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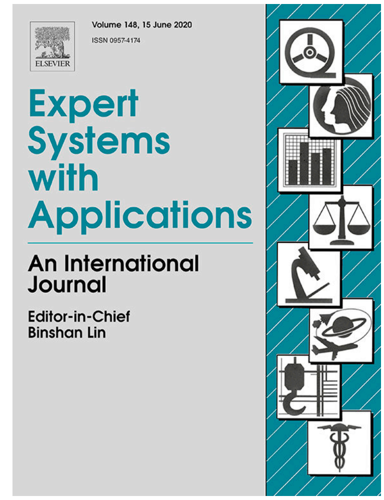

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An Allocation-Routing Optimization Model for Integrated Solid Waste Management

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ABSTRACT

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.

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). Figure 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.

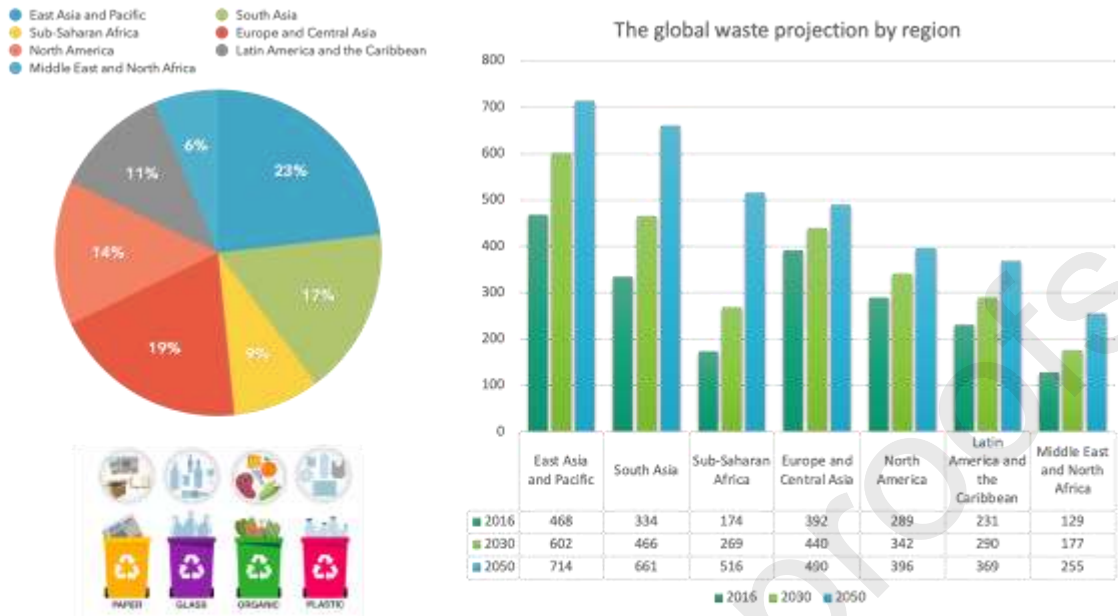


Fig.1. The estimation and share of global waste production by region for the years 2016, 2030, and 2050. Source(s): World Bank; ID 233613 (Statista website).

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., 2021). 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.

The rest of this paper is organized as follows. An overview of the literature is given in Section 2. In Section 3, the problem is described and formulated mathematically. The proposed solution methods in this study are explained in Section 4. In Section 5 several numerical examples are introduced and the parameter tuning of the proposed solution methods is presented. Section 6 presents the computational results and introduced different performance indicators for investigating the quality of results. Finally, the conclusions are discussed in Section 7.

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., 2023). 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 CO_2 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 et al., 2023; 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; 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. 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 Figure 2.

Fig.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 Figure 3. In the next section, the assumptions of the waste management problem under study are presented in detail.

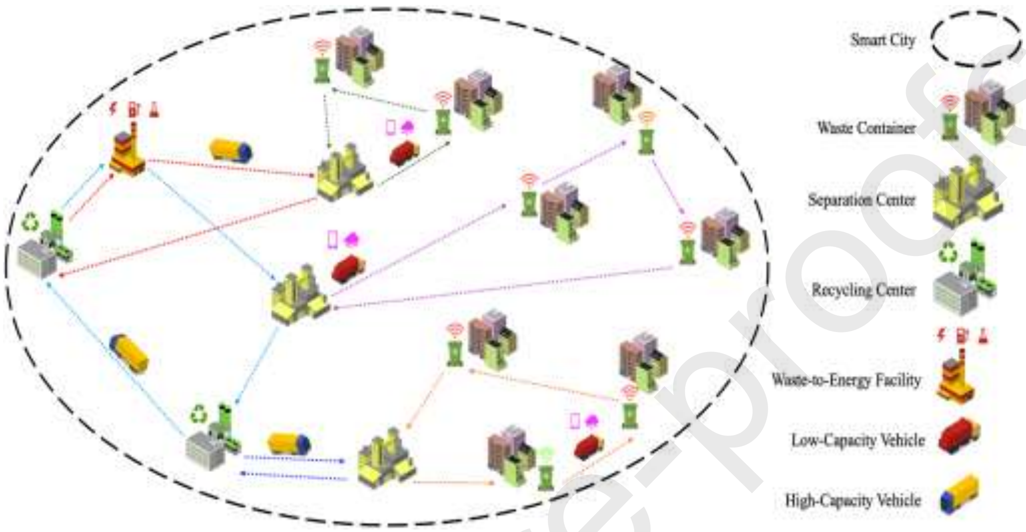


Fig.3. The proposed municipal solid waste network.

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.

3.2. 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 1-3.

Table 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),
$Tr_{i,j}^N$	Travel time between set of nodes including bins and separation centers,
$Tr_{e,f}^P$	Travel time between set of nodes including separation centers and processing plants,
$Tc_{s,h,w}^P$	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*.

3.2.1. 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.

$$\text{Minimize } Z_1 = \sum_{i\in N}\sum_{j\in N}\sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}\, Tr_{i,j}^{N} + \sum_{e\in P}\sum_{f\in P}\sum_{s\in S}\sum_{h\in VH_s} Y_{e,f,s,h}\, Tr_{e,f}^{P} \quad (1)$$

$$\text{Minimize } Z_2 = \sum_{s\in S}\left(\sum_{l\in VL_s} LCV_{s,l} + \sum_{h\in VH_s} HCV_{s,h}\right) \quad (2)$$

$$\text{Maximize } Z_3 = \sum_{s\in S}\sum_{f\in P\setminus S}\sum_{h\in VH_s}\sum_{w\in W} QP_{s,f,h,w}\, Pr_w - QP_{s,f,h,w}\, Tc_{s,h,w}^{P} \quad (3)$$

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.

