



HAL
open science

Optimal Sizing of Tramway Electrical Infrastructures Using Genetic Algorithms

Anass Boukir, Vincent Reinbold, Florence Ossart, Jean Bigeon, Paul-Louis
Levy

► **To cite this version:**

Anass Boukir, Vincent Reinbold, Florence Ossart, Jean Bigeon, Paul-Louis Levy. Optimal Sizing of Tramway Electrical Infrastructures Using Genetic Algorithms. Electrimacs 2022, May 2022, Nancy, France. pp.543-555, 10.1007/978-3-031-24837-5_41 . hal-04292957

HAL Id: hal-04292957

<https://hal.science/hal-04292957v1>

Submitted on 17 Nov 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Optimal Sizing of Tramway Electrical Infrastructures using Genetic Algorithms

Anass Boukir  · Vincent Reinbold  · Florence Ossart  · Jean Bignon  · Paul-Louis Levy

Abstract The increasing electrification of urban public transports requires improving the design of the electrical infrastructures to take into account all the technical and financial challenges involved in the creation of a new line. This paper presents a new optimization tool dedicated to the sizing of tramway electrical infrastructures: power substations, overhead transmission lines, feeders and equipotential bonding. The purpose is to determine the number, positions and technical characteristics of all these components to achieve the best trade-offs between investment costs, energy costs and the quality of the traffic power supply. The sizing problem is formulated as a multi-objective optimization problem and solved using the NSGA-II genetic algorithm. The proposed method is applied to a simple test case and gives good results.

1 Introduction

The electrification of urban public transport is an environmental issue: metro, tramway or trolley bus systems respond to different trade-offs between transport capacity and cost. The choice depends on the local context. Whatever the system, one of the technical and economic challenges is the sizing of the electrical infrastructure, in order to achieve a satisfactory compromise between investment costs, operational costs and power supply reliability.

A. Boukir · V. Reinbold – F. Ossart
 Université Paris-Saclay, CentraleSupélec, CNRS, Laboratoire de Génie Electrique et Electronique de Paris, 91192, Gif-sur-Yvette, France.
 Sorbonne Université, CNRS, Laboratoire de Génie Electrique et Electronique de Paris, 75252, Paris, France
 11 Rue Joliot Curie, 91192 Gif-sur-Yvette
vincent.reinbold@centralesupelec.fr, florence.ossart@centralesupelec.fr

J. Bignon
 LS2N
 Nantes Université, Centrale Nantes, CNRS, LS2N, 44000 Nantes.
bignon-j@univ-nantes.fr

A. Boukir · P.L.Levy
 Artelia
 47 Av. de Lugo, 94600 Choisy-le-Roi
Anass.boukir@arteliagroup.com, paul-louis.levy@arteliagroup.com

In its current form, the process of sizing electrical infrastructure (power substations, overhead or ground power lines, feeders...) follows a trial-and-error approach. The specifications are set in terms of traffic to be supplied on a given line and various environmental constraints (available space to install the infrastructures, accessible network connection points ...). The EN 50388 standards provide recommendations for the distance between substations. Based on these recommendations and their experience, engineers propose an initial configuration. Then, they use a numerical simulator to test different traffic scenarios and check if the standards on voltages and currents are respected in the whole system at each moment during the simulation. If not, the configuration is iteratively adjusted until satisfaction is obtained. This manual approach and the simulation time required to test multiple traffic scenarios prevent a thorough exploration of the solution space. Faced with these constraints, the engineer simply finds a configuration that satisfies the electrical needs of the line, which generally leads to oversized electrical infrastructures.

