Transactions on Energy Systems and Engineering Applications

Article

Multi-objective grounding system optimisation using NSGA-II

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Received: 19 January 2024; Accepted: 16 September 2024; Published: 08 October 2024

Abstract: This study investigates the optimisation of grounding infrastructure in substations by implementing the philosophy of the multi-objective algorithm NSGA-II Elite. A complete description of the operating scheme and the characteristic mechanisms that support the behaviour and development of optimal Pareto solutions is provided. A detailed comparison was made with the optimisation method used in the GMAT program of Aplicaciones Tecnológicas, based on a semi-optimization process derived from the correlation of semi-precision optimisation solutions. The results show that multi-objective optimisation using NSGA-II results in a significant cost reduction compared to the semi-optimization method, although the computational time required to reach the final solution increases significantly. This approach allows a more adequate understanding of optimising the terrestrial substation grid. It highlights its ability to generate more cost-effective and performance-efficient solutions by carefully considering the computing time required.

1. Introduction

In optimisation, modelling plays a key role by providing theoretical frameworks, usually expressed mathematically, that simplify complex realities to study and understand them. This process involves collaboration between the modeller and an expert in representing reality. Modelling is a structured science based on analysis, algorithms, and art since it reflects the individual interpretation of reality. The development of the model requires the input of several experts, such as mathematicians, statisticians, engineers and economists, to balance the need for complete details with the ability to find practical solutions. Models serve as decision-support tools and are indispensable in various disciplines such as economics, finance, engineering, etc. The phases of the model life-cycle include problem identification and mathematical [1].

Specification, resolution, verification and validation, interpretation of results, and implementation and maintenance. Every step has meaning, from detailed information gathering to clear documentation for

How to cite this article: Tenorio, Miriam; Rojas, Angel C.. Multi-objective grounding system optimisation using NSGA-II. *Transactions on Energy Systems and Engineering Applications*, 5(2): 616, 2024. DOI:10.32397/tesea.vol5.n2.616

later use. In particular, multi-purpose optimisation solves problems of multi-purpose functions where it is impossible to focus exclusively on one goal without considering the others. Dominance is a critical concept in the classification of solutions because it allows the identification of non-dominated solutions that form the Pareto front and represent the optimal solutions in the search space. To solve multi-objective problems, we use evolutionary algorithms, such as genetic algorithms, that work on solution populations. These algorithms aim to provide sets of high-quality solutions needed to address challenges in various disciplines.

This study presents an innovative application of the NSGA-II algorithm for optimising grounding systems in substations, which is a significant improvement over traditional semi-optimisation methods. The research stands out for its ability to generate more cost-effective and performance-efficient solutions by considering multiple objectives simultaneously. This is the first time the NSGA-II approach has been used in this type of infrastructure, providing a detailed analysis of the benefits over previous methods.

1.1. Multi-objective optimisation

The field of multi-objective optimisation deals with the complexity of problems with many objective functions. Making decisions based on multiple criteria becomes challenging, as focusing on a single goal is impossible, leading to trade-offs between different goals. To solve such problems, trade-offs must be considered, as the optimal solution for one goal may be inappropriate for others.

Interdisciplinary problems: Multi-objective problems are common across all disciplines and present researchers with ongoing challenges. Importance of Evolutionary Algorithms: The use of evolutionary algorithms, particularly the evolutionary family, is driven by the ability of these population-based approaches to provide high-quality solution sets, a key feature in multi-objective contexts.

1.2. Basic concepts of multi-objective optimisation

The general mathematical formulation of the multi-objective optimisation (MO) problem highlights the need to define criteria to evaluate the quality of solutions. In this context, dominance is introduced as an essential element for classifying solutions and searching for optimal alternatives, considering the existence and quantification of the M-objectives of the problem [2]. An x^1 solution dominates another x^2 solution if it meets two primary conditions:

1. x^1 is not less than x^2 on all objectives
2. x^1 is significantly greater than x^2 in t least one objective.

Violating any of these conditions means that x^1 does not dominate x^2. An extension of this concept of dominance is used to identify the set of non-dominated solutions in the population. Determining the previous undominated set involves a detailed analysis of the dominance between population solutions. Using an iterative approach, solutions for all M objectives are compared and dominant ones are highlighted. At the end of the process, unmarked solutions are considered unmastered and form a Pareto front. This Pareto front, called P', represents the set of solutions not controlled concerning the set P, which may be the search space [2,3]. Figure 1 shows the optimal Pareto sets for different dual objective configurations in the same solution space. In each scenario, the Pareto optimum consists of solutions that lie at the edge of the feasible region of the solutions space. Classifying populations into different levels of non-dominance is done through a five-step procedure. The resulting set represents the best level of the uncontrolled set (first Pareto front) when used for the first time. For additional rankings, temporarily ignore unmastered solutions, repeat the process, and get a second-level unmastered set. -dominated set, etc., until population members are classified at a certain level or on the Pareto front.

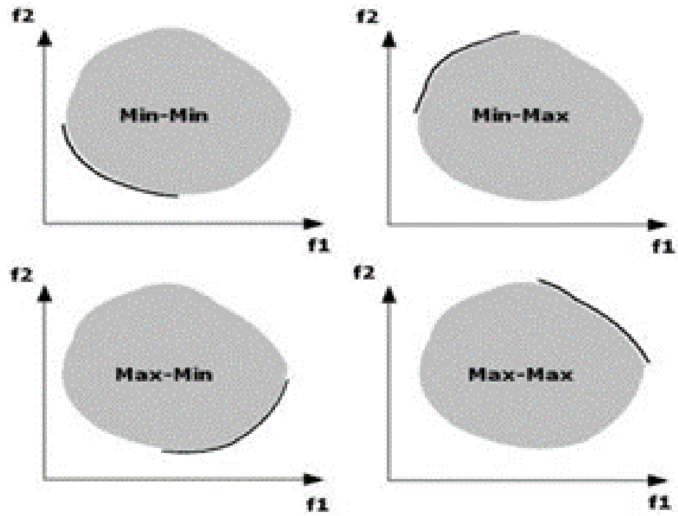

Figure 1. Optimal Pareto fronts for the same solution space.

