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Comparison of Metaheuristics in Solving a Optimal Location of Photovoltaic Generators in a Distribution Network Problem

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Abstract: This study aims to identify optimal locations for Photovoltaic Generators (PVG), within Energy Distribution Systems (EDS) to minimize energy losses. The problem is treated as a combinatorial optimization challenge. The optimal locations are determined using metaheuristics, namely the Differential Evolutionary Algorithm (DEA), Generic Algorithm (GA), Particle Swarm Optimization (PSO), and Tabu Search (TS). The primary goal was to assess the efficacy of these methods in addressing the proposed optimization problem and to conduct a comparative analysis. The performance evaluations were carried out using the IEEE 123 bus test system. Power flow calculations were performed using OpenDSS, while Matlab® was utilized for programming the optimization methods. All four methods demonstrated efficiency by providing solutions that indicated a reduction in energy losses. Notably, the GA and TS stood out, exhibiting the best reduction averages and the lowest standard deviations.

Keywords: Energy losses, evolutionary differential, generic algorithms, metaheuristics, OpenDSS, particle swarm, tabu search.

1. INTRODUCTION

Distributed Generation (DG) is defined as the production of electric energy from concessionaires, permit holders, or authorized agents directly connected to the Electric Distribution Systems (EDS). In Brazil, this definition excludes hydroelectric plants greater than 30 MW or thermoelectric with an efficiency lower than 75% (Brazil, 2004). Among the many advantages of DG, the possibility of postponing investments, meeting the load growth, reducing technical losses and improving the voltage profile of the system are highlighted (Kuffel, 1984). Despite all its benefits, the presence of DG in an EDS can cause several problems, including: bidirectional flow in the lines, greater complexity in planning and operating the system.

There are several types of DG, among which the photovoltaic (PV) type stands out due to its sharp growth in the world (Narasimhan, 2020). This result is due to the increase in electricity demand and the growing potential of solar PV energy. In fact, renewable energy sources, such as solar and wind, due to their low energy density, are better adapted to DG (Walter, 2000). The use of solar generation by PV cells for the production of electrical energy gained space in electrical systems around the world and in Brazil, in particular (Esposito and Fuchs, 2013; REN21, 2022).

Method comparison works have already been performed in the literature, as in Strnad and Prenc (2018), using fictitious EDS and evaluating power losses. Saleh et al. (2018) proposed the comparison of different optimization methods: Whale Optimization Algorithm, Dragonfly Algorithm and Moth-Flame Optimization. These approaches were implemented to identify the optimal location and dimensioning of DG, analyzed simultaneously under two power factors in radial EDS to minimize power losses.

Moradi et al. (2014) proposed a hybrid method based on the Imperialist Competitive Algorithm and the GA method. The objective function (OF) were to reduce power losses, improve the system's voltage profile, increase the voltage stability index, load balance and relieve transmission and distribution capacity for utilities and customers. Mohamed et al. (2017) presented a variant of the Moth Swarm Algorithm, to solve an optimal power flow problem.

Zambrano-Asanza et al. (2021) proposed a GIS-MCDA method for the optimal selection of sites for construction of Photovoltaic Generators (PVG), considering environmental, location, climatic and orographic criteria. The methodology was applied in an EDS in Ecuador. However, the authors did not evaluate energy losses, did not measure the installation's financial return and did not present the test system used in the work.

Lucena et al. (2021) presented a method based on Tabu Search (TS) to determine the optimal location of PVG in order to minimize losses and the consequent economic impact of the installation. The proposed method was effective in solving the problem, so that the optimized solution found reduced system losses without compromising the voltage profile, even improving it, in addition to providing a discounted payback period of less than 6 years.

Dharavat et al. (2022) proposed an effective approach to solve DG and electric vehicle charging station allocation problems in an EDS to reduce power loss and enhance voltage profile. Their best locations and sizes are identified by political optimization algorithm. Although the authors highlighted the performance of the proposed method compared to others, these results were not exposed, making the analysis of the results limited.

