditional combustion engines. The models and frameworks proposed in this dissertation lay the groundwork for optimizing EV routing, ensuring that these vehicles can be deployed efficiently even within the constraints of battery capacity and charging infrastructure. In the long term, as electric vehicle technology continues to improve, logistics systems will become even more sustainable, with reduced reliance on fossil fuels and lower overall emissions. The future of urban logistics is one of integration and innovation, where technologies such as the Internet of Things (IoT), machine learning, and advanced optimization algorithms work in concert to create logistics systems that are not only efficient but also environmentally responsible. By embracing these technologies, cities can significantly reduce their carbon footprint, improve the quality of life for residents, and contribute to global efforts to combat climate change.

In conclusion, this dissertation contributes to the growing body of knowledge on sustainable urban logistics by providing practical solutions for waste management, production-routing, and urban delivery systems. The research highlights the potential of technological innovation to drive significant improvements in urban sustainability, offering a roadmap for future developments in smart city logistics. As cities continue to evolve and face increasing environmental pressures, the integration of advanced optimization models, real-time data, and green technologies will be essential for building smarter, cleaner, and more resilient urban environments.

REFERENCES:

Abdallah, M., Adghim, M., Maraqa, M., & Aldahab, E. (2019). Simulation and optimization of dynamic waste collection routes. *Waste Management & Research : The Journal of the International Solid Wastes and Public Cleansing Association, ISWA*, *37*(8), 793–802. https://doi.org/10.1177/0734242X19833152

Abdel-Shafy, H. I., & Mansour, M. S. M. (2018). Solid waste issue: Sources, composition, disposal, recycling, and valorization. *Egyptian Journal of Petroleum*, *27*(4), 1275–1290. https://doi.org/10.1016/J.EJPE.2018.07.003

Abdi, A., Abdi, A., Fathollahi-Fard, A. M., & Hajiaghaei-Keshteli, M. (2019). A set of calibrated metaheuristics to address a closed-loop supply chain network design problem under uncertainty. *Https://Doi.Org/10.1080/23302674.2019.1610197*, *8*(1), 23–40. https://doi.org/10.1080/23302674.2019.1610197

Abdirad, M., Krishnan, K., & Gupta, D. (2021). A two-stage metaheuristic algorithm for the dynamic vehicle routing problem in Industry 4.0 approach. *Journal of Management Analytics*, *8*(1), 69–83. https://doi.org/10.1080/23270012.2020.1811166

Akbarpour, N., Salehi-Amiri, A., Hajiaghaei-Keshteli, M., & Oliva, D. (2021a). An innovative waste management system in a smart city under stochastic optimization using vehicle routing problem. *Soft Computing*, *25*(8), 6707–6727. https://doi.org/10.1007/S00500-021-05669-6/FIGURES/10

Ali, T., Irfan, M., Alwadie, A. S., & Glowacz, A. (2020). IoT-Based Smart Waste Bin Monitoring and Municipal Solid Waste Management System for Smart Cities. *Arabian Journal for Science and Engineering*, *45*(12), 10185–10198. https://doi.org/10.1007/S13369-020-04637-W/TABLES/7

Alumur, S. A., Campbell, J. F., Contreras, I., Kara, B. Y., Marianov, V., & O'Kelly, M. E. (2021). Perspectives on modeling hub location problems. *European Journal of Operational Research*, *291*(1), 1–17. https://doi.org/10.1016/J.EJOR.2020.09.039

Anagnostopoulos, T., Kolomvatsos, K., Anagnostopoulos, C., Zaslavsky, A., & Hadjiefthymiades, S. (2015). Assessing dynamic models for high priority waste collection in smart cities. *Journal of Systems and Software*, *110*, 178–192. https://doi.org/10.1016/j.jss.2015.08.049

Archetti, C., Guerriero, F., & Macrina, G. (2021). The online vehicle routing problem with occasional drivers. *Computers & Operations Research*, *127*, 105144. https://doi.org/10.1016/J.COR.2020.105144

Armentano, V. A., Shiguemoto, A. L., & Løkketangen, A. (2011). Tabu search with path relinking for an integrated production–distribution problem. *Computers & Operations Research*, *38*(8), 1199–1209. https://doi.org/10.1016/J.COR.2010.10.026

Asefi, H., Shahparvari, S., & Chhetri, P. (2019). Integrated Municipal Solid Waste Management under uncertainty: A tri-echelon city logistics and transportation context. *Sustainable Cities and Society*, *50*, 101606. https://doi.org/10.1016/J.SCS.2019.101606

Asih, A. M. S., Sopha, B. M., & Kriptaniadewa, G. (2017). Comparison study of metaheuristics: Empirical application of delivery problems. *Https://Doi.Org/10.1177/1847979017743603*, *9*. https://doi.org/10.1177/1847979017743603

Aytaç, K., & Korçak, Ö. (2021). IoT based intelligence for proactive waste management in Quick Service Restaurants. *Journal of Cleaner Production*, *284*, 125401. https://doi.org/10.1016/J.JCLEPRO.2020.125401

Babaee Tirkolaee, E., Mahdavi, I., Seyyed Esfahani, M. M., & Weber, G. W. (2020a). A hybrid augmented ant colony optimization for the multi-trip capacitated arc routing problem under fuzzy demands for urban solid waste management. *Waste Management & Research : The Journal of the International Solid Wastes and Public Cleansing Association, ISWA*, *38*(2), 156–172. https://doi.org/10.1177/0734242X19865782

Bahadori-Chinibelagh, S., Fathollahi-Fard, A. M., & Hajiaghaei-Keshteli, M. (2022). Two Constructive Algorithms to Address a Multi-Depot Home Healthcare Routing Problem. *IETE Journal of Research*, *68*(2), 1108–1114. https://doi.org/10.1080/03772063.2019.1642802

Baker, B. M., & Ayechew, M. A. (2003). A genetic algorithm for the vehicle routing problem. *Computers & Operations Research*, *30*(5), 787–800. https://doi.org/10.1016/S0305-0548(02)00051-5

Balseiro, S. R., Loiseau, I., & Ramonet, J. (2011). An Ant Colony algorithm hybridized with insertion heuristics for the Time Dependent Vehicle Routing Problem with Time Windows. *Computers & Operations Research*, *38*(6), 954–966. https://doi.org/10.1016/J.COR.2010.10.011

Baños, R., Manzano-Agugliaro, F., Montoya, F. G., Gil, C., Alcayde, A., & Gómez, J. (2011). Optimization methods applied to renewable and sustainable energy: A review. *Renewable and Sustainable Energy Reviews*, *15*(4), 1753–1766. https://doi.org/10.1016/J.RSER.2010.12.008

Bartz-Beielstein, T., & Markon, S. (2004). Tuning search algorithms for real-world applications: A regression tree based approach. *Proceedings of the 2004 Congress on Evolutionary Computation, CEC2004*, *1*, 1111–1118. https://doi.org/10.1109/CEC.2004.1330986

Bavar, A., Bavar, A., Gholian-Jouybari, F., Hajiaghaei-Keshteli, M., & Mejía-Argueta, C. (2023). Developing new heuristics and hybrid meta-heuristics to address the bi-objective home health care problem. *Central European Journal of Operations Research*, 1–57. https://doi.org/10.1007/S10100-023-00862-4/TABLES/12

Behnamian, J., Fatemi Ghomi, S. M. T., & Zandieh, M. (2009). A multi-phase covering Pareto-optimal front method to multi-objective scheduling in a realistic hybrid flowshop using a hybrid metaheuristic. *Expert Systems with Applications*, *36*(8), 11057–11069. https://doi.org/10.1016/J.ESWA.2009.02.080

Bektaş, T., & Laporte, G. (2011). The Pollution-Routing Problem. *Transportation Research Part B: Methodological*, *45*(8), 1232–1250. https://doi.org/10.1016/J.TRB.2011.02.004

Bello, A. S., Al-Ghouti, M. A., & Abu-Dieyeh, M. H. (2022). Sustainable and long-term management of municipal solid waste: A review. *Bioresource Technology Reports*, *18*, 101067. https://doi.org/10.1016/J.BITEB.2022.101067

Berghman, L., Kergosien, Y., & Billaut, J.-C. (2023). A review on integrated scheduling and outbound vehicle routing problems. *European Journal of Operational Research*. https://doi.org/10.1016/J.EJOR.2022.12.036

Bertsimas, D., Brown, D. B., & Caramanis, C. (2011). Theory and Applications of Robust Optimization. *Https://Doi.Org/10.1137/080734510*, *53*(3), 464–501. https://doi.org/10.1137/080734510

Bibri, S. E. (2018). A foundational framework for smart sustainable city development: Theoretical, disciplinary, and discursive dimensions and their synergies. *Sustainable Cities and Society*, *38*, 758–794. https://doi.org/10.1016/j.scs.2017.12.032

