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# A congestion-based local search for transmission expansion planning problems

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ABSTRACT

Transmission Expansion Planning (TEP) is a challenging task that takes into consideration future representations of electricity consumption behavior and generation capacity/technology. Besides, the investment in new transmission assets is a capital-intensive task, which motivates a clear and well-justified decision-making process. As the most frequent industry practice relies on cost–benefit analysis with the evaluation of individual reinforcements, Metaheuristic Algorithms (MAs) are the most suitable techniques to evaluate candidate projects efficiently. Likewise, the intrinsic features of the problem can be incorporated into these methods taking advantage of the stochastic knowledge, to build more efficient heuristics instead of considering the solver just as a black box. In this way, this paper proposes a congestion-based local search to improve the performance of metaheuristics when solving the TEP problem. The novelty of the method lies in the utilization of the congestion level of the transmission assets to guide the search procedure. Further, this work also presents an up-to-date comparison between five MAs in solving the TEP problem. The experimental experience is conducted using the mentioned MAs in different test systems, and the results confirm that the novel approach is successful in improving the performance of the solution technique while obtaining better solutions in all test cases.

## 1. Introduction

This section provides an overview of the motivation and background for the research, related work, and contributions, as well as the structure and research integrity of the paper. In this work, a congestion-based local search algorithm is proposed to enhance the performance of metaheuristic algorithms in solving Transmission Expansion Planning problems. Additionally, a comprehensive comparison of five metaheuristic algorithms is conducted, highlighting their performance and scalability when solving the problem.

### 1.1. Motivation and background

Transmission Expansion Planning (TEP) aims at identifying a set of new pieces of equipment, such as overhead lines, High Voltage DC (HVDC) architectures, and transformers, to be installed on the grid that will bring more benefits to the system as a whole [1]. As the planning horizon encompasses many years ahead, the first exercise on TEP is to identify how the future grid will look like [2]. Then, it is necessary to choose the most suitable pieces of equipment to reduce internal or cross-border congestion in order to increase socioeconomic welfare. In this way, the scientific community and the industry practices diverge considerably when solving the problem: On one hand, academics often work with complex models solved by linearization assumptions within optimization procedures, as in [3], on the other hand, industry practices rely on cost–benefit analysis by assessing several technical-economic aspects for each candidate project, as in [4].

When handled as an optimization procedure, TEP has non-linear and non-convex natures, and it is an NP-hard problem, which means that the computational time required to solve the problem does not grow polynomially within the problem dimension [5]. For this reason, the scientific community has been working to build TEP-approximated models in order to make the problem workable, [6]. However, there is no guarantee that solutions obtained through approximated models correspond to optimal solutions regarding the original TEP problem [7]. As a matter of fact, there is no guarantee these solutions are even feasible when applied to the complete TEP formulations.

When handled within a cost–benefit analysis, each candidate equipment is analyzed regarding a list of technical indices (economical, environmental, emissions, losses, etc.) [8], and the incremental benefit is assessed by inserting one piece of equipment at a time using the initial topology of the grid, or excluding one piece-of-equipment at a time using the future reference grid [9]. In any case, the commissioning

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**Nomenclature**

**Decision Variables**

| | |
|---|---|
| $\hat{x}$ | Prediction of the investment decision x |
| $f^p, f^q$ | Real and reactive power flow (Lower-level) |
| $p, q$ | Real and reactive generation vectors (Lower-level) |
| $v, \theta$ | Voltage magnitude and angle vectors (Lower-level) |
| $x$ | Investment state for transmission assets (Upper-level) |

**Indexes**

| | |
|---|---|
| $(i, j)$ | Index for buses defining branches (from-to) |
| $i, j$ | Index for bus |
| $t$ | Index for stage |

**Parameters**

| | |
|---|---|
| $\gamma_i$ | Dispatch cost from generator i ($/MWh) |
| $\mathcal{X}$ | Solution vector belonging to $\mathcal{P}$ |
| $\overline{S}$ | Apparent power limit |
| $\phi$ | Dispatch cost function |
| $\underline{\theta}, \overline{\theta}$ | Voltage angle limit |
| $\underline{P}, \overline{P}$ | Bounds for real power generation |
| $\underline{Q}, \overline{Q}$ | Bounds for reactive power generation |
| $\underline{V}, \overline{V}$ | Voltage magnitude limit |
| $c$ | Nominal equipment investment cost |
| $D^p, D^q$ | Real and reactive demand |
| $f^p$ | Active power flow before expansion |
| $G, B$ | Conductance and susceptance matrices |
| $h$ | Number of hours in which the peak load condition is repeated over the year |
| $n_{sol}$ | Number of solutions for the CLS algorithm |
| $r$ | Discount rate |
| $T_{hc}$ | Threshold for the highly congested assets |
| $T_{sc}$ | Threshold for the slightly congested assets |

**sets**

| | |
|---|---|
| $\mathcal{B}$ | Set of all buses in the system |
| $\mathcal{B}_i$ | Set of all buses connected to bus i |
| $\mathcal{HC}$ | Set of highly congested assets |
| $\mathcal{L}$ | Set of pairs of buses defining new projects |
| $\mathcal{P}$ | Set of solutions in the EC |
| $\mathcal{SC}$ | Set of slightly congested assets |
| $\mathcal{T}$ | Set of stages in the planning horizon |

time is considered a fixed parameter, and neither the anticipation nor delaying of the project is considered, which can underestimate the benefit of the project [10].

Metaheuristic techniques allow the problem to be handled as an optimization procedure by considering the full NP-hard model [11]. In this context, the optimality of the final solution plan cannot be ensured anymore (as frequently occurs when using gradient-based methods), instead suboptimal/acceptable solutions are considered as the output [12]. Furthermore, metaheuristic techniques also allow the commissioning time of the projects to be handled as a lower-bound constraint, meaning that the delay of the projects is fully considered in the analysis. Metaheuristic can bridge the gap between the academy and industry when solving the TEP problem [13]. Foremost, the final solution is suitable for the original problem and not for an approximation of the problem (academic drawback) because the commissioning time of projects is explored to bring the most benefit for the system (industry drawback).

Nevertheless, metaheuristics can present different performances and behaviors when solving different optimization problems or even the same problem with different instances. Therefore, the main motivation of this work is to efficiently solve the transmission planning problem by incorporating a local search based on the intrinsic features of the problem while reducing performance variations. Congestion is an important indicator of socio-economic welfare, and regions in the search space that represents highly congested assets can have a negative impact on the outcome of the problem. Therefore, we developed a novel method called Congestion Based Local Search (CLS), which directs the search procedure toward these congested regions, thus improving the efficiency of the optimization process. CLS has the potential to improve the results of transmission planning, with the potential to increase socio-economic welfare.

### 1.2. Related work

In [14–16] TEP is approached using the AC power flow formulation, while in [17–21] TEP is conducted using the DC formulation. A comparison between these two models is provided in [22]. Single-stage TEP formulations can be found in [23,24] and multistage TEP models are available in [25,26]. We refer the readers to [1,27–29] for more details on TEP literature reviews. Recent developments in local search techniques to improve metaheuristic performances have been comprehensively evaluated in [30,31].

As stated before, metaheuristics have been applied in a very large number of publications dealing with TEP problems in the last few years. Discussions about different algorithms used to solve TEP problems are available in [27,29]. On the same line, [32] presents a comparison between several metaheuristic algorithms regarding their performances in solving the TEP problem.

Particle Swarm Optimization (PSO) often presents a good behavior in solving the TEP problem, as in [33] in which it handles a multi-stage TEP considering demand uncertainties, and in [34] whereupon a competitive pool-based electricity market is considered in the TEP problem.

Genetic Algorithm (GA) is one of the most widespread metaheuristics, and it is also frequently used to solve TEP problems, as in [35] in which it was applied to solve single and multi-stage TEP approaches. In [36] GA is applied to solve a multi-objective TEP version based on reliability and market, considering phase shifter transformers.

Evolutionary Particle Swarm Optimization (EPSO) is a powerful algorithm that combines good features from PSO and GA. It was applied to solve a multi-stage TEP problem in [37], in which the goal was to minimize operation and investment costs while ensuring an adequate quality of service along the entire planning horizon. EPSO was also applied in [38] in which a multi-stage and stochastic TEP approach for wind-hydrothermal systems was considered.

Differential Evolution (DE) algorithm often presents good performances when solving complex engineering problems, as in [39] in which it is applied to solve a non-convex and non-linear AC TEP version. An Information Exchange based Clustered Differential Evolution (IE-CDE) was developed in [40] to solve the TEP problem, the proposed hybridization was inspired by ensemble strategies [41] and refresh gap techniques [42].