Lately, some attempts have been proposed to optimize the electrical infrastructure sizing. For example, reference [1] deals with a 25 kV AC system and uses the NSGA-II algorithm in order to optimize the positioning of the feeding substations and the neutral sections between them, with respect to the investment cost on the one hand, and the operational cost on the other hand. The principle of the approach is tested on a simple case. In [2], the authors are interested in the reinforcement of the 660 V DC power system of the Zagreb train network. It is shown that the existing feeding substations can supply the increasing traffic, provided that the distribution cables are reinforced. A power flow model and linear optimization are used to add new supply lines and place their connecting points to minimize voltage drops and operational currents, thereby

ensuring optimal service continuity. Interesting results are obtained, but the use of a linear power flow model does not allow to account for overloaded lines. The objective of the present work is to optimize the sizing process of all electrical infrastructures of a tramway line respecting two criteria: overall cost (infrastructure and energy consumption) and voltage security margin with respect to some traffic uncertainties (service quality). The objective is similar to the references previously mentioned, but the physical model is more complex and involves more decision variables.

The rest of the paper is organized as follows. Section 2 describes the studied system; Section 3 formulates the considered optimization problem, and Section 4 presents the genetic algorithm used to solve it; Section 5 provides first results for a simple test case, and Section 6 concludes.

2 Studied system

The electrical infrastructures of a tramway line are designed to provide the power needed by the trains (Fig. 1). The main elements are the feeding substations, the overhead transmission line (OTL), the rails (return conductor) and the trains. In addition, feeders (conductors parallel to the OTL) and equipotential bonding (local connections between the two OTLs of a two-way line) are used to adjust the electrical network characteristics to the needs.

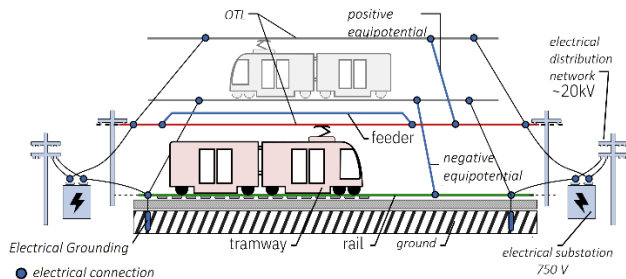


Fig. 1 Electrical infrastructure of a tramway line.

The analysis of this system relies on simulation [3, p. 61-85] [4] and requires detailed enough models to correctly determine all electrical quantities. In the present work, we use an in-house developed simulator. The input data are the physical description of the railway network (line topology, electrical devices position and characteristics) and the description of the intended traffic (position and power needs of all trains versus time). The simulation is a quasi-static one. At each time step, Kirchhoff's laws apply to build the circuit equations of the electrical network (Fig. 2). Solving this set of nonlinear equations gives the voltage at all nodes of the circuit. The currents and powers in all the components are post-processed and compared to limits given by standards in order to check the acceptability of the infrastructures for the simulated traffic (details are given in Section 3.3).

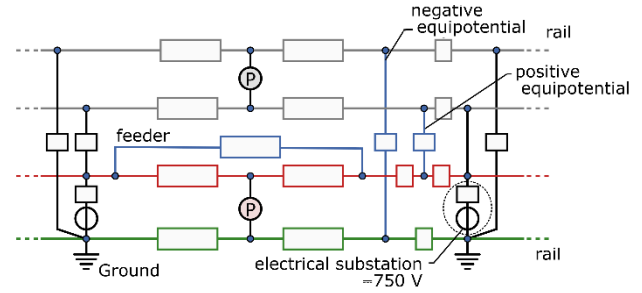


Fig. 2 Electrical model of the feeding system presented in Fig. 1.

3 Formulation of the optimization problem

The final objective of the electrical infrastructure design is to choose all the electrical needed elements and define their characteristics in order to guarantee the best quality of the power supply at the lowest cost. This problematic can be translated into a bi-objective optimization problem.

Optimization variables

The optimization variables are the characteristics of the electrical devices to choose, namely the substations, the feeders and the equipotential positions. Their characteristics are summarized in Table 1. The number of each type of device is not known in advance, a maximum number of each type of device is specified in the problem formulation and if a device does not exist, its characteristic is set to “nonexistent”.