The main goal of optimising MO problems is to identify as many optimal Pareto solutions as possible. In this context, the concept of an elite algorithm for MO problem solving, which proposes modifications of evolutionary algorithms (EA) to find high-quality non-mastered solutions after their execution, is presented.

1.3. NSGA-II Algorithm

NSGA-II (Non-dominated Sorting Elitist Genetic Algorithm), developed by Deb and his team in 2000 [3], is a powerful tool for solving multi-objective Optimisation (MO) problems. This algorithm creates a population decrease Q_t, of size N, generated from the initial population P_t, also of size N.

The next step is to combine the two populations to create a R_t total of $2N$. The solutions are divided into different Pareto fronts using a non-dominated sorting process. Despite the additional effort required for this solution, it is fully justified by the need to verify the overall dominance between the initial and offspring populations.

Once the non-dominated classification process is completed, a new population is generated based on the configuration of the non-dominated fronts. The construction of this unique population starts with the best non-dominated front (F1). It continues by including the solutions of the subsequent fronts (F2, F3, etc.). Since the R_t population has a size of $2N$ and there are only N configurations in the downstream population, not all configurations of the R_t front can be included in the new population. Fronts that cannot be accommodated disappear [3].

As the approach is this second front, the component solutions may outnumber the remaining space in the declining population. In this scenario, it makes sense to implement a configuration selection strategy in sparsely populated areas away from other solutions rather than selecting random configurations to fill the remaining positions in the declining population.

This consideration becomes increasingly relevant as algorithm generation cycles progress. Initially, many fronts survive until the next generation. However, as the process progresses, many configurations are integrated into the first front until the front contains no more than N individuals. Therefore, it is essential that the configurations that are not rejected are of high quality and selected using a methodology that ensures diversity; the idea is to continually encourage configurations that bring diversity closer to the same Pareto front. The algorithm provides solutions that are far apart as the population converges towards the optimal Pareto front.

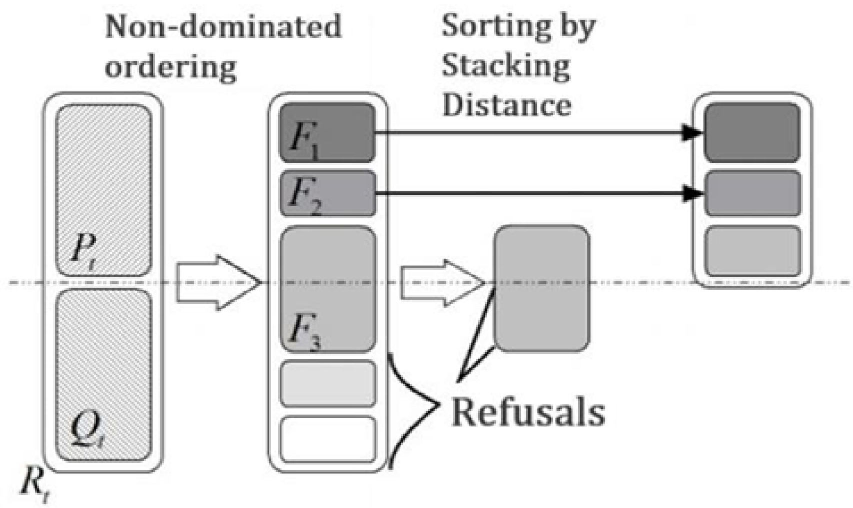

Figure 2. Schematic representation of the individual delivery mechanism of NSGA-II.

In the initial phase of the NSGA-II algorithm, an initialisation technique randomly creates a population of P_0 initial. The population is then ranked according to the levels of non-dominance represented by the Pareto fronts (F_1, F_2, etc.), as shown in Figure 2. Each solution is assigned a fitness function based on its degree of non-dominance (1 is the best degree), which is expected to decrease in the process.

A population of offspring of size NQ_0 is created by applying tournament selection (using the tournament stacking operator, as described below), crossover and mutation. The main steps of the NSGA-II algorithm are described below:

1. Combine the population of initial and descendants to create. $R_t = P_t \cap Q_t$. Perform non-dominated planning on R_t and identify the edges F_i, where $i = 1, 2, \ldots, etc.$
2. Set $P_{t+1} = \emptyset$, and $i = 1$. While $|P_{t+1}| + |F_i| < N$, do $|P_{t+1}| = |P_{t+1}| \cap |F_i|$ and $i = i + 1$.
3. Apply stack sorting ($F_i' < C$, described below) and include in P_i the most distributed solutions in $N - |P_{t+1}|$ using the stack distance values associated with edge F_i.
4. Creating a population of Q_{i+1} descendants from in $P_i + 1$ uses tournament selection for stacking, crossover and mutation.

1.4. Modified NSGA-II algorithm

Alternatively, a modification of the NSGA-II algorithm was proposed to shorten computation times. In the original approach, a descendant population of size N is generated and combined with the initial population P, which means that at least N evaluations of the objective function must be performed for each generation cycle.

To mitigate this limitation, the Chu-Beasley Genetic Algorithm (CBGA) logic is imported, introducing a single individual into the population at each generation cycle, thus significantly reducing the computational effort [4]. In this modification, the descendant population is replaced by a single individual from the crossover operator, which then mutates before being absorbed into the overall population. In this case, the population R has size $N + 1$, in contrast to the original approach where the size is $2N$.

This strategy preserves the necessary conditions for Pareto optimisation and the resulting individual advances to the next generation cycle as a member of population P. Implementing this logic in NSGA-II significantly improves computational efficiency as it reduces the number of Objective Functional Evaluations per generation cycle.

