Multi-objective Optimization Approach for the Allocation of Fast Charging Stations and Distributed Energy Resources

Rafael S. F. Ferraz * **Renato S. F. Ferraz** *
Augusto C. Rueda-Medina * **Jussara F. Fardin** *

* *Programa de Pós-Graduação em Engenharia Elétrica. Departamento de Engenharia Elétrica. Universidade Federal do Espírito Santo, ES, (e-mail:rafael.ferraz@edu.ufes.br, renato.s.ferraz@edu.ufes.br, augusto.medina@ufes.br, jussara.fardin@ufes.br).*

Abstract: The increasing inclusion of Electric Vehicles (EVs) in distribution systems is a global trend due to their several advantages, such as increased autonomy and reduced price. However, the high amount of EVs requires the installation of sufficient EV Charging Stations (EVCSs) to recharge them. If there is no adequate planning for the EVCSs allocation, it can result in a reduction in the power quality indices such as increased power losses in the system and voltage variation outside the limits established in IEEE Std 1547-2018. Therefore, this paper aims to define the best locations for the installation of EVCSs in the system, in addition to performing the optimal allocation and sizing of Distributed Energy Resources (DERs) in order to mitigate the problem related to voltage levels. Moreover, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) was used with the purpose of minimizing the investment and operation costs and voltage deviation in the system. The validation of this methodology was performed using the IEEE 13 and 34 node test feeders, and it was possible to compare optimized solutions based on the Pareto curve for both systems, which made it possible to minimize the objective functions.

Resumo: A crescente inserção de Veículos Elétricos (VEs) no sistema de distribuição de energia elétrica é uma tendência mundial em função das suas diversas vantagens, como aumento da autonomia e a redução no preço. Porém, esse acréscimo da quantidade de VEs exige a instalação de Estações de Carregamento de VE (ECVEs) suficientes para as recargas destes. Caso não haja um planejamento adequado da alocação de ECVEs no sistema, pode-se resultar em redução dos índices de qualidade de energia elétrica como o aumento das perdas no sistema e variação da tensão fora dos limites estabelecidos em IEEE Std 1547-2018. Portanto, com o intuito de mitigar o problema relacionado aos níveis de tensão, esse trabalho visa determinar as melhores localizações para a instalação de ECVEs no sistema, além de realizar a alocação e dimensionamento ótimo de unidades de Geração Distribuída (GD). Para isso, foi utilizado o Algoritmo Genético de Classificação Não Dominado (NSGA-II) com o propósito de minimizar os custos de investimento e de operação e a variação de tensão no sistema. Além disso, a validação dessa metodologia foi realizada a partir dos sistemas de 13 e 34 nós do IEEE, e foi possível comparar soluções otimizadas com base na curva de Pareto para ambos os sistemas, sendo possível minimizar as funções objetivos.

Keywords: charging station; distributed energy resource; electric vehicle; multi-objective algorithm.

Palavras-chaves: algoritmo multibjetivo, estação de carregamento, geração distribuída, veículo elétrico.

1. INTRODUCTION

The increasing inclusion of Electric Vehicles (EVs) in distribution systems presents several benefits, such as reduced reliance on oil-based fuels and lower transportation impact on climate. Moreover, the EV has lower operation and maintenance costs when compared to combustion engine vehicles, making EV a more economical and efficient alternative (Jain et al., 2020; Daina and Polak, 2016). With the rapid growth of the number of EVs, the demand for EV Charging Stations (EVCSs) is also increasing. The EVs recharge is considered as additional demand, which has a significant impact on the different elements that make up the electrical system, such as the operation of the network at low voltage levels (Garcia-Osorio et al., 2013).

Therefore, some works were developed aiming at reasonable planning of charging stations for EVs in order to ensure the steady development of EVCS. Akbari and Fernando (2015) focused on social cost, seeking to minimize

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the queue length at each station, and Chen et al. (2020) used Particle Swarm Optimization (PSO) and Dijkstra shortest path to perform the allocation of EVCSs based, mainly, on traffic flow information. Shukla et al. (2019) applied the Grey Wolf Optimizer (GWO) in order to minimize the power losses and voltage deviation of the distribution system and to maximize the EV flow served by the EVCSs. Silva and Rueda-Medina (2020) used a hybrid methodology, using Genetic Algorithms (GA) and Interior Points method, to allocate EVCSs and Distributed Energy Resources (DERs), and, consequently, to minimize the operational costs of the network; however, it is only suitable for balanced distribution systems.