Other metaheuristic algorithms were applied to solve TEP problems, as Ant Colony Optimization (ACO) in [43], in which the planning problem was approached by considering reliability worth, the Imperialist Competitive Algorithm (ICA) in [44] in which the presence of wind farms with a mixed AC and DC power flow model is considered, the Adaptive Multi-Operator Evolutionary Algorithm (AMOEA) in [45], and Harmony Search (HS) in [46], which provides a TEP study incorporating adequacy–security constraints in the deregulated power system.

In contrast to prior works, this paper offers a comprehensive non-linear and non-convex AC-TEP formulated as a bi-level optimization problem. This is solved over multiple trials with the same initial conditions, in order to ensure a sample size sufficient to satisfy the Central Limit Theorem and other statistical requirements. Furthermore, comparisons between the innovative CLS and pure metaheuristic algorithms were conducted using statistical tests and probabilistic evidence.

### 1.3. Contributions

The main contribution of this work is to propose an effective procedure for identifying the optimal set of transmission network assets in order to minimize system costs. This method is based on a local search algorithm that takes advantage of the intrinsic characteristics of the problem. It allows for a faster and more efficient search for the optimal solution, compared with other mainstream methods. The innovative method takes into account the congestion level of the transmission network assets, which is an important factor that can significantly influence the total cost of the system. The proposed method is presented in detail in Section 3, where a complete description of the algorithm is provided. Additionally, an extensive numerical analysis is also presented in order to illustrate the efficacy of the proposed method.

In this way, to ensure the validity of our approach, it was crucial to acquire a sizable sample of results for which the Central Limit Theorem would hold true. We compared the results of our method with other popular metaheuristics used for the same problem and applied a rigorous statistical test to verify the probability that our model has indeed improved the optimization process.

Furthermore, the analysis was extended to address also a direct comparison of methods, namely Genetic Algorithm, Particle Swarm Optimization, Evolutionary Particle Swarm Optimization, Differential Evolution, and Harmony Search. This second analysis serves as an important contribution to the field, as it offers a clear comparison of the performance of different metaheuristics when solving more than 3.000 TEP problems (running about 1450 h). It is worth noting that the comparison was performed using a comprehensive set of instances and parameters, presented in a statistically robust way. The comparison also includes a study of the scalability of the algorithms, in order to determine their ability to address large-scale TEP problems. The results of this comparison provide a wealth of insights into the relative advantages and disadvantages of different metaheuristics when solving the TEP problem, and offer valuable guidance on the selection of metaheuristics for future works.

### 1.4. Structure and research integrity

This paper is organized as follows: Section 2 presents the TEP mathematical formulation, and Section 3 describes the proposed methodology. The experimental experience is presented in Section 4 in which five different metaheuristic algorithms over 5 different test systems are used to prove the effectiveness and robustness of the proposed method. Lastly, Section 5 discusses the results and Section 6 presents the main conclusions about this work.

Finally, this work takes into account research integrity and open science practices for education and citizen in general. In this way, all codes produced in this paper, as well as the entire process through methodologies and results, are available in the repository indicated in [47].

## 2. TEP mathematical formulation

TEP can be organized as a bi-level optimization problem in which the upper level is related to the investment in new transmission assets (transmission lines, cables, and transformers), and the lower level is related to the future operation conditions (optimal dispatch) considering the investment selected in the first level. The bi-level TEP problem is presented in (1) to (12).

$$\mathcal{Z} = \underset{x}{\text{minimize}} \sum_{t\in\mathcal{T}} \left[ \sum_{(i,j)\in\mathcal{L}} \frac{x_{(i,j),t}.c_{(i,j)} + h.\phi}{(1+r)^t} \right] \tag{1}$$

$$where\ \phi \in \underset{\theta,v,f^p,f^q,p,q}{\text{argmin}} \left\{ \phi = \sum_{i\in\mathcal{B}} p_{i,t}.\gamma_i \right. \tag{2}$$

$$s.t.\ \ p_{i,t} + \sum_{j\in\mathcal{B}_i} f^p_{(i,j),t} - D^p_{i,t} = 0, \forall t\in\mathcal{T}, \forall i\in\mathcal{B} \tag{3}$$

$$q_{i,t} + \sum_{j\in\mathcal{B}_i} f^q_{(i,j),t} - D^q_{i,t} = 0, \forall t\in\mathcal{T}, \forall i\in\mathcal{B} \tag{4}$$

$$f^p_{(i,j),t} = x_{(i,j),t}.[v^2_{i,t}.G_{(i,j)} - v_{i,t}.v_{j,t}.(G_{(i,j)}.cos\theta_{(i,j),t} + B_{(i,j)}.sin\theta_{(i,j),t})], \forall t\in\mathcal{T}, \forall (i,j)\in\mathcal{L} \tag{5}$$

$$f^q_{(i,j),t} = x_{(i,j),t}.[-v^2_{i,t}.B_{(i,j)} + v_{i,t}.v_{j,t}.(B_{(i,j)}.cos\theta_{(i,j),t} - G_{(i,j)}.sin\theta_{(i,j),t})], \forall t\in\mathcal{T}, \forall (i,j)\in\mathcal{L} \tag{6}$$

$$\sqrt{(f^p_{(i,j),t})^2 + (f^q_{(i,j),t})^2} \le \overline{S_{(i,j),t}}, \forall t\in\mathcal{T}, \forall i\in\mathcal{B} \tag{7}$$

$$\underline{P_{i,t}} \le p_{i,t} \le \overline{P_{i,t}}, \forall t\in\mathcal{T}, \forall i\in\mathcal{B} \tag{8}$$

$$\underline{Q_{i,t}} \le q_{i,t} \le \overline{Q_{i,t}}, \forall t\in\mathcal{T}, \forall i\in\mathcal{B} \tag{9}$$

$$\underline{V_{i,t}} \le v_{i,t} \le \overline{V_{i,t}}, \forall t\in\mathcal{T}, \forall i\in\mathcal{B} \tag{10}$$

$$\underline{\theta_{i,t}} \le \theta_{i,t} \le \overline{\theta_{i,t}}, \forall t\in\mathcal{T}, \forall i\in\mathcal{B} \tag{11}$$

$$x_{(i,j),t} \in \{0,1\}, \forall t\in\mathcal{T}, \forall (i,j)\in\mathcal{L} \tag{12}$$

The objective function in (1) minimizes the total system costs comprised of the investment and operation costs. The investment cost is represented by the first term, where the binary variable $x_{(i,j),t}$ representing investment decisions is multiplied by its associated cost $c_{(i,j)}$. The second term of the objective function represents the operation cost, which is obtained using the worst-case scenario of the peak load, repeating a number of hours $h$ during the planning horizon.

The decision variable of the upper level is the binary variable representing investment decisions. The TEP lower-level is presented in (2), and the decision variables are the angle and magnitude voltages in the system nodes $(\theta, v)$, the active and reactive power flow in the transmission assets $(f_p, f_q)$, and the power output of generators $(p, v)$. The real and reactive power balances for each node are presented in (3) and (4), the real and reactive power flow are represented in (5) and (6), respectively, while the apparent power flow is given in (7). The limits for the flexible variable, the real and reactive power output in a generator, the voltage magnitude and angle, are given sequentially in (8) to (11). Finally, the binary condition of investment decisions is presented in (12). For further information regarding this model, we refer readers to [6].

## 3. Proposed methodology

The optimization model performed by the metaheuristic algorithm in this work corresponds to the first stage of the TEP problem, in which the decision variable is $x$. The second stage will be solved by using the package PandaPower [48], which is capable of optimizing the generators' dispatch considering the investment decisions selected in the first stage.

In this way, each metaheuristic algorithm works with a matrix of solution vectors ($\mathcal{P}$). Each row of this matrix contains ($\mathcal{X}$) that is formed by the forecasts of the binary decision variables ($\hat{x}$), that is, $\mathcal{X} = \begin{bmatrix}\hat{x}_{i,1} & \hat{x}_{i,2} & \dots & \hat{x}_{i,N}\end{bmatrix}, \forall i \in 1, 2, \dots, M$, in which M is the number of solution vectors and $N$ is the number of transmission assets to be considered to investment.

### 3.1. Congestion local search

Transmission equipment congestion can occur due to different reasons, such as price differences between bid zones, dispatch of generators with specific technologies or/and prices for a specific operating state, equipment failures, etc. Thus, strong evidence from stakeholders in the electricity sector suggests that increasing the capacity of the congested equipment could bring benefits to the system as a whole. In fact, this is a common approach to several European Transmission Systems Operators (TSOs), i.e. system expansion is often done based on the identification of system bottleneck (e.g. equipment congestion) with a subsequent cost–benefit analysis regarding different solutions for that issue.