Table 1. List and characteristics of the optimization variables

Device	Variable	Nature
SST # i for $i = 1, \max_{SST}$	Position	Continuous
	Power	Discrete
feeder # i for $i = 1, \max_{feeder}$	end1 position	Continuous
	end2 position	Continuous
Equipotential # i for $i = 1, \max_{equipotential}$	Position	Continuous

Objective functions

The sizing purpose is to minimize the costs i.e., investment and energy consumption, and to maximize the quality of the tramway's power supply. These objectives, detailed hereafter, are usually antagonistic and the decision maker needs objective criteria to choose the best compromise for a given situation.

The total cost is the sum of the investment and the energy costs.

Investment cost = $\sum_{devices} \text{cost of each device}$

The energy cost is calculated by post-processing the results of simulation and extrapolating it over the tramway lifetime (30 years). It includes Joule's losses from electrical substation to the train, powertrain losses and mechanical power imposed by the traffic.

The power supply quality is assessed by a voltage security margin that guarantees that the supply voltage of each tramway will never drop below a certain value despite traffic uncertainties such as delayed trains or non-compliance with speed profiles. The IEC 38 standard specifies the minimum value of train voltage. The voltage drop depends on the traffic and is sensitive to both trains' position and required power. A significant voltage drop indicates that the feeding line is undersized with respect to the power to be supplied to the trains. To take into account traffic uncertainties, the sizing is done using a critical voltage value above the standard. This difference will be referred as the "voltage security margin" and denoted by ΔV_{margin} in the paper. It is defined by $\Delta V_{margin} = V_{min\ simulation} - V_{min\ IEC\ 38}$, where $V_{min\ IEC\ 38}$ denotes the minimum value specified by the standard IEC 38 and $V_{min\ simulation}$ is the minimum value monitored during the simulation for the considered traffic.

Constraints

The constraints are either related to device location and civil engineering constraints or related to electrical constraints and technical standards.

When constructing a tramline, urbanism constraints determine the possible locations of the substations and may severely limit the possible locations. The electrical overhead line connects with feeders on the overhead line support poles, approximately 50 m apart from each other. The same thing for equipotential connections. This imposes the position of feeder ends and equipotential connections to be at the same location than the support poles.

Regarding electrical constraints, each train voltage level must remain in the range defined by the standard IEC 38.

$$500\text{ V} < U < 900\text{ V} \text{ (1000 V in case of regenerative braking).}$$

Each substation current must respect the standard CEI 46, namely $I < I_n$ in steady state, $I < 1.5 I_n$ for 2 hours and $I < 3 I_n$ for 1 minute. Lastly, the ground/rail potential difference must remain below the safety limits defined in the standards NF F 60-100 or NF EN 50163.

Table 2. The ground/rail voltage limit values as a function of duration time

Duration (s)	U (V)
>300	120
300	150
1	160
0,9	165
0,8	170
0,7	175

4 Optimization method NSGA II:

Problem characteristics and optimization method choice

The optimization problem we are dealing with is characterized by discrete and continuous variables, by a nonlinear black-box model, constraints on the input and output of the model, and possibly antagonistic objectives. As we are interested in the compromise between these objectives, we need an optimization method based on the notion of Pareto dominance [5] and the non-dominated sorting genetic algorithm (NSGA-II) appears to be well suited [6][7].

Genetic algorithms[8] are heuristic methods based on a population of individuals. Each individual corresponds to a point of the search space and is characterized by a chromosome. A chromosome is a set of genes, each one coding a feature of the individual. The population evolves from one generation to the next through selection, crossover and mutation operators. Selection is based on non-dominated sorting and keeps the best individuals while crossover and mutation generate new individuals in order to explore the search space.

The next section explains how NSGA-II is implemented for our sizing problem: the genes are defined, as well as the crossover and mutation operators.

Genetic Algorithm elements: Chromosome and genes

Individuals are points of the search space and their chromosome contains the genes corresponding to the different optimization variables. In our problem, the maximum number of each type of device (substations, feeders, equipotential connections) is specified in the problem formulation. The chromosome contains a fixed number of genes, enabling to code the information needed for the maximum number of devices. Each gene contains information about a specific device, this information being either a technical one or an indicator of non-existent device.