Moreover, Martins and Trindade (2015) used GA for the optimal allocation of EVCSs in urban area. The objectives of this paper were to minimize the power losses and to minimize the distance between the stations to the center of the feeder. Esmaeeli et al. (2020) applied GA for the optimal scheduling of charging of EVs considering uncertainties of DER to minimize the power loss and voltage regulation. It is important to mention that the objective functions of both papers are based on the sum of the two functions, in which each one is multiplied by a weight; however, the combined weighted sum transforms the optimization problem into a single objective problem, which is not equivalent to the original multi-objective problem because the extra weighting coefficients could be arbitrary, and the final solutions still depend on these coefficients (Yang, 2014).

In this paper, the optimal allocation of EVCSs was performed for a 15% load addition of EVs in the distribution system. Furthermore, DERs were inserted with the purpose of reducing the voltage deviation caused by the insertion of this new load in the system. Therefore, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) was used to optimally allocate the EVCSs in the distribution system, in addition to performing the DERs sizing and siting. Furthermore, the objective functions of this problem formulation are the voltage deviation and the DERs investment and operation costs. The IEEE 13 and 34 node test feeders were adopted to evaluate the proposed methodology. The main contributions of this paper are:

- The multi-objective programming approach, adopted in this paper to solve the optimization problem, is capable of mutually minimizing the objective functions taking the non-domination concept into account;
- The non-linear DER reactive power capability, presented in the IEEE 1547-2018, was included in the mathematical formulation of the optimization problem;
- Most papers consider the optimal placement of EVCSs only, however, in this work, it was considered the simultaneous optimal planning of EVCSs and DER power units;
- In this work, the allocation and sizing were performed based on the daily irradiance and temperature curves, in addition to the daily curves of the system demand and the EV load.

The remainder of the paper is organized as follows: Section 2 describes the methodology about the mathematical formulation of the optimal EVCSs and DERs allocation. Section 3 presents the multi-optimization method applied: NSGA-II. Section 4 depicts the daily EVCS curve. In Section 5, the results and discussions related to the optimization problem are shown. Finally, concluding remarks are provided in Section 6.

2. FORMULATION FOR THE EVCS AND DER ALLOCATION PROBLEM

This section presents the mathematical formulation for the optimal allocation of EVCSs. It is important to remark that there is no emphasis on their sizing, since a fixed value of added demand was established, which is approximately 15% of the demand of each system used. Additionally, the DERs allocation and sizing were also carried out, since its insertion is important for the reduction of the voltage variation; however, the costs of installing these DERs were analyzed.

EVCSs and DERs placement have influenced the voltage drop in distributions networks; thus, the first objective consists in the minimization of the voltage deviation for each phase and each node of the distribution network, as it can be observed in (1), where V_{ij} is the voltage, in pu, at node i at phase j.

$$OF_1 = \sum_{i=1}^{i_m} \sum_{j=1}^{j_m} |V_{ij} - 1| \tag{1}$$

As mentioned previously, DER integration can increase the overall costs, if it is not properly planned. Therefore, the second objective function, presents in (2), is based on the minimization of these costs. Equation (2) presents three terms, in which the first is the annualized investment cost of the DER, the second term is the substation annual operation cost and the third one is the DER annual operation cost (Ferraz et al., 2020).

$$\begin{aligned} OF_2 = \sum_{t=1}^{t_m} \sum_{i=1}^{i_m} z_g C_t + 365 \sum_{y=1}^{y_m} ec^S P_y^S \\ + \sum_{y=1}^{y_m} \sum_{i=1}^{i_m} ec^{DER} P_{y,g}^{DER} \end{aligned} \tag{2}$$

where C_t is the annualized installation cost of the DER of type t, in US\$; z_g indicates the presence of DER at node i, thus, it is a binary variable. P_y^S and $P_{y,g}^{DER}$ are the active power provided by substation and DER, respectively. The variables ec^{DER} and ec^S are, respectively, the energy cost for the DER and substation, in US\$/kWh. Moreover, the index y represents the time, in hours, for which the substation and DER are providing active power and the index m is the maximum value of each variable.