A noteworthy example of this last statement is the Identification of the System Needs (IoSN) performed by the European Network of Transmission System Operators for Electricity (ENTSO-E) in its European Network Development Plan (TYNDP), as described in [9]. On the other hand, slightly congested transmission equipment suggests little activity in that branch, which may be due to several factors, such as low demand, generators with technology/prices not suitable for that state of operation, etc.

In this way, developing a local search around highly congested assets seems to be logically straightforward, as well as avoiding investments in assets that are slightly congested. Therefore, the proposed CLS algorithm aims to improve the search procedure (regarding efficiency, and robustness) by contemplating analysis of the most congested equipment while also canceling investments in less congested equipment, as presented in Algorithm 1 and in Fig. 1.

Regarding Algorithm 1 for CLS, the input parameters are $n_{sol}, T_{hc}, T_{sc}, f^p$, and $\mathcal{P}$, which represent the number of solutions to be analyzed in the CLS algorithm, the threshold for highly congested, the threshold for slightly congested, the currently active power flow over the equipment, and the set of solutions, respectively. Besides, the prediction value $\hat{x}$ for the decision variables $x$ belongs to the vector of solutions $\mathcal{X}$ coming from the set of solutions $\mathcal{P}$. In line 1 of Algorithm 1, the assets that present an active power flow higher than $T_{hc}$, are designed to the set of highly congested assets $\mathcal{HC}$, while in line 2 the assets that present an active power flow lower than $T_{sc}$, are designed to the set of slightly congested equipment $\mathcal{LC}$.

The CLS procedure starts at line 3 for a predefined number of solutions ($n_{sol}$), thus, after sorting a random solution vector $\mathcal{X}_i$ and storing it with its corresponding fitness value $Z(\mathcal{X}_i)$, the analysis of the highly congested assets takes place (line 6). In this way, from the solution vector $\mathcal{X}_i$, each binary prediction $\hat{x}$ with value 0 (representing the non-investment in that asset) that belongs to the set of highly congested assets $\mathcal{HC}$ has the value changed to 1 (representing the investment in that asset) and the new fitness function is calculated using Eqs. (1) to (12) in line 8. If the new fitness function gets a reduced cost, the solution vector $\mathcal{X}_i$ has got improved and this solution is stored with the corresponding fitness function, otherwise, the binary modification is revoked.

Then, the slightly congested analysis takes place on line 14. Similarly to the high congested analysis, from the solution vector $\mathcal{X}_i$, each binary prediction $\hat{x}$ with value 1 (representing the investment in that asset) that belongs to the set of slightly congested assets $\mathcal{LC}$ has the value changed to 0 (representing the non-investment in that asset) and the new fitness function is calculated using Eqs. (1) to (12) in line 15. If the new fitness function gets a reduced cost, the solution vector $\mathcal{X}_i$ has got improved and this solution is stored with the corresponding fitness function, otherwise, the binary modification is revoked. After running the same procedure for $n_{sol}$ solution vectors, the CLS procedure ends by returning the updated set of solutions.

**Algorithm 1** Congestion-based Local Search (CLS)

**Require:** $n_{sol}, T_{hc}, T_{sc}, f^p, \mathcal{P}$ ▷ CLS parameters.
**Ensure:** $\hat{x} \in \mathcal{X} \in \mathcal{P}$ ▷ $\hat{x} \in (0, 1)$
1: $\hat{x} \in \mathcal{HC} \iff f^p(\hat{x}) > T_{hc}$ ▷ identifying the set of highly congested assets.
2: $\hat{x} \in \mathcal{SC} \iff f^p(\hat{x}) < T_{sc}$ ▷ identifying the set of slightly congested assets.
3: **for** $i$ *in* $n_{sol}$ **do**
4: Choose a random solution $\mathcal{X}_i \in \mathcal{P}$
5: $sol_{old} \leftarrow \mathcal{X}_i$ and $val_{old} \leftarrow \mathcal{Z}(\mathcal{X}_i)$
6: **for** $j$ *in* $\mathcal{HC}$ **do**
7: $\hat{x} = 1 \in \mathcal{X}_i, \forall \hat{x} = 0 \in \mathcal{X}_i \cap \mathcal{HC}_j$ ▷ Highly congested assets.
8: Calculate the new value of $\mathcal{Z}(\mathcal{X}_i)$
9: **if** $Z(\mathcal{X}_i) < val_{old}$ **then**
10: $sol_{old} \leftarrow \mathcal{X}_i$ and $val_{old} \leftarrow \mathcal{Z}(\mathcal{X}_i)$
11: **else**
12: $\hat{x} = 0, \forall \hat{x} = 1 \in \mathcal{X}_i \cap \mathcal{HC}_j$
13: **end if**
14: **end for**
15: **for** $j$ *in* $\mathcal{SC}$ **do**
16: $\hat{x} = 0 \in \mathcal{X}_i, \forall \hat{x} = 1 \in \mathcal{X}_i \cap \mathcal{SC}_j$ ▷ Slightly congested assets.
17: Calculate the new value of $\mathcal{Z}(\mathcal{X}_i)$
18: **if** $Z(\mathcal{X}_i) < val_{old}$ **then**
19: $sol_{old} \leftarrow \mathcal{X}_i$ and $val_{old} \leftarrow \mathcal{Z}(\mathcal{X}_i)$
20: **else**
21: $\hat{x} = 1, \forall \hat{x} = 0 \in \mathcal{X}_i \cap \mathcal{SC}_j$
22: **end if**
23: **end for**
24: $\mathcal{X}_i \leftarrow sol_{old}$ and $\mathcal{Z}(\mathcal{X}_i) \leftarrow val_{old}$
25: **end for**
26: **Return:** $\mathcal{P}$

### 3.2. Validation of the method

Comparing stochastic methods to verify their performances requires an independent methodology, selected so that it ensures the comparison process is performed flawlessly and clearly. Thus, the process of comparison and validation of the proposed method goes through four stages shown in Fig. 2, and this process is carried out for each metaheuristic algorithm, using each of the test systems separately.

- Stage 1: Hyperparameter Tuning
  In this stage, several configurations of the metaheuristic algorithms are tested (such as the number of solutions, number of iterations, etc.) for each of the test systems. It is expected that the different configurations will lead to different performances, and furthermore, that the same configuration will lead to different performances for different test systems. Thus, considering the performances of a set of configurations, decision-making must be established to choose the best configuration for the method, this decision-making is established in the following stage.
- Stage 2: Probability of Winning
  In this statistical test from Ref. [49], several games with the results of the hyperparameter tuning are performed in order to obtain the probability that a configuration is better than the others (that is, to beat the others), in this way, the configuration with the highest probability of winning will be chosen to be the configuration of that metaheuristic algorithm in that test system.
- Stage 3: Metaheuristic Simulations
  In this stage, several metaheuristic algorithms are simulated, using their best configurations established in previous stages, for several test systems. The simulations of each metaheuristic algorithm in each of the test systems are performed in 30 trials, which is a number of trials large enough to secure the Central