As an example, Fig. 3 shows the chromosome and the genes for a problem with a maximum number of 4 substations, 8 equipotential connections and 3 feeders. Gene#1 contains the position of SST#1. Gene#4 contains the position of SST#4, if SST#4 exists. Gene#13 and gene#14 contain the positions of the ends of feeder#1, if feeder#1 exists.

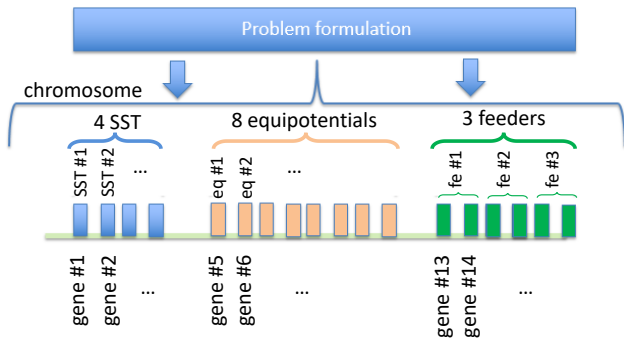


Fig. 3 Chromosome and genes of an individual

Crossover operator

The crossover operator creates an offspring from two parents randomly chosen in the mating pool [6, p. 89-90]. First, one of the parents is duplicated. Then, a gene of the offspring is randomly selected and updated with a new value calculated by a weighted average between the values of the parents' gene, based on the fitness value of each parent. If the selected gene is non-existent, the operator randomly selects another one. Offspring that violate one of the problem constraints are attributed a very bad fitness score so that they will be eliminated at the next generation.

Mutation operator

The mutation operator is designed to increase the diversity of the population in order to avoid individuals trapped in local minima [6, p. 91-93]. First, an individual randomly selected in the mating pool is duplicated. Then one of his genes is randomly chosen and set to a new random value (including non-existent device).

Influence of the hyper-parameters

The quality of an offspring generation directly depends on the NSGA-II hyper-parameters: mutation and crossover rates, population size and number of generations. The crossover (resp. mutation) rate defines the percentage of offspring created by crossover (resp. mutation) in a new generation. In the present work, offspring are generated either by crossover or mutation, so that the sum of the crossover and mutation rates is 100%. If the population size is small, the search space is poorly sampled and lacks diversity. This can lead to premature convergence towards a local minimum. On the other hand, a too large population may unnecessarily increase the computation time. The number of generations should be large enough to allow sufficient exploration of the search space, but again, a too large number may lead to unnecessary computation if the population does no longer evolve. The total number of evaluations of the model is the product of the population size by the number of generations, divided by 2 since 50% of the individuals are passed from one generation to the next.

The next section presents the results obtained for a simple test case.

5 Results

Test case

For the test case we choose a 5 km bi-directional line, with a stop at each end, a +5% slope along the first 500 m and -5% slope along the last three kilometers.

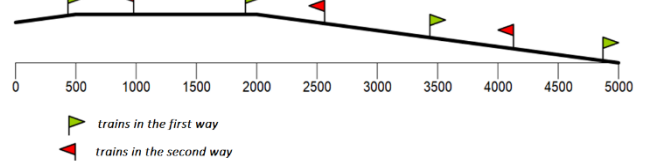


Fig. 4 Line profile and train traffic.

The traffic consists of tramways departing every 6 minutes in each direction. Fig. 5 shows (simulation result) the position and the traction power variations over time for a single tramway, traveling in one direction: the tramway accelerates, then moves at constant speed and finally decelerates.