Constraint (3) is related to the voltage upper and lower limits which, in this paper, must meet the criteria established in IEEE (2018), where V^{min} and V^{max} are the minimum and maximum voltages, respectively; and, constraint (4) is related to the maximum number of DER (n_{DER}^{max}) that can be allocated in the system.

$$V^{min} \leq V_{ij} \leq V^{max} \tag{3}$$

$$n_{DER} \leq n_{DER}^{max} \tag{4}$$

The DERs used in this work are photovoltaic generators, and the power values are given in the function of the solar illumination intensity and the temperature, as observed in Equations (5) and (6), where P_{DER} is the output active power of the DER; T_a and T_c are the surface temperature of the photovoltaic cells and environmental temperature, respectively; k and α are the power temperature coefficient and the wind speed coefficients, respectively. Moreover, G_c is the illumination intensity; and P_{STC}, G_{STC} and T_{STC} are standard test conditions, related to the output power, illumination intensity and temperature, respectively (Wang et al., 2018).

$$P_{DER} = P_{STC}\frac{G_c}{G_{STC}}\left[1 + k(T_c - T_{STC})\right] \tag{5}$$

$$T_c = T_a + \alpha G_c \tag{6}$$

In this work, some constraints based on Standard IEEE 1547-2018 (IEEE, 2018) are considered. This standard specifies the attributes of reactive and active power control requirements of the inverters, which are associated with each DER unit, depending on the category in which this system will operate (Category A or B). Following the study carried out in Ferraz et al. (2020), only DER units with Category B performance were considered in this paper in order to deal with power quality issues that the large amount of dispersed generators integrated could cause in the distributed system.

Figure 1 presents the graphic of reactive power capability of DER with Category B, where the constraints could be observed in (7), (8), (9) and (10) (IEEE, 2018). The minimum steady-state active power capability corresponds to 5% of the rated active power (P_{rated}), the maximum capability of reactive power injection is 44% of the rated apparent power of the inverter based DER (S_{rated}) and the maximum capability of reactive power absorption is 44% of S_{rated} (IEEE, 2018).

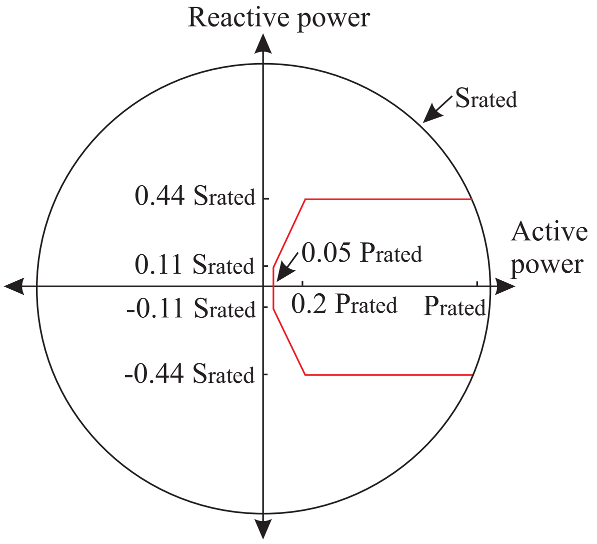

Figure 1. Reactive power capability of the category B based on IEEE 1547-2018.

$$(P_{DER})^2 + (Q_{DER})^2 \leq (S_{rated})^2 \tag{7}$$

$$P_{DER} \geq 0.05 S_{rated} \tag{8}$$

$$-0.44 S_{rated} \leq Q_{DER} \leq 0.44 S_{rated} \tag{9}$$

$$-2.2 P_{DER} \leq Q_{DER} \leq 2.2 P_{DER} \tag{10}$$

Finally, the active and reactive power balance in the distribution system, observed in (11) and (12), respectively, must be guaranteed.

