IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 26 July 2024, accepted 28 August 2024, date of publication 6 September 2024, date of current version 19 September 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3455945

RESEARCH ARTICLE

A Novel Railway Power Systems Design Methodology Using Genetic Algorithms: Models and Application

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ABSTRACT The development and the upgrade of railway networks is one of the strategies to reach decarbonization targets in the transportation field, thanks to the considerably lower energy consumption of electric trains with respect to other vehicles, typically fossil fuel powered. The design process of electric railway power systems is complex, requiring advanced simulation tools. The paper proposes a novel methodology for the design of the electrical power system of railway tracks, using genetic optimization. For this purpose, the authors developed ROAR, a flexible simulation and optimization software that generates optimized railway power system designs, helping engineers find the most efficient design solutions from a technical and economic feasibility perspective. After validating the simulation engine and comparing it with well-established software, the proposed method was applied to an operational electrified railway line in Italy to assess the effectiveness of the optimization algorithm. The results demonstrate excellent convergence properties, finding a different infrastructure design that achieves the same electrical performance, reducing costs with respect to the existing design.

INDEX TERMS Genetic algorithms, multi-objective optimization, simulation software, rail transportation power system.

I. INTRODUCTION

In recent years, the need for decarbonization has fueled increasing interest in the electric transport of light and heavy loads, for both short and long distances [1]. Railway systems have always been an attractive alternative to other electric vehicles, such as buses, passenger cars, and two-wheelers, because of their lower energy consumption and associated additional savings in CO_2 emissions. For example, taking a train instead of a car for medium-length distances would reduce emissions by around 80% [2]. In fact, high-capacity urban railways require approximately 10% of the energy required to cover the same distance traveled by passenger cars [3]. In addition to emissions savings, counteracting global warming, the development of rail transport has great potential for improving citizens' quality of life, as it reduces air pollution, traffic and noise caused by cars and buses. Therefore, governments worldwide have always supported the development of railway networks, adopting it as a key strategy to achieve a smaller carbon footprint for their countries. In 2021, the Italian Government planned to invest approximately 24 billion euros by 2027 for the construction [4] of new railway lines and the upgrade of existing ones.

The adoption of train transport is contingent on the development of railway infrastructure, requiring high initial costs and long construction times. The design process of railway systems is complex because of the large number of components involved and the high level of interdependence between them. Therefore, the comparison of different design solutions and the evaluation of their performance is not an easy task, especially when dealing with electrical aspects, where simplified linear models are not sufficiently accurate in most cases.

The associate editor coordinating the review of this manuscript and approving it for publication was Christian Pilato.

Carrying out simulations is often the best way to consider all relevant aspects before the construction of these types of systems, whose cost is usually quite high. Simulations provide the opportunity to detect critical issues during the power system design process when there is still a chance to modify most parameters and avoid problems. Once a sufficiently secure design has been established, iterative simulations can be employed to assess the advantages of various deviations from the baseline configuration. The process is inherently intricate and time-consuming, necessitating refinement of the initial design. Furthermore, in the contemporary context, it is crucial to conduct a precise preliminary energy assessment to ensure the adoption of appropriate measures to optimize energy efficiency [5], [6] and achieve a design solution that is both technically and economically feasible.

This paper proposes a novel design strategy employing the development of an accurate simulation software coupled with a custom meta-heuristic optimization algorithm, adapted for the peculiarity of railway power system features. The method is based on two main tools: the ROAR-simulator tool, a DC railway system simulator, and the ROAR-optimization tool, a custom genetic algorithm to optimize the electrification design, both of which are written in Python language, exploiting its capabilities to overcome the limitations imposed by older languages.

Overall, the ROAR software allows a drastic reduction in the design process time, giving the engineers a set of already optimized solutions. In particular, this procedure enables the optimization of the placement and sizing of the electrical substations and the sizing of the conductors, considering the phenomena involved in the entire electrical system of one or more transport lines. Additionally, it allows for the comparison of various design solutions, with the aim of optimizing energy savings through the recovery of braking energy from vehicles and the exchange of power between vehicles using the traction line.

The sections are arranged as follows: Section II provides a general overview of railway systems models and optimization techniques, outlining and comparing different needs of modeling. Section III presents the general structure of the ROAR software, Section IV describes the mathematical models used to simulate the multi-physical system, and Section V describes the validation of the simulation tool, performed comparing simulation results by ROAR with those calculated by an older validated software. Section VI describes the optimization algorithm, and Section VII analyzes the results of a case study, comparing the optimized design calculated by ROAR with the actual design of an existing electrified railway line. Section VIII presents conclusions and possible future research directions.

II. LITERATURE REVIEW

A. RAILWAY SYSTEM SIMULATORS

Electric railway systems require dedicated simulation tools because of the peculiar features of loads (trains) that move over time and space, changing their kinematic and dynamic performance. This specific aspect introduces additional complexity in the software with respect to conventional power system simulators, where loads do not change their positions or connection points over time. Numerous scientific studies in the literature have employed railway system simulators developed using different approaches and architectures according to the specific needs of every study.

Among the most widely adopted simulation software in the literature, MATLAB [7] offers a high-level interpreted language with a comprehensive Integrated Development Environment (IDE) and several ready-to-use toolboxes and functionalities. It provides basic object-oriented programming features with totally dynamic typing, without any type-checking system. MATLAB Coder can be used to compile standalone applications to C/C++ to gain performance but with less flexibility.

Simulink/Simscape is an interesting cyber-physical system modeling tool integrated into MATLAB IDE, allowing the construction of simulation models by simply connecting blocks together. Since it does not require writing code, it can significantly reduce the development time of simple simulation models; however, this type of graphical interface becomes difficult to use for complex projects because of the large number of blocks connected. However, these tools are becoming popular owing to their user-friendliness, fueling research on layout optimization and automatic block placement techniques [8].

OpenModelica [9] is an open-source modeling and simulation environment developed and supported by a non-profit organization. In some ways, it is similar to Simscape, but it offers the double option of creating models in graphical form or using code. In addition, the code is compiled into C/C++ every time the models are modified, enabling considerable performance levels. Moreover, OpenModelica has an advanced system for type checking, which also supports generic types, but dynamic typing is not supported because the system is based on the traditional paradigm of C/C++, resulting in limited flexibility.

B. LOW-LEVEL VS HIGH-LEVEL LANGUAGES

The selection of the programming language (or framework) for software may be the most important choice because it deeply influences the characteristics of the resulting program.

Low-level languages (e.g. C/C++ and FORTRAN) are still used as the core of comprehensive simulation frameworks, and high-level languages are suitable for building both simple and sophisticated simulators. As confirmed by its great diffusion, object-oriented programming is an incredibly powerful approach for handling the high complexity required by real-world problems, which can be addressed in a simple way using design patterns. Custom software can remarkably benefit from open-source libraries, whose exploitation can considerably reduce the development time owing to code reuse, but it may be difficult to find such libraries for specific applications.

C. RAILWAY SYSTEMS OPTIMIZATION

In past years, most studies on the performance improvements of railway power systems regarded two main aspects [5]:

- changes in human behavior, modifying the driving style of the driver, and timetable optimization;
- improving infrastructure using stationary and on-board energy storage systems for braking energy recovery, integration of renewable sources and energy exchange with electric vehicles.