2. Application of correlation methods to semi-exact optimisation solutions

2.1. Optimal design of substation grounding grids.

The development of computer systems has made it possible to implement programs to design and analyse grounding systems based on highly accurate mathematical algorithms. However, the complexity of these methods has limited their application on a larger scale, leading to many approximation approaches. Although these methods have produced acceptable practical results, the inherent errors motivate the search for more accurate and efficient alternatives. The Maxwell imaging technique for designing and analysing grounding systems is classified as semi-precise. This method allows for dealing with very complex systems, considering both uniform resistance soils and multilayer soils. Compared to the process for designing substation grounding grids proposed by IEEE STD 80 2013, the Maxwell imaging method can reduce errors by up to 20%, depending on the grid size. Note that the IEEE method is limited to designing rectangular grids with uniform grids over the entire surface.

2.2. Determination of the number of wires in a stitch system..

General guidelines must be followed to determine the optimal number of wires in a mesh structure, and several factors must be considered. The main objective is to ensure that the grounding grid meets the specified requirements of step voltage (V_{pass}) and touch voltage (V_{cont}) within the allowable limits (V_{tol}), avoiding unnecessary oversizing that could generate high costs.

At the same time, the project aims to achieve sufficient voltage while minimising construction costs. The process starts with determining the allowable touch voltage while minimising construction costs. The process begins with choosing the permissible touch voltage. The voltage at which the grounding grid will be constructed. At the same time, the project aims to achieve sufficient voltage while minimising construction costs. The process starts with determining the permissible touch voltage, which is influenced by factors such as the damage duration, the topsoil's resistivity and the added artificial material (on average around $3000\Omega m$). It is essential to determine the pipe's laying Depth and diameter. In addition, when considering the size of the grid, it is necessary to consider whether to include vertical bars in the structure or additional elements in the corner modules of the grid. The next step is to start the preventive configuration, initially using only horizontal elements without bars. The starting point is this basic configuration, often a perimeter configuration including the protected area. Then, the number of lines in the grid gradually increases until an acceptable voltage value is reached, as shown in Figure 3.

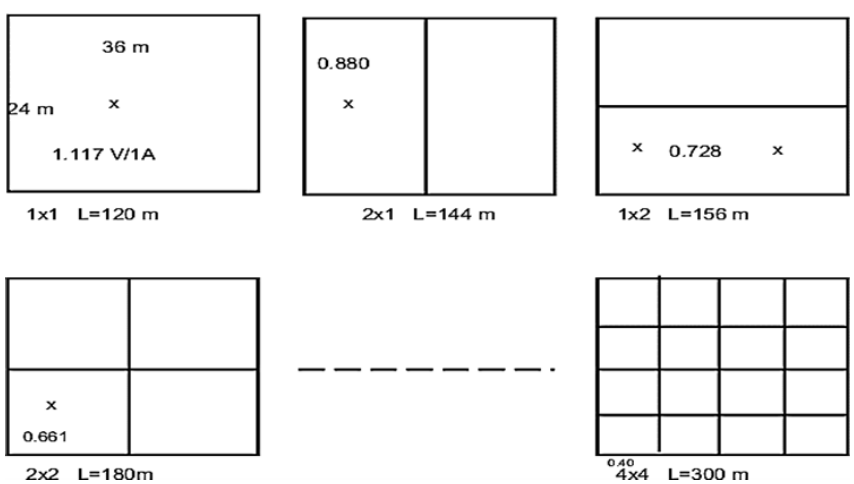

Figure 3. Touch voltage in V/1A for different configurations.

2.3. Optimisation of grounding grids.

An optimal methodology for designing rectangular grids with conductors equally spaced in both directions was identified. The procedure consists of gradually increasing the number of wires in the grid, adding the variant with the lowest total number of wires until the condition $V_{cont} V_{tol}$ is fulfilled. This first project is considered the first phase of the whole optimisation process. However, the resulting grids exhibit higher voltages in the corner modules, indicating overfitting. The second phase aims to equalise the voltages in all modules.

This second optimisation phase aims to reduce the number of pipes and trenches while maintaining the same maximum voltage or minimising the maximum pressure. Figure 4 illustrates these optimisation strategies. The configuration in

1. Represents the first stage solution that satisfies V_{tol}.
2. Reducing the total number of cables by 9% is possible, thus slightly reducing the maximum voltage. If the maximum voltage in a) does not coincide with V_{tol}.
3. Indicates the possibility of reducing this value by 13% using unequal wire spacing [4, 5].

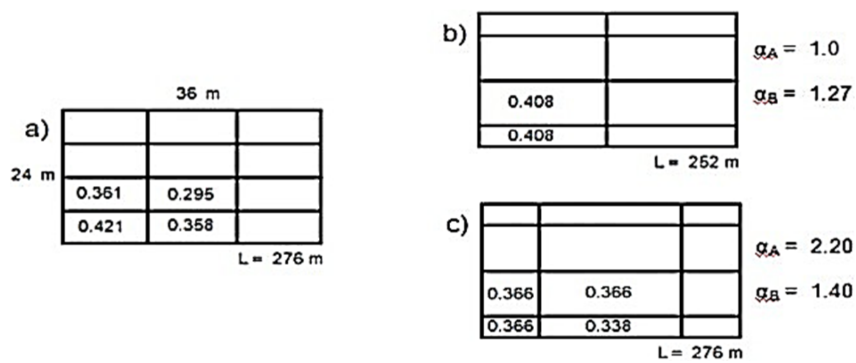

Figure 4. Uniformly cross-linked mesh in V/1A.

The fundamental challenge in achieving an optimal solution in a regular grounding grid is determining the spacing between conductors so that the maximum touch and step voltages are equal. While this can be achieved in simple configurations, achieving the ideal situation in more complex cases is impossible.

Therefore, a simple method is presented based on exact optimisation processes for a regular grid. Any performance function shown in Figure 5 was selected to determine the position of the grid elements.