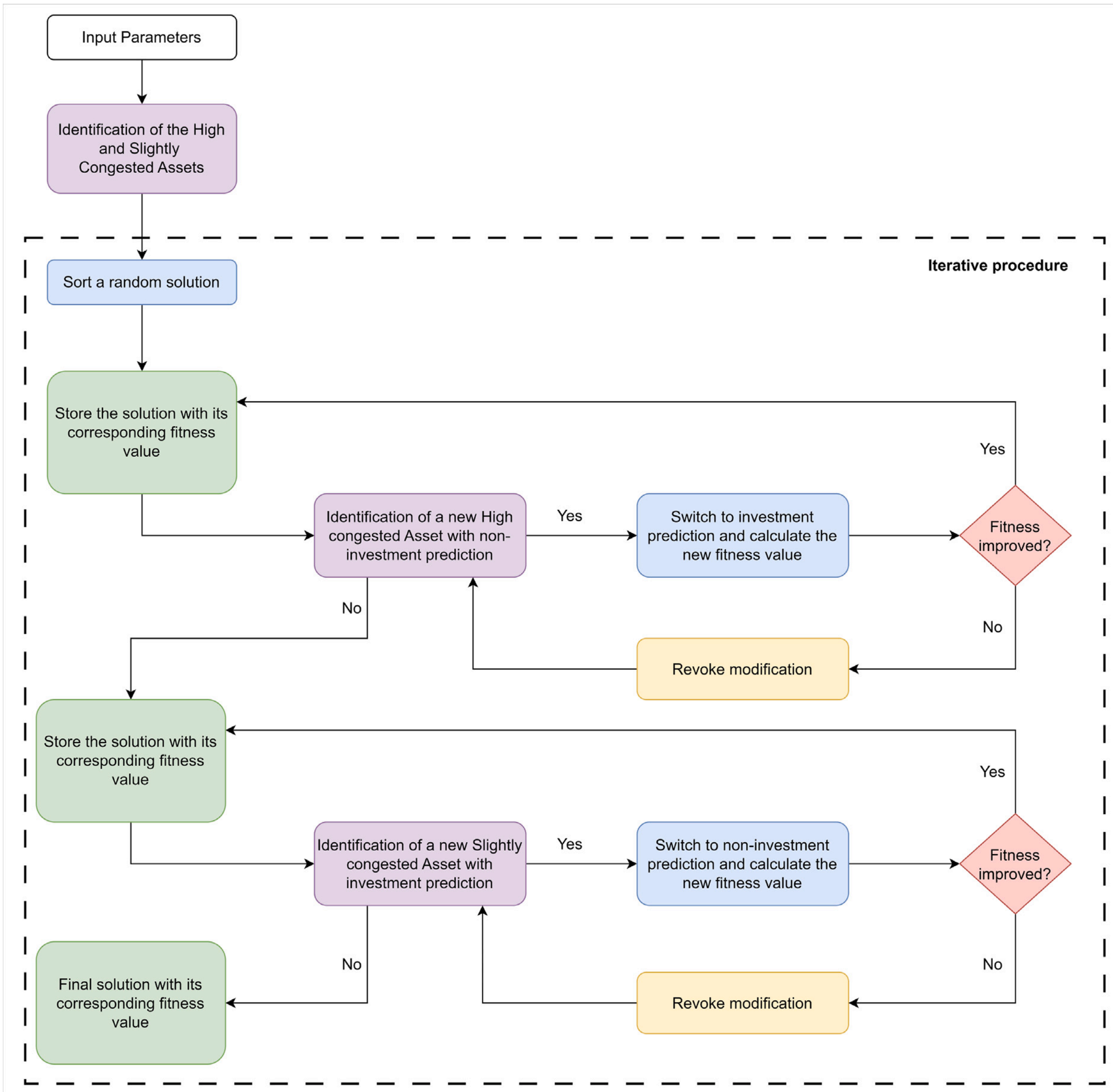


**Fig. 1.** Diagram of the CLS method.

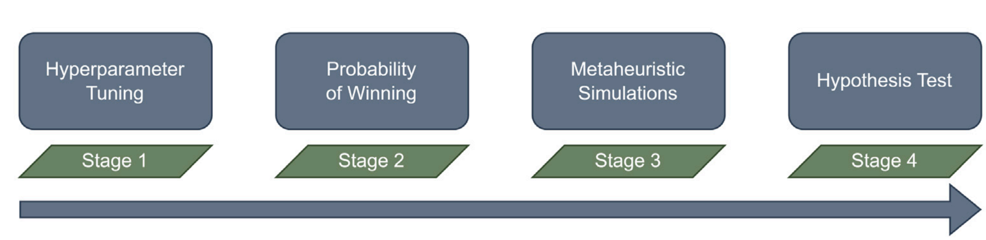


**Fig. 2.** Validation of the method.

Limit Theorem. Thus, the statistical characteristics of this sample of solutions obtained in each of the metaheuristic algorithms in each of the test systems are, in fact, reliable values for the population of solutions for that metaheuristic algorithm for that test system (the sample mean is equal to the population mean). Finally, after simulations of the metaheuristic algorithms, the proposed model is merged together so that these algorithms can be compared with and without CLS.

- Stage 4: Hypothesis Test

The goal is to find out if the hybridization of each metaheuristic algorithm with CLS leads to an improvement in performance. Thus, the Null Hypothesis ($H_o$) is "the hybridization of the proposed method does not lead to an improvement of the metaheuristic algorithms". Therefore, the null hypothesis will be tested by comparing the *p*-value against the statistical significance. The *p*-value is the probability of obtaining a sample outcome, given that the value stated in the null hypothesis is true, while statistical significance describes a decision made concerning a value stated

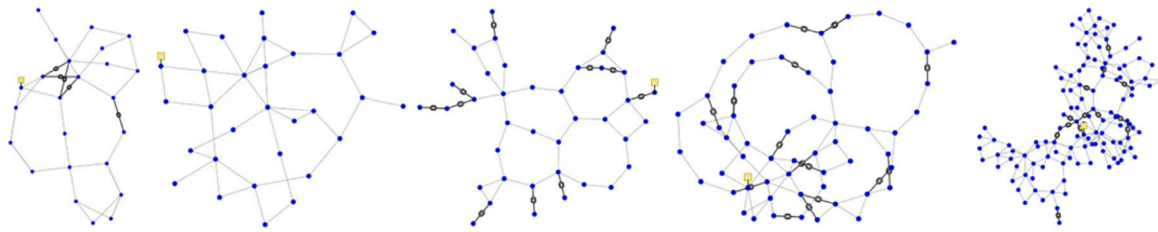

**Fig. 3.** Topology of the case studies. From the left: Net 1, Net 2, Net 3, Net 4 and Net 5.

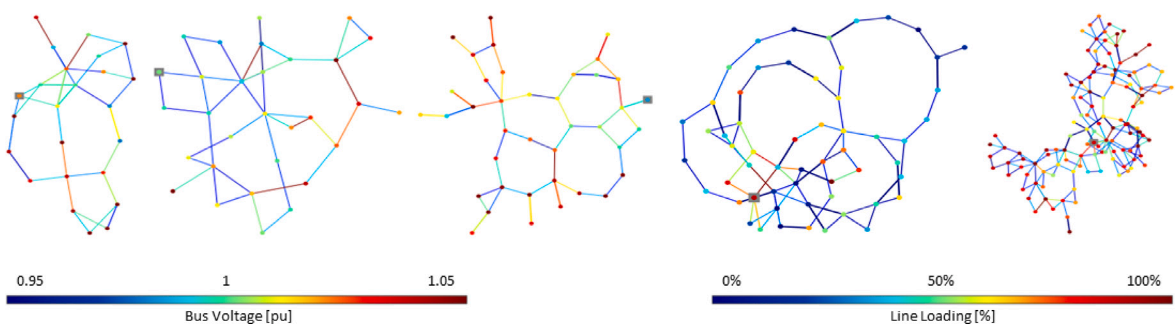


**Fig. 4.** Current bottlenecks on the case studies. From the left: Net 1, Net 2, Net 3, Net 4, and Net 5.

in the null hypothesis. Thus, if the $p$-value is lower than the statistical significance, the decision should be to reject the null hypothesis in favor of the alternative, which in this case is "the hybridization of the proposed model leads to a better performance of the metaheuristic algorithms". In this work, both Z-Statistical Test [50] and Wilcoxon Statistical Test [51] will be used to decide whether the $H_o$ is rejected or not. The Z-test verifies how many standard deviations a sample mean deviates from the population mean stated in $H_o$, while the Wilcoxon test assesses if two related paired samples come from the same distribution.

## 4. Experimental experience

### 4.1. Outline of the tests

For the simulations in this work, five different metaheuristic algorithms were used: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Evolutionary Particle Swarm Optimization (EPSO). Differential Evolution (DE), and Harmony Search (HS). In all cases, only the number of iterations and solution per population were left free to be optimized in the hyperparameter tuning. The remaining input parameters were selected based on previous publications, and they are briefly described below.

- Genetic Algorithm (GA)
  *PyGAD*, an open-source Python library for building the GA, available in Ref. [52], was employed by considering the parent selection type as "rank", the crossover type as "single point", the mutation type as "random", and the percentage of genes for mutation as 10, as in Ref. [22].
- Particle Swarm Optimization (PSO)
  In this case, the PSO algorithm from Ref. [22] was employed by considering the cognitive and social parameters as 2.05 and the construction coefficient equals 0.729.
- Evolutionary Particle Swarm Optimization (EPSO)
  In this case, the EPSO algorithm from the previous publication in Ref. [6] was used, and the replication parameter is equal to 3.
- Differential Evolution (DE)
  The DE algorithm developed in [53] was employed by using the scale factor as 0.25 and the crossover rate as 0.75.
- Harmony Search (HS)
  The HS algorithm developed in [54] was used with the following parameters: Algorithm knowledge is 0.92, harmony memory rate is 0.25, and the communication factor is 0.60.