$$\sum_{i=1}^{n}\left(P_i^{load} - Re\left\{V_i i_i^* - Y_i^* \left|V_i\right|\right\}\right) = 0 \tag{11}$$

$$\sum_{i=1}^{n}\left(Q_i^{load} - Imag\left\{V_i i_i^* - Y_i^* \left|V_i\right|\right\}\right) = 0 \tag{12}$$

It is important to note that P_i^{load} and Q_i^{load} are the load active and reactive power values, respectively; i_i is the current injection and Y_i is the shunt admittance. Moreover, these four variables refer to the node i, and Re and $Imag$ correspond to the real and imaginary parts of the complex values, respectively. Finally, the three-phase power flow solution method used was the backward–forward sweep (Cheng and Shirmohammadi, 1995).

3. OPTIMIZATION METHOD

The new scenario of the power system forces a change in duties and objectives of traditional planning and it compels to take into account several objectives that are in mutual conflict (Celli et al., 2005). An important concept in multi-objective optimization is the Pareto front, which is a set of non-dominated solutions; if no objective can be improved worsening at least one other objective.

Many works have used the NSGA-II method to solve multi-objective problems. NSGA-II is an algorithm based on an elitist ordering by dominance. Its objective is to classify the individuals of a set by boundaries, with the best individuals at the first boundary by criteria of dominance of the whole set, which is named Pareto front (Deb et al., 2002). Figure 2 shows the flowchart which summarizes the NSGA-II algorithm, adapted to the problem presented in this paper.

4. EVCS DEMAND CURVE

Celli et al. (2014) obtained the daily load curves of fast charging stations through Monte Carlo simulation. The determination of this curve is based on the selection of some deterministic variables, such as the penetration of EVs in the system and the number of EVs owners that have the domestic slow charge availability. Moreover, it is necessary to select some random variables, for example, the battery capacity of the EV, the characteristics of the driver, the departure hour and the kind of employment and the departure hour of the return trip (Celli et al., 2014). In Figure 3, it is possible to observe the EVCS demand curve, in pu, proposed in Celli et al. (2014) and applied in Martins and Trindade (2015).

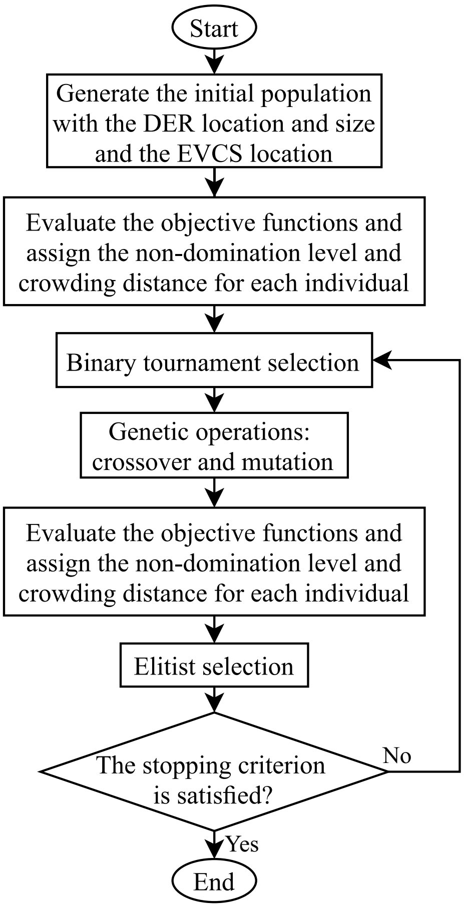

Figure 2. Flowchart of the NSGA-II.

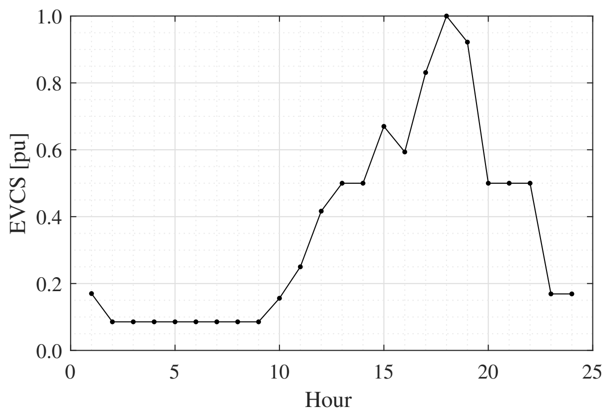

Figure 3. EVCS demand curve.