Boudia, M., Louly, M. A. O., & Prins, C. (2007). A reactive GRASP and path relinking for a combined production–distribution problem. *Computers & Operations Research*, *34*(11), 3402–3419. https://doi.org/10.1016/J.COR.2006.02.005

Boussaïd, I., Lepagnot, J., & Siarry, P. (2013). A survey on optimization metaheuristics. *Information Sciences*, *237*, 82–117. https://doi.org/10.1016/J.INS.2013.02.041

Braekers, K., Ramaekers, K., & Van Nieuwenhuyse, I. (2016). The vehicle routing problem: State of the art classification and review. *Computers & Industrial Engineering*, *99*, 300–313. https://doi.org/10.1016/J.CIE.2015.12.007

Cascetta, E. (2009). *Random Utility Theory*. 89–167. https://doi.org/10.1007/978-0-387-75857-2_3

Çevik, A., Weber, G. W., Eyüboğlu, B. M., & Oğuz, K. K. (2017). Voxel-MARS: a method for early detection of Alzheimer's disease by classification of structural brain MRI. *Annals of Operations Research*, *258*(1), 31–57. https://doi.org/10.1007/S10479-017-2405-7/FIGURES/8

Chand Malav, L., Yadav, K. K., Gupta, N., Kumar, S., Sharma, G. K., Krishnan, S., Rezania, S., Kamyab, H., Pham, Q. B., Yadav, S., Bhattacharyya, S., Yadav, V. K., & Bach, Q. V. (2020). A review on municipal solid waste as a renewable source for waste-to-energy project in India: Current practices, challenges, and future opportunities. *Journal of Cleaner Production*, *277*, 123227. https://doi.org/10.1016/J.JCLEPRO.2020.123227

Chen, C., Wen, Z., Wang, Y., Zhang, W., & Zhang, T. (2022). Multi-objective optimization of technology solutions in municipal solid waste treatment system coupled with pollutants cross-media metabolism issues. *Science of The Total Environment*, *807*, 150664. https://doi.org/10.1016/J.SCITOTENV.2021.150664

Chen, J., Dan, B., & Shi, J. (2020). A variable neighborhood search approach for the multi-compartment vehicle routing problem with time windows considering carbon emission. *Journal of Cleaner Production*, *277*, 123932. https://doi.org/10.1016/J.JCLEPRO.2020.123932

Chen, S., Chen, R., Wang, G. G., Gao, J., & Sangaiah, A. K. (2018). An adaptive large neighborhood search heuristic for dynamic vehicle routing problems. *Computers & Electrical Engineering*, *67*, 596–607. https://doi.org/10.1016/J.COMPELECENG.2018.02.049

Chen, X., Feng, L., & Soon Ong, Y. (2012). A self-adaptive memeplexes robust search scheme for solving stochastic demands vehicle routing problem. *International Journal of Systems Science*, *43*(7), 1347–1366. https://doi.org/10.1080/00207721.2011.618646

Cheng, C., Zhang, L., & Thompson, R. G. (2018a). Disaster waste clean-up system performance subject to time-dependent disaster waste accumulation. *Natural Hazards*, *91*(2), 717–734. https://doi.org/10.1007/S11069-017-3151-5/TABLES/3

Cheng, C., Zhang, L., & Thompson, R. G. (2018b). Reliability analysis for disaster waste management systems. *Waste Management*, *78*, 31–42. https://doi.org/10.1016/J.WASMAN.2018.05.011

Cheng, C., Zhang, L., & Thompson, R. G. (2019). Reliability analysis of road networks in disaster waste management. *Waste Management*, *84*, 383–393. https://doi.org/10.1016/J.WASMAN.2018.11.027

Cheng, C., Zhu, R., Thompson, R. G., & Zhang, L. (2021). Reliability analysis for multiple-stage solid waste management systems. *Waste Management*, *120*, 650–658. https://doi.org/10.1016/J.WASMAN.2020.10.035

Cheraghalipour, A., Hajiaghaei-Keshteli, M., & Paydar, M. M. (2018). Tree Growth Algorithm (TGA): A novel approach for solving optimization problems. *Engineering Applications of Artificial Intelligence*, *72*, 393–414. https://doi.org/10.1016/J.ENGAPPAI.2018.04.021

Cheraghalipour, A., Paydar, M. M., & Hajiaghaei-Keshteli, M. (2017). An Integrated Approach for Collection Center Selection in Reverse Logistics. *International Journal of Engineering*, *30*(7), 1005–1016. https://doi.org/10.5829/ije.2017.30.07a.10

Cheraghalipour, A., Paydar, M. M., & Hajiaghaei-Keshteli, M. (2018). A bi-objective optimization for citrus closed-loop supply chain using Pareto-based algorithms. *Applied Soft Computing Journal*, *69*, 33–59. https://doi.org/10.1016/J.ASOC.2018.04.022

Chouhan, V. K., Khan, S. H., & Hajiaghaei-Keshteli, M. (2021a). Metaheuristic approaches to design and address multi-echelon sugarcane closed-loop supply chain network. *Soft Computing*, *25*(16), 11377–11404. https://doi.org/10.1007/S00500-021-05943-7

Chouhan, V. K., Khan, S. H., & Hajiaghaei-Keshteli, M. (2022). Sustainable planning and decision-making model for sugarcane mills considering environmental issues. *Journal of Environmental Management*, *303*, 114252. https://doi.org/10.1016/J.JENVMAN.2021.114252

Colombaroni, C., Mohammadi, M., & Rahmanifar, G. (2020). Makespan minimizing on multiple travel salesman problem with a learning effect of visiting time. *WSEAS Transactions on Systems and Control*, *15*, 508–526. https://doi.org/10.37394/23203.2020.15.50

da Silva Júnior, O. S., Leal, J. E., & Reimann, M. (2021). A multiple ant colony system with random variable neighborhood descent for the dynamic vehicle routing problem with time windows. *Soft Computing*, *25*(4), 2935–2948. https://doi.org/10.1007/S00500-020-05350-4

Dabia, S., Ropke, S., van Woensel, T., & de Kok, T. (2013). Branch and price for the time-dependent vehicle routing problem with time windows. *Transportation Science*, *47*(3), 380–396. https://doi.org/10.1287/TRSC.1120.0445

Darvish, M., Archetti, C., & Coelho, L. C. (2019). Trade-offs between environmental and economic performance in production and inventory-routing problems. *International Journal of Production Economics*, *217*, 269–280. https://doi.org/10.1016/J.IJPE.2018.08.020

Das, S. K., Pervin, M., Roy, S. K., & Weber, G. W. (2021). Multi-objective solid transportation-location problem with variable carbon emission in inventory management: a hybrid approach. *Annals of Operations Research*, 1–27. https://doi.org/10.1007/S10479-020-03809-Z/TABLES/14

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, *6*(2), 182–197. https://doi.org/10.1109/4235.996017

di Maria, F., Sisani, F., Contini, S., Ghosh, S. K., & Mersky, R. L. (2020). Is the policy of the European Union in waste management sustainable? An assessment of the Italian context. *Waste Management*, *103*, 437–448. https://doi.org/10.1016/J.WASMAN.2020.01.005

Dubey, S., Singh, P., Yadav, P., & Singh, K. K. (2020). Household Waste Management System Using IoT and Machine Learning. *Procedia Computer Science*, *167*, 1950–1959. https://doi.org/10.1016/J.PROCS.2020.03.222

Eglese, R., Maden, W., & Slater, A. (2006). A Road TimetableTM to aid vehicle routing and scheduling. *Computers and Operations Research*, *33*(12), 3508–3519. https://doi.org/10.1016/J.COR.2005.03.029

Elgharably, N., Easa, S., Nassef, A., & el Damatty, A. (2022). Stochastic Multi-Objective Vehicle Routing Model in Green Environment With Customer Satisfaction. *IEEE Transactions on Intelligent Transportation Systems*, 1–19. https://doi.org/10.1109/TITS.2022.3156685

Eligüzel, İ. M., Özceylan, E., & Weber, G. W. (2022). Location-allocation analysis of humanitarian distribution plans: a case of United Nations Humanitarian Response Depots. *Annals of Operations Research*, 1–30. https://doi.org/10.1007/S10479-022-04886-Y/TABLES/12

Elshaer, R., & Awad, H. (2020). A taxonomic review of metaheuristic algorithms for solving the vehicle routing problem and its variants. *Computers & Industrial Engineering*, *140*, 106242. https://doi.org/10.1016/J.CIE.2019.106242