In this work, five different test systems from Ref. [48] are used in the simulations. The characteristics of the used test systems are presented in Table 1, all the data including the investment costs for each asset of each test system are available in Ref. [47]. The threshold for highly congested assets $T_{hc}$ and the threshold for slightly congested assets $T_{sc}$ in all simulations were considered as 70% and 30% respectively. In this way, each of the test systems that were used has its own set of highly congested ($\mathcal{HC}$) and slightly congested ($\mathcal{SC}$) assets. The topologies of the test system are presented in Fig. 3, while the current bottlenecks before expansion (line congestion and bus voltage) are presented in Fig. 4.

Finally, for all simulations performed in this work, the number of hours in the peak period ($h$) was considered as 365, and the list of projects to be considered in the planning exercise corresponds to the current transmission lines in each test system, with a maximum of 3 additions per branch.

### 4.2. Metaheuristic configuration

For the hyperparameter tuning, four different configurations were considered to be explored over 15 trials per metaheuristic algorithm and test system. These configurations were pre-selected based on the past works cited in the previous section, and they are presented in Table 2.

Regarding the statistical test to choose between the four metaheuristic configurations per algorithm, the Probability of Winning test, formally presented in Section 3.2, was employed by considering 1000 games per test. The results are presented in Fig. 5 in which the $y$-axis represents the probability of winning (%) and the $x$-axis represents the configurations. The final configuration for each metaheuristic algorithm for each of the test systems was the configuration with the higher probability of winning.

**Table 1**
Test systems data.

| Test system | Total load (MW) | Gen. capacity (MW) | Transmission lines | Buses | $\mathcal{HC}$ | $\mathcal{LC}$ |
|---|---|---|---|---|---|---|
| Net 1 | 3762.00 | 4234.56 | 33 | 24 | 4 | 15 |
| Net 2 | 189.20 | 255.00 | 41 | 30 | 5 | 24 |
| Net 3 | 6879.65 | 7393.10 | 35 | 39 | 5 | 12 |
| Net 4 | 1250.80 | 1400.00 | 63 | 57 | 6 | 47 |
| Net 5 | 5599.44 | 12 092.52 | 173 | 118 | 19 | 106 |

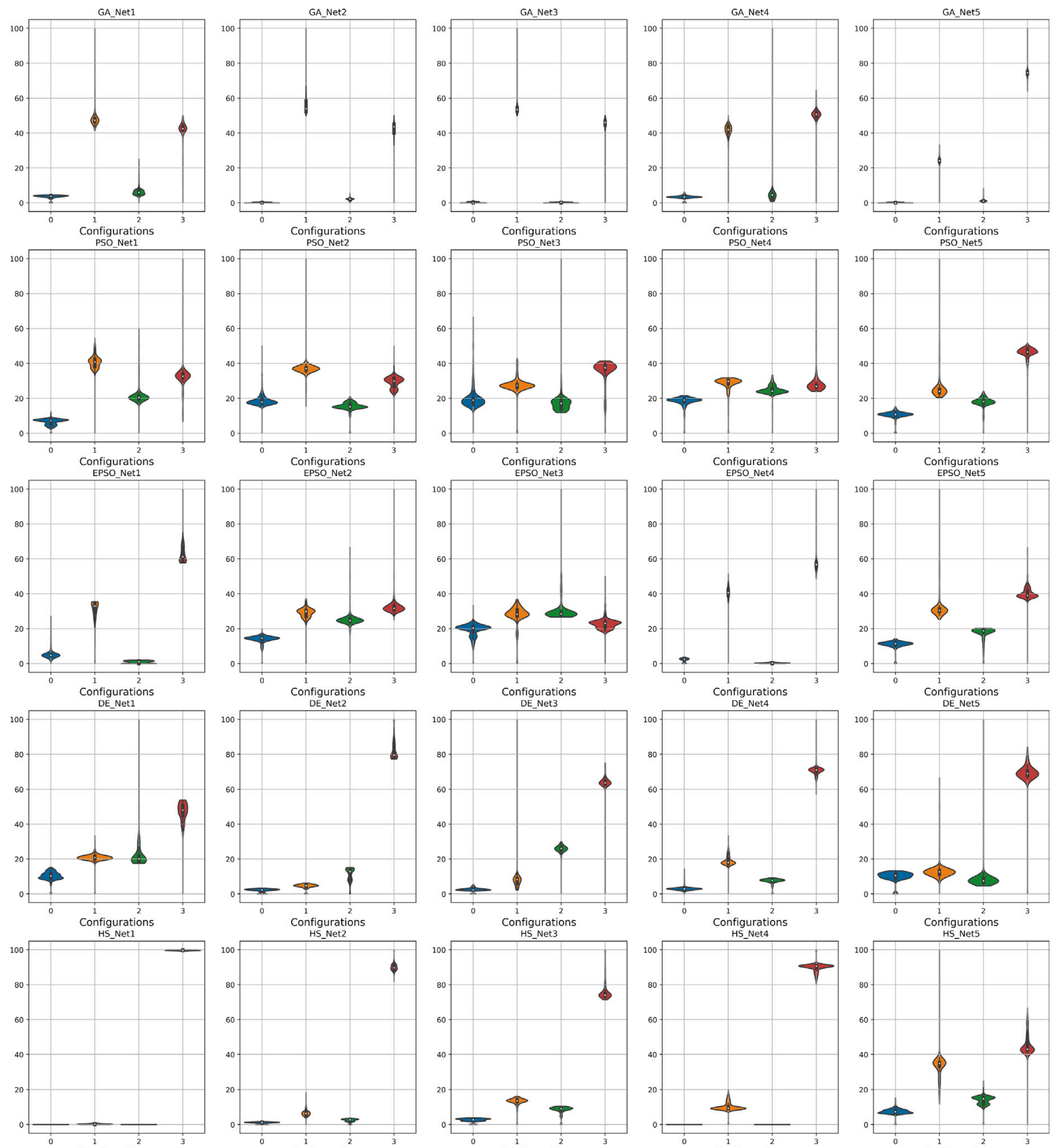


**Fig. 5.** Probability of winning of the different configurations.

### 4.3. Metaheuristic performances to solve the TEP problem

As mentioned earlier in Section 1.3, the first contribution of this work is an up-to-date comparison of five different metaheuristic algorithms on five different test systems using thirty trials to assert the Central Limit Theorem. In this way, Figs. 6 to 10 present the results obtained for each test system in this first analysis. For each of the mentioned figures, the left side shows the dispersion of the obtained fitness functions for each metaheuristic algorithm, while the right side presents the box plot for the time required to solve the TEP problem over the trials for each one of the metaheuristic algorithms.