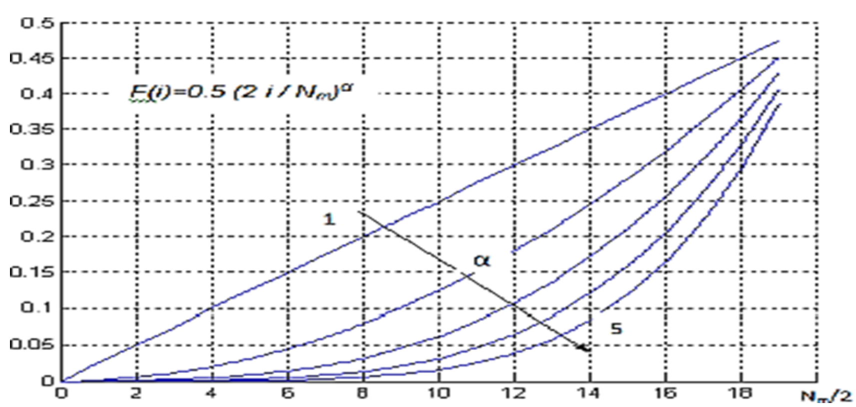

Figure 5. Position function of a grounding grid.

F(i) and F(j) represent the coordinates in percentage units in the columns and rows, respectively, where Nm is the number of modules on the corresponding page. The parameter essential for each side is determined by correlations of semi-exact optimisation solutions. The choice of functions can vary, so mixed or discontinuous functions are also possible.

Therefore, the position on the X-axis of each column of elements of length B of the irregular mesh in Figure 6 depends on the selected function:

$$x(i) = 0.5A(2i/NmA)\alpha A, \tag{1}$$

$$i = 0, 1, 2, 3 \ldots ENT(NmA/2),$$

$$x(NmA - i) = A - x(i). \tag{2}$$

Also, the position of each row of elements of length A is on the Y-axis:

$$y(j) = 0.5B(2j/N_{mB})^{\alpha B}, \tag{3}$$

$$j = 0, 1, 2, 3 \ldots ENT(N_{mB}/2),$$

$$y(N_{mB} - j) = B - y(j). \tag{4}$$

The values of αA and αB are determined by correlating semi-exact optimisation solutions for grids of different sizes, module numbers and aspect ratios [4,5].

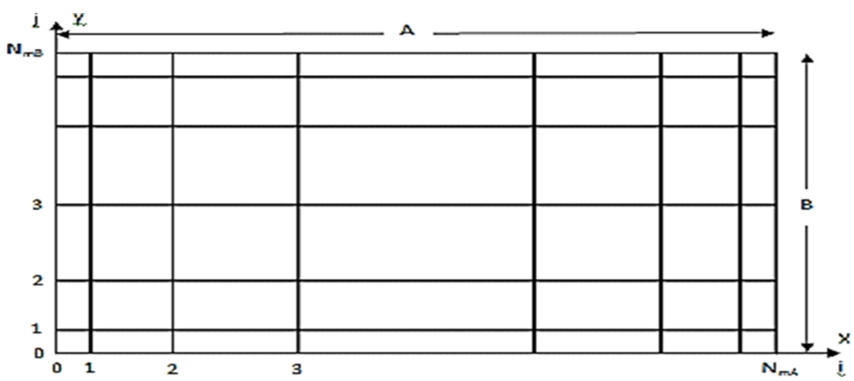

Figure 6. Grounding grid with irregular conductor spacing.

2.4. Parameters αA and αB for a rectangular mesh.

The values of αA and αB, shown below, were derived from the correlation of semi-optimisation results of rectangular grids of different sizes, several modules and aspect ratios. For the longer side A:

$$\alpha_A = \alpha_0(0.685e^{0.378K}). \tag{5}$$

A small side B:

$$\alpha_B = \alpha_0(1 - 0.0789 \ln K). \tag{6}$$

Taube α_0 is the value corresponding to a grid of area $A \times B$:

$$\alpha_0 = 1.154 + 0.170 \ln N_m + 0.0445 \ln \sqrt{AB}, \tag{7}$$

where:

$$K = A/B, \tag{8}$$

$$N_m = (N_{mA} + N_{mB})/2. \tag{9}$$

Factor 1.154, 0.170 and 0.0445 in Expression 9, derived from correlated semi-optimisation results for rectangular grids, do not provide an optimal solution for grids of different sizes. A solution to this problem could be to find specific coefficients for each grid by minimising the differences between the maxima of the other modules that make up the grid and using these coefficients as variables in the optimisation function. MatLab used the `fminsearch` function for this purpose.

2.5. Optimisation of conductor cross-section and burial depth.

The cost function we want to minimise (10) evaluates the increase or decrease in cost as a function of the pipe diameter and installation depth

$$\text{Cost}_{\text{Total}} = \text{Cost}_{\text{conductor}} \cdot \text{Long}_{\text{conductor}} + \text{Cost}_{\text{mov}} \cdot \text{Prof} \cdot \text{Long}_{\text{conductor}} \cdot 0.5, \tag{10}$$

where:

- $\text{Cost}_{\text{Total}}$ = Total cost to minimise.
- $\text{Cost}_{\text{Conductor}}$ = The cost of a conductor based on its diameter.
- $\text{Long}_{\text{Conductor}}$ = Total length of the conductor.
- Cost_{mov} = Cost of moving one cubic metre of soil.
- Prof = Depth of burial.
- 0.5 = Excavation width in metres.

This optimisation process was performed using the Matlab function `fmincon`, which defines constraints on the minimum and maximum conductor cross-sections and the minimum and maximum burial depths. The main objective is to minimise the total costs, considering the relationship between the pipe diameter, the total length and the laying depth. These settings allow an effective grid optimisation of cable length and ensure contact and step voltages below the permissible values and satisfactory ground resistance.

3. Use of the multi-objective algorithm NSGA-II

The NSGA-II algorithm, a tool available online and programmed in MatLab, was used to perform multi-objective Optimisation in the design of floor grids. This algorithm is characterised by its ability to find optimal solutions by allowing the simultaneous implementation of multiple objectives.