Erdem, M. (2022). Optimisation of sustainable urban recycling waste collection and routing with heterogeneous electric vehicles. *Sustainable Cities and Society*, *80*, 103785. https://doi.org/10.1016/J.SCS.2022.103785

Eshtehadi, R., Demir, E., & Huang, Y. (2020). Solving the vehicle routing problem with multi-compartment vehicles for city logistics. *Computers & Operations Research*, *115*, 104859. https://doi.org/10.1016/J.COR.2019.104859

Euchi, J., Yassine, A., & Chabchoub, H. (2015). The dynamic vehicle routing problem: Solution with hybrid metaheuristic approach. *Swarm and Evolutionary Computation*, *21*, 41–53. https://doi.org/10.1016/J.SWEVO.2014.12.003

Expósito-Márquez, A., Expósito-Izquierdo, C., Brito-Santana, J., & Moreno-Pérez, J. A. (2019). Greedy randomized adaptive search procedure to design waste collection routes in La Palma. *Computers & Industrial Engineering*, *137*, 106047. https://doi.org/10.1016/J.CIE.2019.106047

Faccio, M., Persona, A., & Zanin, G. (2011). Waste collection multi objective model with real time traceability data. *Waste Management*, *31*(12), 2391–2405. https://doi.org/10.1016/J.WASMAN.2011.07.005

Fasihi, M., Tavakkoli-Moghaddam, R., Najafi, S. E., & Hajiaghaei-Keshteli, M. (2021). Optimizing a bi-objective multi-period fish closed-loop supply chain network design by three multi-objective meta-heuristic algorithms. *Scientia Iranica*, *0*. https://doi.org/10.24200/SCI.2021.57930.5477

Fateme Attar, S., Mohammadi, M., Reza Pasandideh, S. H., & Naderi, B. (2022). Formulation and exact algorithms for electric vehicle production routing problem. *Expert Systems with Applications*, *204*, 117292. https://doi.org/10.1016/J.ESWA.2022.117292

Fathollahi-Fard, A. M., Hajiaghaei-Keshteli, M., & Tavakkoli-Moghaddam, R. (2018). The Social Engineering Optimizer (SEO). *Engineering Applications of Artificial Intelligence*, *72*, 267–293. https://doi.org/10.1016/J.ENGAPPAI.2018.04.009

Feng, W., & Figliozzi, M. (2013). An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: A case study from the USA market. *Transportation Research Part C: Emerging Technologies*, *26*, 135–145. https://doi.org/10.1016/J.TRC.2012.06.007

Ferrucci, F., & Bock, S. (2015a). A general approach for controlling vehicle en-route diversions in dynamic vehicle routing problems. *Transportation Research Part B: Methodological*, *77*, 76–87. https://doi.org/10.1016/J.TRB.2015.03.003

Ferrucci, F., & Bock, S. (2016). Pro-active real-time routing in applications with multiple request patterns. *European Journal of Operational Research*, *253*(2), 356–371. https://doi.org/10.1016/J.EJOR.2016.02.016

Ferrucci, F., Bock, S., & Gendreau, M. (2013). A pro-active real-time control approach for dynamic vehicle routing problems dealing with the delivery of urgent goods. *European Journal of Operational Research*, *225*(1), 130–141. https://doi.org/10.1016/J.EJOR.2012.09.016

Fleischmann, B., Gietz, M., & Gnutzmann, S. (2004). Time-varying travel times in vehicle routing. *Transportation Science*, *38*(2), 160–173. https://doi.org/10.1287/TRSC.1030.0062

Fogarassy, C., Hoang, N. H., & Nagy-Pércsi, K. (2022). Composting Strategy Instead of Waste-to-Energy in the Urban Context—A Case Study from Ho Chi Minh City, Vietnam. *Applied Sciences 2022, Vol. 12, Page 2218*, *12*(4), 2218. https://doi.org/10.3390/APP12042218

Frohner, N., Horn, M., & Raidl, G. R. (2021). Route Duration Prediction in a Stochastic and Dynamic Vehicle Routing Problem with Short Delivery Deadlines. *Procedia Computer Science*, *180*, 366–370. https://doi.org/10.1016/J.PROCS.2021.01.175

Fujdiak, R., Masek, P., Mlynek, P., Misurec, J., & Olshannikova, E. (2016a, September 21). Using genetic algorithm for advanced municipal waste collection in Smart City. *2016 10th International Symposium on Communication Systems, Networks and Digital Signal Processing, CSNDSP 2016*. https://doi.org/10.1109/CSNDSP.2016.7574016

Fumero, F., & Vercellis, C. (1999). Synchronized Development of Production, Inventory, and Distribution Schedules. *Https://Doi.Org/10.1287/Trsc.33.3.330*, *33*(3), 330–340. https://doi.org/10.1287/TRSC.33.3.330

Geetha, S., Poonthalir, G., & Vanathi, P. T. (2013). Nested particle swarm optimisation for multi-depot vehicle routing problem. *International Journal of Operational Research*, *16*(3), 329–348. https://doi.org/10.1504/IJOR.2013.052336

Gendreau, M. (2003). An Introduction to Tabu Search. *Handbook of Metaheuristics*, 37–54. https://doi.org/10.1007/0-306-48056-5_2

Gendreau, M., Potvin, J. Y., Bräysy, O., Hasle, G., & Løkketangen, A. (2008). Metaheuristics for the vehicle routing problem and its extensions: A categorized bibliography. *Operations Research/ Computer Science Interfaces Series*, *43*, 143–169. https://doi.org/10.1007/978-0-387-77778-8_7/COVER

Ghannadpour, S. F., Zandieh, F., & Esmaeili, F. (2021). Optimizing triple bottom-line objectives for sustainable health-care waste collection and routing by a self-adaptive evolutionary algorithm: A case study from tehran province in Iran. *Journal of Cleaner Production*, *287*, 125010. https://doi.org/10.1016/J.JCLEPRO.2020.125010

Gholami, F., Paydar, M. M., Hajiaghaei-Keshteli, M., & Cheraghalipour, A. (2019). A multi-objective robust supply chain design considering reliability. *Https://Doi.Org/10.1080/21681015.2019.1658136*, *36*(6), 385–400.

Gholian Jouybari, F., Afshari, A. J., & Paydar, M. M. (2016). Electromagnetism-like Algorithms for The Fuzzy Fixed Charge Transportation Problem. *Journal of Industrial Engineering and Management Studies*, *3*(1), 39–60. http://jiems.icms.ac.ir/article_41223.html

Gholian-Jouybari, F., Afshari, A. J., & Paydar, M. M. (2018a). Utilizing new approaches to address the fuzzy fixed charge transportation problem. *Https://Doi.Org/10.1080/21681015.2018.1437791*, *35*(3), 148–159. https://doi.org/10.1080/21681015.2018.1437791

Gholian-Jouybari, F., Hashemi-Amiri, O., Mosallanezhad, B., & Hajiaghaei-Keshteli, M. (2022). Metaheuristic Algorithms for a Sustainable Agri-food Supply Chain Considering Marketing Practices under Uncertainty. *Expert Systems with Applications*, 118880. https://doi.org/10.1016/J.ESWA.2022.118880

Gholian-Jouybari, F., Hashemi-Amiri, O., Mosallanezhad, B., & Hajiaghaei-Keshteli, M. (2023a). Metaheuristic algorithms for a sustainable agri-food supply chain considering marketing practices under uncertainty. *Expert Systems with Applications*, *213*, 118880. https://doi.org/10.1016/J.ESWA.2022.118880

Glover, F., & Laguna, M. (1997). Tabu Search Background. *Tabu Search*, 1–24. https://doi.org/10.1007/978-1-4615-6089-0_1

Golshahi-Roudbaneh, A., Hajiaghaei-Keshteli, M., & Paydar, M. M. (2017). Developing a lower bound and strong heuristics for a truck scheduling problem in a cross-docking center. *Knowledge-Based Systems*, *129*, 17–38. https://doi.org/10.1016/J.KNOSYS.2017.05.006

Goodson, J. C., Ohlmann, J. W., & Thomas, B. W. (2012). Cyclic-order neighborhoods with application to the vehicle routing problem with stochastic demand. *European Journal of Operational Research*, *217*(2), 312–323. https://doi.org/10.1016/J.EJOR.2011.09.023

Guo, K., Hu, S., Zhu, H., & Tan, W. (2022). Industrial information integration method to vehicle routing optimization using grey target decision. *Journal of Industrial Information Integration*, *27*, 100336. https://doi.org/10.1016/J.JII.2022.100336

Guo, N., Qian, B., Na, J., Hu, R., & Mao, J. L. (2022). A three-dimensional ant colony optimization algorithm for multi-compartment vehicle routing problem considering carbon emissions. *Applied Soft Computing*, *127*, 109326. https://doi.org/10.1016/J.ASOC.2022.109326