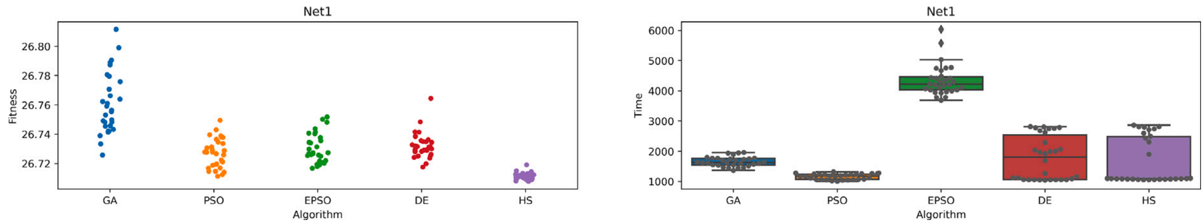


**Fig. 6.** Metaheuristic algorithms performances — Net 1.

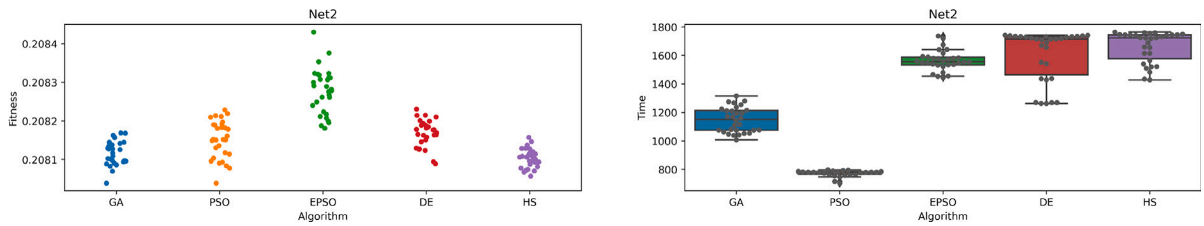


**Fig. 7.** Metaheuristic algorithms performances — Net 2.

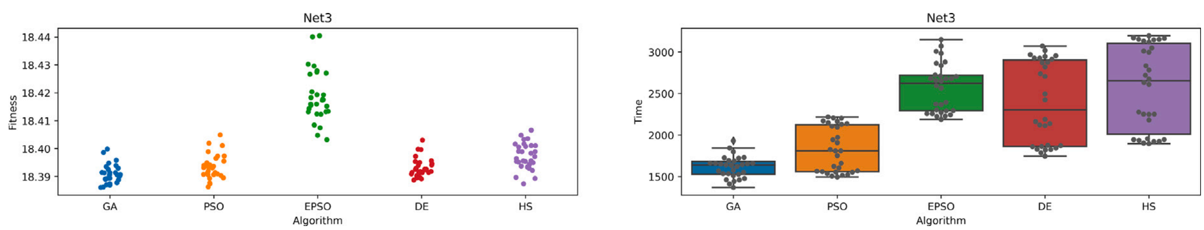


**Fig. 8.** Metaheuristic algorithms performances — Net 3.

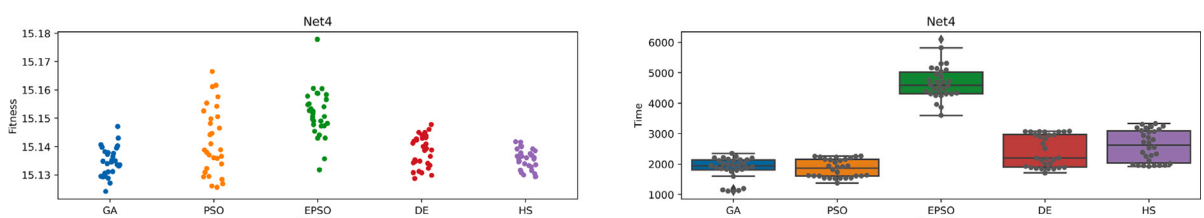


**Fig. 9.** Metaheuristic algorithms performances — Net 4.

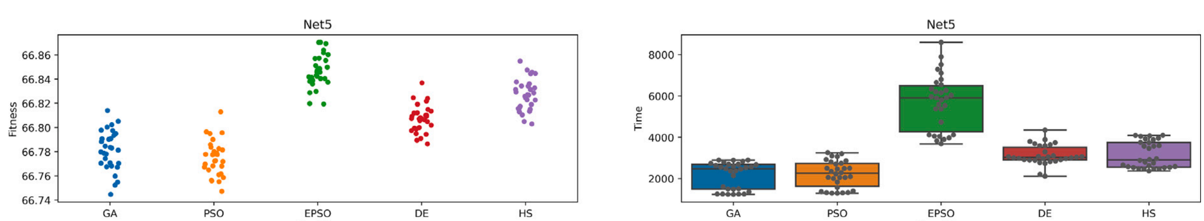


**Fig. 10.** Metaheuristic algorithms performances — Net 5.

As a way to allow the comparison between the metaheuristic algorithms on the different test systems, the time required to solve the problem and the fitness function were scaled. In this way, the time required to solve the problem is scaled by test systems considering the highest value found by an algorithm EC. On the other hand, all fitness function values were scaled considering the smallest value that was obtained. The complete scaled results are presented in Fig. 11 while Fig. 12 presents the scaled results per algorithm and test system.

### 4.4. Proposed methodology performances on TEP

In this section, the results obtained by the hybridization of the metaheuristic algorithms with the proposed CLS algorithm are presented, also using thirty trials. In this way, Figs. 13 to 17 presents the results obtained for each of the five test systems. In the mentioned figures, the chart on the left shows the dispersion of the fitness functions found by the metaheuristic algorithms in comparison with their hybridization with the CLS. The central chart presents this comparison in terms of

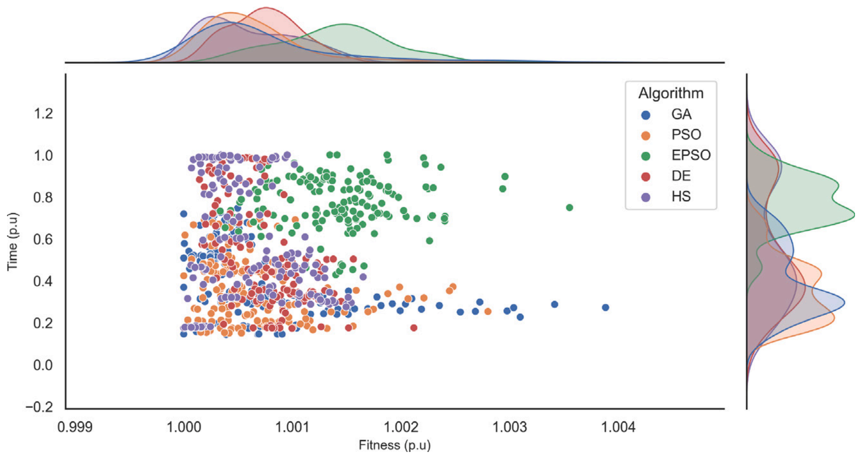


**Fig. 11.** Complete scaled results.

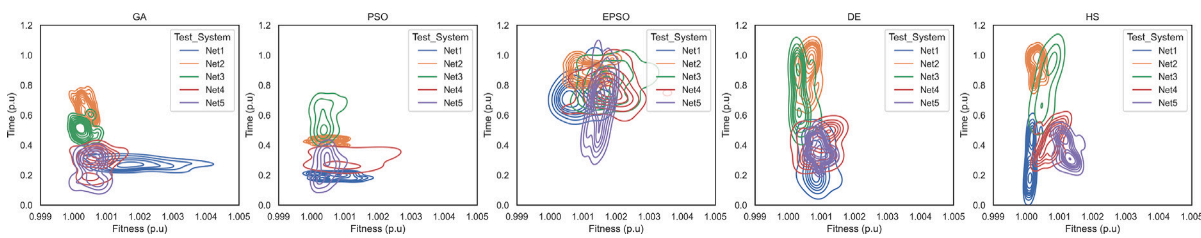


**Fig. 12.** Scaled results per metaheuristic algorithm and test system.

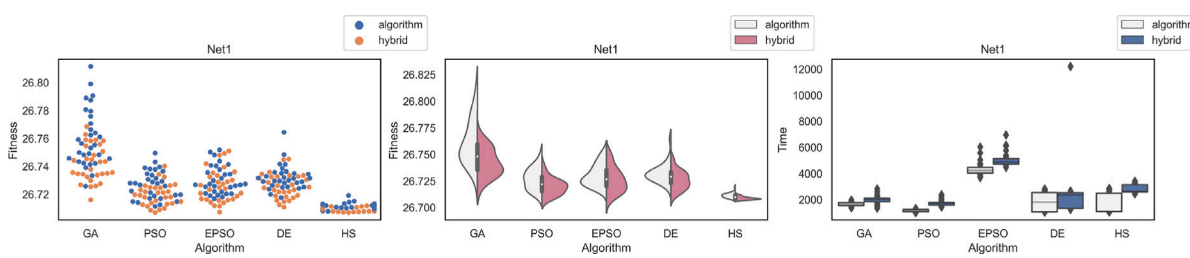


**Fig. 13.** Metaheuristic and hybrid CLS performances — Net 1.

**Table 2**
Configurations for the hyperparameter tuning.

| Config. | GA | | PSO, EPSO, DE, HS | |
|---|---|---|---|---|
| | Iterations | Solutions | Iterations | Solutions |
| 0 | 50 | 30 | 30 | 20 |
| 1 | 50 | 50 | 30 | 30 |
| 2 | 100 | 30 | 50 | 20 |
| 3 | 100 | 50 | 50 | 30 |

**Table 3**
Configurations selected for each test system and algorithm.

| | Net 1 | Net 2 | Net 3 | Net 4 | Net 5 |
|---|---|---|---|---|---|
| GA | 1 | 1 | 1 | 3 | 3 |
| PSO | 1 | 1 | 3 | 1 | 3 |
| EPSO | 3 | 3 | 1 | 3 | 3 |
| DE | 3 | 3 | 3 | 3 | 3 |
| HS | 3 | 3 | 3 | 3 | 3 |

fitness distribution and should be observed together with the chart on the left for a better analysis. Finally, the chart on the right brings the box plot for the time required to solve the problem by using metaheuristic algorithms and the hybrid option.