3.2.2. Constraints

According to the above-mentioned assumptions and definition of the problem, the constraints of the MSW network are presented in Eqs. (4)-(30). The general VRP constraints between waste bins and separation centers are shown in Eqs. (4)-(7). Eq. (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. (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. (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. (4) and (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. (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

$$\sum_{i\in N}\sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l} \leq 1 \qquad \forall\, j \in N\backslash S, \tag{4}$$

$$\sum_{i\in N}\sum_{j\in S\backslash\{s\}} X_{i,j,s,l} + \sum_{i\in S\backslash\{s\}}\sum_{j\in N} X_{i,j,s,l} = 0, \qquad \forall\; s \in S, l \in VL_{s,} \tag{5}$$

$$\sum_{i\in N}\sum_{s\in S}\sum_{l\in VL_s} X_{i,i,s,l} = 0 \tag{6}$$

$$\sum_{i\in N} X_{i,j,s,l} = \sum_{i\in N} X_{j,i,s,l} \qquad \forall\; j \in N, s \in S, l \in VL_{s,} \tag{7}$$

Eq. (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. (9) ensures that there must be a route for an assigned bin to a separation center, and Eq. (10) determines if a low-capacity vehicle at a separation center is selected for a specific route. Eqs. (11) and (12) compute respectively the total quantity of solid waste and the quantity of a particular type of waste collected at a separation center. Eqs. (13) and (14) show the capacity constraints for the separation centers and the low-capacity vehicles in collection of waste materials.

$$\frac{Wt_j}{Cap\mathcal{B}_j\ \mathcal{TL}_j} - 1 \leq \mathcal{M}\left(\sum_{i\in N}\sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}\right) - \varepsilon\left(1 - \sum_{i\in N}\sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}\right) \quad \forall\ j \in N\backslash S, \tag{8}$$

$$\sum_{i\in N}\sum_{l\in VL_s} X_{i,j,s,l} \geq B_{j,s} \quad \forall\ j \in N\backslash S, s \in S, \tag{9}$$

$$\sum_{i\in N}\sum_{j\in N} X_{i,j,s,l} \leq \mathcal{M}\ LCV_{s,l} \quad \forall\ s \in S, l \in VL_s, \tag{10}$$

$$\sum_{b\in N\backslash S} B_{b,s} Wt_b = QS_s \quad \forall\ s \in S, \tag{11}$$

$$QW_{w,s} = \delta_w QS_s \quad \forall\ w \in W, s \in S, \tag{12}$$

$$QS_s \leq CapS_s \quad \forall\ s \in S, \tag{13}$$

$$\sum_{i\in N}\sum_{j\in N\backslash S} X_{i,j,s,l}\, Wt_j \leq CapL_{s,l} \quad \forall\ s \in S, l \in VL_{s}, \tag{14}$$

Eqs. (15) and (16) provide the arrival time of a vehicle at bin j, if path *(i,j)* is dedicated to the vehicle, and Eq.(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. (18).

$$Ar_j - (Ar_i + Tr_{i,j}^N + ScT_i) \leq \mathcal{M}(1 - \sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}) \quad \forall\ i \in N, j \in N\backslash S, \tag{15}$$

$$Ar_j - (Ar_i + Tr_{i,j}^N + ScT_i) \geq \mathcal{M}(1 - \sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}) \quad \forall\ i \in N, j \in N\backslash S, \tag{16}$$

$$ET_j\left(\sum_{i\in N}\sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}\right) \leq Ar_j \leq LT_j\left(\sum_{i\in N}\sum_{s\in S}\sum_{l\in VL_s} X_{i,j,s,l}\right) \quad \forall\ j \in N\backslash S, \tag{17}$$

$$Ar_i - Ar_j \leq \mathcal{M}(1 - \sum_{s \in S} \sum_{l \in VL_s} X_{i,j,s,l}) \qquad \forall \ \ \mathrm{i} \in \mathrm{N}, \mathrm{j} \in \mathrm{N} \backslash \mathrm{S}, \ (18)$$

Similarly, the routing, conservation flow, and subtour-elimination constraints among separation centers and processing plants are presented in Eqs. (19)-(23). Eqs. (19) and (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. (21) represents that there is no path between a node and itself, and Eqs. (22) and (23) show the conservation flow and subtour-elimination constraints, respectively.

$$\sum_{e \in P} Y_{e,f,s,h} \leq 1 \qquad \forall \ \ f \in P \backslash S \, , s \in S, h \in VH_s, \qquad (19)$$

$$\sum_{e \in P} \sum_{f \in S \backslash \{s\}} Y_{e,f,s,h} + \sum_{e \in S \backslash \{s\}} \sum_{f \in P} Y_{e,f,s,h} = 0 \qquad \forall \ \ s \in S, h \in VH_s, \qquad (20)$$

$$\sum_{e \in P} \sum_{s \in S} \sum_{h \in VH_s} Y_{e,e,s,h} = 0 \qquad (21)$$

$$\sum_{e \in P} Y_{e,f,s,h} = \sum_{e \in P} Y_{f,e,s,h} \qquad \forall \ \ f \in P, s \in S, h \in VH_s, \qquad (22)$$

$$\zeta_{e,s,h} - \zeta_{f,s,h} \leq \mathcal{M}(1 - Y_{e,f,s,h}) \qquad \forall \ \ e \in P, f \in P \backslash S, s \in S, h \in VH_s, (23)$$

Eqs. (24) and (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. (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. (27) and (28). Finally, the binary and positive integer variables of the proposed model are shown in Eqs. (29) and (30).

$$\sum_{e \in P} \sum_{f \in P} Y_{e,f,s,h} \leq \mathcal{M} \ HCV_{s,h} \qquad \forall \ \ s \in S, h \in VH_{s,} \qquad (24)$$

$$QP_{s,f,h,w} \leq \mathcal{M}(\sum_{e \in P} Y_{e,f,s,h}) \qquad \forall\ f \in P\backslash S, s \in S, h \in VH_s, w \in W, \tag{25}$$

$$\sum_{f \in P\backslash S} \sum_{h \in VH_s} QP_{s,f,h,w} \leq QW_{w,s} \qquad \forall\ s \in S, w \in W, \tag{26}$$

$$\sum_{f \in P\backslash S} \sum_{w \in W} QP_{s,f,h,w} \leq CapH_{s,h} \qquad \forall\ s \in S, h \in VH_s, \tag{27}$$

$$\sum_{s \in S} \sum_{h \in VH_s} QP_{s,f,h,w} \leq Cap\mathcal{P}_{f,w} \qquad \forall\ f \in P\backslash S, w \in W, \tag{28}$$

$$X_{i,j,s,l},\ B_{b,s},\ Y_{e,f,s,h},\ LCV_{s,l},\ HCV_{s,h} \in \{0,1\} \qquad \forall\ i \in N,\ j \in N,\ b \in N\backslash S,\ e \in P,\ f \in P,\ s \in S,\ l \in VL_s,\ h \in VH_s, \tag{29}$$

$$QS_s, QW_{w,s}, QP_{s,p,h,w}, Ar_b, \zeta_{p,s,h} \geq 0 \text{ and integer} \qquad \forall\ s \in S,\ p \in P\backslash S,\ h \in VH_s,\ w \in W,\ b \in N\backslash S, \tag{30}$$

