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Hosting Capacity of Electric Vehicles on LV/MV Distribution Grids—A New Methodology Assessment

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Abstract: The need to evolve cleaner, decentralized, and digitalized energy distribution systems and services includes the electrification of means of transport as Electric Vehicles (EVs) achieve a greater market share. In this context, this work presents and applies, through a case study, the proposal of a new methodology for calculating the hosting capacity of EVs in low- and medium-voltage distribution systems. The proposal of a new methodology that combines deterministic and stochastic methods, while considering several operational criteria, as well as being applicable in both low and medium voltage, shows itself as a more germane and innovate approach. The results obtained demonstrated that the hosting capacity of EVs for the transformers pertinent to the distribution system under study is 100% for more than 50% of the simulations performed. The conductor overload criterion is the main limiting factor, representing 36.69% of violations for the 3.6 kW charger and 52.14% for the 7 kW charger. According to the executed evaluated projections, the distribution system under investigation will posses the capacity to host the growth of EVs in any of the scenarios presented in this study until 2025 for the 3.6 kW charger.

Keywords: electric vehicle; power quality; hosting capacity; distribution grid

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1. Introduction

Electric vehicle technology has already become a significant reality when it comes to the subject of reducing the emission of greenhouse gases (e.g., CO_2, NH_4, and N_2O), as these do not emit pollutants while in operation. If one also takes into consideration that Brazil has a large percentage of its energy matrix based on clean sources, the arrival of EVs will bring about a substantial environmental benefit. However, the impact produced by the electrification of the means of transport in the distribution system must be evaluated carefully. In view of the figures presented by DENATRAN [1], Brazil has more than 107 million vehicles, of which only 54,340 are electric, a category that encompasses hybrid, plug-in, and purely electric vehicles. Whilst keeping these changes in mind, the distribution system must manifestly adapt to these new loads, taking into account the variety of chargers available on the market, which are classified under the denominations of slow, semi-fast, fast AC, and fast DC chargers. Recharging EVs can produce several effects on the distribution grid; these can be highlighted as voltage drop, an increase in the level of unbalance (single-phase or two-phase chargers), the overload of grid components (cables and transformers), along with an increase in electrical losses, an increase in harmonic distortion, and aggravation of voltage and current transients during short-circuit events, among others [2].

The computational tools used to model the interactions between the electrical system, consumers, and generators have increased in importance over recent years due to the entry of Distributed Energy Resources (DERs) and the increased electrification of the means of transport. The complexity in which the new electrical system is inserted requires new tools to assess the impacts brought about by these technologies; in addition, dimensioning the Hosting Capacity (HC) of the electrical system takes on greater importance for energy concessionaires. In this scenario, several methodologies are being developed using tools aimed at programming languages, among which Python stands out, which is an object-oriented language of free use [3].

In the literature, it appears that EV charging is evaluated through a significant number of load flow studies, which vary in their assumptions, analysis methods, and performance criteria of the distribution grid. Deterministic, stochastic, or time series methodologies are used to determine the hosting capacity of electric vehicles on the distribution grid.

Deterministic simulations produce a single value for the hosting capacity of EVs, but these do not reflect the uncertainties inherent in the process, thus making adjustments necessary to obtain the real behavior of the systems used. In this case, a stochastic approach is more appropriate, yielding a distribution of EV hosting capacity.

The methodologies to evaluate the hosting capacity used have some research gaps, and these methodologies take into account random charging scenarios of EVs' entry percentages at peak load times, while using only one type of charger. This capacity is evaluated through grid performance criteria and electrical energy quality requirements such as transformer overload, conductor overload, undervoltage, voltage unbalance, and harmonic distortion. However, these criteria are used individually; alternatively, a small number of combinations are considered to restrict the hosting capacity value. The simulations are used in real distribution systems or test systems, such as the IEEE 33 buses, which can be of low or medium voltage; however, they are not evaluated together.

Given this review, the proposal of a new methodology that combines deterministic and stochastic methods, which considers several operational criteria and which can be applied at low and medium voltage at the same time, becomes more appropriate and innovative, filling the research gaps.

Therefore, this paper proposes a new methodology using free software (OpenDSS and Python), to calculate the hosting capacity of electric vehicles on distribution grids. OpenDSS is the software of choice for simulating the power flow and harmonics; the software is controlled through the COM interface via the Python programming language. The criteria used to evaluate the hosting capacity individually and jointly involve the following requirements: (I) voltage compliance, (II) thermal limits of distribution lines and cables, (III) overload in transformers, (IV) voltage unbalance, and (V) the total harmonic distortion of voltage.

The proposed methodology was tested and validated using, as a case study, part of the low- and medium-voltage distribution system of the Distribution System Operator (DSO), DME Distribuição S.A., in the Brazilian city of Poços de Caldas/MG.