For a better comparative analysis between pure metaheuristic algorithms and their hybridization with CLS, Fig. 18 presents the results scaled by test systems, analogous to what was done in the previous section. In addition, the Z and Wilcoxon statistic tests were used in the results obtained in order to verify whether the null hypothesis $H_o$, formally presented in Section 3.2, can be considered true. In this way, Figs. 19 and 20 presents the p-values obtained using these two tests. These values must be interpreted as being the probabilities that the results obtained with the hybridization of the metaheuristic and CLS algorithms come from the same population as the results obtained using only the pure metaheuristic algorithms.

## 5. Discussion

In this section, an in-depth analysis of the results presented in the last section is carried out.

- Regarding the probability of winning, presented in Fig. 5, the metaheuristic algorithms have reached the best performances for the test systems according to Table 3:
- Regarding the results obtained with pure metaheuristic algorithms, presented in Figs. 6 to 10:
  - Fig. 6: HS algorithm has presented a superior performance when solving the TEP problem for the Net 1 test system, it

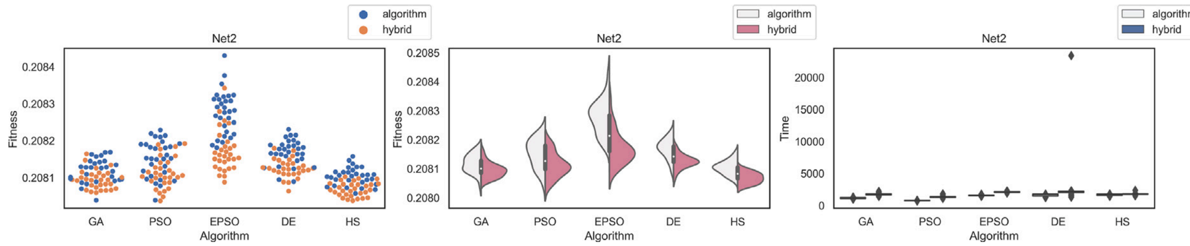


**Fig. 14.** Metaheuristic and hybrid CLS performances — Net 2.

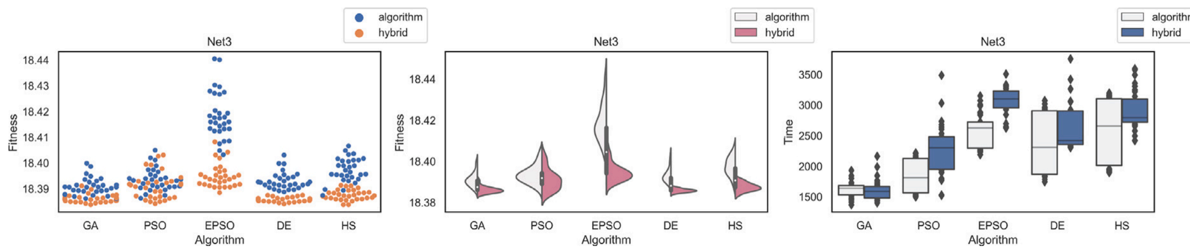


**Fig. 15.** Metaheuristic and hybrid CLS performances — Net 3.

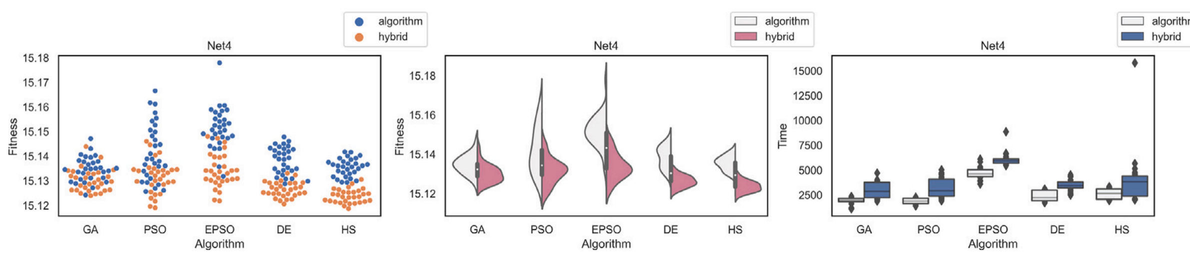


**Fig. 16.** Metaheuristic and hybrid CLS performances — Net 4.

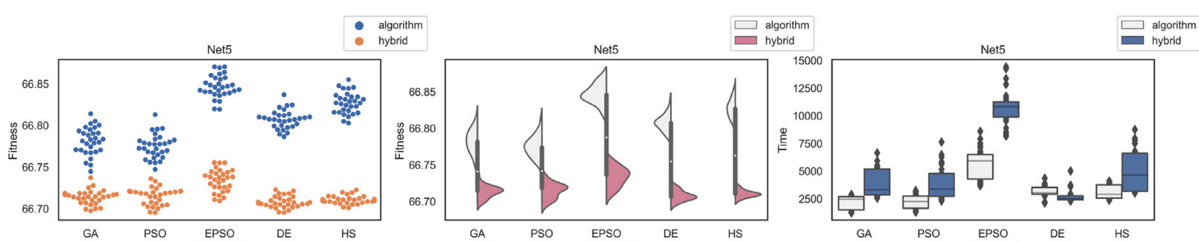


**Fig. 17.** Metaheuristic and hybrid CLS performances — Net 5.

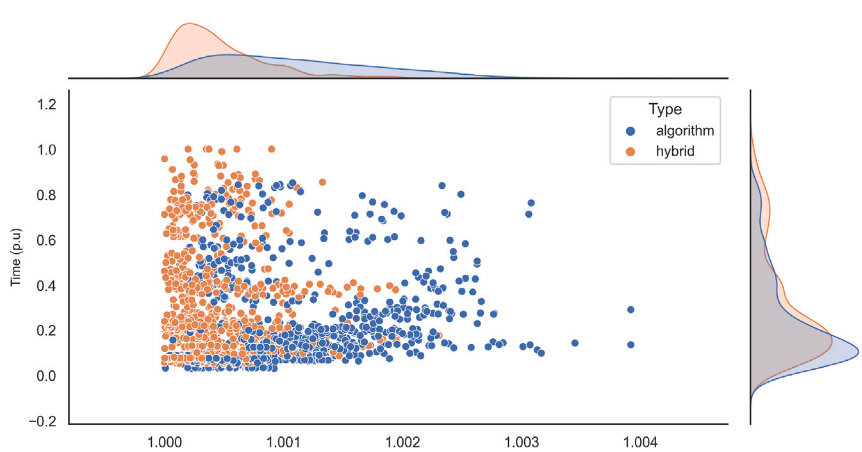


**Fig. 18.** Scaled results for the comparison between metaheuristic and hybrid CLS algorithms.

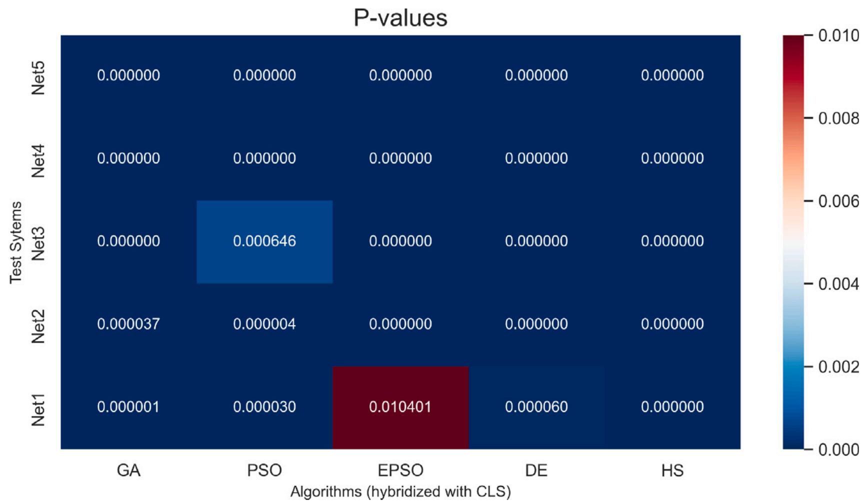


**Fig. 19.** Z statistical test — P-values for the null hypothesis $H_o$.

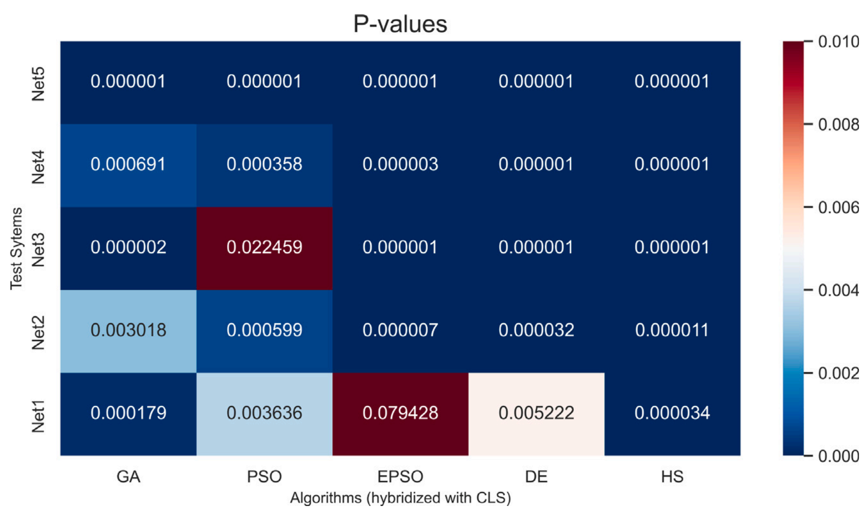


**Fig. 20.** Wilcoxon statistical test — P-values for the null hypothesis $H_o$.

presents a reduced dispersion around the best solution over the thirty trials. PSO algorithm has presented an acceptable performance as well but uses a reduced computational time when compared to the HS algorithm.