This optimisation process begins by specifying a set of constraints, including the range of allowable horizontal conductor diameters, the Depth of lay, the coordinates of the Y and X axes, and the minimum and maximum number of conductors in both directions. A multi-objective function to be optimised tries to minimise the following parameters:

1. Difference between maximum contact voltage and tolerated voltage (f_1):

$$f_1 = abs(V_{\text{max}} - V_{\text{mptol}}).$$

2. Difference between the maximum and minimum voltage of the grid module (f_2):

$$f_2 = Dif - \text{Maximum\&Minimum}.$$

3. Grid costs (f_3):

$$f_3 = Cost_{ev} + Cost_{eh} + Cost_u + Cost_{dt} + Cost_{he}.$$

Where:

- $Cost_{ev}$: Cost of vertical electrodes.
- $Cost_{eh}$: Cost of horizontal electrodes.
- $Cost_u$: Cost of joints.
- $Cost_{dt}$: Cost of ground movement.
- $Cost_{he}$: Cost of operation of vertical electrodes.

In addition, the constraints require that the distance between cables must be greater than 3 metres and that the difference between the maximum and allowed touch voltage must be positive. Figure 7 shows the $f1$, $f2$ and $f3$ variants for the first 100 that satisfy all the constraints. This range of solutions represents optimal choices that effectively balance the stated objectives, considering the complex design constraints of the terrestrial grid.

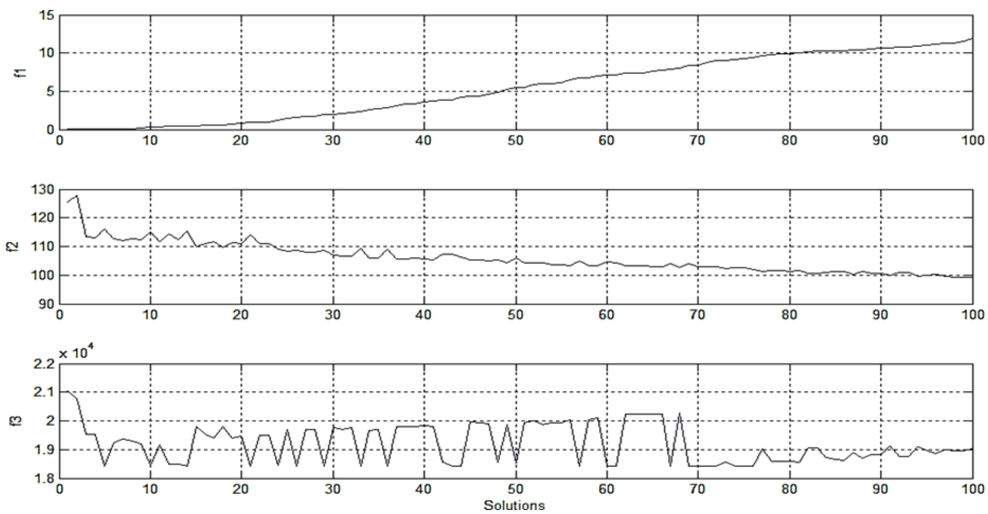

Figure 7. Variants $f1$, $f2$ and $f3$ in the first 100 variants offered by NSGA II.

4. Comparison of two optimisation methods.

This section thoroughly compares two optimisation approaches: a method based on a semi-optimization process and the multi-objective NSGA-II algorithm. These methods were applied to two identical ponds, one 50 x 40 meters and the other 220 x 180 meters, to evaluate their effectiveness. Figures 8 and 9 provide a detailed view of the configuration of each grid, while Table 1 provides general data for both structures.

As seen in Figures 10 and 11, the maximum contact stresses on the two links are not uniform, are higher on the angle modules and decrease towards the interior of the links. This voltage variation allows the threads to be strategically redistributed from the inside to the outside, which can eliminate the threads and thus reduce the overall length of the thread. In other words, the evenly connected grid is optimised for cable length. It should also be noted that in both cases, the maximum contact stresses are below the limits the human body tolerates, guaranteeing the structure's safety.

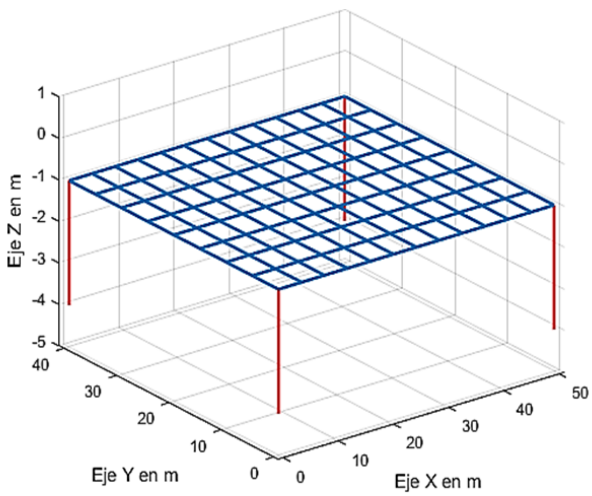

Figure 8. Mesh size 50 x 40 m, uniform mesh size.

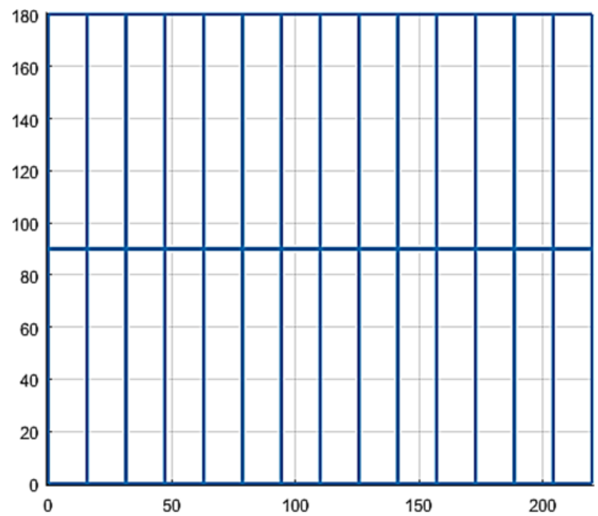

Figure 9. Mesh size 220 x 180 m, uniformly gridded.