Janamala and Radha Rani (2022) used the Archimedes Optimization Algorithm (AOA) to determine optimal locations and sizes for PV systems in EDS. Their study showed that AOA outperformed other nature-inspired heuristic algorithms in terms of convergence and redundancy for complex, non-linear, and multivariable optimization problems. However, they did not specify the parameterization of the other methods used for comparison.

In the literature review, it is clear that there is no impartial comparison of the proposed methods. Thus, this article stands out for minimizing bias in the parameterization of the analyzed methods.

This work is inserted in this context, treating the installation of a PVG in the EDS as a combinatorial optimization problem, which is solved via local solution methods, that is, metaheuristics (Yang et al., 2013). For this article, Differential Evolutionary Algorithm (DEA), GA, Particle Swarm Optimization (PSO), and TS methods were selected, due to their strong presence in the state of the art on the topic of optimization methods, in addition to having already proven themselves suitable for solving problems such as the one addressed in this article Meira et al. (2023); Pereira (2021); Junqueira et al. (2021); Lucena et al. (2021) . Despite the use of TS method is still incipient to solve problems of optimal PVG installation, it was also selected, due to the fact that it reduces the frequency with which solutions are trapped in a sub-optimal space (Gomes, 2009).

This article aims to address the problem of determining the optimal placement of PVG to minimize electrical energy losses. The use of metaheuristics will provide the buses on which the PVG will be installed. Then, the calculation of the system energy losses, is performed.

The article was organized into six sections, including this introductory section, as follows: section 2 presents the problem formulation, section 3 presents the optimization methods, section 4 presents the methodology, section 5 presents the analysis of the results, and finally, section 6 presents the inferred conclusions.

2. PROBLEM FORMULATION

Solar energy is an energy derived from the Sun's light and heat. The primary method for converting solar energy into electricity is through the PV effect.

A PVG uses the PV effect to generate electrical energy. It comprises PV panels, with each panel consisting associations of PV modules, which, in turn, consists of encapsulated PV cells electrically connected. The PV cell converts sunlight into electrical energy by exciting electrons in semiconductor materials when exposed to sunlight.

Beyond supplying electricity to consumers, PV generation offers various benefits, including reducing electrical losses, enhancing the voltage profile and enabling economic operation. The contribution of each PVG depends on its capacity and solar incidence at the installation site. Consequently, the utilization of PVG facilities may vary based on their positioning in the EDS. Results are also contingent on the installed load, whether in the form of consumption or generation (Strnad and Prenc, 2018).

The problem to be solved in this work is to estimate the optimal location of PVG in order to minimize electrical energy losses. The sum of energy losses is calculated for each section of the feeder, according to Equation 1.

$$\text{Minimize } \Delta E = \sum_{i=1}^{n} \Delta E_i, \tag{1}$$

where: n is the size of the feeder and ΔE_i is the energy loss of the i section.

In addition, the following restrictions were considered: a PVG cannot be allocated in the substation; the maximum number of iterations of the method and the error allowed; the capacity of the PVG that can be installed was considered to be 30% of the total power demand of each system (Vianna et al., 2018) and the list with the characteristics of the PV panels and the area for installation are provided. The percentage that determines the maximum power level to be installed was selected based on a survey carried out from a bibliographic review on the subject, corroborated by Vianna et al. (2018) and other related authors.

3. OPTIMIZATION ALGORITHMS

An algorithm, such as Algorithm 1, is a process of well-defined instructions for solving a problem (Knuth, 1997), being used for optimization and classified as: deterministic, where the same input always yields the same output; and stochastic, relying on probability rules.

Algorithm 1 Metaheuristic Representation

Require:
1: Method parameters, Amount of search agents, Population size, Amount of iterations

Ensure: Maximize or minimize the OF

2: Initialize the set of search agents and evaluates them
3: **while** (stop criterion is not satisfied) **do**
4: Steps of the metaheuristic search process
5: **end while**
6: Returns the best position and its solution

Concerning algorithm resolution mechanisms, heuristic and metaheuristics stand out, offering near-optimal solutions at a lower computational cost. Among the metaheuristics available in the literature, four methods were selected: TS, DEA, GA, and PSO. They were selected because they are suitable for solving combinatorial optimization problems and their local optima escape properties.