3.2.3. 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:

$$\text{Maximize} \sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s}\sum_{w\in W} QP_{s,f,h,w}\,Pr_w - QP_{s,f,h,w}\,Tc^P_{s,h,w}$$
$$\Rightarrow \quad \text{Minimize} \; -\left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s}\sum_{w\in W} QP_{s,f,h,w}\,Pr_w - QP_{s,f,h,w}\,Tc^P_{s,h,w}\right) \tag{31}$$

Then, Eq. (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. (32)-(33). These equations ensure that Eq. (31) can be satisfied at a given confidence level.

$$\text{Minimize} \quad \Psi \tag{32}$$

Subject to

$$\mathcal{P}ro\,b\left(-\left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s}\sum_{w\in W} QP_{s,f,h,w}\,Pr_w - QP_{s,f,h,w}\,Tc^P_{s,h,w}\right)\leq \Psi\right)\geq \eta, \tag{33}$$

Now, let's define a new variable (Υ) to simplify the proposed chance constraint Eq. (33) as follows:

$$\Upsilon = -\left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s}\sum_{w\in W} QP_{s,f,h,w}\,Pr_w - QP_{s,f,h,w}\,Tc^P_{s,h,w}\right) - \Psi \tag{34}$$

$$\mathcal{P}\,rob(\Upsilon \leq 0) \geq \eta, \tag{35}$$

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:

$$E(\Upsilon) = -\left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s}\sum_{w\in W} QP_{s,f,h,w}\,\mu_w - QP_{s,f,h,w}\,Tc^P_{s,h,w}\right) - \Psi, \tag{36}$$

$$Var(\Upsilon) = \sum_{w\in W}\sigma_w^2\left(\sum_{s\in S}\sum_{f\in P\backslash S}\sum_{h\in VH_s} QP_{s,f,h,w}\right)^2, \tag{37}$$

As shown in Eq. (37), the variance of the sum of $\mathrm{Pr_w}$variables equal the sum of their variances. Since variable Υ follows a normal distribution with mean $(\mathrm{E}(\Upsilon))$ and variance $(\mathrm{Var}(\Upsilon))$, $\mathcal{Z} = \frac{\Upsilon - \mathrm{E}(\Upsilon)}{\sqrt{\mathrm{Var}(\Upsilon)}}$ is a standard normal random variable and Eq. (35) can be rewritten as follows:

$$\mathcal{P}rob\left(\frac{\Upsilon - E(\Upsilon)}{\sqrt{Var(\Upsilon)}} \leq \frac{-E(\Upsilon)}{\sqrt{Var(\Upsilon)}}\right) = \mathcal{P}rob\left(\mathcal{Z} \leq \frac{-E(\Upsilon)}{\sqrt{Var(\Upsilon)}}\right) = \Phi\left(\frac{-E(\Upsilon)}{\sqrt{Var(\Upsilon)}}\right) \geq \eta, \quad (38)$$

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

$$\Phi^{-1}(\eta)\sqrt{Var(\Upsilon)} \leq -E(\Upsilon), \quad (39)$$

$$\Phi^{-1}(\eta)\sqrt{\sum_{w\in W}\sigma_w^2\left(\sum_{s\in S}\sum_{f\in P\setminus S}\sum_{h\in VH_s}QP_{s,f,h,w}\right)^2} \leq \left(\sum_{s\in S}\sum_{f\in P\setminus S}\sum_{h\in VH_s}\sum_{w\in W}QP_{s,f,h,w}\,\mu_w - QP_{s,f,h,w}\,Tc_{s,h,w}^{P}\right) + \Psi, \quad (40)$$

Hence, Eq. (40) provides the deterministic equivalent of the chance constraint proposed in Eq. (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) with Eq. (32) and add Eq. (40) to the system constraints.

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.

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. (41)-(44). Eq. (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. (42) and (43).

$$\text{Minimize} \quad \sum_{o=1}^{O} \left(\frac{d_o^- + d_o^+}{Goal_o} \right) \tag{41}$$

Subject to

$$F_o(x) - d_o^+ + d_o^- = Goal_o \qquad \forall\, o = \{1, \dots, O\}, \tag{42}$$

$$S_c(x)\ (\leq or\ = or\ \geq)\ 0 \qquad \forall\, c = \{1, \dots, C\}, \tag{43}$$

$$d_o^+,\ d_o^- \geq 0 \qquad \forall\, o = \{1, \dots, O\}, \tag{44}$$

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:

$$d_o^- = \begin{cases} Goal_o - F_o(x) & if\ \ Goal_o > F_o(x) \\ 0 & otherwise \end{cases} \qquad \forall\, o = \{1, \dots, O\}, \tag{45}$$

$$d_o^+ = \begin{cases} F_o(x) - Goal_o & if\ Goal_o < F_o(x) \\ 0 & otherwise \end{cases} \qquad \forall\, o = \{1, \dots, O\}, \tag{46}$$

The proposed mathematical model in this study can be reformulated by GP approach, as shown in Eqs. (47)-(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.

Minimize $\sum_{o=1}^{3}\left(\frac{d_o^+}{Goal_o}\right)$ (47)

Subject to

$Z_1 - d_1^+ + d_1^- = Goal_1,$ (48)

$Z_2 - d_2^+ + d_2^- = Goal_{2,}$ (49)

$\Psi - d_3^+ + d_3^- = Goal_3,$ (50)

Eqs. (4)–(30), and Eq. (40), (51)

$d_1^+, d_2^+, d_3^+, d_1^-, d_2^-, d_3^- \geq 0$, (52)

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:

Minimize / Maximize $Z = \{ f_1(x), f_2(x), \ldots\ldots, f_n(x) \},$ (53)

Subject to

$g(x) \leq 0,$ (54)

$x \in X,$ (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.

4.2.1. 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 Figure 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(−Δf_i / T)
                If h <= P_i
                    Update the best solution s = s′
        Update temperature (T=α*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.4. Pseudo-code of MOSA.

4.2.2. 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 P_m, mutation rate P_c, and maximum iteration I_m
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 < I_m
    For j in [1: (P_c * 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: (P_m * 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.5. Pseudo-code of NSGA-II.

4.2.3. 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 Figure 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 ($\Delta f_1 <= 0$ and $\Delta f_2 >= 0$)

Update the best solution

Update the solution

else if (($\Delta f_1 >= 0$ and $\Delta f_2 >= 0$) or ($\Delta f_1 <= 0$ and $\Delta f_2 <= 0$)) Δf_1.

Keep the current solution in the Pareto set

else

Set P1 = exp ($-\Delta f_1 / T$) and P2 = exp ($-\Delta f_2 / T$)

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.6. The pseudo-code of MOKASA.