5. RESULTS AND DISCUSSIONS

In Figures 4 and 5, it is possible to observe the IEEE 13 and 34 node test feeders, respectively, which were used in this work to verify the applicability of the proposed methodology. Some considerations are important to be made in respect to both systems. The voltage regulator between nodes 1-2 of the IEEE 13 node test feeder and the voltage regulators between the nodes 7-8 and 19-20 of the IEEE 34 node test feeder were disregarded with the purpose of analyzing if the DERs integration was able to improve the voltage profile between the limits established in IEEE (2018), which are 0.88 and 1.10 pu for lower and upper limits, respectively.

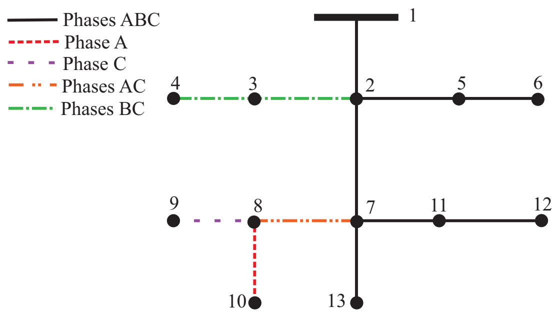

Figure 4. IEEE 13-Node Test Feeder.

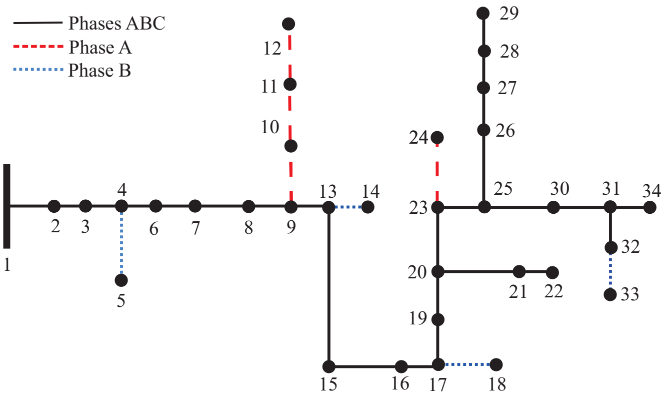

Figure 5. IEEE 34-Node Test Feeder.

The allocation of EVCSs and DERs was performed in three-phase nodes, thus, it is possible to select 7 and 25 nodes of IEEE 13 and 34 node test feeders, respectively. Regarding the EVCS allocation, Martins and Trindade (2015) allocated one EVCS in the IEEE 33 node system. In Silva and Rueda-Medina (2020), 7 EVCSs were allocated in the IEEE 37 node system. Therefore, in this paper, it was selected 2 and 5 EVCSs for the IEEE 13 and 34 node test feeders, respectively. According to Martins and Trindade (2015), the power consumption of each charger in fast charging mode is around 50 kW. As a new demand of 15% on both systems was previously determined, the EVCS in the IEEE 13 node test feeder has a maximum capacity of 500 kW, which would be possible to charge approximately 10 EVs simultaneously. For the IEEE 34 node test feeder, the EVCSs would allow the charging of approximately 6 EVs simultaneously.

With regard to the number of DERs, in Batista et al. (2020), 6 DERs were chosen for allocation in IEEE 13, 34 and 123 node test feeders in order to ensure the greatest diversity of buses choices. In Sahib et al. (2017), tests were carried out on systems with IEEE 37 node test feeder, selecting 9 and 37 DERs. In this paper, the relation chosen between the number of DERs and the number of buses in the system was 40%. Thus, 5 and 15 DERs were determined for IEEE 13 and 34 node test feeders, respectively.

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Furthermore, in Figures 6 and 7, it is possible to observe the illumination intensity profile and temperature profile, respectively, of the city of Campina Grande in Brazil (INMET, 2020). The temperature values are considerably high, which describes the behavior of a location with a tropical climate.