In recent years, several optimization methods for timetable management have been proposed using various techniques. In [10] a genetic algorithm was used to time shift loads, smoothing the load profile, thereby significantly reducing the maximum traction power. A different approach was used in [11] where a two-step optimization, with linear programming and a genetic algorithm, was performed to synchronize the train schedules to reduce both waiting time and energy consumption. A hybrid approach was used in [12] where a genetic algorithm was employed to optimize both the driving style and timetable, using a metro station in China as a reference.

On-board energy storage systems have been already adopted by some rail transit companies since such systems offer several advantages, including peak power reduction, minimized losses, voltage stabilization, and the ability to operate without overhead catenaries. Among the different technologies, in [13] an energy management system has been explored to reduce the energy consumption of fuel cell/supercapacitor hybrid trains. Conversely, in [6] a battery-based storage solution was sized for placement in a substation using particle swarm optimization.

In some studies, stationary storage is used also for the integration of renewable sources into the railway power system. [14] analyses the connection of renewable sources and batteries to the catenary, whereas [15] describes a totally renewable railway power system, with batteries both in stations and on-board. Reference [16] investigates the use of batteries inside substations for energy exchange between trains braking regeneratively and electric vehicles connected to recharging points in the parking lots of stations; [17] performs similar study, including also renewable sources.

About the enhancement of existing rail infrastructure, various approaches to optimization problems have been explored. In [18] a simplified system representation was employed to reduce the optimization to a mixed-integer linear programming problem. A more complex representation led the same authors to use a genetic algorithm to optimize the spacing between the autotransformers [19]. Additionally, a complete optimization of the system, including the position of the substation, the position of the autotransformers, and the catenary configuration, was proposed in [20]. The problem of the optimal positioning, which is studied in this paper, has been already treated regarding the effect on the electrification [21], the maximization of the regenerative breaking energy [22] and the seismic risk [23] but has never treated in a multi-objective problem optimized with a meta-heuristic algorithm.

In this study, the authors exploited a genetic algorithm, namely aNSGA-II, to optimize both the sizing and placement of the electrical substations along the railway line. The main problem addressed with this method is the strong influence of the meta-parameters of the genetic algorithm on the number of electrical substations. This influence arises from the encoding of the railway power system design into the genetic algorithm. The authors propose a novel design methodology that aims to achieve the following advancements:

- the ability to use a non-simplified representation of the railway system within a simulation tool that addresses all the non-linearities of the multi-physical nature of the system, including train driver behavior in normal and fault scenarios;
- the implementation of an innovative crossover function to eliminate the influence of the meta-heuristic parameters of the genetic algorithm on the number of substations;
- the use of new indicators to evaluate the quality of the voltage profile of traction lines, and to assess the response of the system in the event of a fault.

III. ROAR SOFTWARE OVERVIEW

ROAR software is a powerful cross-platform simulation and optimization software for railway systems, written in Python, to speed up the design process of new lines or upgrades to existing ones. Data entry, simulation, and optimization setup were carefully designed to be seamless, and the computation engine exhibited good performance.

A. ROAR SOFTWARE ARCHITECTURE

ROAR software exploits high-level capabilities of Python language to achieve an improved trade-off between flexibility, complexity, and speed in simulations, to harness the great flexibility of general-purpose physical modeling frameworks used for research, with the simplicity and computational performance of commercial software. Unlike other high-level object-oriented languages (e.g. Java and C#), Python provides an optional static type-checking system that ensures a way to detect errors before runtime, simultaneously leaving the chance of not defining fixed types for situations where a lot of flexibility is required. For performance-sensitive situations, the Cython compiler can be used to compile Python code into C, allowing for the combination of the superior computational speed of low-level languages with the power of high-level code, thus taking the best of both worlds.

ROAR software consists of two tools: ROAR-simulator, and ROAR-optimization. As shown in Fig. 1, the ROAR-simulator acts as the inner part of the software, simulating a DC railway system, computing all the relevant physical quantities, and calculating the key technical performance indices to evaluate the design and compare it with different ones. Instead, ROAR-optimization is responsible for the generation of different designs to be simulated and compared: it acts as the controller of a meta-heuristic multi-objective optimization process [24], [25], exploring a wide set of technical choices to find the best trade-off between performance and total system costs [26]. For ROAR-optimization, the authors realized a custom version of a multi-objective Non-dominated Sorting Genetic Algorithm (NSGA-II) [27], [28].

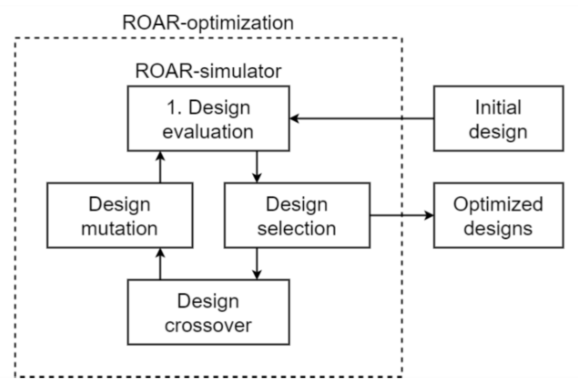

FIGURE 1. ROAR-software architecture.

B. SIMULATION INPUT AND OUTPUT

Fig. 2 shows the input data of ROAR-simulator. Each box represents an object responsible for a single aspect of the simulation. Every object can be replaced with a customized version to allow the software to simulate behaviors that are different from standard ones.

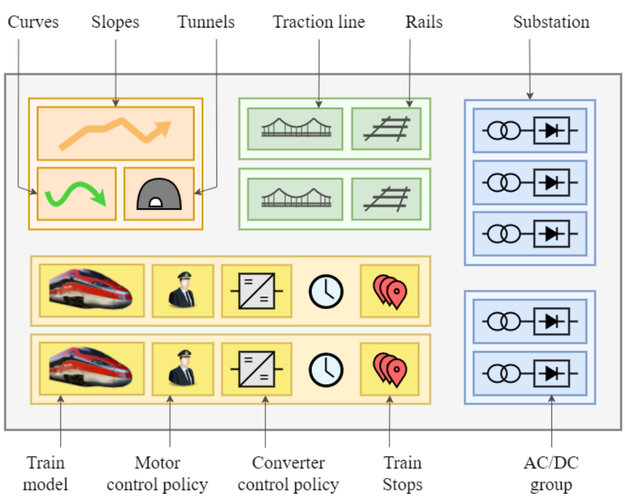

FIGURE 2. Inputs of ROAR-simulator.

Table 1 summarizes the ROAR-simulator outputs for each simulated component. In addition to the instantaneous values of the mechanical and electrical quantities, the software

TABLE 1. Outputs of roar-simulator.

Component	Quantity	
	Instantaneous	**Total**
Line	Line current Line current density Line power loss	Total line energy loss
Substation	DC bus voltage Current injected into line Power exchange with the grid	Total energy injected into the grid Total energy drawn from the grid Net energy exchange with the grid
Train	Position x Speed v Acceleration a Pantograph: • voltage V • current I_{line} • power P_{line}	Energy exchange with the line: • energy drawn from the line • energy injected into the line • net energy exchange
	Mechanical power: • delivered by motors • dissipated by brakes Electric power losses: • into rheostats • into motors • into converters	Mechanical energy: • delivered by motors • dissipated by brakes Electric energy losses: • into rheostats • into motors • into converters

evaluates the energy flows in the system, calculating different types of losses, as shown in the Sankey diagram depicted in Fig. 3. Fig. 4 reports different aspects of a railway system. First, a train driver behavior model calculates the desired force to be applied to each train, depending on train position, speed, and speed limits. Then, a simplified model of train motors, converters, and their control systems, computes the real driving force (or braking force) applied to each train, depending on the adsorbed electrical power, computed towards a system load flow. In some cases, due to electrical limitations (e.g. low values of line voltage, regulated by technical standards), the applied forces can be different from the desired ones. Finally, a mechanical model is used to calculate the acceleration of each train, to update their speeds and positions. After the simulation has been completed, a post-processing phase calculates total values (e.g. adsorbed energy, losses) for each component (e.g. train, substation).