3.1 Tabu Search

The TS method, introduced by Glover (1986), is a metaheuristic designed for solving complex combinatorial optimization problems through local search. The method initiates with an initial feasible solution and identifies the best solution within the neighborhood obtained by applying operations. A movement is defined as the operation applied to a given solution, generating a neighboring solution. Notable features include (Lucena, 2020):

(1) Neighborhood refers to the set of all moves for a solution. If a specific movement cannot modify the solution's region, it is introduced a Tabu List (TL);
(2) The prohibition operation involves storing attributes of executed moves in the TL. When a new move is attempted, the TL is consulted (Gomes, 2009);
(3) Aspiration criterion serves as a rule that replaces restrictions. If a move is prohibited by the TL, aspiration criterion may allow it under certain conditions.

The pseudocode of the TS method is presented in Algorithm 2, based on (Lucena, 2020).

Algorithm 2 TS method pseudocode.

Require: Common parameters (Algorithm 1)
1: **while** (stop criterion is not satisfied) **do**
2: Evaluate the OF, initialize TL and Aspiration Criterion
3: **if** Some movement is on TL **then**
4: Does not perform that move
5: **end if**
6: Evaluate allowed movements and identifies the best solution
7: Put the movement that led to that solution in the TL
8: Return to item 3
9: **end while**

3.2 Differential Evolutionary Algorithm

The DEA method, proposed by Storn and Priece in 1995 (Price and Storn, 1995), deals with a simple population-based system, which uses the search technique that emerged from attempts to solve the Chebychev problem. The idea of using weighted vector difference to perturb the population was introduced. This difference is multiplied by a mutation factor, added to a third vector, randomly selected. The modified vector components are mixed with the components of a random vector. All vectors are evaluated by the value of their OF, using a numerical value associated with the individual's adaptation. The DEA method pseudocode is presented in Algorithm 3.

Algorithm 3 Pseudocode of DEA method.

Require: Common parameters (Algorithm 1)
while (stop criterion is not satisfied) **do**
Evaluate the OF for the initial solution
Perform mutation → Crossover
Evaluate OF → Selection
Returns the best position and its solution
end while

3.3 Genetic Algorithm

The GA method was proposed by Holland in the 1960s and emulates the process of evolution through an iterative process, which involves creating a population, assessing their fitness, and generating a new population through genetics changes (Holland et al., 1975).

Briefly, the GA method starts with a random population evolving through successive iterations (or generations). In each generation, a new population is formed, derived from the original one through crossover and mutation operations. In the loop of the generation, all individuals in the population are evaluated by a survival criterion, which determines which individuals should survive. This process is repeated until a complete evolution of the population to the ideal solution occurs (Sakawa, 2012). The pseudocode of the GA method is presented in Algorithm 4.

Algorithm 4 Pseudocode of the GA method.

Require: Common parameters (Algorithm 1)
while (stop criterion is not satisfied) **do**
if Number of generations $<$ maxIte **then**
Execute: Crossing → Mutation → Selection
Select the best individual of the generation
else
Returns the best position and its solution
end if
Returns the best position and its solution from the set
end while

3.4 Particle Swarm Optimization

The PSO method was proposed by Eberhart and Kennedy (1995) and is based on the behavior of a set of birds, bees or fish. Each individual, also called a particle, is represented by a vector referring to its current position and its current velocity or change in position.

The movement of a particle to the next position depends on three main parameters: the change in position; the best particle experience; and the best experience of the particle group. The process of moving a particle by the PSO method is presented in Algorithm 5.

Algorithm 5 PSO method pseudocode.

Require: Common parameters (Algorithm 1)
while (stop criterion is not satisfied) **do**
Identifies $\vec{P}_{i_{best}}(t)$ and $\vec{G}_{best}(t)$ and calculate speed and new position
if There was a change in positions **then**
Modify population
end if
end while
Returns the best position and its solution

4. METHODOLOGY

The proposed solution involves the integrated use of two software tools, Matlab® and OpenDSS. OpenDSS is recognized as a standard tool for EDS loss studies and is endorsed by the National Electric Energy Agency (ANEEL) in Brazil. The methodology used to solve the problem is described in Figure 1 and detailed below.