Gutierrez-Alcoba, A., Rossi, R., Martin-Barragan, B., & Embley, T. (2023). The Stochastic Inventory Routing Problem on Electric Roads. *European Journal of Operational Research*. https://doi.org/10.1016/J.EJOR.2023.02.024

Hajar, Z., Btissam, D., & Mohamed, R. (2018). Onsite medical waste multi-objective vehicle routing problem with time windows. *Proceedings - GOL 2018: 4th IEEE International Conference on Logistics Operations Management*, 1–5. https://doi.org/10.1109/GOL.2018.8378086

Hajiaghaei-Keshteli, M., & Aminnayeri, M. (2014a). Solving the integrated scheduling of production and rail transportation problem by Keshtel algorithm. *Applied Soft Computing*, *25*, 184–203. https://doi.org/10.1016/J.ASOC.2014.09.034

Hajiaghaei-Keshteli, M., & Aminnayeri, M. (2014b). Solving the integrated scheduling of production and rail transportation problem by Keshtel algorithm. *Applied Soft Computing*, *25*, 184–203. https://doi.org/10.1016/J.ASOC.2014.09.034

Hajiaghaei-Keshteli, M., Rahmanifar, G., Mohammadi, M., Gholian-Jouybari, F., Klemeš, J. J., Zahmatkesh, S., Bokhari, A., Fusco, G., & Colombaroni, C. (2023). Designing a multi-period dynamic electric vehicle production-routing problem in a supply chain considering energy consumption. *Journal of Cleaner Production*, 138471. https://doi.org/10.1016/J.JCLEPRO.2023.138471

Hakanen, J., Rados, S., Misitano, G., Saini, B. S., Miettinen, K., & Matkovic, K. (2022). Interactivized: Visual Interaction for Better Decisions with Interactive Multiobjective Optimization. *IEEE Access*, 1–1. https://doi.org/10.1109/ACCESS.2022.3161465

Hannan, M. A., Begum, R. A., Al-Shetwi, A. Q., Ker, P. J., al Mamun, M. A., Hussain, A., Basri, H., & Mahlia, T. M. I. (2020). Waste collection route optimisation model for linking cost saving and emission reduction to achieve sustainable development goals. *Sustainable Cities and Society*, *62*, 102393. https://doi.org/10.1016/J.SCS.2020.102393

Harris, I., Naim, M., Palmer, A., Potter, A., & Mumford, C. (2011). Assessing the impact of cost optimization based on infrastructure modelling on CO2 emissions. *International Journal of Production Economics*, *131*(1), 313–321. https://doi.org/10.1016/J.IJPE.2010.03.005

Hashemi-Amiri, O., Ghorbani, F., & Ji, R. (2023a). Integrated supplier selection, scheduling, and routing problem for perishable product supply chain: A distributionally robust approach. *Computers & Industrial Engineering*, *175*, 108845. https://doi.org/10.1016/J.CIE.2022.108845

Hashemi-Amiri, O., Mohammadi, M., Rahmanifar, G., Hajiaghaei-Keshteli, M., Fusco, G., & Colombaroni, C. (2023). An allocation-routing optimization model for integrated solid waste management. *Expert Systems with Applications*, *227*, 120364. https://doi.org/10.1016/J.ESWA.2023.120364

Hassan, M. N., Najmi, A., & Rashidi, T. H. (2019). A two-stage recreational destination choice study incorporating fuzzy logic in discrete choice modelling. *Transportation Research Part F: Traffic Psychology and Behaviour*, *67*, 123–141. https://doi.org/10.1016/J.TRF.2019.10.015

Hedar, A.-R., & Bakr, M. A. (2014). Three Strategies Tabu Search for Vehicle Routing Problem with Time Windows. *Computer Science and Information Technology*, *2*(2), 108–119. https://doi.org/10.13189/CSIT.2014.020208

Holland, J. H. (1984). Genetic Algorithms and Adaptation. *Adaptive Control of Ill-Defined Systems*, 317–333. https://doi.org/10.1007/978-1-4684-8941-5_21

Huang, Y., Zhao, L., van Woensel, T., & Gross, J. P. (2017). Time-dependent vehicle routing problem with path flexibility. *Transportation Research Part B: Methodological*, *95*, 169–195. https://doi.org/10.1016/J.TRB.2016.10.013

Hvattum, L. M., Løkketangen, A., & Laporte, G. (2006). Solving a Dynamic and Stochastic Vehicle Routing Problem with a Sample Scenario Hedging Heuristic. *Https://Doi.Org/10.1287/Trsc.1060.0166*, *40*(4), 421–438. https://doi.org/10.1287/TRSC.1060.0166

Ichoua, S., Gendreau, M., & Potvin, J. Y. (2003). Vehicle dispatching with time-dependent travel times. *European Journal of Operational Research*, *144*(2), 379–396. https://doi.org/10.1016/S0377-2217(02)00147-9

Iswari, T., & Asih, A. M. S. (2018). Comparing genetic algorithm and particle swarm optimization for solving capacitated vehicle routing problem. *IOP Conference Series: Materials Science and Engineering*, *337*(1), 012004. https://doi.org/10.1088/1757-899X/337/1/012004

Jadaan, O. al, Jadaan, O. al, Rajamani, L., & Rao, C. R. (2008). Non-dominated ranked genetic algorithm for Solving multiobjective optimization Problems. *NRGA", JOURNAL OF THEORETICAL AND APPLIED INFORMATION TECHNOLOGY*, 60--67. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.207.9427

Janssens, G. K., Caris, A., & Ramaekers, K. (2009). Time Petri nets as an evaluation tool for handling travel time uncertainty in vehicle routing solutions. *Expert Systems with Applications*, *36*(3 PART 2), 5987–5991. https://doi.org/10.1016/J.ESWA.2008.07.001

Jatinkumar Shah, P., Anagnostopoulos, T., Zaslavsky, A., & Behdad, S. (2018). A stochastic optimization framework for planning of waste collection and value recovery operations in smart and sustainable cities. *Waste Management*, *78*, 104–114. https://doi.org/10.1016/j.wasman.2018.05.019

Ji, Y., Ji, S., & Ji, T. (2022). Considering the Carbon Penalty Rates to Optimize the Urban Distribution Model in Time-Varying Network. *Complexity*, *2022*, 1–17. https://doi.org/10.1155/2022/1013861

Jiménez-Rosado, M., Perez-Puyana, V., & Romero, A. (2023). The use of biowaste for the production of biodegradable superabsorbent materials. *Current Opinion in Food Science*, *49*, 100975. https://doi.org/10.1016/J.COFS.2022.100975

Johansson, O. M. (2006). The effect of dynamic scheduling and routing in a solid waste management system. *Waste Management*, *26*(8), 875–885. https://doi.org/10.1016/J.WASMAN.2005.09.004

Jorge, D., Pais Antunes, A., Rodrigues Pereira Ramos, T., & Barbosa-Póvoa, A. P. (2022a). A hybrid metaheuristic for smart waste collection problems with workload concerns. *Computers & Operations Research*, *137*, 105518. https://doi.org/10.1016/J.COR.2021.105518

Juan, A., Faulin, J., Grasman, S., Riera, D., Marull, J., & Mendez, C. (2011). Using safety stocks and simulation to solve the vehicle routing problem with stochastic demands. *Transportation Research Part C: Emerging Technologies*, *19*(5), 751–765. https://doi.org/10.1016/J.TRC.2010.09.007

Kang, K. D., Kang, H., Ilankoon, I. M. S. K., & Chong, C. Y. (2020). Electronic waste collection systems using Internet of Things (IoT): Household electronic waste management in Malaysia. *Journal of Cleaner Production*, *252*, 119801. https://doi.org/10.1016/j.jclepro.2019.119801

Kara, G., Özmen, A., & Weber, G. W. (2019). Stability advances in robust portfolio optimization under parallelepiped uncertainty. *Central European Journal of Operations Research*, *27*(1), 241–261. https://doi.org/10.1007/S10100-017-0508-5/TABLES/3

Karakatič, S. (2021). Optimizing nonlinear charging times of electric vehicle routing with genetic algorithm. *Expert Systems with Applications*, *164*, 114039. https://doi.org/10.1016/J.ESWA.2020.114039

Kaza, S., Yao, L. C., Bhada-Tata, P., & van Woerden, F. (2018). What a Waste 2.0. *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050*. https://doi.org/10.1596/978-1-4648-1329-0

Keshari, S. K., Kansal, V., & Kumar, S. (2021). An intelligent way for optimal controller placements in software-defined–IoT networks for smart cities. *Computers & Industrial Engineering*, *162*, 107667. https://doi.org/10.1016/J.CIE.2021.107667