C. LOAD FLOW

For each simulated time step, the software builds the electrical model of the system, then calculates voltages performing one or more load flows, with a final check to verify the voltage stability of the solution (to detect voltage collapse). The Newton-Raphson method was preferred over the Gauss-Seidel method because of its faster convergence at the expense of relatively higher complexity. The computed voltage value at each node (train pantograph or substation busbars) is used as the initial value for the load flow of the subsequent simulation step. This simple trick drastically

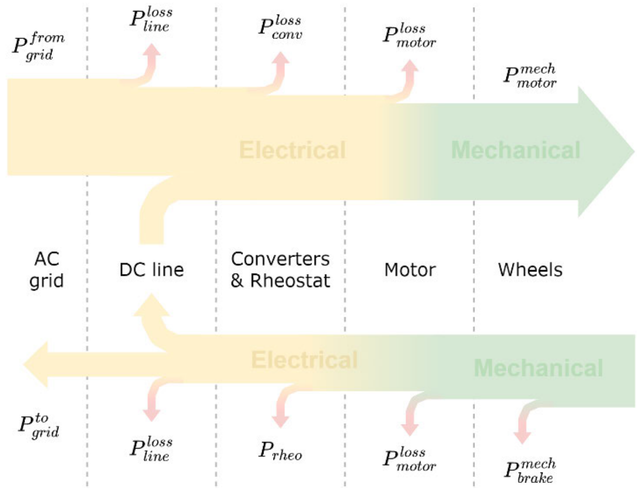

FIGURE 3. Energy flows and losses calculated by ROAR-simulator.

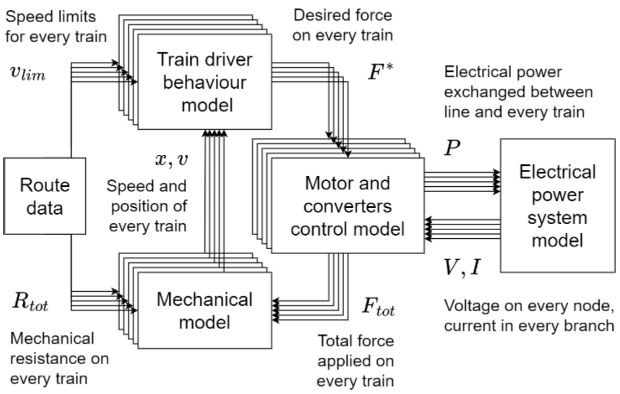

FIGURE 4. Simulation algorithm of ROAR-simulator.

reduces the number of iterations required to reach convergence (e.g. 3 iterations for 10^{-5} precision), thus decreasing the total simulation time. When one or more trains pass near a substation, the electrical model of the system can have one or more branches with "low resistance" (resistance values below 1% of the other ones), which may prevent the load flow from converging properly. To avoid these situations, before performing the load flow the software checks for the existence of low-resistance branches and simplifies the network to an equivalent network without these types of branches. Every group of nodes connected by low-resistance branches are incorporated into a single "super-node."

D. FAULT SIMULATION AND AUTOMATIC TRAFFIC REDUCTION

ROAR software simulates each design solution not only considering a healthy power system. In fact, it takes into account the effect of faults, which may affect the transport capacity of the railway. This enables the evaluation of the robustness of the power system, highlighting the advantages of more expensive solutions that may be excluded beforehand.

In particular, ROAR simulates the same power system multiple times, every time assuming a different fault among a set of chosen faults. As shown in Fig. 5, the optimizer gradually reduces the power and/or frequency of the trains until an acceptable system operation is achieved, without violating the basic technical constraints: maximum current for overhead conductors and conversion groups, and minimum line voltage.

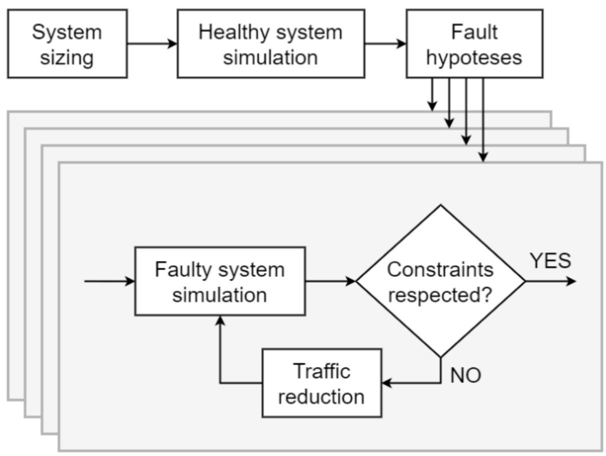

FIGURE 5. Normal and faulty railway power system simulation, performed by ROAR software.

IV. MODELS OF RAILWAY SYSTEM COMPONENTS

A. TRAINS

1) MECHANICAL MODEL

In ROAR, each train is modeled as a point mass moving along a curvilinear path (strictly following its track) using a 1-D model. At every simulation step, the acceleration of each train is calculated according to 2^{nd} Newton's law, and then train speed v and position x are updated by integrating the motion equations. As described further in paragraph IV-A.3, driving and braking forces are applied according to the train control algorithm (train driver behavior simulation), which considers various constraints, such as the speed limit imposed by route curves. For mechanical resistance, all terms (aerodynamic, rolling, curve, and slope resistances) depend on the geodetic features of the route, such as slope angle and radius of curvature of the track at the train position.

2) ELECTRICAL MODEL

Under normal conditions, the mechanical power delivered to the train wheels ($P_w > 0$) is provided entirely by the motors ($P_{motor}^{mech} = P_w$), and it is controlled to be equal to the value set by the train driver (P_w^*), so the electrical power adsorbed from the line ($P_{line} > 0$) is independent of the voltage V (constant power control). When the power system is heavily loaded, the line voltage V is low and converters decrease the adsorbed electrical power to avoid large currents that may damage the line or the train converters themselves. Most converters

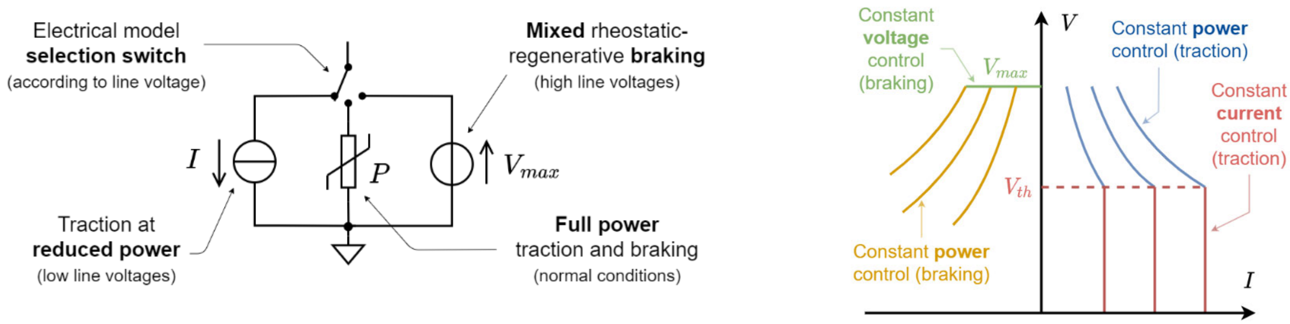

FIGURE 6. Electrical model used by ROAR-simulator for every train: equivalent circuit (left) and associated I-V characteristic (right).

switch to constant current control mode if the line voltage is below a fixed voltage threshold V_{th}, so the mechanical power delivered to the train wheels is smaller than the value set by the driver ($P_w < P_w^*$).