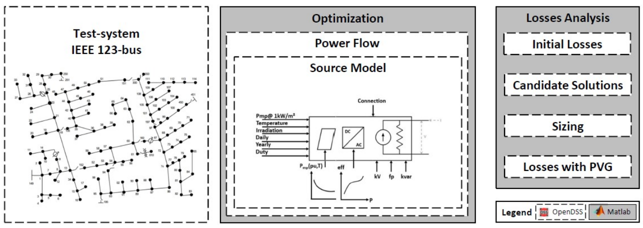

Figure 1. Methodology.

Initially, the solution is coded. Then, the test-system is selected incorporating various load types and equipment. Data on irradiance and temperature are collected for solar power simulations. The power flow calculation is performed, so that the energy losses are measured in OpenDSS. Then, results are exported to Matlab® for analysis and optimization.

4.1 Solution encoding

For the proposed problem, a solution is characterized by a vector filled with 0 and 1, as shown in Figure 2, indicating, respectively, the absence and presence of a PVG.

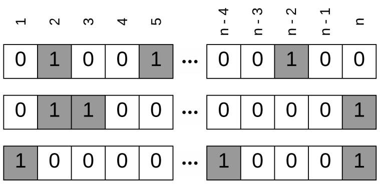

Figure 2. Solution encoding.

4.2 Test-system

The methodology begins with the selection of the test system, presented in Figure 3.

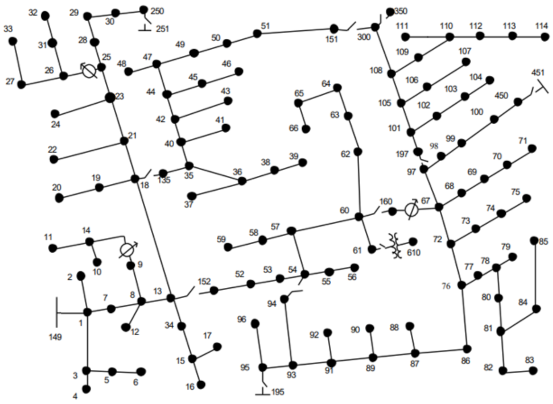

Figure 3. System-test 123 buses (Kersting, 2000).

This system has 123 buses, featuring sections with voltages of 115, 4.16, and 0.48 kV. It includes multiple-phase lines, diverse load types such as constant power, constant impedance, and current loads. Additionally, the system incorporates three-phase power transformers, shunt capacitors, disconnect switches, and voltage regulators.

The test system data are collected and designed in OpenDSS, which will execute the power flow. The data from this initial analysis are exported to Matlab®, which will be used as a database for the results obtained and for the execution of the optimization methods.

In addition to the limitations of the problem, optimization methods have specific restrictions, which must also be respected. In this way, when a stopping criterion, either from the method or from the convergence process of solving the problem, is reached, the best result obtained in the executed iterations is selected.

4.3 Environmental Data

Data on local irradiance and panel temperature were collected at the Laboratório de Eletrônica Industrial e Acionamento de Máquinas (LEIAM) of the Universidade Federal de Campina Grande (UFCG). The actual daily load curve associated with the system comes from the Bela Vista substation of Energisa Borborema, located in the city of Campina Grande. The curves were collected from a real system, in order to simulate the power generated by each PVG and are shown in Figure 4.

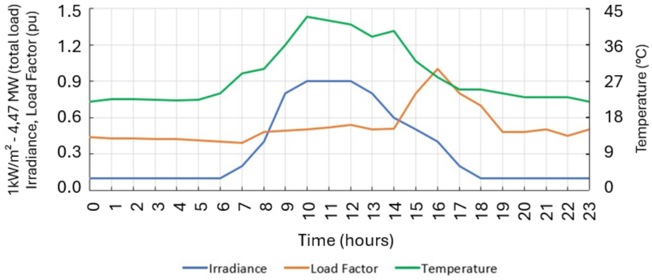

Figure 4. Temperature, Irradiance and Load Curve.