Keskin, M., Branke, J., Deineko, V., & Strauss, A. (2023). Dynamic multi-period vehicle routing with touting. *European Journal of Operational Research*, *310*(1), 168–184. https://doi.org/10.1016/J.EJOR.2023.02.037

Khalilpourazari, S., Mirzazadeh, A., Weber, G. W., & Pasandideh, S. H. R. (2019). A robust fuzzy approach for constrained multi-product economic production quantity with imperfect items and rework process. *Https://Doi.Org/10.1080/02331934.2019.1630625*, *69*(1), 63–90. https://doi.org/10.1080/02331934.2019.1630625

Khouadjia, M. R., Sarasola, B., Alba, E., Jourdan, L., & Talbi, E. G. (2012). A comparative study between dynamic adapted PSO and VNS for the vehicle routing problem with dynamic requests. *Applied Soft Computing*, *12*(4), 1426–1439. https://doi.org/10.1016/J.ASOC.2011.10.023

Kilic, E., Ali, S. S., Weber, G. W., & Dubey, R. (2014). A value-adding approach to reliability under preventive maintenance costs and its applications. *Https://Doi.Org/10.1080/02331934.2014.917301*, *63*(12), 1805–1816. https://doi.org/10.1080/02331934.2014.917301

Kim, G., Ong, Y. S., Cheong, T., & Tan, P. S. (2016). Solving the dynamic vehicle routing problem under traffic congestion. *IEEE Transactions on Intelligent Transportation Systems*, *17*(8), 2367–2380. https://doi.org/10.1109/TITS.2016.2521779

Kim, Y. J., & Chung, B. do. (2023). Energy consumption optimization for the electric vehicle routing problem with state-of-charge-dependent discharging rates. *Journal of Cleaner Production*, *385*, 135703. https://doi.org/10.1016/J.JCLEPRO.2022.135703

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. *Science*, *220*(4598), 671–680. https://doi.org/10.1126/SCIENCE.220.4598.671

Kirkpatrick, S., & Swendsen, R. (1985). Statistical Mechanics and Disordered Systems. *Article in Communications of the ACM*, *28*(4), 363–373. https://doi.org/10.1145/3341.3344

Kok, A. L., Hans, E. W., & Schutten, J. M. J. (2012). Vehicle routing under time-dependent travel times: The impact of congestion avoidance. *Computers and Operations Research*, *39*(5), 910–918. https://doi.org/10.1016/J.COR.2011.05.027

Kumar, R. S., Kondapaneni, K., Dixit, V., Goswami, A., Thakur, L. S., & Tiwari, M. K. (2016). Multi-objective modeling of production and pollution routing problem with time window: A self-learning particle swarm optimization approach. *Computers & Industrial Engineering*, *99*, 29–40. https://doi.org/10.1016/J.CIE.2015.07.003

Kumar, S. N., & Panneerselvam, R. (2012). A Survey on the Vehicle Routing Problem and Its Variants. *Intelligent Information Management*, *2012*(03), 66–74. https://doi.org/10.4236/IIM.2012.43010

Kuo, Y., Wang, C. C., & Chuang, P. Y. (2009). Optimizing goods assignment and the vehicle routing problem with time-dependent travel speeds. *Computers and Industrial Engineering*, *57*(4), 1385–1392. https://doi.org/10.1016/J.CIE.2009.07.006

Lee, B. H. Y., & Waddell, P. (2010). Residential mobility and location choice: A nested logit model with sampling of alternatives. *Transportation*, *37*(4), 587–601. https://doi.org/10.1007/S11116-010-9270-4/TABLES/2

Li, X., Tian, P., & Leung, S. C. H. (2010). Vehicle routing problems with time windows and stochastic travel and service times: Models and algorithm. *International Journal of Production Economics*, *125*(1), 137–145. https://doi.org/10.1016/J.IJPE.2010.01.013

Li, Y., Chu, F., Chu, C., & Zhu, Z. (2019). An efficient three-level heuristic for the large-scaled multi-product production routing problem with outsourcing. *European Journal of Operational Research*, *272*(3), 914–927. https://doi.org/10.1016/J.EJOR.2018.07.018

Li, Y., Chu, F., Côté, J. F., Coelho, L. C., & Chu, C. (2020). The multi-plant perishable food production routing with packaging consideration. *International Journal of Production Economics*, *221*, 107472. https://doi.org/10.1016/J.IJPE.2019.08.007

Liao, Y., Kaviyani-Charati, M., Hajiaghaei-Keshteli, M., & Diabat, A. (2020). Designing a closed-loop supply chain network for citrus fruits crates considering environmental and economic issues. *Journal of Manufacturing Systems*, *55*, 199–220. https://doi.org/10.1016/J.JMSY.2020.02.001

Lin, C., Choy, K. L., Ho, G. T. S., Chung, S. H., & Lam, H. Y. (2014). Survey of Green Vehicle Routing Problem: Past and future trends. *Expert Systems with Applications*, *41*(4), 1118–1138. https://doi.org/10.1016/J.ESWA.2013.07.107

Lin, Z., Ooi, J. K., & Woon, K. S. (2021). An integrated life cycle multi-objective optimization model for health-environment-economic nexus in food waste management sector. *Science of The Total Environment*, 151541. https://doi.org/10.1016/J.SCITOTENV.2021.151541

Liu, L., & Liao, W. (2021). Optimization and profit distribution in a two-echelon collaborative waste collection routing problem from economic and environmental perspective. *Waste Management*, *120*, 400–414. https://doi.org/10.1016/J.WASMAN.2020.09.045

Lorini, S., Potvin, J. Y., & Zufferey, N. (2011). Online vehicle routing and scheduling with dynamic travel times. *Computers and Operations Research*, *38*(7), 1086–1090. https://doi.org/10.1016/J.COR.2010.10.019

Lotfi, R., Kargar, B., Gharehbaghi, A., & Weber, G. W. (2022). Viable medical waste chain network design by considering risk and robustness. *Environmental Science and Pollution Research*, *29*(53), 79702–79717. https://doi.org/10.1007/S11356-021-16727-9/FIGURES/13

Lu, J., Chen, Y., Hao, J. K., & He, R. (2020). The Time-dependent Electric Vehicle Routing Problem: Model and solution. *Expert Systems with Applications*, *161*. https://doi.org/10.1016/J.ESWA.2020.113593

Mahéo, A., Rossit, D. G., & Kilby, P. (2022). Solving the integrated bin allocation and collection routing problem for municipal solid waste: a Benders decomposition approach. *Annals of Operations Research*, *322*(1), 441–465. https://doi.org/10.1007/S10479-022-04918-7/FIGURES/5

Malandraki, C., & Daskin, M. S. (1992). Time dependent vehicle routing problems: Formulations, properties and heuristic algorithms. *Transportation Science*, *26*(3), 185–200. https://doi.org/10.1287/TRSC.26.3.185

Mamashli, Z., Nayeri, S., Tavakkoli-Moghaddam, R., Sazvar, Z., & Javadian, N. (2021). Designing a sustainable–resilient disaster waste management system under hybrid uncertainty: A case study. *Engineering Applications of Artificial Intelligence*, *106*, 104459. https://doi.org/10.1016/J.ENGAPPAI.2021.104459

Manouchehri, F., Nookabadi, A. S., & Kadivar, M. (2020). Production routing in perishable and quality degradable supply chains. *Heliyon*, *6*(2), e03376. https://doi.org/10.1016/J.HELIYON.2020.E03376

Marinakis, Y., Marinaki, M., & Migdalas, A. (2019). A multi-adaptive particle swarm optimization for the vehicle routing problem with time windows. *Information Sciences*, *481*, 311–329. https://doi.org/10.1016/J.INS.2018.12.086

Martikkala, A., Mayanti, B., Helo, P., Lobov, A., & Ituarte, I. F. (2023). Smart textile waste collection system – Dynamic route optimization with IoT. *Journal of Environmental Management*, *335*, 117548. https://doi.org/10.1016/J.JENVMAN.2023.117548

Midya, S., Roy, S. K., & Weber, G. W. (2021). Fuzzy multiple objective fractional optimization in rough approximation and its aptness to the fixed-charge transportation problem. *RAIRO - Operations Research*, *55*(3), 1715–1741. https://doi.org/10.1051/RO/2021078

Mirjalili, S., & Lewis, A. (2015). Novel performance metrics for robust multi-objective optimization algorithms. *Swarm and Evolutionary Computation*, *21*, 1–23. https://doi.org/10.1016/J.SWEVO.2014.10.005

Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey Wolf Optimizer. *Advances in Engineering Software*, *69*, 46–61. https://doi.org/10.1016/J.ADVENGSOFT.2013.12.007