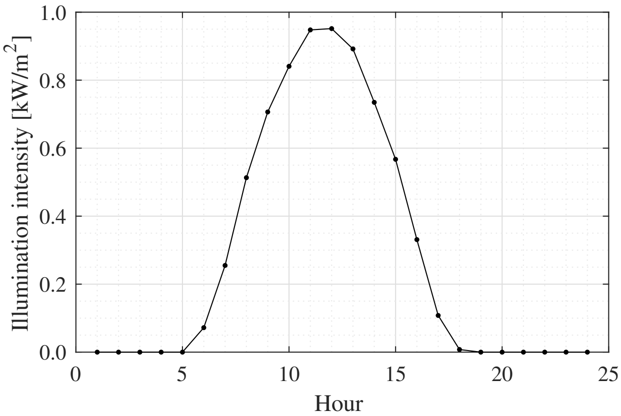

Figure 6. Daily illumination intensity curve.

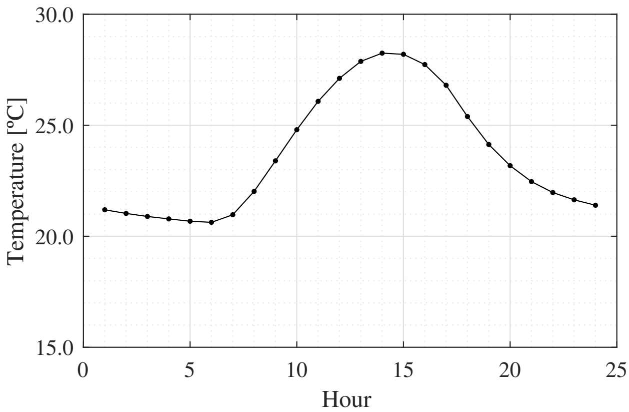

Figure 7. Daily temperature curve.

With respect to obtaining the daily variation of the system loads of IEEE 13 and 34 node test feeders, 13 and 34 demand curves referring to working days were randomly selected, respectively, from a database in the city of Campina Grande, Brazil (ENERGISA, 2020). Each selected daily curve was normalized and, in Figure 8, it is possible to observe the average of the curves obtained for each system, in which the black curve is the load profile of the IEEE 13 node test feeder, whereas the blue one is the load profile of the IEEE 34 node test feeder. Both curves present a typical behavior of a residential installation, where the maximum value occurs at 18 h. In addition, between 10 and 18 h, the demanded load is higher than 80%.

Moreover, some parameters, present in Equation (2), must be defined. It was determined that the energy costs of the substation and the DER are 0.08 and 0.03 US$/kWh, respectively. Furthermore, in this work, two DERs capacities were considered: 50 kW, with 15,000 US$ of annualized investment cost, and 100 kW, with 30,000 US$ of annualized investment cost (Rueda-Medina et al., 2013).

Initially, the NSGA-II algorithm was applied to the IEEE 13 node test feeder. The simulation was performed considering a population of 100 individuals, with a crossover probability of 90%, a mutation probability of 10% and the maximum number of generations used was 200. In Figure 9, it is possible to observe the Pareto front, which presents the voltage deviation and the variation of the cost, in US$. Thus, it was selected the endpoint and some intermediate individuals of this Pareto front to perform a comparison of the objective functions OF_1 and OF_2, as observed in Table 1. The voltage deviation and total cost of the IEEE 13 node test feeder without the allocation of EVCS and DERs are, respectively, 23.637 V and 1.652×10^6 US$.

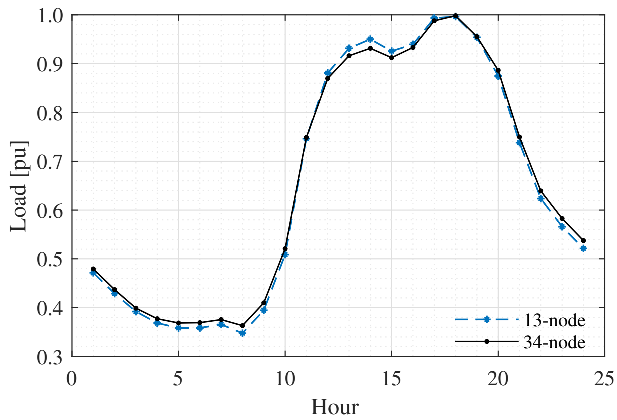

Figure 8. Daily load curves.