In contrast to the previous case, where the limit imposed by the electrical supply system results in a discrepancy between the driver's command and the train behavior ($P_w \neq P_w^*$), braking ($P_w^* < 0$) must always be accomplished as determined by the driver for safety reasons. During regenerative braking, under normal conditions, the mechanical power adsorbed by the motors ($P_{motor}^{mech} < 0$) is fed back to the line ($P_{line} < 0$). Therefore, also in this case, the electrical power exchanged with the line is independent of voltage. This is true only if the line voltage is below its maximum limit V_{max}, otherwise, the converters switch to constant voltage control, reducing the power regenerated to the DC line. The excess "unregenerable" power is dissipated into mechanical brakes ($P_{brake}^{mech} > 0$) and/or train rheostats ($P_{rheo} > 0$), performing a mixed regenerative-rheostatic braking.

ROAR software allows the simulation of trains with different types of energy regeneration control: each train has its converter control policy, which defines how converters are controlled according to the desired driving or braking power P_w^* and pantograph voltage V. However, custom converter control policy objects can be defined, allowing the simulation of more complex converter control modes. This can be applied to all trains or only a few of them.

The equivalent circuit used by ROAR to simulate every train, depicted in Fig. 6, is composed of three electrical components:

- a non-linear constant-power load (or generator) for normal driving (or braking) operation;
- a current generator for traction operation at reduced power when the line voltage is low;
- a voltage generator, for mixed regenerative-rheostatic braking when line voltage is high.

At every simulation time step the software evaluates the conditions listed in Table 2 to determine the component to use in the equivalent circuit. The model considers the efficiency of motors (η_{motor}) and converters (η_{conv}), which defines the global train efficiency ($= \eta_{conv}\, \eta_{motor}$).

TABLE 2. Conditions for the calculation of energy flows.

Desired wheel power	Voltage condition	Action
$P_w^* > 0$ (driving)	$V \geq V_{th}$	$P_{motor}^{mech} = P_w^*$ $P_{line} = P_{motor}^{mech}/\eta$
	$V < V_{th}$	$I_{line} = P_w^*/\eta/V_{th}$ $P_{motor}^{mech} = P_w^*\, V/V_{th}$
$P_w^* < 0$ (braking)	-	$P_{line} = 0$ $P_{rheo} = \eta\, P_{motor}^{mech}$
	-	$P_{line} = \eta\, P_{motor}^{mech}$ $P_{rheo} = 0$
	$V < V_{max}$	
	$V = V_{max}$	$P_{rheo} = -\,\eta\, P_{motor}^{mech} + P_{line}$

3) TRAIN DRIVER BEHAVIOR

In general, simulating man-in-the-loop systems requires the use of complex statistical models. However, a simplified approach can be adopted to analyze which actions the train driver should perform to comply with train running constraints (e.g. decrease the speed before a curve) and objectives (e.g. running time minimization). The train driver behavior simulation algorithm depends on the configured motor control policy, which is composed of a list of control rules, in a well-defined priority order. As shown in Fig. 7, each control rule is responsible for a particular action to be taken by the train driver (e.g., maintaining a constant speed, braking at maximum power, etc.) based on a condition (e.g. when the train speed is close to the limit or when the train exceeds the speed limit, etc.).

At every simulation time step, the condition of the first control rule is evaluated, and the corresponding action is taken only if the condition is satisfied. The second condition is evaluated only if the previous one is not satisfied, and so on. This allows the control to consider high-priority constraints before low-priority constraints. Before evaluating the control conditions, the software calculates the constraints to comply with (listed in Table 3), which may vary from time to time. For example, the maximum train acceleration a_{max} depends

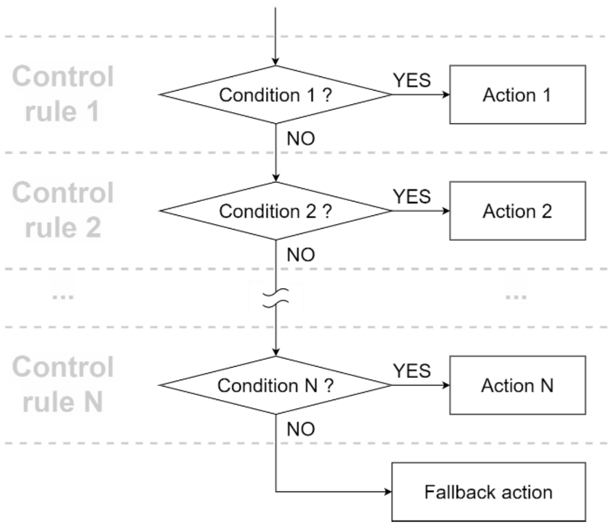

FIGURE 7. Train driver behavior simulation algorithm used by the default motor control policy in ROAR software.

TABLE 3. Constraints for motor control policy.

Constrained quantity	Constraint symbol	Constraint imposed by
Train speed	v_{lim}	Line wires and curves
Driving force	$F_{m,max}$	Motor capability Passengers' comfort
Braking force	$F_{b,max}$	
Train acceleration	a_{max}	Motor capability Mechanical resistances Passengers' comfort

TABLE 4. Standard motor control rules in roar-simulator.

Control rule	Condition	Action
Brake to reach speed limit	$v - d_{max}\Delta t \leq v_{lim}$	$a = (v_{lim} - v)/\Delta t$
Max brake above the speed limit	$v > v_{lim}$	$F_{tot} = -F_{b,max}$
Brake before speed limit	$d_{safe} > 0.6\ d_{max}$	$a = -0.75\ d_{safe}$
Coasting	$d_{safe} > 0.4\ d_{max}$	$F_{tot} = 0$
Maintain constant speed near the limit	$\lvert v - v_{lim}\rvert \leq v_{tol}$	$a = 0$
Accelerate to speed limit	$v + a_{max}\Delta t \geq v_{lim}$	$a = (v_{lim} - v)/\Delta t$
Max accelerates below the speed limit	$v < v_{lim}$	$F_{tot} = +F_{m,max}$

on the path slope in the current position, so a_{max} must be updated at every simulation step.