Mohammadi, M., Rahmanifar, G., Hajiaghaei-Keshteli, M., Fusco, G., Colombaroni, C., & Sherafat, A. (2023). A dynamic approach for the multi-compartment vehicle routing problem in waste management. *Renewable and Sustainable Energy Reviews*, *184*, 113526. https://doi.org/10.1016/J.RSER.2023.113526

Mojtahedi, M., Fathollahi-Fard, A. M., Tavakkoli-Moghaddam, R., & Newton, S. (2021a). Sustainable vehicle routing problem for coordinated solid waste management. *Journal of Industrial Information Integration*, *23*, 100220. https://doi.org/10.1016/j.jii.2021.100220

Mosallanezhad, B., Ali Arjomandi, M., Hashemi-Amiri, O., Gholian-Jouybari, F., Dibaj, M., Akrami, M., & Hajiaghaei-Keshteli, M. (2023). Metaheuristic optimizers to solve multi-echelon sustainable fresh seafood supply chain network design problem: A case of shrimp products. *Alexandria Engineering Journal*, *68*, 491–515. https://doi.org/10.1016/J.AEJ.2023.01.022

Mosallanezhad, B., Chouhan, V. K., Paydar, M. M., & Hajiaghaei-Keshteli, M. (2021). Disaster relief supply chain design for personal protection equipment during the COVID-19 pandemic. *Applied Soft Computing*, *112*, 107809. https://doi.org/10.1016/J.ASOC.2021.107809

Mosallanezhad, B., Gholian-Jouybari, F., Cárdenas-Barrón, L. E., & Hajiaghaei-Keshteli, M. (2023). The IoT-enabled sustainable reverse supply chain for COVID-19 Pandemic Wastes (CPW). *Engineering Applications of Artificial Intelligence*, *120*, 105903. https://doi.org/10.1016/J.ENGAPPAI.2023.105903

Mosallanezhad, B., Hajiaghaei-Keshteli, M., & Triki, C. (2021). Shrimp closed-loop supply chain network design. *Soft Computing*, *25*(11), 7399–7422. https://doi.org/10.1007/S00500-021-05698-1/FIGURES/28

Mousavi, R., Salehi-Amiri, A., Zahedi, A., & Hajiaghaei-Keshteli, M. (2021). Designing a supply chain network for blood decomposition by utilizing social and environmental factor. *Computers & Industrial Engineering*, *160*, 107501. https://doi.org/10.1016/J.CIE.2021.107501

Nakandhrakumar, R. S., Rameshkumar, P., Parthasarathy, V., & Thirupathy Rao, B. (2021). Internet of Things (IoT) based system development for robotic waste segregation management. *Materials Today: Proceedings*. https://doi.org/10.1016/J.MATPR.2021.02.473

Nesmachnow, S., Rossit, D., & Toutouh, J. (2018a). Comparison of Multiobjective Evolutionary Algorithms for Prioritized Urban Waste Collection in Montevideo, Uruguay. *Electronic Notes in Discrete Mathematics*, *69*, 93–100. https://doi.org/10.1016/J.ENDM.2018.07.013

Nezhadroshan, A. M., Fathollahi-Fard, A. M., & Hajiaghaei-Keshteli, M. (2021). A scenario-based possibilistic-stochastic programming approach to address resilient humanitarian logistics considering travel time and resilience levels of facilities. *International Journal of Systems Science: Operations & Logistics*, *8*(4), 321–347. https://doi.org/10.1080/23302674.2020.1769766

Ng, K. K. H., Lee, C. K. M., Zhang, S. Z., Wu, K., & Ho, W. (2017). A multiple colonies artificial bee colony algorithm for a capacitated vehicle routing problem and re-routing strategies under time-dependent traffic congestion. *Computers & Industrial Engineering*, *109*, 151–168. https://doi.org/10.1016/J.CIE.2017.05.004

Nidhya, R., Kumar, M., v. Ravi, R., & Deepak, V. (2020). Enhanced Route Selection (ERS) algorithm for IoT enabled smart waste management system. *Environmental Technology & Innovation*, *20*, 101116. https://doi.org/10.1016/J.ETI.2020.101116

Okulewicz, M., & Mańdziuk, J. (2019). A metaheuristic approach to solve Dynamic Vehicle Routing Problem in continuous search space. *Swarm and Evolutionary Computation*, *48*, 44–61. https://doi.org/10.1016/J.SWEVO.2019.03.008

Ooi, J. K., Woon, K. S., & Hashim, H. (2021). A multi-objective model to optimize country-scale municipal solid waste management with economic and environmental objectives: A case study in Malaysia. *Journal of Cleaner Production*, *316*, 128366. https://doi.org/10.1016/J.JCLEPRO.2021.128366

Özmen, A., Kropat, E., & Weber, G. W. (2016). Robust optimization in spline regression models for multi-model regulatory networks under polyhedral uncertainty. *Https://Doi.Org/10.1080/02331934.2016.1209672*, *66*(12), 2135–2155. https://doi.org/10.1080/02331934.2016.1209672

Pal, K., Sachan, S., Gholian-Jouybari, F., & Hajiaghaei-Keshteli, M. (2023). An analysis of the security of multi-area power transmission lines using fuzzy-ACO. *Expert Systems with Applications*, *224*, 120070. https://doi.org/10.1016/J.ESWA.2023.120070

Pandelis, D. G., Karamatsoukis, C. C., & Kyriakidis, E. G. (2013). Finite and infinite-horizon single vehicle routing problems with a predefined customer sequence and pickup and delivery. *European Journal of Operational Research*, *231*(3), 577–586. https://doi.org/10.1016/J.EJOR.2013.05.050

Pelletier, S., Jabali, O., & Laporte, G. (2016). 50th Anniversary Invited Article—Goods Distribution with Electric Vehicles: Review and Research Perspectives. *Https://Doi.Org/10.1287/Trsc.2015.0646*, *50*(1), 3–22. https://doi.org/10.1287/TRSC.2015.0646

Peng, H., An, C., Ng, K. T. W., Hao, J., & Tian, X. (2023). Advancing cleaner municipal waste transport through carbon accounting in the cap-and-trade system. *Transportation Research Part D: Transport and Environment*, *114*, 103560. https://doi.org/10.1016/J.TRD.2022.103560

Plevris, V., & Solorzano, G. (2022). A Collection of 30 Multidimensional Functions for Global Optimization Benchmarking. *Data 2022, Vol. 7, Page 46*, *7*(4), 46. https://doi.org/10.3390/DATA7040046

Pourreza Movahed, Z., Kabiri, M., Ranjbar, S., & Joda, F. (2020). Multi-objective optimization of life cycle assessment of integrated waste management based on genetic algorithms: A case study of Tehran. *Journal of Cleaner Production*, *247*, 119153. https://doi.org/10.1016/J.JCLEPRO.2019.119153

Raeesi, R., & Zografos, K. G. (2020). The electric vehicle routing problem with time windows and synchronised mobile battery swapping. *Transportation Research Part B: Methodological*, *140*, 101–129. https://doi.org/10.1016/J.TRB.2020.06.012

Rahman, M. W., Islam, R., Hasan, A., Bithi, N. I., Hasan, M. M., & Rahman, M. M. (2022). Intelligent waste management system using deep learning with IoT. *Journal of King Saud University - Computer and Information Sciences*, *34*(5), 2072–2087. https://doi.org/10.1016/J.JKSUCI.2020.08.016

Rahmanifar, G., Mohammadi, M., Sherafat, A., Hajiaghaei-Keshteli, M., Fusco, G., & Colombaroni, C. (2023a). Heuristic approaches to address vehicle routing problem in the Iot-based waste management system. *Expert Systems with Applications*, *220*, 119708. https://doi.org/10.1016/J.ESWA.2023.119708

Rahmanifar, G., Mohammadi, M., Sherafat, A., Hajiaghaei-Keshteli, M., Fusco, G., & Colombaroni, C. (2023b). Heuristic approaches to address vehicle routing problem in the Iot-based waste management system. *Expert Systems with Applications*, *220*, 119708. https://doi.org/10.1016/J.ESWA.2023.119708

Rahmanifar, G., Mohammadi, M., Sherafat, A., Hajiaghaei-Keshteli, M., Fusco, G., & Colombaroni, C. (2023c). Heuristic approaches to address vehicle routing problem in the Iot-based waste management system. *Expert Systems with Applications*, *220*, 119708. https://doi.org/10.1016/J.ESWA.2023.119708

Rajabi-Kafshgar, A., Gholian-Jouybari, F., Seyedi, I., & Hajiaghaei-Keshteli, M. (2023). Utilizing hybrid metaheuristic approach to design an agricultural closed-loop supply chain network. *Expert Systems with Applications*, *217*, 119504. https://doi.org/10.1016/J.ESWA.2023.119504

Ramos, T. R. P., de Morais, C. S., & Barbosa-Póvoa, A. P. (2018). The smart waste collection routing problem: Alternative operational management approaches. *Expert Systems with Applications*, *103*, 146–158. https://doi.org/10.1016/J.ESWA.2018.03.001

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, *53*, 49–57. https://doi.org/10.1016/J.OMEGA.2014.11.009

Rossit, D. G., & Nesmachnow, S. (2022). Waste bins location problem: A review of recent advances in the storage stage of the Municipal Solid Waste reverse logistic chain. *Journal of Cleaner Production*, *342*, 130793. https://doi.org/10.1016/J.JCLEPRO.2022.130793

Rossit, D. G., Nesmachnow, S., Toutouh, J., Rossit, D. G., Nesmachnow, S., & Toutouh, J. (2019). A bi-objective integer programming model for locating garbage accumulation points: a case study.