4.4 Photovoltaic Panels

Studies related to PV energy usually require the construction of a model of the PV cell in the form of equivalent electrical circuits. Among the various models available in the specialized literature, the OpenDSS model was selected, shown in Figure 5.

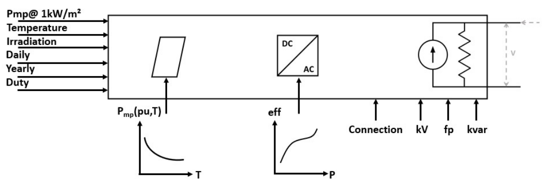

Figure 5. Block diagram of the PVG system model.

The current version of the model combines the PVG and the inverter to perform simulations with a sampling interval greater than or equal to 1 second.

Basically, the model has an active power injected at the interconnection point, P, which is a function of irradiation, temperature, converter efficiency, grid voltage and rated power panel at the maximum power point (P_{mp}), as presented in Equation 2:

$$P = P_{mp}\left(\frac{1kW}{m^2}\right) \cdot ir(t_0)_{pu} \cdot ir_{(base)} \cdot P_{mp}(T(t_0))_{(pu)}, \quad (2)$$

where: P is the power output; $P_{mp}\left(\frac{1kW}{m^2}\right)$ the rated power at maximum power point; $ir(t_0)_{pu}$: the value of irradiance in pu at instant t_0; $ir_{(base)}$ the maximum irradiance on the selected day and $P_{mp}(T(t_0))_{(pu)}$ the correction factor of P_{mp} as a function of temperature at instant t_0.

The active power supplied by the PV system is presented in Equation 3:

$$P_{out}(t) = P_t \cdot eff(P_{out}(t)), \quad (3)$$

where $eff(P_{out}(t))$ is the inverter efficiency.

The maximum number of PVG that can be installed on each bus and their capacity are calculated. For this, it was considered that each bus provides a fixed area.

The PV panels available for installation were: BYD (400 Wp), Trina Solar (410 Wp), Canadian (415 Wp), and Jinko (440 Wp). All selected panels occupy 2.01 m² (Lucena et al., 2021).

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4.5 Adjustments of Optimization Methods

Metaheuristic methods were selected to solve the proposed problem, given that the search space is large, which is directly proportional to the number of buses in the system. The optimization methods selected for this work require adjustments and definitions of their parameters, presented in the Table 1, and described below.

Table 1. Parameters used in DEA, GA, PSO, and TS methods.

Method	Parameter	Value	Method	Parameter	Value
TS	Max. Iterations	12	DEA	Max. Iterations	100
	Population size	10		Population size	40
	Amount of Mov.	29		Sum limit	570
	Asp. Criteria	0.5		Crossover rate	0.8
PSO	Max. Iterations	190		Mutation fator	0.6
	Population size	14	GA	Population size	10
	Coef. of inertia	0.7298		Generations	10
	Particle Accel. Coef.	1.4982		Ages	8
	Global Accel. Coef.	1.4982		Crossover rate	0.6
	Damping coef.	0.99		Mutation factor	0.2

The parameters presented in the Table 1 were determined based on the works (Pereira, 2021; Meira et al., 2023; Junqueira et al., 2021; Lucena, 2020). The comparison in the process of convergence of methods took place in an impartial manner and guaranteed a more technical analysis of the results. The association of the values presented in the Table 1 will total the number of executions of the objective function that were performed in each method.

Tabu Search For the TS method, the following steps are performed: creation of an initially empty TL and generation of the initial random population.

Then, the neighborhood of each solution is created by shifting bits and the losses are calculated. Thus, the movement that gave rise to the solution that presented the best solution is selected, which will be placed in the TL until the aspiration criterion occurs. Finally, new individuals are generated as long as the process does not violate the stopping criteria and, through it, the results are presented.

Differential Evolutionary Algorithm For the DEA method, the process requires the establishment of each parameter used, such as: number of vectors (nPop), mutation factor (F), crossover rate (CR) and number of iterations (MaxIt). Once this is done, the initial population is generated randomly within the search space, in a uniformly distributed way (Oliveira et al., 2006).