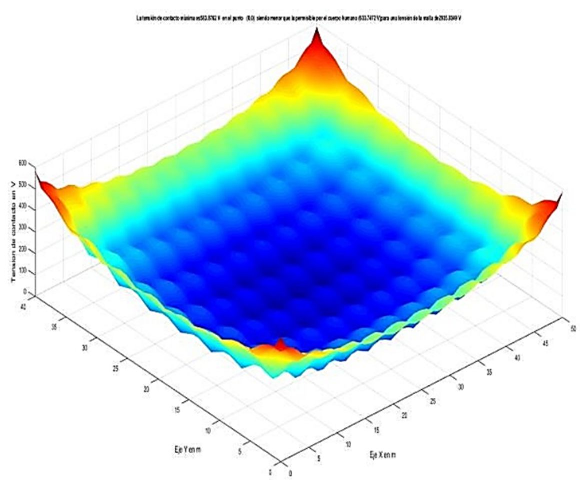

Figure 10. Mesh size 50 x 40 m, uniform mesh size.

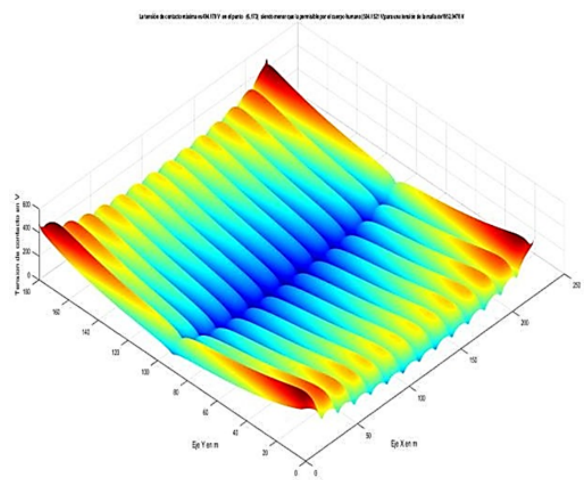

Figure 11. Mesh size 220 x 180 m, uniformly gridded.

4.1. Optimization of the grid using the semi-optimization method.

The optimised configurations shown in Figures 12 and 13 are obtained by subjecting the grids to a semi-optimisation process, with the corrected resistance values and other general data listed in Table 1. The procedure for obtaining an optimised grid begins by determining the distribution of the cables along the Y-axis, as well as the tension and cross-section of the cable. Figures 14 and 15 show these optimised grids' contact voltages and remarkable uniformity across all modules.

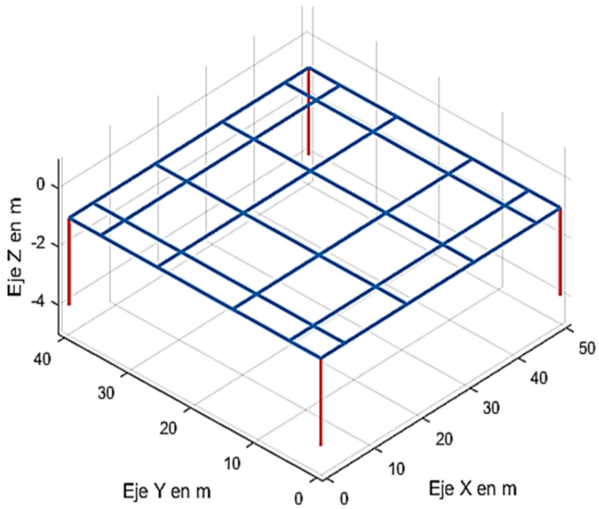

Figure 12. 50 x 40 m grid optimised by the semi-optimisation method.

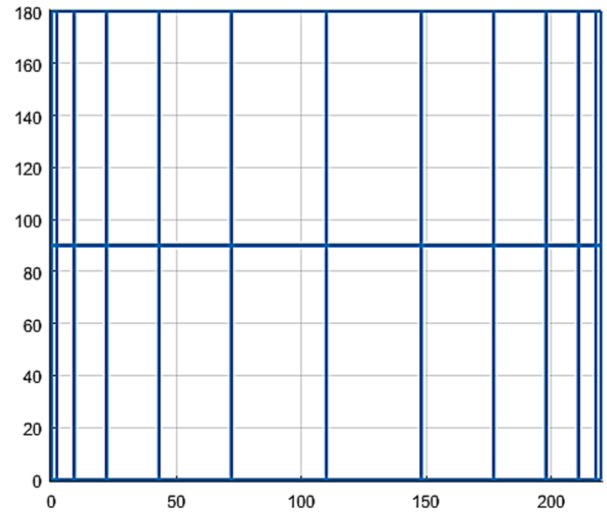

Figure 13. 220 x 180 m grid optimised by semi-optimisation.

Optimisation allows the elimination of conductors and achieves a significant reduction of approximately 21.4% compared to a uniformly connected grid. Once a mesh size optimised for the length of the conductor is reached, the burial depth and cross-section of the cable are optimised. This process minimises a cost function that ensures contact and pass-through voltages below tolerable limits and a lower-than-desired grounding resistance. The optimisation results are detailed in Table 1, revealing an optimal proposal that implies a decrease in the burial depth.

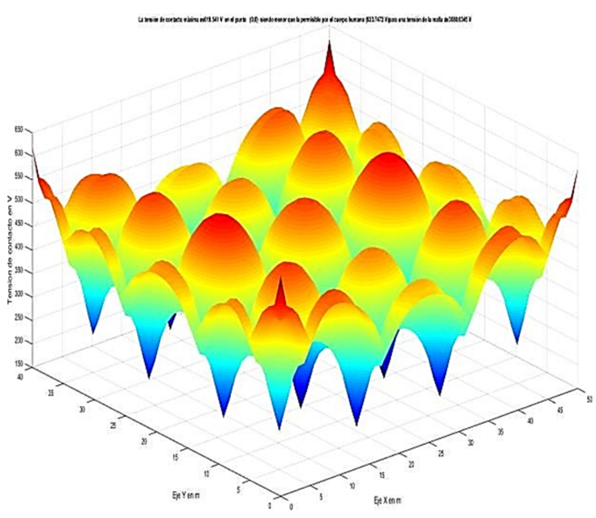

Figure 14. Contact voltage of an optimised mesh of 50 x 40 m.