ROAR software library contains different control rules to allow the user to build his motor control policy according to his needs. Table 4 lists the control rules (in their priority order) used in the default policy.

d_{safe} is the "minimum safe brake deceleration," i.e. the deceleration needed to perform a braking to target to:

- a station, where the train must stop ($v^* = 0$)
- a speed limit change point ($v^* = v_{lim}$)

In general, it is useful to think in terms of "critical points," i.e. points where trains should reach speed $v = v^*$ at position $x = x^*$, so stations can be considered as zero-speed limit change points. If $d_{safe} > d_{max}$ the train is not able to brake safely, in fact, its maximum deceleration is not sufficient to perform proper braking to the target, thus the train will decelerate less than needed, stopping after the station or reaching the new speed limit too late, exceeding it for some time, as shown in Fig. 8.

The minimum safe brake deceleration d_{safe} is evaluated as follows. For each critical point i ahead of the train, in its running direction, then only the lowest value is considered for the train control, as shown in Fig. 9.

$$d_{safe,i} = \frac{v^2 - (v_i^*)^2}{\lvert x_i^* - x\rvert} \qquad d_{safe} = \min_{\mathrm{i}}(d_{safe,i})$$

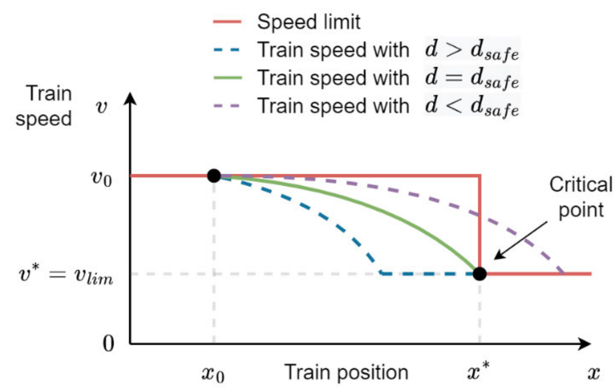

FIGURE 8. Comparison of speed profiles of a train, braking at different decelerations, before a critical point.

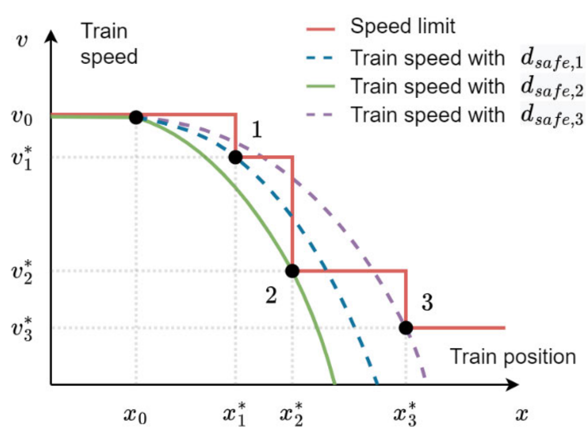

FIGURE 9. Determination of the minimum safe brake deceleration for one train, based on the three critical points ahead of it.

As shown in Table 4, some constant coefficients are used. These coefficients are needed to ensure a proper safety margin so that the train can brake without problems even if the real maximum deceleration is lower than the evaluated one. In fact, d_{max} considers the local path characteristics to calculate the total mechanical resistance of the train. Since the path constantly changes along the route (and the air resistance varies with speed) the maximum deceleration d_{max} is always evaluated with some error. This coefficient can be optimized depending on the path, but the values reported in the table are a good compromise for common real-world cases.

Another important purpose of the coefficients is to avoid control instability, which can occur due to the discrete nature of the simulation. In fact, due to the variability of the mechanical resistance (and thus the maximum deceleration), the control could oscillate between two control rules, changing from one to another, at every simulation step. The difference between the coefficient in condition (0.6) and the control action (0.75) ensures a proper margin, acting like a hysteresis, keeping the train in the same state when approaching a critical point, and avoiding an oscillating behavior.

Similar to converter control policies, also custom motor control policies and control rules can be customized as needed, allowing the simulation of more complex train driver behaviors to be applied to all trains or just a few trains.

B. ELECTRICAL SUBSTATIONS

Electrical Substations (ESS) are simulated through simple Thevenin equivalent circuits, thus modeling the voltage drop at substation DC busbars as proportional to the total current injected into the line. For one-directional substations, i.e. which do not allow energy regeneration from the DC line to the AC grid, the software checks the sign of the total current injected into the line. If the current is negative, i.e. some substations would transfer power from DC to AC, the load flow calculation is repeated, turning off (disconnecting from the DC line) substations with negative currents. These substations are also simulated as turned off for the following simulation steps, then are turned on again when the calculated busbar voltage becomes greater than the Thevenin equivalent voltage. For bidirectional substations, i.e. substations equipped with DC/AC inverters to allow energy flow from the line to the power grid, two different Thevenin equivalent resistance and no-load voltage values can be used, one for each energy flow direction, as shown in Fig. 10.

C. TRACTION LINES

DC traction lines are simply modeled by the software as resistive branches, calculating the total equivalent resistance of all the conductors: contact wires, load-bearing wires, and feeder wires, connected in parallel. For contact wires, a usury factor is used to consider the reduction in the gauge due to mechanical usury over time. The resistance of rails is also considered in the model, as an additional resistance in series with each branch. Fig. 11 shows the complete electrical model of a small system with 2 tracks, 3 trains and 3 one-directional substations.

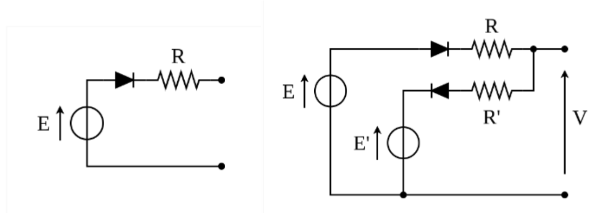

FIGURE 10. Equivalent circuits used by ROAR-simulator for the electrical substations: (left) one-directional, (right) bidirectional.

In the future, ROAR software will be expanded to consider the thermal behavior of line conductors and AC/DC conversion groups in substations, to improve the assessment of the thermal limits of the components and more accurately evaluate the ability of the system to handle power overloads.

V. ROAR-SIMULATOR VALIDATION

The results obtained from the ROAR-simulator tool have been rigorously compared with those from "Recupera" software. "Recupera" has a proven track record of validity, confirmed through extensive experimental measurements, and has been employed successfully in numerous projects [5], [6], [7], showing a high correspondence between simulation results and experimental data.

A. TEST RAILWAY SYSTEMS

Software validation was performed on two case studies: a first simple test with a train on an existing railway line in Piedmont (northern Italy), and another one with multiple trains on a test high-speed railway line.

The first case study consisted of:

- a 16.5 km single track line, with variable speed limit between 60 and 90 km/h, various curves and a short tunnel;
- a "Minuetto" train by Alstom equipped with two driving coaches (ALe 501 and ALe 502), with nominal electrical power of 3.5 MW, stopping on 5 stations;
- 3 kV DC traction line with 4 conductors per track:
  - 2 contact wires (100 mm^2, with 0.7 usury factor);
  - 2 load bearing wires (120 mm^2);
- 1 electrical substation at position 5.3 km, equipped with 2 AC/DC groups of 5.4 MW each;
- simulation of 17 minutes with time step of 5 seconds.