4.3. 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 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 5, bins (3) and (9) are allocated to vehicle (2) at separation center (2), and the visiting sequence of these bins is ($3 \rightarrow 9$) 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 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

5. 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 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
Small	P1	7	2	2	1	2	2
	P2	10	2	2	1	2	2
	P3	15	3	2	1	2	2
	P4	20	3	2	1	2	2
	P5	25	3	2	1	2	2
Medium	P6	30	4	2	2	2	2
	P7	45	5	2	2	2	2
	P8	60	5	2	2	3	3
	P9	75	6	3	2	3	3
	P10	90	6	3	2	4	4
Large	P11	110	7	3	3	4	4
	P12	150	8	3	3	5	5
	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., 2018). In this work, the smaller “signal to noise ratio” is better for each algorithm due to the nature of the optimization problem. Eq. (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. (57)) (Colombaroni, Mohammadi, and Rahmanifar 2020).

$$S/N = -10 \times \log\left(\sum (y^2)/n\right) \quad (56)$$

$$y = \mathcal{C}/\mathcal{V} \quad (57)$$

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 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

Meta-heuristics	Parameter	Parameter Level			Optimum Level
		L1	*L2*	*L3*	
	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

6. 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.

6.1. 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:

(i). **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., 2023).

(ii). 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:

$$SNS = \sqrt{\frac{\sum_{i=1}^{n}(\bar{c} - c_i)^2}{n-1}} \qquad (58)$$

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.

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

$$MID = \frac{\sum_{i=1}^{n} \sqrt{\left(\frac{f_{1i} - f_1^{best}}{f_{1,total}^{max} - f_{1,total}^{min}}\right)^2 + \left(\frac{f_{2i} - f_2^{best}}{f_{2,total}^{max} - f_{2,total}^{min}}\right)^2}}{n} \quad (59)$$

(iv). 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.60):

$$MS = \frac{1}{M} \sum_{m=1}^{M} \left(\frac{\min(F_{i,known}^{max}, F_{i,true}^{max}) - \max(F_{i,known}^{min}, F_{i,true}^{min})}{F_{i,true}^{max} - F_{i,true}^{min}} \right)^2 \quad (60)$$

(v). 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. (61).

$$HV = \text{volume}\left(\bigcup_{i=1}^{|R|} b_i \right) \quad (61)$$

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

(vi). 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.

6.2. 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 9−12. Accordingly, based on the average result obtained from all test problems, the best algorithm regarding each indicator is determined, as shown in Table 13.

Table 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 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 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 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 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

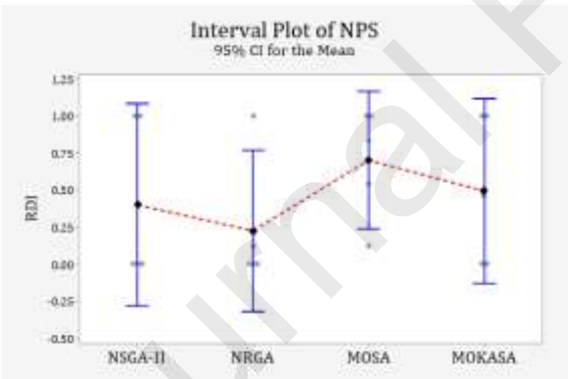
In this study, we conducted a comprehensive comparative analysis of four popular multi-objective optimization algorithms across small, medium, and large-sized problems. Our findings indicate that NSGA-II outperforms the other algorithms with respect to NPS and MS indicators for small-sized problems. 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.

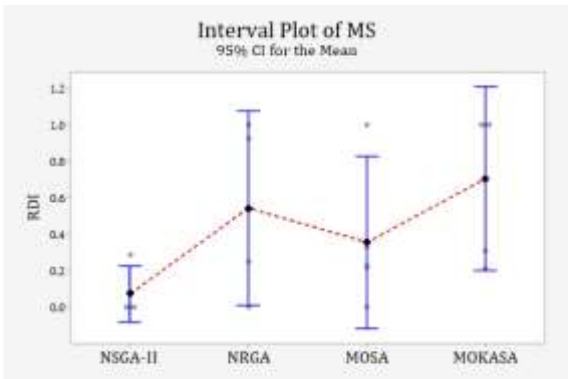
Additionally, to facilitate a graphical comparison of our results, we present mean plots and Least Significant Difference (LSD) values for the performance indicators. To obtain these plots and values, we convert the obtained performance metric values to the Relative Deviation Index (RDI) using Eq. (62) 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).

$$RDI = \frac{\left|S_{Alg} - S_{best}\right|}{S_{max} - S_{min}} \quad (62)$$

In Eq. (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 7, 8, and 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 Figure 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 Figure 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 Figure 9. The RDI is utilized to have the same scale for different performance indicator using Eq. (62). Figure 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, Figures 11-14 and Tables 14-17 describe the statistical description of performance metrics and do compare all algorithms in terms of variance and standard deviation.