The DEA method performs the mutation, in which each vector is modified by adding the weighted vector difference between two random vectors to a third vector (Oliveira et al., 2006). To complement the search process, the DEA method performs the crossover, aiming to increase the diversity of individuals (Price and Storn, 1995). Finally, the selection operator aims to select the individuals with the best characteristics for the next generation.

Genetic Algorithm The GA method starts with the generation of an initial random population, all individuals being different from each other. For each individual, the OF is calculated. Then, the crossings are carried out, in which two individuals are randomly selected, which will have cut-off points for exchanging stretches of their characteristic vectors. After the crosses, mutations are applied to some individuals. Finally, the selection is applied, which takes place through a tournament and the one with the best result will be kept for the next iterations.

Particle Swarm Optimization The procedure of the PSO method is performed so that all the movement is performed using the method algorithm, however, as the OF used was the same for all methods, the vector with the buses in which the PVG would be installed needs to be converted to a binary pattern before each OF run. The process of moving a particle by the PSO method is shown in Figure 6.

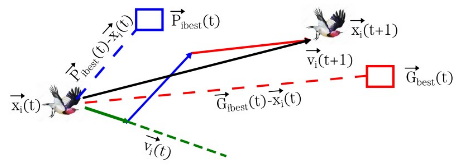

Figure 6. Particle movement by PSO method.

4.6 Calculation of Losses

The energy losses were obtained using the *Energy Meter* in OpenDSS. An EnergyMeter object is a smart meter connected to a terminal of a element that simulates the behavior of a real meter. It measures not only the power and energy values at your location, but also the losses and overload values within a defined region (Dugan, 2020).

In this study, it was connected to the first line after the substation and provided a record of losses for one day, with 24 measurement points.

5. RESULTS

The amount of PV panels in each bus was calculated by dividing the area of each bus by the area occupied by each panel. It was determined that 362 panels fit in each bus.

With a total system load of 4.47 MW, the 30% penetration capacity restricted the installation of PVG to a maximum of 1.34 MW. Consequently, the system installation capacity was divided by the designated installation capacities, revealing that PVG would be implemented at 8 buses in the system. Initially, the feeder without PVG incurred energy losses amounting to 128.06 kWh/day.

This procedure was carried out with the aim of taking advantage of the largest possible area available for the installation of PVG, in order to maintain the total installed power at the specified penetration level. It is also important to highlight that, according to a Brazilian normative resolution, the installation of 1.34 MW divided into 8 buses is configured as minigeneration, that is, a generating plant with an installed power above 75 kW and less than or equal to 5 MW (ANEEL, 2012). The graph in Figure 7 shows the results of the executions of each of the programmed optimization methods.

Figure 7. Result of execution of each method.

It is also known that the size of the search space for the problem was determined according to the combinatorial analysis (combination) Equation 4.

$$C_{n,p} = \frac{n!}{p!\,(n-p)!} \tag{4}$$

were: n is the number of feeder sections and p the number of PVG installed. For this analysis, $n = 123$ and $p = 8$, so the size of the search space $C_{n,p} = 1,029,873,432,159$.

In Table 2, a summary of the results obtained in each of the programmed optimization methods is presented.

Table 2. Summary of Results.

Method	Power of Panels	Total Installed Power	Buses	Loss Reduction
TS	400 W	1158.40 kW	66 69 71 76 83 94 111 114	4.590%
DEA	400 W	1158.40 kW	64 70 71 83 93 101 110 112	4.529%
GA	410 W	1187.36 kW	70 108 109 110 111 112 113 114	4.629%
PSO	410 W	1187.36 kW	67 76 77 83 89 105 110 113	4.520%

Still analyzing Table 2, it is observed that the TS and DEA methods indicated the installation of PVG compounds by 400 W panels each, while the GA and PSO methods indicated PVG compounds by 410 W. Thus, the total power installed by Bar and, consequently, were different.

5.1 Average and Standard Deviation

From the results above, it was possible to infer that there are differences between the solutions found by each of the methods, either by the average of the values found or by the standard deviation of the results. Thus, the mean and standard deviation of the samples were calculated, presented in Table 3.

Table 3. Mean and std deviation of results.