The second case study consisted of:

- a 90 km double track line, with 2 curves and 2 tunnels;
- 5 minutes departures with "Frecciarossa" ETR500 with nominal electrical power of 11 MW;
- 3 kV DC traction line with 5 conductors per track:
  - 2 contact wires (150 mm^2, with 0.7 usury factor);
  - 2 load bearing wires (120 mm^2);
  - 1 feeder wire (150 mm^2);

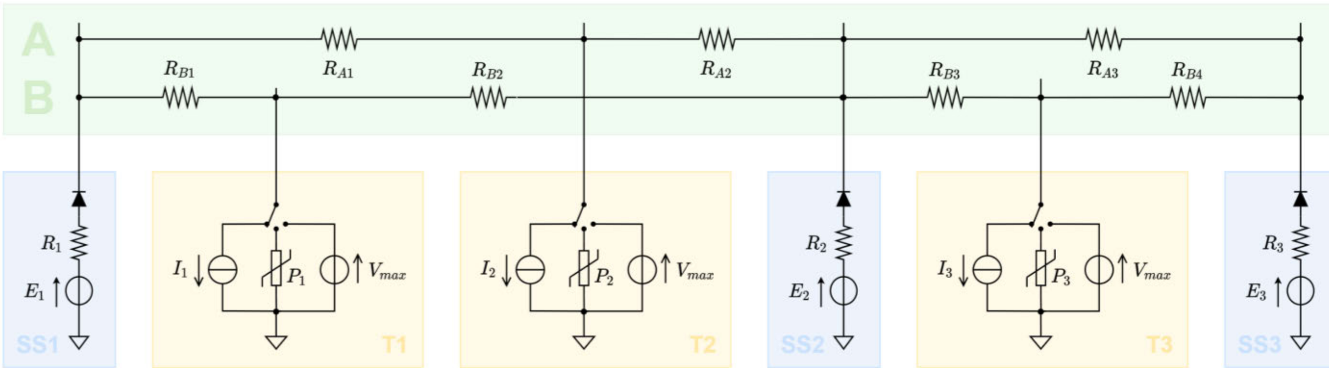

FIGURE 11. Equivalent circuit used by ROAR for a system composed by 2 tracks (green), 3 trains (yellow) and 3 one-directional substations (blue).

- 7 electrical substations quite uniformly distributed over the route, equipped with Italian standard high-speed AC/DC groups (5.4 MW each, no-load voltage: 3.6 kV);
- 2 parallel points, between the traction lines of the 2 tracks;
- simulation of 45 minutes with time step of 15 seconds, having 5 trains on each track at the same time.

The reference simulator Recupera performs the load flow using the Gauss-Seidel method with per-unit values. The software was set to its minimum allowed values for the base power (100 W) and power error tolerance (1%) to run it at its highest accuracy for comparison. The maximum error tolerance of ROAR-simulator has been set to the same value (1 W) to perform a fair comparison.

B. VALIDATION RESULTS

The results obtained through Recupera and ROAR-simulator were compared by calculating the difference between the power and voltage values at the pantographs of each train. Simulation results are very satisfactory: in the first test (Fig. 12) the power difference remains below 150 W for the entire simulation, except for a few peaks. The voltage difference is always below 0.2 V, apart from some points, where the difference keeps below 1.5 V. The second test (Fig. 13) showed even better results, with the power difference below 50 W for the entire simulation, except for a few peaks that never exceed 100 W. The voltage difference is always below 1 V, except for the extreme points of the line.

Table 5 shows a comparison of the total energies from the grid to trains and line losses calculated by the two software. As before, the difference between the values is minimal ($< 1\%$). Several other validation tests (not described here) were performed, obtaining similar results, thus confirming the quality and correctness of ROAR-simulator models and algorithms.

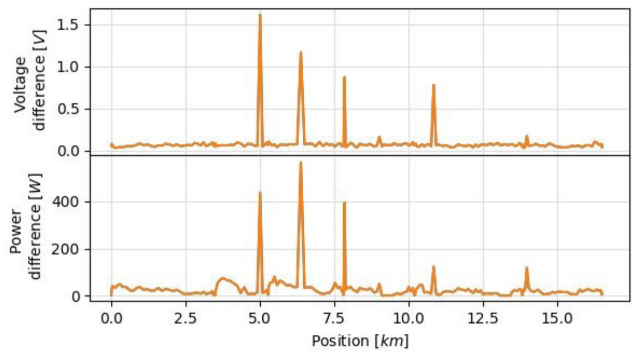

FIGURE 12. Difference between the reference simulator and ROAR, in voltage and power at the pantograph of Minuetto train, for the first test case study.

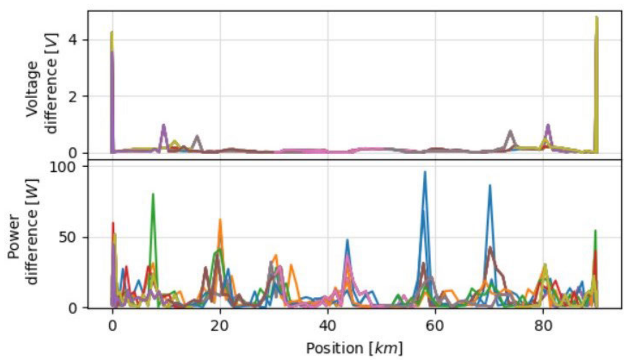

FIGURE 13. Difference between the reference simulator and ROAR, in voltage and power at each Frecciarossa train pantograph, for the second test case study.

VI. POWER SYSTEM DESIGN OPTIMIZATION ALGORITHM

To introduce increasingly advanced and intelligent performances for the modeling and simulation of these systems, the simulator for power system design was completed with an optimization tool created specifically for this type of

TABLE 5. Comparison between total energy results provided by the reference simulator Recupera and roar.

Case study	Energy [MWh]	Reference	ROAR	Difference
1	From grid	0.5592	0.5545	0.0047 (0.84%)
	To trains	0.5019	0.4977	0.0042 (0.83%)
	Line losses	0.0573	0.0568	0.0005 (0.87%)
2	From grid	44.72	44.50	0.22 (0.49%)
	To trains	41.56	41.37	0.19 (0.34%)
	Line losses	3.16	3.13	0.03 (0.95%)

application. This tool is primarily based on the a-NSGA-II algorithm [27], which treats different railway power system design solutions as distinct members of a population. As a genetic algorithm, ROAR-optimization relies on four fundamental operators (evaluation, selection, crossover, mutation) used sequentially to improve the performance of individuals, mirroring a natural selection process.

Due to the particular nature of this problem, the crossover operator has been customized to eliminate the influence of the meta-parameters of the genetic algorithm on the structure of the solutions [26]. As mentioned previously, the main purpose of the ROAR-optimization tool is to determine the optimal railway power system design. Specifically, our goal was to optimize:

- the placement of Electrical Substations (ESS);
- the number of AC/DC conversion groups for each ESS;
- the placement of Parallel Points (PP);
- the catenary configuration, i.e. conductors' section.

The main issue with this optimization problem is the unknown number of elements that must be placed, i.e. the number of substations and parallel points. This number strongly affects the performance of the system, in fact, fewer substations reduce capital costs but result in higher energy losses and inferior voltage quality. When encoding power system design data for the optimization problem, the variability in the number of elements implies variable lengths of the solutions. In the context of a genetic algorithm, this leads to chromosomes of variable lengths, imposing a modification of the crossover operator to mix two chromosomes with different lengths. To ensure that no meta-heuristic parameter influences chromosome length, a novel crossover operator was developed. In the following, the four operators used by the ROAR-optimization algorithm are described.