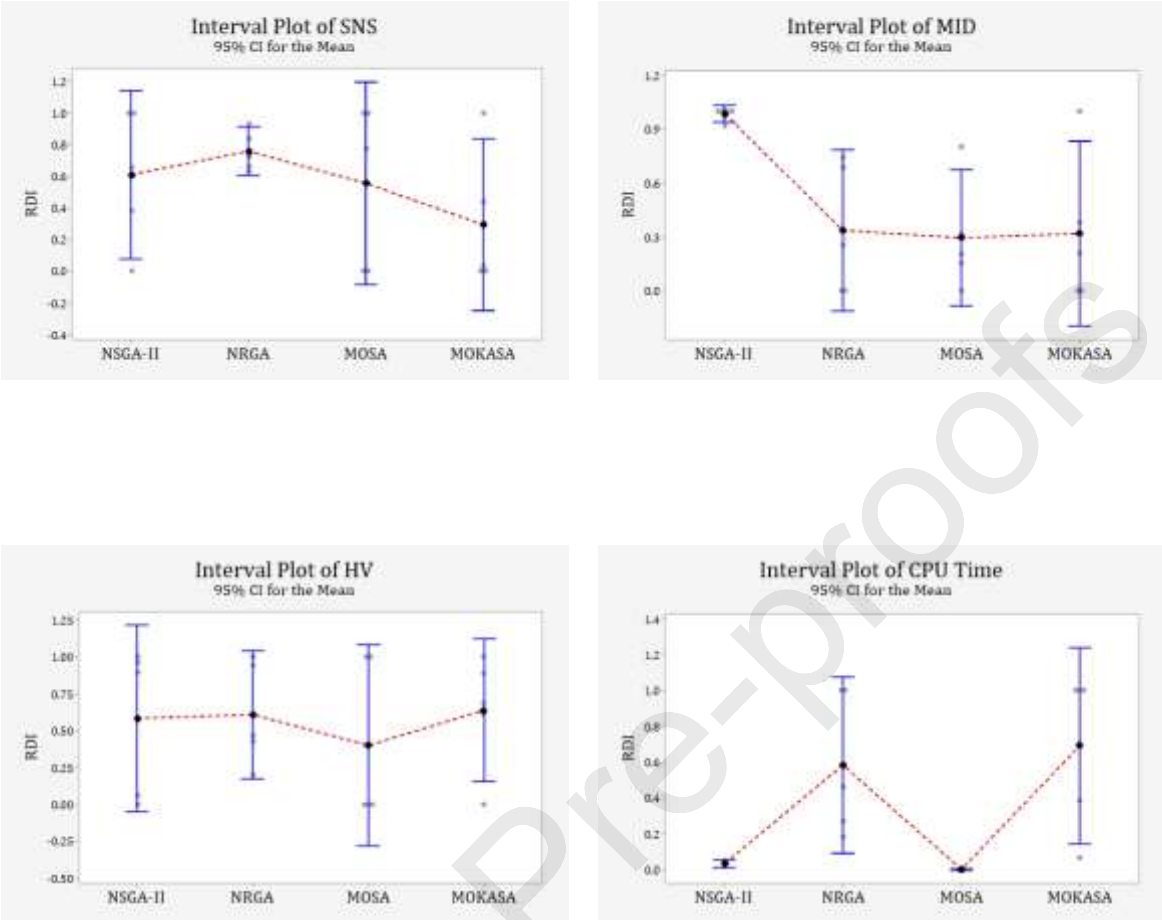


Fig.7. Interval Plot of small-sized problems based on performance metrics.

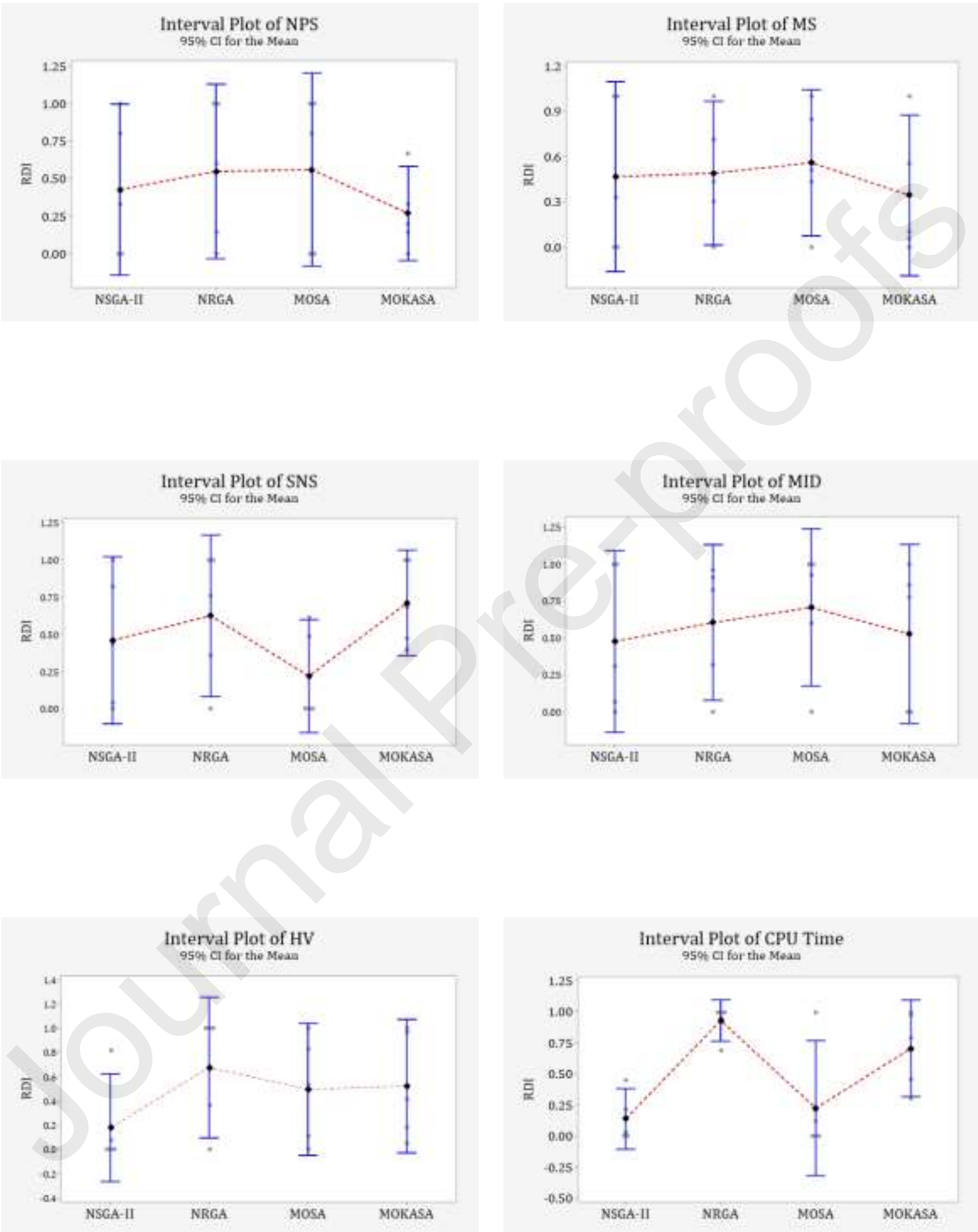


Fig.8. Interval Plot of medium-sized problems based on performance metrics.