Revista Facultad de Ingeniería Universidad de Antioquia, *93*, 70–81. https://doi.org/10.17533/UDEA.REDIN.20190509

Rossit, D. G., Toutouh, J., & Nesmachnow, S. (2020a). Exact and heuristic approaches for multi-objective garbage accumulation points location in real scenarios. *Waste Management*, *105*, 467–481. https://doi.org/10.1016/J.WASMAN.2020.02.016

Russell, R. A. (2017). Mathematical programming heuristics for the production routing problem. *International Journal of Production Economics*, *193*, 40–49. https://doi.org/10.1016/J.IJPE.2017.06.033

Sadeghi-Moghaddam, S., Hajiaghaei-Keshteli, M., & Mahmoodjanloo, M. (2019). New approaches in metaheuristics to solve the fixed charge transportation problem in a fuzzy environment. *Neural Computing and Applications*, *31*(1), 477–497. https://doi.org/10.1007/s00521-017-3027-3

Sahebjamnia, N., Goodarzian, F., & Hajiaghaei-Keshteli, M. (2020). Optimization of Multi-period Three-echelon Citrus Supply Chain Problem. *Journal of Optimization in Industrial Engineering*, *13*(1), 39–53. https://doi.org/10.22094/JOIE.2017.728.1463

Sahib, F. S., & Hadi, N. S. (2021). Truck route optimization in Karbala city for solid waste collection. *Materials Today: Proceedings*. https://doi.org/10.1016/J.MATPR.2021.06.394

Salehi-Amiri, A., Akbapour, N., Hajiaghaei-Keshteli, M., Gajpal, Y., & Jabbarzadeh, A. (2022a). Designing an effective two-stage, sustainable, and IoT based waste management system. *Renewable and Sustainable Energy Reviews*, *157*, 112031. https://doi.org/10.1016/J.RSER.2021.112031

Salehi-Amiri, A., Jabbarzadeh, A., Hajiaghaei-Keshteli, M., & Chaabane, A. (2022). Utilizing the Internet of Things (IoT) to address uncertain home health care supply chain network. *Expert Systems with Applications*, *208*, 118239. https://doi.org/10.1016/J.ESWA.2022.118239

Saravanan, A., Karishma, S., Senthil Kumar, P., & Rangasamy, G. (2023). A review on regeneration of biowaste into bio-products and bioenergy: Life cycle assessment and circular economy. *Fuel*, *338*, 127221. https://doi.org/10.1016/J.FUEL.2022.127221

Savku, E., & Weber, G. W. (2018). A Stochastic Maximum Principle for a Markov Regime-Switching Jump-Diffusion Model with Delay and an Application to Finance. *Journal of Optimization Theory and Applications*, *179*(2), 696–721. https://doi.org/10.1007/S10957-017-1159-3/METRICS

Schenekemberg, C. M., Scarpin, C. T., Pécora, J. E., Guimarães, T. A., & Coelho, L. C. (2021). The two-echelon production-routing problem. *European Journal of Operational Research*, *288*(2), 436–449. https://doi.org/10.1016/J.EJOR.2020.05.054

Seker, S. (2022). IoT based sustainable smart waste management system evaluation using MCDM model under interval-valued q-rung orthopair fuzzy environment. *Technology in Society*, *71*, 102100. https://doi.org/10.1016/J.TECHSOC.2022.102100

Shang, C., Ma, L., & Liu, Y. (2023). Green location routing problem with flexible multi-compartment for source-separated waste: A Q-learning and multi-strategy-based hyper-heuristic algorithm. *Engineering Applications of Artificial Intelligence*, *121*, 105954. https://doi.org/10.1016/J.ENGAPPAI.2023.105954

Shi, Y., & Eberhart, R. (1998). Modified particle swarm optimizer. *Proceedings of the IEEE Conference on Evolutionary Computation, ICEC*, 69–73. https://doi.org/10.1109/ICEC.1998.699146

Smit, S. K., & Eiben, A. E. (2009). Comparing parameter tuning methods for evolutionary algorithms. *2009 IEEE Congress on Evolutionary Computation, CEC 2009*, 399–406. https://doi.org/10.1109/CEC.2009.4982974

Sohag, M. U., & Podder, A. K. (2020). Smart garbage management system for a sustainable urban life: An IoT based application. *Internet of Things*, *11*, 100255. https://doi.org/10.1016/J.IOT.2020.100255

Solomon, M. M. (1987). ALGORITHMS FOR THE VEHICLE ROUTING AND SCHEDULING PROBLEMS WITH TIME WINDOW CONSTRAINTS. *Operations Research*, *35*(2), 254–265. https://doi.org/10.1287/OPRE.35.2.254

Statista - The Statistics Portal for Market Data, Market Research and Market Studies. (n.d.). Retrieved June 14, 2023, from https://0-www-statista-com.biblioteca-ils.tec.mx/

Szulc, W., Rutkowska, B., Gawroński, S., & Wszelaczyńska, E. (2021). Possibilities of Using Organic Waste after Biological and Physical Processing—An Overview. *Processes 2021, Vol. 9, Page 1501*, *9*(9), 1501. https://doi.org/10.3390/PR9091501

Talbi, E.-G. (2009). *Metaheuristics: From Desing to Implementation. John Wiley & Sons, Inc.* 624. https://www.wiley.com/en-sg/Metaheuristics%3A+From+Design+to+Implementation+-p-9780470278581

Taş, D., Dellaert, N., van Woensel, T., & de Kok, T. (2013). Vehicle routing problem with stochastic travel times including soft time windows and service costs. *Computers & Operations Research*, *40*(1), 214–224. https://doi.org/10.1016/J.COR.2012.06.008

Tasouji Hassanpour, S., Ke, G. Y., Zhao, J., & Tulett, D. M. (2023). Infectious waste management during a pandemic: A stochastic location-routing problem with chance-constrained time windows. *Computers & Industrial Engineering*, *177*, 109066. https://doi.org/10.1016/J.CIE.2023.109066

Tirkolaee, E. B., Abbasian, P., & Weber, G. W. (2021). Sustainable fuzzy multi-trip location-routing problem for medical waste management during the COVID-19 outbreak. *The Science of the Total Environment*, *756*. https://doi.org/10.1016/J.SCITOTENV.2020.143607

Tirkolaee, E. B., Goli, A., Gütmen, S., Weber, G. W., & Szwedzka, K. (2022). A novel model for sustainable waste collection arc routing problem: Pareto-based algorithms. *Annals of Operations Research*, 1–26. https://doi.org/10.1007/S10479-021-04486-2/TABLES/10

Tirkolaee, E. B., Mahdavi, I., & Mehdi Seyyed Esfahani, M. (2018). A robust periodic capacitated arc routing problem for urban waste collection considering drivers and crew's working time. *Waste Management*, *76*, 138–146. https://doi.org/10.1016/J.WASMAN.2018.03.015

Toutouh, J., Rossit, D., & Nesmachnow, S. (2019). Computational intelligence for locating garbage accumulation points in urban scenarios. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *11353 LNCS*, 411–426. https://doi.org/10.1007/978-3-030-05348-2_34/COVER

Toutouh, J., Rossit, D., & Nesmachnow, S. (2020). Soft computing methods for multiobjective location of garbage accumulation points in smart cities. *Annals of Mathematics and Artificial Intelligence*, *88*(1–3), 105–131. https://doi.org/10.1007/S10472-019-09647-5/METRICS

Tsai, F. M., Bui, T. D., Tseng, M. L., Wu, K. J., & Chiu, A. S. (2020). A performance assessment approach for integrated solid waste management using a sustainable balanced scorecard approach. *Journal of Cleaner Production*, *251*, 119740. https://doi.org/10.1016/J.JCLEPRO.2019.119740