– Fig. 7: GA and HS algorithms had the best performances to solve the TEP problem in Net 2, while the PSO reached an acceptable performance, but used much less computational time. The GA used an average of 60% of the time required by the HS.
– Fig. 8: GA and DE algorithms had found the best solutions for Net 3, nevertheless, GA presented a better performance since it used much less computational time to solve the problem. EPSO presented a very poor performance since it did not find the best solutions and used a high computational time to solve the problem.
– Fig. 9: Once again GA and HS algorithms were able to find the best solutions for Net 4, and once again the GA presented a better performance since it used much less computational time to solve the problem. EPSO once again performed poorly, finding expensive solutions at a high computational cost.
– Fig. 10: GA and PSO presented quite similar performance, while also a superior performance to the other algorithms to solve the TEP problem using the Net 5 test system.

- Considering the scaled data from the results obtained with pure metaheuristic algorithms, presented in Fig. 11, GA has the most left-skewed distribution for the fitness function, indicating that it was the metaheuristic algorithm with better performance regarding the final solution. Furthermore, GA and PSO presented the most left-skewed distribution for the time required to solve the problem, which indicates that these metaheuristic algorithms can solve the problem faster than others.
- Looking at the scaled data per metaheuristic algorithm and test system, presented in Fig. 12:
  – GA chart: GA was able to find solutions very close to the best solution found for the Net 2, Net 3, Net 4, and Net 5 test systems, using much less computational time than the other algorithms. However, it presented a very large dispersion of values for the fitness of Net 1. This indicates that GA is better used in more complex test systems with large search spaces.
  – PSO chart: PSO presented a better performance when compared to GA in the Net 1 and Net 2 test systems, both in the value found for the solutions and for the computational cost. On the other hand, PSO had a lower performance in both attributes in Net3 and Net 4 test systems and a very similar performance in Net 5. This indicates that this algorithm should be preferably used in small systems.

- EPSO chart: The scattered and shifted contours to the right and upwards of the EPSO graph suggest that the algorithm did not perform well on any test system when compared to the other metaheuristic algorithms.
- DE chart: This algorithm presented an intermediate performance without much oscillation in almost all test systems, with highlights for the performance of test systems Net 1, Net 4, and Net 5.
- HS chart: This algorithm presented an excellent performance in the Net 1, Net 2, and Net 4 test systems regarding the quality of solutions, even though it requires more computational time.

• Regarding the hybridization between the metaheuristic algorithms and the proposed CLS algorithm, presented in Figs. 13 to 17, the graph on the left shows the thirty trials without overlap for both classes, the pure metaheuristic algorithms and hybridized with CLS, so it is possible to observe how each trial of both classes behaved. The central graph presents the distributions for both classes together, so it is possible to observe the displacement of the mean and the dispersion of the samples directly. Finally, the graph on the right shows the distribution of the time required for both classes.

- Fig. 13: Observing the graph on the left, it is possible to notice that, in general, the hybrid algorithm, in all the metaheuristic algorithms, presents cheaper solutions than the pure metaheuristic algorithms when solving TEP for the Net 1 test system. The central figure confirms this observation since the hybrid algorithms present a much more left-skewed distribution. The rightmost figure indicates that the hybrid class requires a little more time to complete the task.
- Fig. 14: For the Net 2 test system, the leftmost figure shows that the points of the hybrid model are positioned at a lower level than the ones for the pure metaheuristic models, indicating that the solutions are cheaper for the first class. The central figure confirms this hypothesis from the displacement of the mean to a lower value of the fitness function. The time required in both classes to solve Net 2 was practically the same.
- Figs. 15 and 16: Observing the results for the Net 3 and Net 4 test system, the figures on the left show that there is a greater displacement between the points of the hybrid models with the pure metaheuristic models so that the hybrid model is lower. The central figures confirm this displacement and also show that the hybrid model has a smaller dispersion of the results for the fitness function. The time required for the hybrid model is larger than the time for the pure model for the Net 3 and Net 4 test systems.
- Fig. 17: In the case of the TEP results for the Net 5 test system, the hybrid model achieved a remarkable result, placing the points much further down than in the previous results (figure on the left). The distribution of results for both classes confirms this remarkable displacement. The time required for the hybrid class is considerably higher than that used by pure metaheuristic algorithms.

• In relation to the scaled data for the comparison between metaheuristic and hybrid CLS algorithms presented in Fig. 18, the hybrid version presented a much more left-skewed distribution for the fitness function, indicating that the values for investment are reduced when compared to the pure metaheuristic version. On the other hand, the hybrid version also presented a slightly right-skewed distribution for computational time, which is justified by the apparent improvement in the final solution.

• Finally, the evident improvement in the final solution from the hybridization of metaheuristic and the proposed CLS algorithms are checked using the Z and Wilcoxon statistical tests. Accordingly, Figs. 18 and 19 present the p-values for the null hypothesis $H_o$ that states that the hybridization and the pure metaheuristic algorithms come from the same population (and consequently, the hybridization does not bring any performance advantage). Regarding the Z-test, even considering a very conservative level of significance as 0.025, all p-values are lower. On the other hand, in the Wilcoxon test, only one $p$-value was higher than this conservative level of significance. These results strongly indicate a rejection of the null hypothesis in favor of the alternative hypothesis $H_1$, which states that hybridization improves the metaheuristic algorithms.

## 6. Conclusion

This work presented a new neighborhood search algorithm, called Congestion-based Local search, which was able to improve the performance of metaheuristic algorithms used to solve the transmission expansion planning problem. The proposed method was applied in five different metaheuristic algorithms, with different search methods and complexity. Furthermore, the model was applied to five different test systems, with different degrees of complexity and size of the search space. The performance improvement was confirmed by a robust inferential statistical analysis, in which the hypothesis test indicated a probability greater than 99.98% of evidence of improvement of the proposed method.

The obtained results indicate that the proposed model presents improvement in all metaheuristic algorithms used, reducing the cost of the obtained solutions and increasing the reliability of the algorithms since they reduce the dispersion of the final results. In addition, the results also indicate that the proposed hybrid approach provides benefits in all test systems and that the method increases its efficiency in large instances that are more difficult to be solved, using a justified and slightly more computational time.

In addition to the new method, this work also provides an up-to-date comparison of metaheuristic algorithms to solve the transmission expansion planning problem. In this sense, the results indicate a superior performance for the Genetic Algorithm and the Particle Swarm Optimization, the former being more suited to solve TEP problems for more complex transmission systems.

Finally, as the proposed method is based on robust evidence related to the underlying problem, this study is confined to transmission planning problems and the implementation in other types of problems should consider specific alterations to the local search procedure. Further exploration of the proposed local search should concentrate on multi-stage TEP models.

## CRediT authorship contribution statement

**Phillipe Vilaça:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Visualization. **Luiz Oliveira:** Formal analysis, Investigation. **João Saraiva:** Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing – original draft, Visualization.

## Declaration of competing interest

None of the authors of this paper has a financial or personal relationship with other people or organizations that could inappropriately influence or bias the content of the paper.

It is to specifically state that “No Competing interests are at stake and there is No Conflict of Interest” with other people or organizations that could inappropriately influence or bias the content of the paper.

## Data availability

Data will be made available on request.


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## Ethical procedure

The research meets all applicable standards with regard to the ethics of experimentation and research, and the following is being certified/declared true.

As an expert scientist and along with co-authors of concerned field, the paper has been submitted with full responsibility, following due ethical procedure, and there is no duplicate publication, fraud or plagiarism.

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