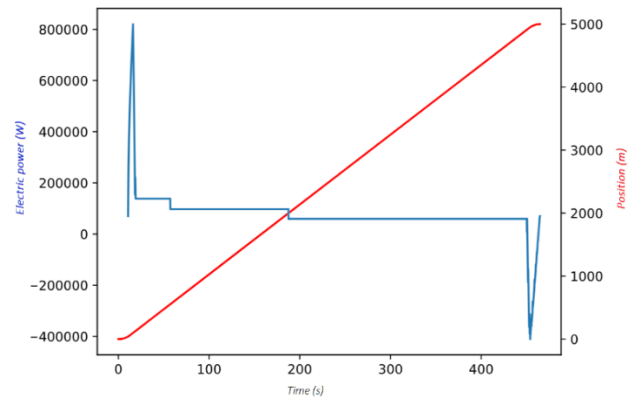


Fig. 5 Position and traction power time profile of a single tramway. All streetcar traveling in the same direction have the same profile, with a 6 mn shift.

The maximum number of substations and equipotential connections are set to 5 and 1 respectively and there is no feeder. Hence, the individual chromosome contains six genes (Fig. 3), each one coding the position or the nonexistence of the corresponding device.

The two objective functions, cost and voltage security margin, have been described in Section 3.2.

There is no position constraint and the electrical constraints are those described in Section 3.3.

Choice of the hyper-parameters

A parametric study was carried out in order to adjust the hyper-parameters of the algorithm. The necessity of a good

initialization of the starting population, mixing empirical engineer knowledge and random choices, was also highlighted.

The first step of the parametric study is to determine a good population size. All the other hyper-parameters being kept constant, the population size has been increased until a value that guarantees the convergence is obtained. For this example, a population of 100 individuals is large enough to obtain good convergence results. Starting population can be initialized using both random sampling or engineering rule of thumb. For instance, distance between successive substations is generally about 1.5 to 2 kilometers depending on the traffic. The influence of the initialization was studied by comparing optimization processes starting with random initial population or a combination of random sampling and engineer knowledge. The later accelerate convergence as it enhances the number of viable individuals in the initial population.

The second step of the parametric study is to assess the influence of the mutation rate, for a fixed population size $N_{pop} = 100$. We have first tested constant mutation rates of 5%, and 10%. Then we have tested a dynamic mutation rate, as proposed in [9]: the mutation rate linearly increases from 0% at the first generation to 100% at the last one. Our test confirm that the dynamic rate improves the convergence.

At this stage, we characterized the convergence by the reproducibility of the results with ten different runs and by the consistency of these results with the ones intuitively expected on this simple example.

Table 3 reports some of the results of the parametric study that leads the following hyper-parameters for the considered test case. For this example, the best combination is a dynamic mutation rate with an initialization of the first generation with the half of individuals generated completely randomly and the rest generated based on engineer knowledge. We noticed that reproducibility of the optimization results can be reached with 200 generations.

Table 3. Example of results of the parametric study, for $N_{pop} = 100$

Mutation rate	Population initialization	maximum number of generations to reach convergence
Fixed rate : 5%	Random	500
Fixed rate : 10%	Random	no convergence
Dynamic rate : 0→100%	Random	300
Dynamic rate : 0→100%	knowledge + random	200

Results

Fig. 6 shows results in the objective space. It represents the non-dominated individuals at each generation. Each point represents an individual that was non-dominated at some point of the evolution process. The crosses represent the empirical Pareto frontier at the last generation. The color indicates at which generation the individual appeared. We can easily see that the performances of the non-dominated solutions constantly improve throughout generations. We also notice that the individuals of the final Pareto frontier appeared after the 60th generation.