A. EVALUATION OPERATOR

The evaluation operator is the ROAR-simulator tool. Since the ROAR-simulator is a comprehensive railway system simulator, it enables the evaluation of various aspects of the electric power system design. In the specific context of this case study, the evaluation concerned four objectives: voltage quality, fault response, substations cost, and catenary cost.

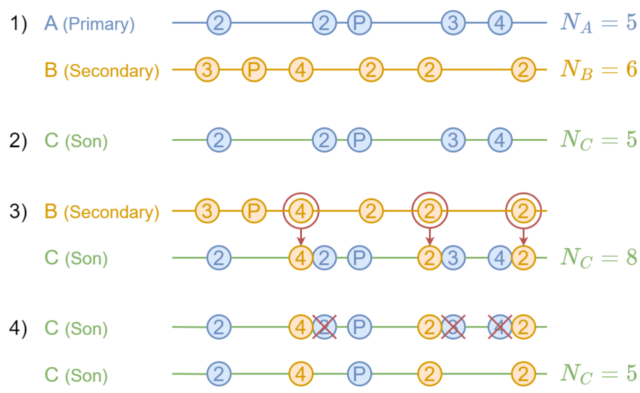

FIGURE 14. Example crossover between two railway power system design solutions, performed by ROAR-optimization.

B. SELECTION OPERATOR

The selection operator employed is the classical a-NSGAII binary tournament. The solutions are initially sorted based on their membership in the Pareto frontier and then ranked by their crowding distance. This selection method showed good convergence and excellent search capability to avoid local minima.

C. CROSSOVER OPERATOR

The novel crossover operator implemented in ROAR-optimization acts as follows:

1. Given the two chromosomes that need to be mixed, one becomes the ''primary'' chromosome (A), and the other one becomes the ''secondary'' chromosome (B). The primary has N_A substations and parallel points, and the secondary has N_B.
2. Initially, a ''son'' chromosome (C) is created cloning the primary, thus inheriting the number N_A, configuration and location of its substations and parallel points.
3. Next, $N_B/2$ substations and parallel points, rounded by excess, are randomly chosen from the secondary chromosome and added to the son chromosome.
4. The closest existing substations and parallel points are then removed from the son chromosome. Parallel points within a minimum distance from any substation are also removed.
5. Finally, the process is repeated swapping the roles of primary and secondary chromosomes to create another chromosome.

Fig. 14 reports an example, showing substations and parallel points as circles, each one with the number of conversion groups inside. For the sake of completeness, Table 6 reports a sample chromosome of a design solution.

D. MUTATION OPERATOR

The mutation operator performs a random modification of a solution, randomly choosing among 9 actions: adding,

TABLE 6. Example chromosome of an electrical design solution.

Catenary	Substations													Parallel points				
540 mm^2	5	20	43	65	92	120	143	167	179	201	210	\	\	33	130	\	\	**Position [km]**
	2	3	2	4	3	2	3	3	2	2	2	\	\	\	\	\	\	**No. of AC/DC conversion groups**

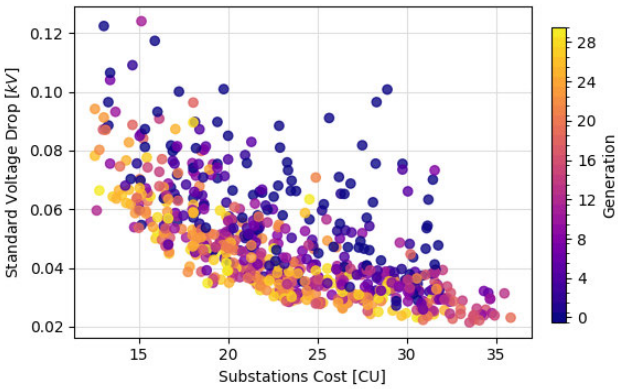

FIGURE 15. Possible electrical designs (656) for the Via Formia route, generated by ROAR-optimization, plotted on a 3D solution space.

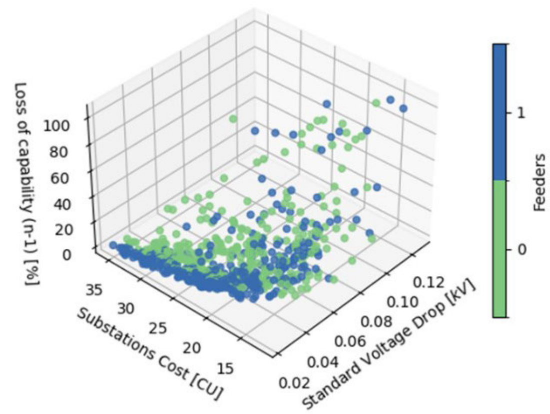

FIGURE 16. Possible electrical designs (656) for the Via Formia route, generated by ROAR-optimization, plotted on a 3D solution space.

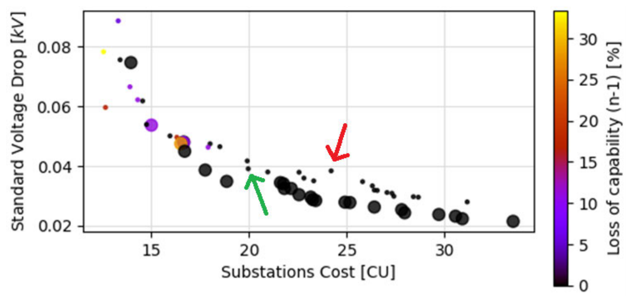

FIGURE 17. Pareto-optimal electrical design solutions (54) for the Via Formia route, generated by ROAR-optimization.

shifting, removing a substation or a parallel point, adding or removing a conversion group in a substation, and changing the catenary configuration. To enhance the flexibility of the program, a weighted system was introduced for the random choice of the mutation action, favoring some mutation modifications over others. Specifically, higher weights were assigned to changes in substations and catenary, as opposed to modifications to the parallel points. This reflects the common practice among railway power system designers to limit the number of parallel points.

VII. CASE STUDY

A. TRACK AND TRAFFIC

The testbed for this novel railway power system design procedure is the ''Rome-Naples via Formia,'' an Italian historical railway, electrified in the 1930s. This railway was selected to compare the results obtained using the proposed method with those of a real project. The track is 214 km long, encompassing 25 train stations and 16 electrical substations. Given the high capacity and traffic of this railway, the traffic scenario developed for this test comprises two urban areas (near Rome and Naples respectively) with trains every 5 min in the areas, and a suburban area (in the middle) with a train every 15 min. The optimization algorithm was configured to use between 8 and 20 substations and an equal number of parallel points. Two configurations were considered for catenary wires: the first utilized 540 mm^2 of copper alloy, and the second involved a catenary configuration with 690 mm^2, achieved by incorporating an extra feeder (150 mm^2).

B. ROLLING STOCK

The rolling stock is composed of two train types. The first is E464, consisting of 10 cars, including 2 driving cars. This train features a maximum speed of 160 km/h, a calculated mass of 464 t, and 3.5 MW of maximum electrical power. The second train type is E404, also consisting of 10 cars, including 2 driving cars. It can reach 220 km/h, has a total mass of 576 tons and 6.4 MW maximum electrical power. ROAR-simulator allows the configuration of all main characteristics of the rolling stock to closely simulate real-world conditions. All train characteristics needed for the study were collected, but only the most interesting are described here.

C. OBJECTIVES

The following four objectives were considered: voltage quality, substations and parallel point cost, catenary cost, and loss of capability in the event of an ESS failure.