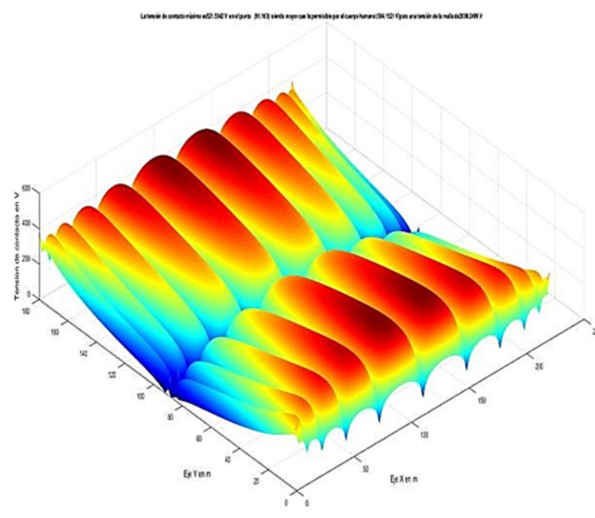

Figure 15. Optimised grid contact voltages of 220 x 180 m.

Table 1. Comparative summary of the two optimisation methods.

Data	50x40			220x180		
	Uniform	**Semi-opt.**	**NSGA II**	**Uniform**	**Semi-opt.**	**NSGA II**
Soil resistivity		$100\ \Omega \cdot m$			$100\ \Omega \cdot m$	
Number of horizontal conductors by X-axis	9	6	6	3	3	10
Number of horizontal conductors by Y-axis	13	6	5	15	13	3
Number of vertical electrodes	4	4	4	0	0	0
Depth of burial		1 m			1 m	
Diameter of horizontal conductors	0.01326 m	0.0136 m	0.0105 m	0.01326 m	0.016 m	0.016 m
Diameter of vertical electrodes	0.02 m	0.02 m	0.02 m	0.016 m	0.016 m	0.016 m
Length of vertical electrodes		3 m			3 m	
Resistivity of the substation surface layer		$3000\ \Omega \cdot m$			$3000\ \Omega \cdot m$	
Thickness of the top layer		0.15 m			0.15 m	
Maximum current injected into the ground		3000 A			8000 A	
Weight of persons		70 kg			70 kg	
Grounding resistance	$0.978\ \Omega$	$0.999\ \Omega$	$0.999\ \Omega$	$0.244\ \Omega$	$0.25\ \Omega$	$0.26\ \Omega$
Total length of conductors	970 m	540 m	550 m	3360 m	3000 m	2740 m
Total cost of installation	6644 USD	3011 USD	1894 USD	21930 USD	16339 USD	9540 USD

4.2. Grid Optimization with NSGA II.

This study presented an innovative approach to significantly increasing the efficiency of grounding grids at substations. Applying the NSGA II method for mesh optimisation resulted in improved structures (see Figures 16 and 17) that show significant improvements in strength and several aspects listed in Table 1.

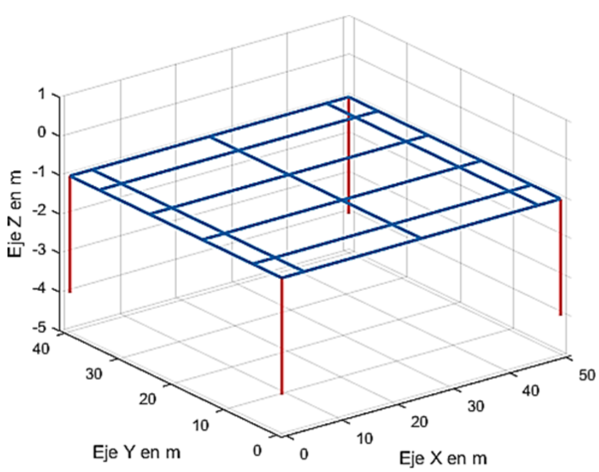

Figure 16. The 50 x 40 m grid was optimised with NSGA II.

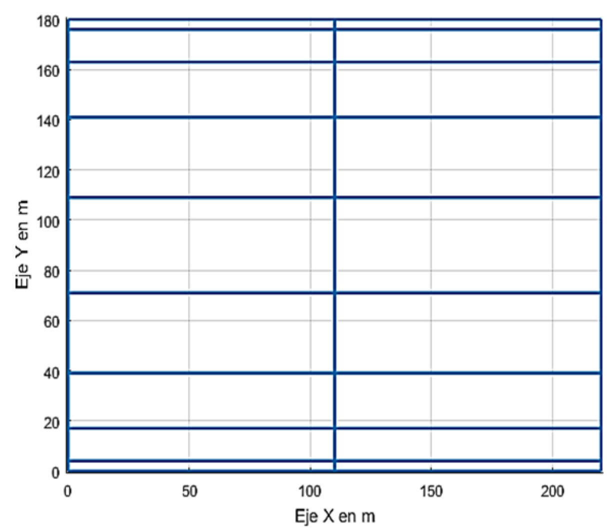

Figure 17. The 220 x 180 m grid was optimised with NSGA II.

A detailed analysis of the contact voltage distributions, clearly shown in Figures 18 and 19, shows a significant improvement in uniformity between different grid modules, highlighting the method's effectiveness in increasing overall performance. A rigorous comparative study based on the information presented in Table 1 demonstrates the superiority of the NSGA II method over traditional approaches. However, these advances in Optimisation result in longer computation times, suggesting the need to explore strategies that balance precision and efficiency when implementing the NSGA II approach.