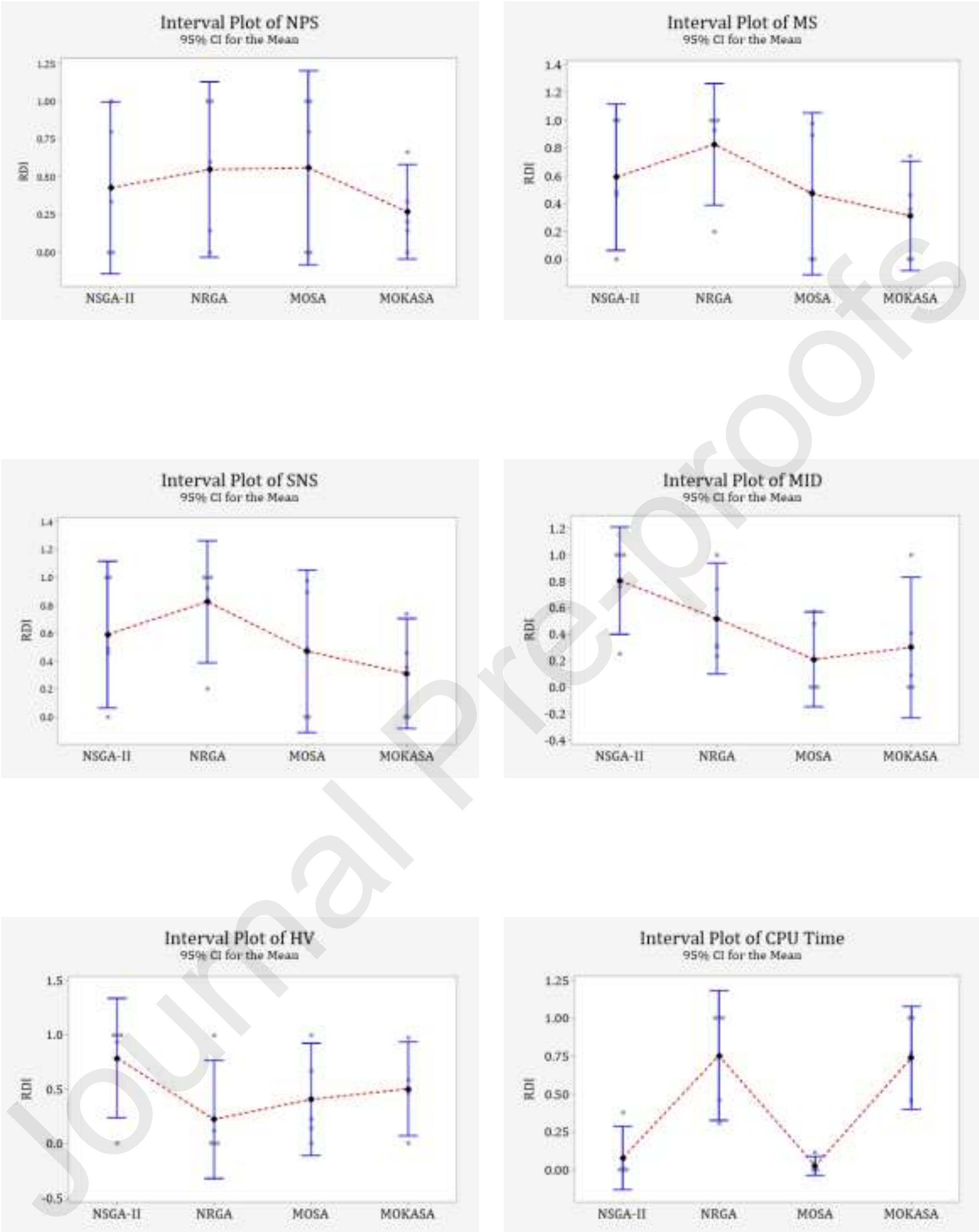


Fig.9. Interval Plot of large-sized problems based on performance metrics.

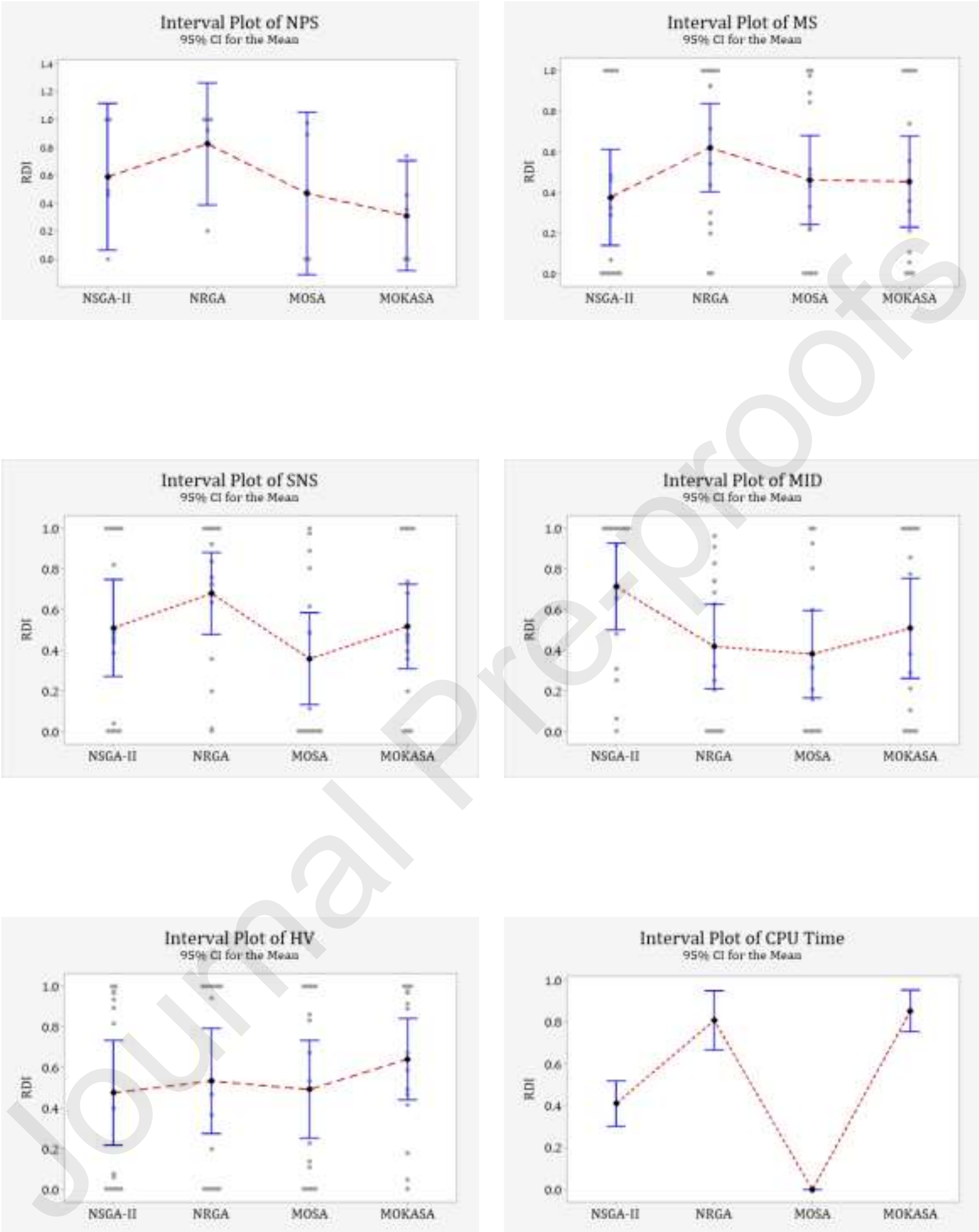


Fig.10. Interval Plot of overall performance metrics for all dimensions.

Table 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

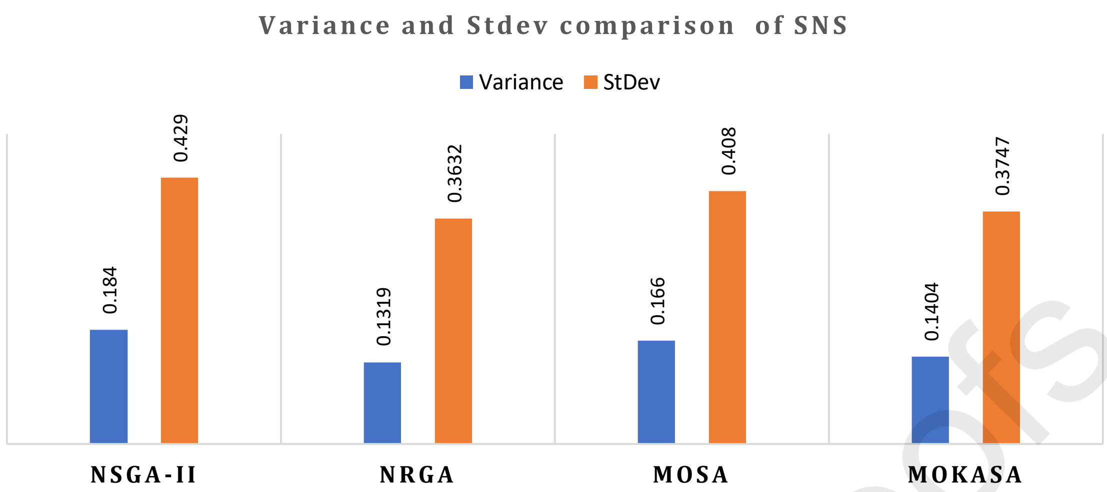


Fig. 11. Variance and Stdev comparison of SNS.