Method	Average	Standard Deviation
TS	4.44	0.052
GA	4.47	0.068
DEA	4.30	0.105
PSO	3.97	0.217

The results of the GA and TS methods were quite similar, making it necessary to carry out other comparative tests. The following were selected: coefficient of variation (CV), used in the evaluation of the dispersion of results, the Herfindahl-Hirschman index (HHI), which measures concentration and the convergence speed.

5.2 Coefficient of Variation

The CV is a measure of dispersion used to estimate the precision of experiments to express the standard deviation as a percentage of the mean, according to Equation 5.

$$CV = \frac{StandardDeviation}{Mean} = \frac{\sigma}{\mu} \tag{5}$$

5.3 Herfindahl-Hirschman Index

The HHI is generally used to measure the market concentration of companies, but in this work it was used to evaluate the concentration of the solutions found for the proposed problem. The index is based on Eqs. 6 and 7.

$$P_i = \frac{X_i}{\sum_{i=1}^{N} X_i} \tag{6}$$

$$HHI = \sum_{i=1}^{N} {P_i}^2 \cdot 1000 \tag{7}$$

Thus, the analysis of the results was expanded from the study of these two indices, whose values are presented in Table 4.

Table 4. Calculated CV and HHI.

Method	CV Index	HHI
TS	1.18%	25.00337
DEA	1.52%	10.00230
GA	2.46%	10.00597
PSO	5.48%	10.02972

With these indices, it is clear that there is a greater difference between the results obtained in the GA and TS methods. Despite the TS method having presented an average of the results slightly lower than the one obtained in the GA method, the CV and the HHI indicate that the TS method presents a smaller dispersion of the results.

5.4 Convergence Speed

The third analysis was carried out by observing the graph in Figure 8, that shows the convergence process of the methods for the best results of each of them for a total of 8,000 OF executions, which takes into account the maximum number of iterations of each method for each process.

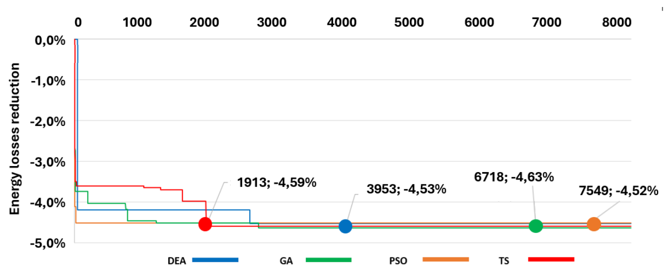

Figure 8. Convergence speed of methods.

From the analysis of the convergence speed, it is highlighted that the GA and PSO methods presented the highest initial speeds, followed by the TS and DEA. The DEA and PSO methods were stuck in local optima and, consequently, presented the two worst results obtained. The GA and TS methods obtained the best results, with emphasis on the TS method, which reached its best value in less than 20% of the maximum number of iterations established.

6. CONCLUSIONS

This work aimed to compare metaheuristics in solving a combinatorial optimization problem, which aims to minimize energy losses in an electricity distribution system with the installation of photovoltaic generators.

Four optimization methods were programmed: genetic algorithm (GA), differential volutionary algorithm (DEA), particle swarm (PSO) and tabu search (TS), to determine the optimal location of photovoltaic generators (PVG). The methods were selected due to their ability to solve combinatorial optimization problems. The methodology developed was applied to the test system of 123 buses, in which eight PVG were positioned on the feeder.

The methods used proved to be effective in solving the problem, making a comparison between them necessary. It was verified, from the analysis of the average of the results and the standard deviation, that the methods of the genetic algorithm and the tabu search were more efficient. However, the proximity of the results made it necessary to evaluate other indices.

For this comparison, the coefficient of variation and the Herfindahl-Hirschman index, both used to assess the measure of dispersion of results, were analyzed. For these results, the TS method presented better results, indicating that, for this test system analyzed in this proposed problem, it is the best method to be used.

Besides what was previously mentioned, an examination of the convergence speed of the method reveals that despite not starting as the fastest, the Tabu Search method achieved the most optimal result in the shortest time. Therefore, it is considered that, taking into account the characteristics of the test system and the proposed problem, the use of the Tabu Search method presents the best results.

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