Valentini, M. P., Carrese, F., Colombaroni, C., Conti, V., Corazza, M., Lelli, M., Mohammadi, M., Orchi, S., Ortenzi, F., Rahmanifar, G., Tomasino, G., & Fusco, G. (2023). A platform to optimize urban deliveries with e-vans. *TeMA - Journal of Land Use, Mobility and Environment*, *16*(2), 403–423. https://doi.org/10.6093/1970-9870/9911

Vamsi Krishna Reddy, A. K., & Venkata Lakshmi Narayana, K. (2022). Meta-heuristics optimization in electric vehicles -an extensive review. *Renewable and Sustainable Energy Reviews*, *160*, 112285. https://doi.org/10.1016/J.RSER.2022.112285

Vidal, T., Crainic, T. G., Gendreau, M., & Prins, C. (2014). A unified solution framework for multi-attribute vehicle routing problems. *European Journal of Operational Research*, *234*(3), 658–673. https://doi.org/10.1016/J.EJOR.2013.09.045

Walker, J., & Ben-Akiva, M. (2002). Generalized random utility model. *Mathematical Social Sciences*, *43*(3), 303–343. https://doi.org/10.1016/S0165-4896(02)00023-9

Wang, F., Liao, F., Li, Y., Yan, X., & Chen, X. (2021). An ensemble learning based multi-objective evolutionary algorithm for the dynamic vehicle routing problem with time windows. *Computers & Industrial Engineering*, *154*, 107131. https://doi.org/10.1016/J.CIE.2021.107131

Wang, J., Cevik, M., Amin, S. H., & Parsaee, A. A. (2021). Mixed-integer linear programming models for the paint waste management problem. *Transportation Research Part E: Logistics and Transportation Review*, *151*, 102343. https://doi.org/10.1016/J.TRE.2021.102343

Wang, X. (2018). The heterogeneous fleet location routing problem with simultaneous pickup and delivery and overloads. *Discrete and Continuous Dynamical Systems - S. 2019, Volume 12, Pages 1147-1166*, *12*(4 & 5), 1147. https://doi.org/10.3934/DCDSS.2019079

Wang, Y., Zhou, J., Sun, Y., Fan, J., Wang, Z., & Wang, H. (2023). Collaborative multidepot electric vehicle routing problem with time windows and shared charging stations. *Expert Systems with Applications*, *219*, 119654. https://doi.org/10.1016/J.ESWA.2023.119654

Weber, G. W., Uğur, Ö., Taylan, P., & Tezel, A. (2009). On optimization, dynamics and uncertainty: A tutorial for gene-environment networks. *Discrete Applied Mathematics*, *157*(10), 2494–2513. https://doi.org/10.1016/J.DAM.2008.06.030

Weber, G. W., Yolcu Okur, Y., Yerlikaya Özkurt, F., Kuter, S., Özmen, A., & Karimov, A. (2013). *Stochastic Hybrid Systems of Financial and Economical Processess: Identificatied, Optimized and Controlled*. https://open.metu.edu.tr/handle/11511/61683

Wolpert, D. H., & Macready, W. G. (1997). No free lunch theorems for optimization. *IEEE Transactions on Evolutionary Computation*, *1*(1), 67–82. https://doi.org/10.1109/4235.585893

Wu, H., Yang, B., & Tao, F. (2020). Optimization of Vehicle Routing for Waste Collection and Transportation. *International Journal of Environmental Research and Public Health*, *17*(14), 1–26. https://doi.org/10.3390/IJERPH17144963

Wu, W., Shen, L., Zhao, Z., Harish, A. R., Zhong, R. Y., & Huang, G. Q. (2023). Internet of Everything and Digital Twin enabled Service Platform for Cold Chain Logistics. *Journal of Industrial Information Integration*, *33*, 100443. https://doi.org/10.1016/J.JII.2023.100443

Xiang, X., Qiu, J., Xiao, J., & Zhang, X. (2020). Demand coverage diversity-based ant colony optimization for dynamic vehicle routing problems. *Engineering Applications of Artificial Intelligence*, *91*, 103582. https://doi.org/10.1016/J.ENGAPPAI.2020.103582

Xiang, X., Tian, Y., Zhang, X., Xiao, J., & Jin, Y. (2021). A Pairwise Proximity Learning-Based Ant Colony Algorithm for Dynamic Vehicle Routing Problems. *IEEE Transactions on Intelligent Transportation Systems*. https://doi.org/10.1109/TITS.2021.3052834

Xiao, Y., Zhang, Y., Kaku, I., Kang, R., & Pan, X. (2021). Electric vehicle routing problem: A systematic review and a new comprehensive model with nonlinear energy recharging and consumption. *Renewable and Sustainable Energy Reviews*, *151*, 111567. https://doi.org/10.1016/J.RSER.2021.111567

Xiaoyi, Z., Dongling, W., Yuming, Z., Manokaran, K. B., & Benny Antony, A. (2021). IoT driven framework based efficient green energy management in smart cities using multi-objective distributed dispatching algorithm. *Environmental Impact Assessment Review*, *88*, 106567. https://doi.org/10.1016/j.eiar.2021.106567

Yang, J., Tao, F., & Zhong, Y. (2022). Dynamic routing for waste collection and transportation with multi-compartment electric vehicle using smart waste bins. *Https://Doi.Org/10.1177/0734242X211069738*, *40*(8), 1199–1211. https://doi.org/10.1177/0734242X211069738

Yazdani, M., Kabirifar, K., Frimpong, B. E., Shariati, M., Mirmozaffari, M., & Boskabadi, A. (2021). Improving construction and demolition waste collection service in an urban area using a simheuristic approach: A case study in Sydney, Australia. *Journal of Cleaner Production*, *280*, 124138. https://doi.org/10.1016/J.JCLEPRO.2020.124138

Yindong, S., Liwen, P., & Jingpeng, L. (2021). An improved estimation of distribution algorithm for multi-compartment electric vehicle routing problem. *Journal of Systems Engineering and Electronics*, *32*(2), 365–379. https://doi.org/10.23919/JSEE.2021.000030

Young, K., Wang, C., Wang, L. Y., & Strunz, K. (2013). Electric vehicle battery technologies. *Electric Vehicle Integration into Modern Power Networks*, 15–56. https://doi.org/10.1007/978-1-4614-0134-6_2

Zahedi, A., Salehi-Amiri, A., Smith, N. R., & Hajiaghaei-Keshteli, M. (2021a). Utilizing IoT to design a relief supply chain network for the SARS-COV-2 pandemic. *Applied Soft Computing*, *104*. https://doi.org/10.1016/J.ASOC.2021.107210

Zahedi, A., Salehi-Amiri, A., Smith, N. R., & Hajiaghaei-Keshteli, M. (2021b). Utilizing IoT to design a relief supply chain network for the SARS-COV-2 pandemic. *Applied Soft Computing*, *104*, 107210. https://doi.org/10.1016/J.ASOC.2021.107210

Zantalis, F., Koulouras, G., Karabetsos, S., & Kandris, D. (2019). A Review of Machine Learning and IoT in Smart Transportation. *Future Internet 2019, Vol. 11, Page 94*, *11*(4), 94. https://doi.org/10.3390/FI11040094

Zhang, H., Zhang, Q., Ma, L., Zhang, Z., & Liu, Y. (2019). A hybrid ant colony optimization algorithm for a multi-objective vehicle routing problem with flexible time windows. *Information Sciences*, *490*, 166–190. https://doi.org/10.1016/J.INS.2019.03.070

Zhang, J., Luo, K., Florio, A. M., & Van Woensel, T. (2023). Solving large-scale dynamic vehicle routing problems with stochastic requests. *European Journal of Operational Research*, *306*(2), 596–614. https://doi.org/10.1016/J.EJOR.2022.07.015

Zhang, J., & Woensel, T. Van. (2023). Dynamic vehicle routing with random requests: A literature review. *International Journal of Production Economics*, *256*, 108751. https://doi.org/10.1016/J.IJPE.2022.108751

Zhang, Z., Luo, Z., Baldacci, R., & Lim, A. (2020). A Benders Decomposition Approach for the Multivehicle Production Routing Problem with Order-up-to-Level Policy. *Https://Doi.Org/10.1287/Trsc.2019.0964*, *55*(1), 160–178. https://doi.org/10.1287/TRSC.2019.0964

Zhou, B., & Zhao, Z. (2022). Multi-objective optimization of electric vehicle routing problem with battery swap and mixed time windows. *Neural Computing and Applications*, *34*(10), 7325–7348. https://doi.org/10.1007/S00521-022-06967-2

Zhu, L., Rousseau, L. M., Rei, W., & Li, B. (2014). Paired cooperative reoptimization strategy for the vehicle routing problem with stochastic demands. *Computers & Operations Research*, *50*, 1–13. https://doi.org/10.1016/J.COR.2014.03.027