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

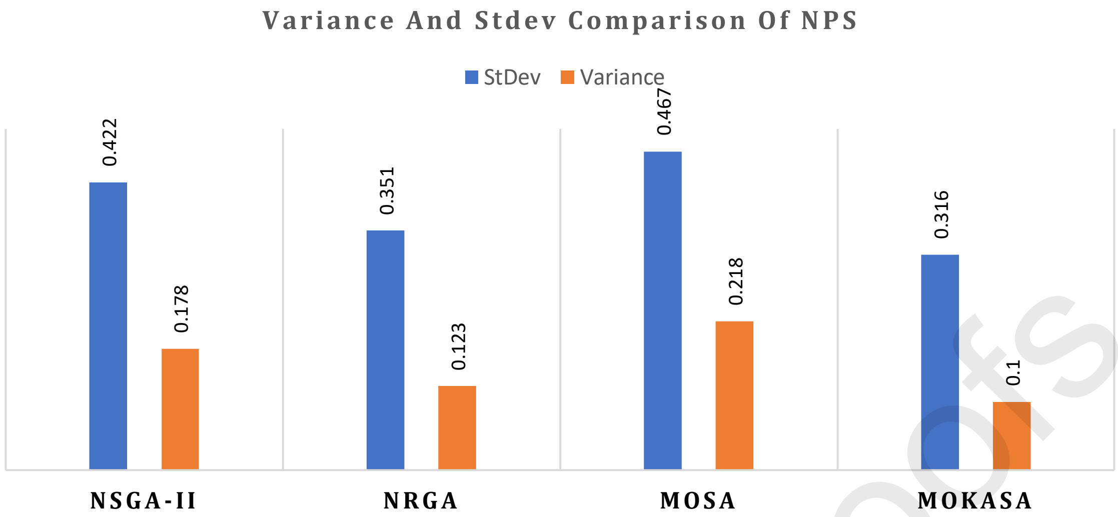


Fig. 12. Variance and Stdev comparison of NPS.

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

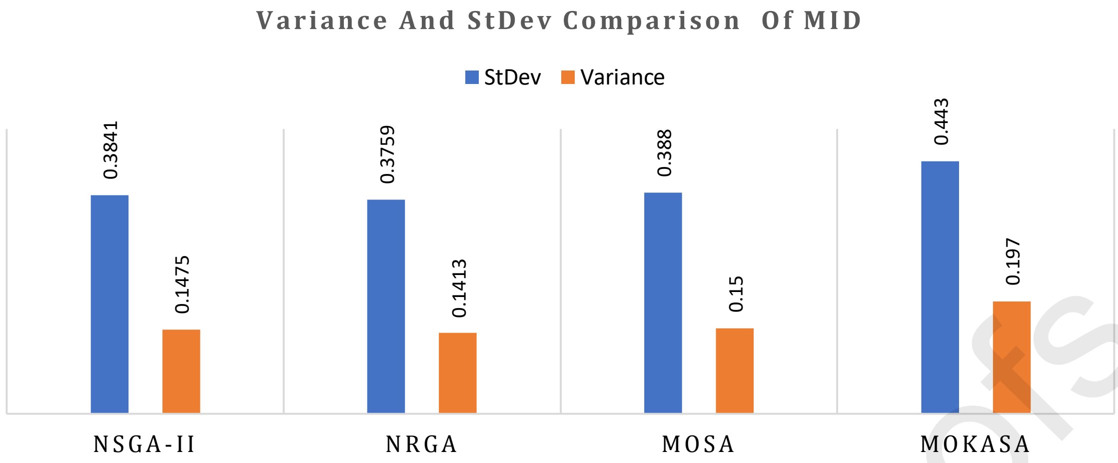


Fig. 13. Variance and Stdev comparison of MID.

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

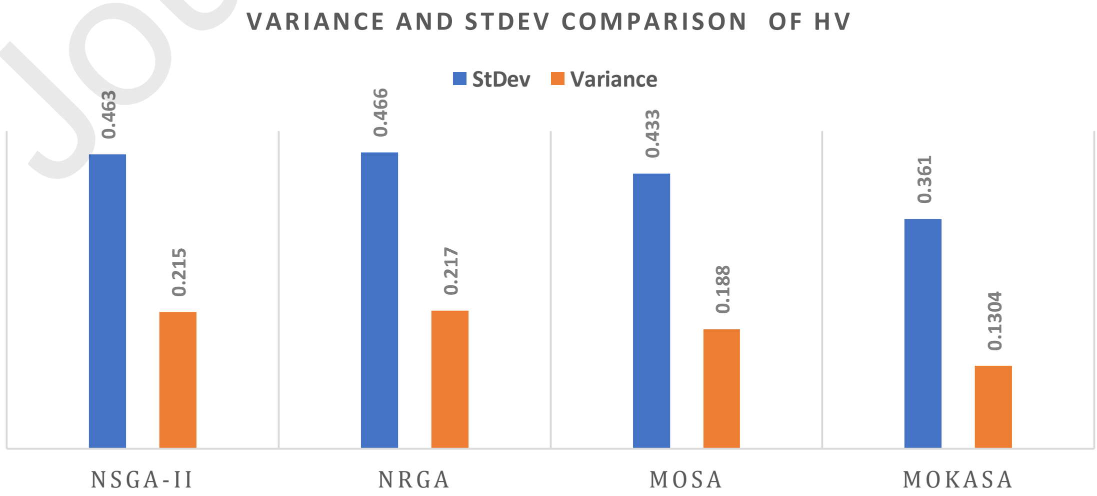


Fig. 14. Variance and Stdev comparison of HV.

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.