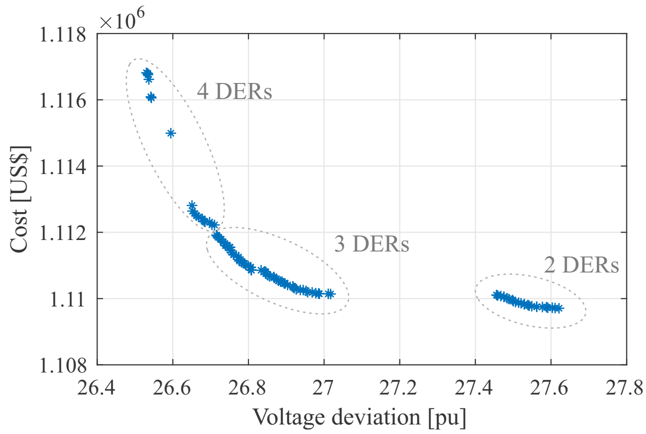

Figure 9. Pareto front for the IEEE 13 node test feeder.

Table 1. Some individuals of the NSGA-II for the IEEE 13 node test feeder.

DER nodes	**EVCS nodes**	OF_1 (V)	OF_2 (10^6 US$)
11, 13	2, 3	27.621	1.109
3, 11, 13	2, 3	26.985	1.110
3, 11, 13	2, 3	26.715	1.111
2, 3, 11, 13	9, 13	26.595	1.115
2, 3, 11, 13	9, 13	26.530	1.117

It can be noted, in Table 1, that the last individual presents the greater amount of DERs selected, with 4 DERs, and, as a consequence, there was a reduction of 3.950% of voltage deviation when compared to the first individual. From Figure 9, it is possible to observe some variations of the

Pareto front curve that can be explained in terms of the number of DERs inserted in the system. In the solutions which present voltage deviation between 26.530 pu and 26.668 pu, 4 DERs were allocated; 3 DERs were allocated in the solutions with voltage deviation between 26.678 pu and 27.017 pu; and, finally, only 2 DERs were allocated in the solutions with voltage deviation between 27.456 pu and 27.621 pu. All individuals, in Table 1, showed a significant cost reduction when compared to the original system (without EVCS and DERs), where the first and last individuals showed a reduction of 32.869% and 32.385%, respectively. Regarding the EVCSs allocation, these devices were allocated to nodes 2 and 3 in some solutions and to nodes 9 and 13 in other solutions, as presented in Table 1. Furthermore, even with the allocation of 4 DER units in the first individual, there was an increase of 11.602% of voltage deviation when compared to the original system (without EVCS and DERs), due to the addition of the new demand, composed of EVCSs.

It can be observed in Table 1 that some results presented the same nodes for the allocation of DERs and EVCSs; nevertheless, the values of the objective functions are different. The reason for this variation is the different values of active and reactive power for each individual. To illustrate these differences, the active and reactive power values for the second and third individuals were presented in Table 2, which directly influence the investment and operation costs and the voltage deviation of the system.

Table 2. Active and reactive power of the DER for the IEEE 13 node test feeder.

	Active Power (kW)		**Reactive Power (kVAr)**	
DER node	**2nd result**	**3rd result**	**2nd result**	**3rd result**
3	94.385	94.309	30.359	29.499
11	99.818	94.024	5.817	34.001
13	49.989	49.756	-10.590	-10.2193

Figure 10 shows the Pareto front for the IEEE 34 node test feeder achieved using the NSGA-II, considering a population of 100 individuals, with a crossover probability of 90%, a mutation probability of 10% and the maximum number of generations used was 250. Thus, some individuals were selected in a similar way to the previous system, as depicted in Table 3. Moreover, it is important to note that the voltage deviation and total cost of the IEEE 34 node test feeder without the allocation of EVCSs and DERs are, respectively, 64.607 V and $7.427{\times}10^5$ US$.