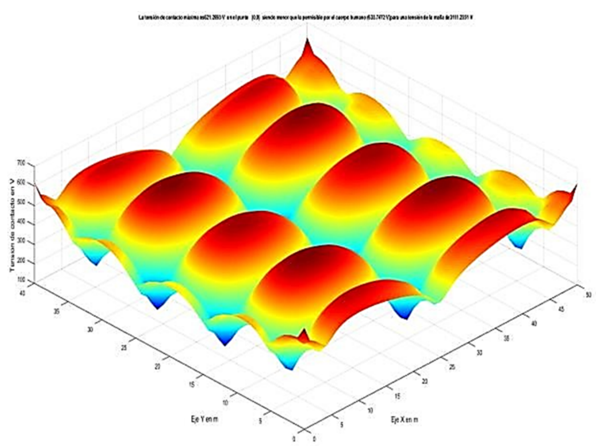

Figure 18. Contact voltages of an optimised 50 x 40 m. grid using NSGA II.

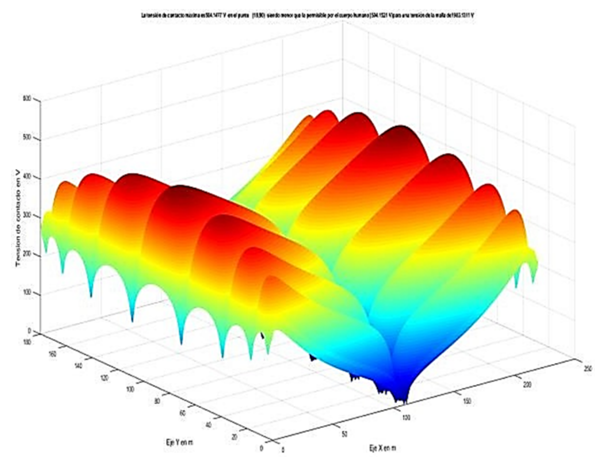

Figure 19. Contact voltages Optimised grid using NSGA II of 220 x 180 m.

The NSGA II-based grid optimisation discovered in this study serves as a transformative catalyst, paving the way for a new era of ground grid enhancement. This method reduces costs by 68% for a 50x40m grid and 53% for a 220x180m grid compared to the original configurations but also outperforms the semi-precision optimisation method, achieving cost reductions of 43% and 37%., respectively. As Studio advances, this methodology, backed by improved resistance levels, optimal tactile load uniformity, and comprehensive benchmarking, could redefine the landscape.

In summary, this results in:

- Cost reduction: Compared to semi-precise optimisation methods, significant cost reductions of 68% on 50x40m grids and 53% on 220x180m grids were achieved.
- Improved performance: Implementing NSGA-II significantly improved the uniformity of contact voltages and the overall performance of the grids.
- Practical application: This work provides a more effective solution for optimising grounding networks in substations, ensuring safety and functionality under strict voltage limits.

5. Conclusions

Concisely restate the hypothesis and most important findings. Summarise the significant findings, contributions to existing knowledge, and limitations. What are the future directions? In optimising grounding grids in substations, this research has produced valuable knowledge that advances in this field.

1. The careful selection of appropriate parameters as cost indicators appears to be an essential element in assessing the Optimisation of the soil grid. This robust approach allows for a holistic assessment that addresses critical aspects of grid performance. The effectiveness of the NSGA II algorithm compared to the existing correlation method for semi-precision optimisation solutions is evident during our research. Although the correlation method is considered satisfactory, the NSGA II algorithm surpasses it with better optimisation results. This result represents a promising step towards developing excellent grounding net designs.
2. Implementing the multi-objective optimisation technique allows fundamental discoveries but requires more computational time. Although the computation time is much longer than that of the correlation method for semi-precision optimisation solutions, the significant improvement in Optimisation and

the reduction of costs make the multi-objective technique more efficient. This result is consistent with previous research [4], highlighting the importance of optimising performance and efficiency.

This study highlights the complex nuances of multi-purpose Optimisation of substation grounding grids. The NSGA II algorithm's performance, even considering the longer computation times, represents an important step towards improving the grid design and the electricity system's overall performance. At the end of this journey, the search for optimal configurations of the grounding grid remains dynamic and evolving, with potential for innovation and continuous improvement.

The Recommendations for future researchers:

1. Explore strategies to reduce computational time: Although NSGA-II significantly improves results, its longer computational time can be challenging. Future studies could focus on developing strategies that balance accuracy and time efficiency.
2. Extend the research to different grounding network topologies: Testing the algorithm in other configurations or more complex scenarios can help validate and extend its applicability.
3. Incorporate other optimisation criteria: In addition to cost and performance, it would be interesting to consider factors such as environmental impact or durability of materials in future studies.

Funding: This research received no external funding.

Author contributions: Miriam Lucero-Tenorio and Angel C. Valcárcel Rojas contributed to the conceptualization and validation of the research. Miriam Lucero-Tenorio was responsible for the methodology, formal analysis, data curation, and the original draft preparation. Angel C. Valcárcel Rojas developed the software and conducted the investigation. Both authors participated in writing, reviewing, and editing the manuscript. Angel C. Valcárcel Rojas provided supervision thr project.

Disclosure statement: The authors declare no conflict of interest.

References

[1] Ramón Alfonso Gallego, Antonio Escobar, and Rubén Romero. Técnicas de optimización combinatorial. *Universidad Tecnológica de Pereira*, pages 19–77, 2006.

[2] E. Zitzler and L. Thiele. Multiobjective evolutionary algorithms: a comparative case study and the strength pareto approach. *IEEE Transactions on Evolutionary Computation*, 3(4):257–271, 1999.

[3] Kalyanmoy Deb, Amrit Pratap, Sameer Agarwal, and TAMT Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. *IEEE transactions on evolutionary computation*, 6(2):182–197, 2002.

[4] Kalyanmoy Deb, Samir Agrawal, Amrit Pratap, and T Meyarivan. *A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II*, page 849–858. Springer Berlin Heidelberg, 2000.

[5] L.E. Schrage. *Optimization Modeling with LINDO*. Duxbury Press, 1997.