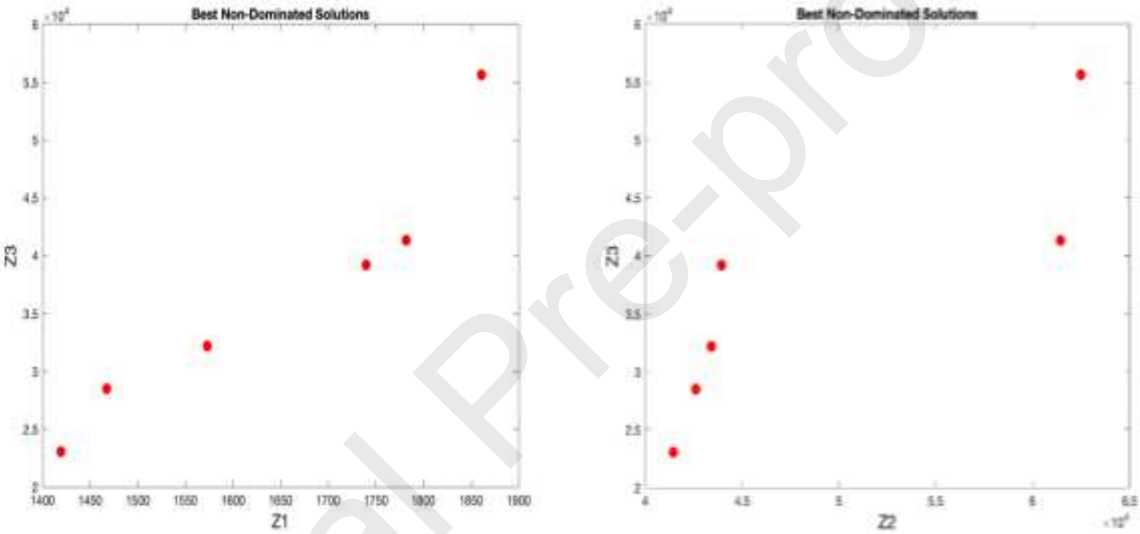


Fig.15. Pareto front of MOKASA for test problem 1.

Table 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

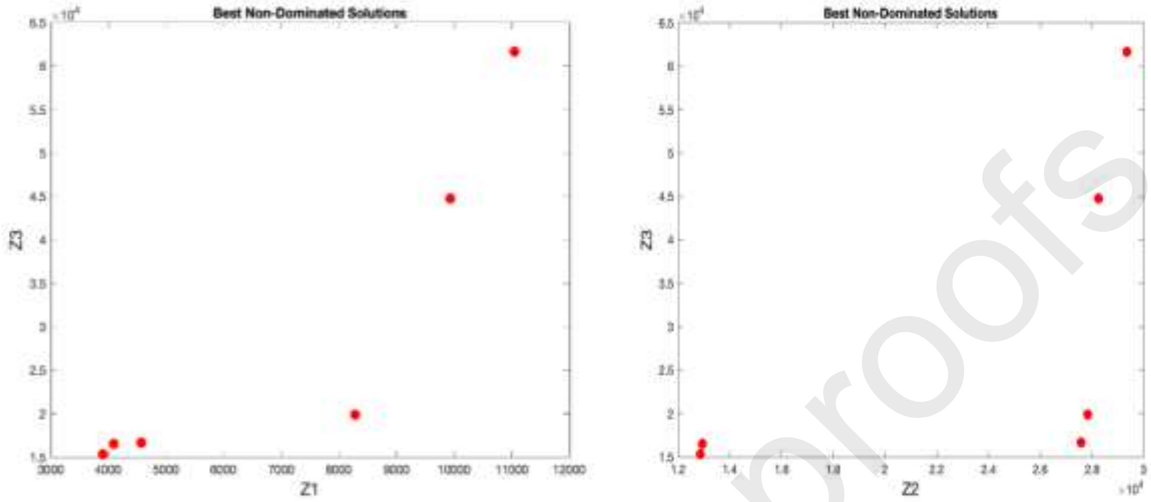


Fig.16. Pareto front of MOKASA for test problem 2.

Table 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.

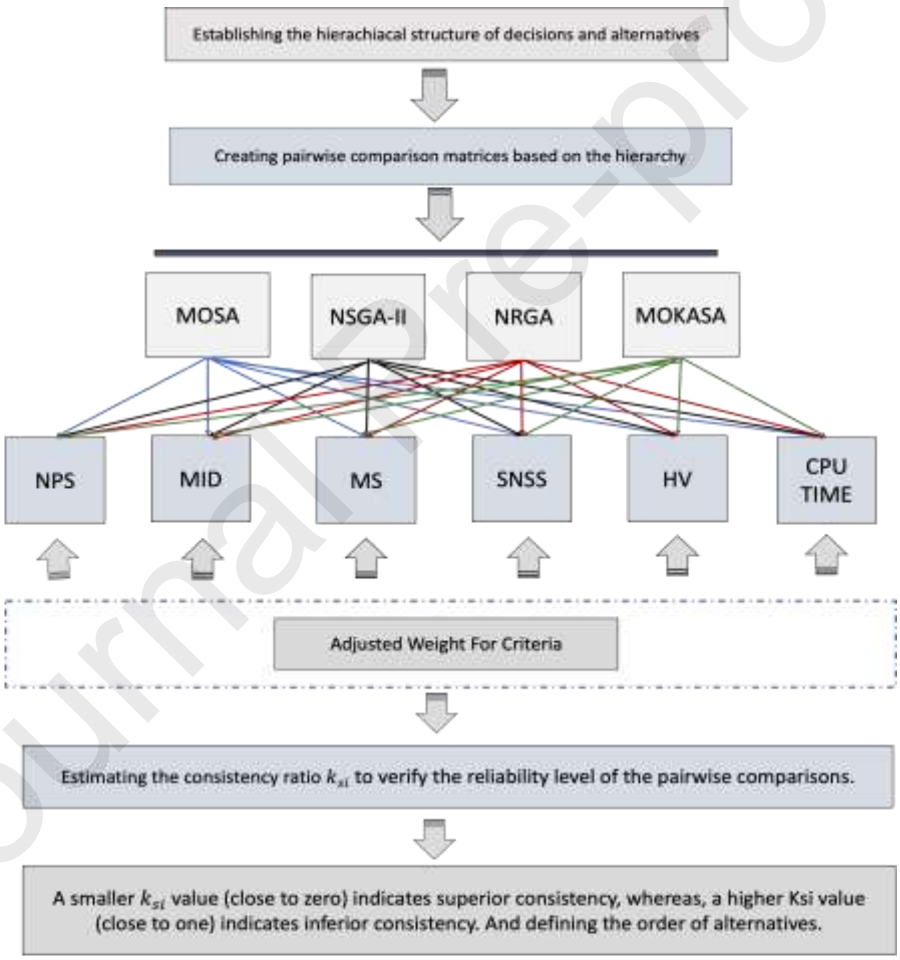


Fig.17. The hierarchical representation of alternatives and criteria.

7. 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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Credit authorship contribution statement

Omid Hashemi-Amiri and Mostafa Mohammadi developed the project, the main conceptualization, data curation, formal analysis ideas, and mathematical formulation. Golman Rahmanifar worked on the investigation of the technical details, methodology, performed the optimization, and writing-original draft. Mostafa Hajiaghaei-Keshteli, Gaetano Fusco, and Chiara Colombaroni supervised the designing the methodology, findings of this work, and they worked out the validation, writing - review & editing. All authors discussed the results and contributed to the final manuscript.