In Table 3, the allocation of 8 DERs resulted in a reduction of 0.231% of voltage deviation when compared to the original system, even with the allocation of 5 EVCSs; however, there is an increase of 25.146% of overall cost of the system. From the Pareto set approximation, shown in Figure 10, it is possible to observe that all 100 individuals are concentrated in 5 regions of the graph. In each of these regions, the individuals present the same amount of DERs with the same locations; therefore, the small variations of the cost and voltage deviation are caused by a low modification of the DERs operating points. The Pareto front, presented in Figure 10, for the IEEE 34 node test feeder was similar to the one depicted in Mendoza et al. (2007), which performed the allocation of automatic voltage regulators and they also did not obtain a curve like the IEEE 13 node test feeder (Figure 9) that presented more variation between the solutions.

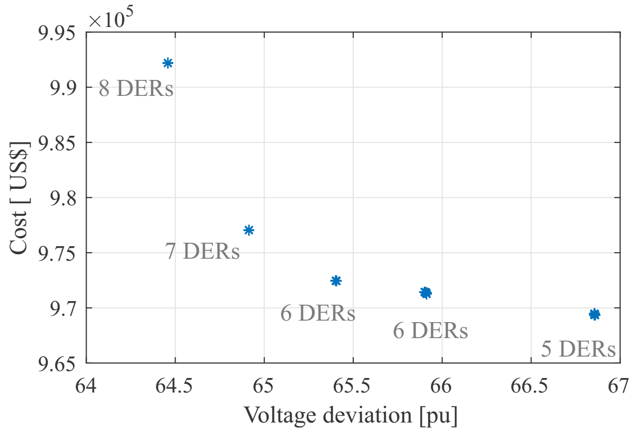

Figure 10. Pareto front for the IEEE 34 node test feeder.

Table 3. Some individuals of the NSGA-II for the IEEE 34 node test feeder.

DER nodes	**EVCS nodes**	OF_1 (V)	OF_2 $(10^5 US\$)$
2, 16, 17, 20, 31	6, 8, 9, 20, 25	66.860	9.693
2, 13, 16, 17, 20, 31	6, 8, 9, 20, 22	65.912	9.712
2, 16, 17, 20, 27, 31	6, 8, 9, 20, 25	65.403	9.725
2, 13. 16, 17, 20, 26, 31	6, 8, 9, 20, 22	64.913	9.770
2, 8, 16, 17, 20, 26, 27 31	6, 8, 9, 22, 25	64.458	9.922

6. CONCLUSIONS

In this paper, it was proposed the EVCSs allocation in order to meet the increasing insertion of EVs in the system. Moreover, the allocation and sizing of DERs were also performed with the purpose of minimizing the impacts caused by the EVCSs in the voltage deviation, considering the total costs of the system in the problem formulation. The method used was the NSGA-II since two objective functions were applied, and the verification of the effectiveness of the methodology was carried out in the IEEE 13 node and 34 node test feeders.

Therefore, it was possible to allocate the EVCSs and DERs in the systems, in which all constraints were met for the 24-hour period, such as the lower and upper voltage limit, maximum number of DER, in addition to the non-linear DER reactive power capability, presented in the IEEE 1547-2018. It was noticeable the importance of inserting DERs in the system in order to reduce the impacts caused by EVCSs. The allocation of 9 DERs resulted in a reduction of 0.231% of voltage deviation when compared to the original system, even with the allocation of 5 EVCSs in the IEEE 34 node test feeder.

For the Pareto front of the IEEE 13 node test feeder, it can be observed that the endpoint individuals presented a variation of 3.950% and 0.716%, regarding costs and

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voltage deviation, respectively. And, with respect to the IEEE 34 node test feeder, the costs and voltage deviation of the endpoint individuals showed a variation of 3.593% and 2.308%, respectively. Moreover, based on the Pareto front, the electrical system operator can determine the best solution to the cost and voltage deviation problem to meet the system planning requirements, since all the solutions are equally valid from the point of view of multi-objective optimization.

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