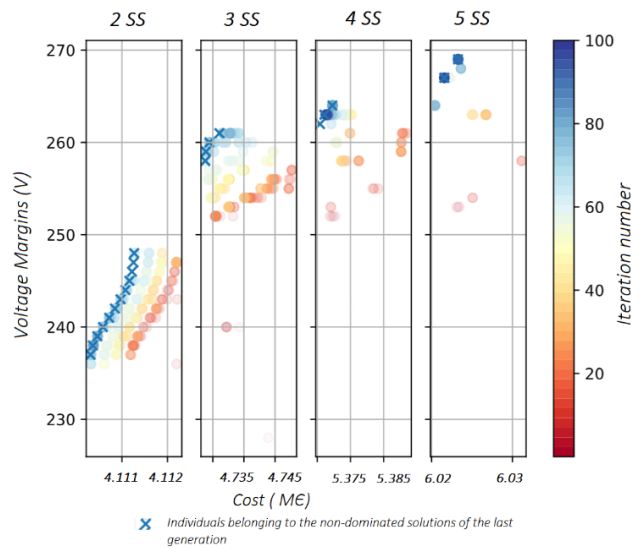


Fig. 6 Non-dominated individuals in the objective space, for each generation. The crosses represent the empirical Pareto frontier at the last generation. The other points represent individuals that were non-dominated at some point of the evolution.

For better readability, the graph has been split into four parts. Each subgraph focuses on a group of individuals with the same number of substations (2, 3, 4 or 5). These groups do not overlap because the investment costs are very different for 2, 3, 4 or 5 substations. One should notice that the horizontal scales are slightly different.

The behaviors of the solutions are quite different for 2 and 3 substations. In the case of 2 substations, the voltage margin is much more sensitive to the cost than in the case of 3 substations. The decision maker can either choose a solution with 2 substations and a low voltage margin, or a solution with 3 substations and a more comfortable voltage margin. This result is consistent with the engineer experience, but Fig.6 provides quantified information to support this choice.

In the next figures, we analyze the evolution of the non-dominated individuals in the solution space. To avoid overloading figures, we focus the analysis on the non-dominated individuals with 2 substations. Fig. 7 and Fig. 8 respectively show the evolution of the substations and the

positions of the equipotential connections. The points color indicates the cost. We notice the evolution of the devices position and the decrease of the total cost as the selection process progresses.

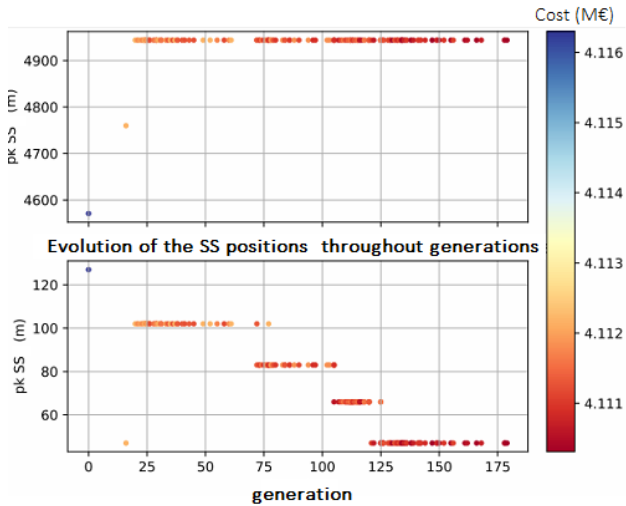


Fig. 7 Non-dominated solutions with 2 substations: evolution of the substations' positions. The points color indicates the cost (M€).

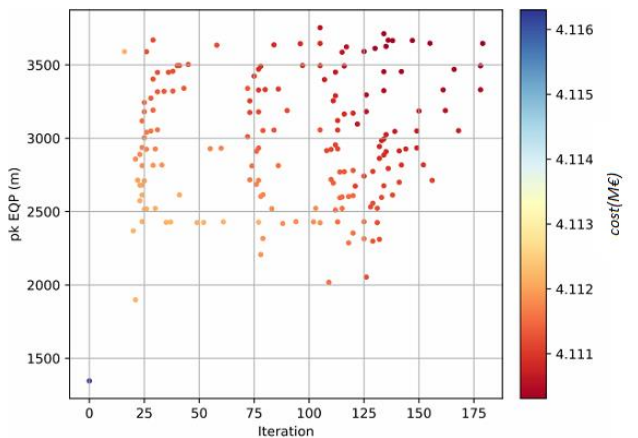


Fig. 8 Non-dominated solutions with 2 substations: evolution of the equipotential position. The points color indicates the cost (M€).