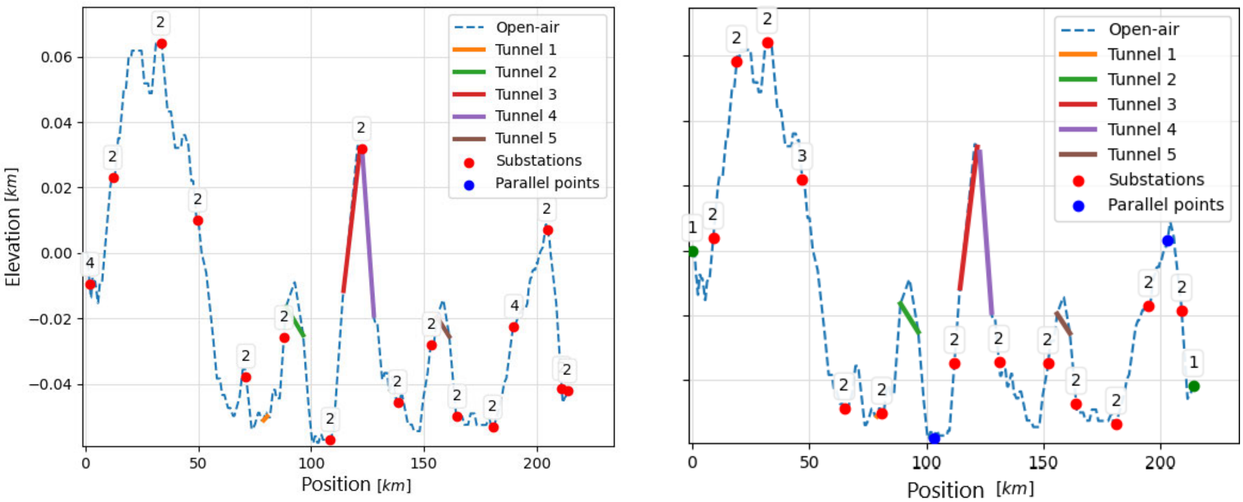

FIGURE 18. Existing substations placement of Rome-Naples via Formia railway (left) and optimal placement by ROAR software (right).

1) VOLTAGE QUALITY

To quantify voltage quality, we introduce the Standard Voltage Drop (SVD) metric as follows, where V_r denotes the rated line voltage and V_{ij} denotes the pantograph voltage of the i-th train at time j.

$$\mathrm{SVD} = \sqrt{\frac{\sum_{i,j=1}^{k,h} \left(V_r - V_{ij}\right)^2}{kh}}$$

The SVD metric gives greater importance to the points with a higher voltage drop. The use of this metric as an objective to minimize pushes the algorithm to optimize the system so that the voltage profile along the line is as homogeneous as possible.

2) COSTS

In the absence of readily available cost information for electrical railway infrastructure in the literature, a parametric cost estimation approach was employed. The presence of an Electrical Substation (ESS) corresponds to 1 Cost Unit (CU). A conversion group, which includes a 12-pulse rectifier and its transformers, corresponds to 0.25 CU, whereas one Parallel Point (PP) costs 0.125 CU. The cost associated with the catenary was considered separately, due to the difficulty in estimating the need for upgrading the conductor suspension system.

3) FAULT ROBUSTNESS

An important part of this study was the evaluation of the impact of losing an entire substation on the performance of the railway power system, considering the unavailability of an entire ESS chosen among the 3 most loaded ones. The evaluation of the performance loss was based on a transport capability indicator, calculated as the product of the train power and train frequency. This value was expressed as a percentage, with a fully operational system corresponding to 100%. In the event of a fault, the reduction in the maximum power of trains or their frequency involves a loss of capability, adopted as the fourth objective of the optimization.

D. SIMULATIONS

In total, 656 individuals were simulated. Such a wide range of solutions allows designers to choose among different design options based on project requirements.

Initially, the convergence of the algorithm was verified by focusing on two opposing objectives. In fact, a single objective is insufficient to confirm the convergence of a multi-objective optimization algorithm; on the other hand, considering all four objectives at once is not practical. Fig. 15 shows a scatter plot to visualize the trend of voltage quality and the cost of substations along the generations, represented by the color of the points. As generations increase, the solutions move closer to the origin of the axes, where the "ideal optimum" is located. This illustrates the simultaneous minimization of two contrasting objectives, performed by the algorithm.

Fig. 16, presenting a 4-dimensional global representation (3 spatial dimensions and 1 color dimension) of the solutions, reveals that a large number of solutions exhibited a 0% capability loss in the event of a fault, i.e. showing very high robustness. Also, it confirms that the auxiliary feeder notably increases voltage quality.

After verifying the convergence of the method, it is possible to manually select the final design according to project requirements and priorities, e.g. the robustness to faults can be secondary to the containment of costs. The authors performed the selection with the aim of obtaining a final design comparable to the existing one, to compare the results of the proposed method to a real design.

The following considerations were applied to the set of solutions: suboptimal solutions were eliminated, and only non-dominated (Pareto-optimal) solutions were retained.

Only solutions with 0% capability loss (for a single fault) were considered, discarding the other ones. Additionally, designs with no extra feeder were preferred to facilitate a direct comparison with existing electrification. The remaining 54 solutions are shown in Fig. 17. The red arrow indicates the real electrification design of the ''Via Formia'' route, and the chosen optimized solution is indicated by the green arrow.

Remarkably, the selected solution exhibited equivalent electrical performance in terms of loss of capability and standard voltage drop, with lower construction costs. A detailed comparison between the actual electrification and the solution generated by the new optimization procedure is presented in Fig. 18.

Cost reduction is primarily derived from a different substation distribution and the replacement of some substations with parallel points, which is noteworthy, given the divergence from modern practices.

VIII. CONCLUSION

In this study, a novel method for railway electrification design is proposed. The method consists of a non-simplified railway system simulator coupled with a custom genetic optimization algorithm. The models were validated by comparing the results with those calculated using another simulator, obtaining less than 1% error. The method has proven to have fast convergence and produces a wide variety of Pareto-optimal solutions, among which the designer can choose, to find an optimal trade-off between technical performance and overall system cost. The algorithm was tested on an existing railway in Italy, challenging the existing design in terms of substation cost, optimizing their distribution along the path, and replacing some of them with parallel points without reducing system robustness to faults. A limit of the proposed method is the fixed cost of substations: in practice, the realization of a substation requires its connection to the power grid, with the construction of a new power line, whose cost depends on its rated voltage and power, and the distance between the substation and the grid. Other factors influencing substation cost include the characteristics of the territory near the railway, affecting the cost of the land to be acquired for the construction of the substation and the power line. The algorithm may be improved including a position-dependent substation cost model, allowing the algorithm to prefer locations where constructing a substation is simple and cheaper. However, this enhancement of the algorithm would necessitate additional information, not straightforward to collect or estimate, requiring additional time, and possibly leading to biased optimization solutions in case of wrong estimation of such parameters. For this reason, the actual convenience in introducing this functionality requires more investigation. Also, the implementation of energy storage models would allow the simulation of batteries, inside substations or onboard, to evaluate the techno-economic convenience of their use for both urban and long-distance railway systems.

ACKNOWLEDGMENT

As recommended in IEEE Access Author Guidelines, the authors used the AI-based system Paperpal Preflight to improve the writing of all sections of the article.

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