Fig. 9 plots the best scores of each objective, among the non-dominated individuals with 2 substations. The improvement mainly takes place during the first generations and until the 125th generation. As very close results were obtained for ten different runs, we are confident that the algorithm has converged.

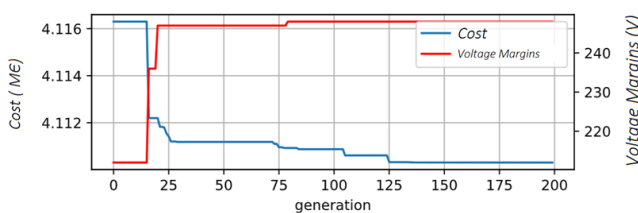


Fig. 9 Non-dominated solutions with 2 substations: evolution of the best objective values.

6 Conclusion

The first optimization results are consistent with a trial and error approach. The Pareto fronts provide objective information on the possible trade-offs between cost on the one hand and power feeding quality on the other hand. The use of a simple example with a few optimization variables makes it possible to validate the tool with results that can be intuitively found. Obtaining the same results with ten different runs consolidates our confidence in the optimization results. The next step will be to apply this method to a more realistic and complex case.

References

- [1] M. Soler, J. López, J. M. Mera Sánchez de Pedro, et J. Maroto, « Methodology for Multiobjective Optimization of the AC Railway Power Supply System », *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, n° 5, p. 2531-2542, oct. 2015, doi: 10.1109/TITS.2015.2412460.
- [2] T. Capuder, L. Lugaric, J. Brekalo-Strbic, et S. Krajcar, « Optimizing the train power system in Zagreb », in *2009 IEEE Vehicle Power and Propulsion Conference*, sept. 2009, p. 41-45. doi: 10.1109/VPPC.2009.5289872.
- [3] R. Vial, « Vers un dimensionnement optimal structure-commande de système multi-convertisseurs : Application aux réseaux de tramways », Thèse, Université de Grenoble, 2012. [En ligne]. Disponible sur: <https://tel.archives-ouvertes.fr/tel-00734684>
- [4] B. Desjouis, G. Remy, F. Ossart, C. Marchand, J. Bignon, et E. Sourdille, « A new generic problem formulation dedicated to electrified railway systems », in *2015 International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles (ESARS)*, Aachen, Germany, mars 2015, p. 1-6. doi: 10.1109/ESARS.2015.7101437.
- [5] K. Deb et H. Gupta, « Searching for Robust Pareto-Optimal Solutions in Multi-objective Optimization », in *Evolutionary Multi-Criterion Optimization*, vol. 3410, C. A. Coello Coello, A. Hernández Aguirre, et E. Zitzler, Éd. Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, p. 150-164. doi: 10.1007/978-3-540-31880-4_11.
- [6] K. Deb, *Multi-objective optimization using evolutionary algorithms*. Wiley, 2001.
- [7] K. Deb, S. Agrawal, A. Pratap, et T. Meyarivan, « A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II », in *Parallel Problem Solving from Nature PPSN VI*, vol. 1917, M. Schoenauer, K. Deb, G. Rudolph, X. Yao, E. Lutton, J. J. Merelo, et H.-P. Schwefel, Éd. Berlin, Heidelberg: Springer Berlin Heidelberg, 2000, p. 849-858. doi: 10.1007/3-540-45356-3_83.
- [8] M. Mitchell, *An Introduction to Genetic Algorithms*. The MIT Press, 1998. doi: 10.7551/mitpress/3927.001.0001.
- [9] A. Hassanat, K. Almohammadi, E. Alkafaween, E. Abunawas, A. Hammouri, et V. B. S. Prasath, « Choosing Mutation and Crossover Ratios for Genetic Algorithms—A Review with a New Dynamic Approach », *Information*, vol. 10, n° 12, Art. n° 12, déc. 2019, doi: 10.3390/info10120390.