2. Hosting Capacity—State-of-the-Art

Over the last decade, an increasing number of technical publications have been produced on the hosting capacity of Distributed Generation (DG) and electric vehicles on electric grids [4–14]. Contents range from theoretical analyses (e.g., simulations) to experimental results (laboratory tests and field experiments).

By definition [15], "Hosting Capacity is the amount of new production or consumption that can be connected to the grid without compromising the reliability or quality of electric power of other customers". The aspects considered in the HC studies are distribution transformer overload, feeder overload, voltage magnitude deviations, current and voltage unbalances, and harmonic distortion [16].

Several methodologies are used to determine the hosting capacity [17–25]. According to [26], deterministic simulations use known and predefined input data to produce a single hosting capacity result; these simulations are used in traditional distribution system planning practices, in which the type of charger and the charging location are established. Deterministic assessments generally consider fixed periods for slow charging: overnight charging is performed at home, so an EV is added to a maximum charging condition; during the day, loading is carried out at work; in this case, a minimum load condition is considered [27]. This methodology has the disadvantage of not employing uncertainty concerning the location where the EV will be charged. The uncertainties surrounding EV charging vary depending on the type of vehicle, charger technology (manufacturer), power, charging location on the distribution grid, and other technical characteristics, which are often unknown.

As indicated by [28], these limitations, associated with the deterministic method, can be overcome by the use of stochastic methods. For [4], the modeling of the random variables of interest can be represented by the uniform distribution, Poisson, Gauss, binomial, among others. Thus, after performing the simulations, the hosting capacity will also be characterized by a probability density.

For [29], the stochastic methodology is the procedure that best models the uncertainties of the distribution grid. However, it requires more time and computational effort when the model or quantity of uncertainties are considered. One of the benefits of the stochastic model is that numerous possible EV recharging situations are evaluated, whereas in the deterministic case, only a single situation is simulated.

Stochastic evaluations are preferred and often performed in Monte Carlo simulations [30–33]. In these studies, representative daily load profiles and EV energy consumption are evaluated based on statistical data on driver behavior; these are randomly selected and added to the load profiles, while considering different EV penetrations on the distribution grid.

The most-relevant uncertainties are random, such as customer consumption and the EV loading profile; the relationship between the variables is, however, lost over time, which constitutes the fundamental obstacle of stochastic methods. In addition, the impacts of chargers on the control elements of the system, at reduced time scales, are normally excluded from the stochastic method, thus requiring their inclusion through field measurements, which make the DSO closer to its real state. Such measurements are defined by [34], as time series.

According to [35], the use of time series in the evaluation of the hosting capacity produces more accurate results, as these use real measurements from the system. The time series method is highly dependent on data and reveals more information about the effects of EV dynamics on the distribution system. For [4], the implementation of the method was complex because the sampling rate of these data can directly influence the accuracy of the determination of the hosting capacity. Although this type of methodology tends to inspire more confidence in the accuracy of its results, the large amount of data requires a high computational time.

Table 1 presents the list of papers that use Deterministic (D), Stochastic (S), and Time Series (TS) methods. The performance criteria included in the table are Undervoltage (UV), Conductor Thermal limit (CT), Transformer Overload (TO), Total Harmonic Distortion (THD), and Voltage Unbalance (VU).

From Table 1, one can not that the methodology proposed in this work does not only include time series.

Table 1. List of papers, methods, and performance criteria for evaluating the hosting capacity of EVs.

Papers	Methods			Performance Criteria				
	D	S	TS	UV	CT	TO	THD	VU
[26]		x		x				
[17]	x			x	x	x		
[19]		x	x			x		
[5]		x	x	x				
[27]		x		x				
[20]		x						x
[25]			x	x	x			
[32]		x	x	x	x		x	x
[23]		x		x	x			
New Methodology	**x**	**x**		**x**	**x**	**x**	**x**	**x**

3. New Methodology for Assessing VE Hosting Capacity

As already mentioned, this work proposes a new methodology for analyzing the hosting capacity of EVs on low- and medium-voltage distribution grids, based on the real characteristics of the system and on the combination of deterministic and stochastic methods for evaluating the hosting capacity. The methodology is separated into two stages, low and medium voltage, which can be simulated either together or separately. Through use of the methodology, it is possible to initially determine the hosting capacity of the EVs for different types of chargers downstream of the transformer, that is at low voltage. Following this, based on these results, we carried out the verification of the impact upstream of the transformer, namely on the medium-voltage feeder.

In Figure 1, the flowchart of the proposed methodology is demonstrated to evaluate the hosting capacity of EVs on distribution grids.

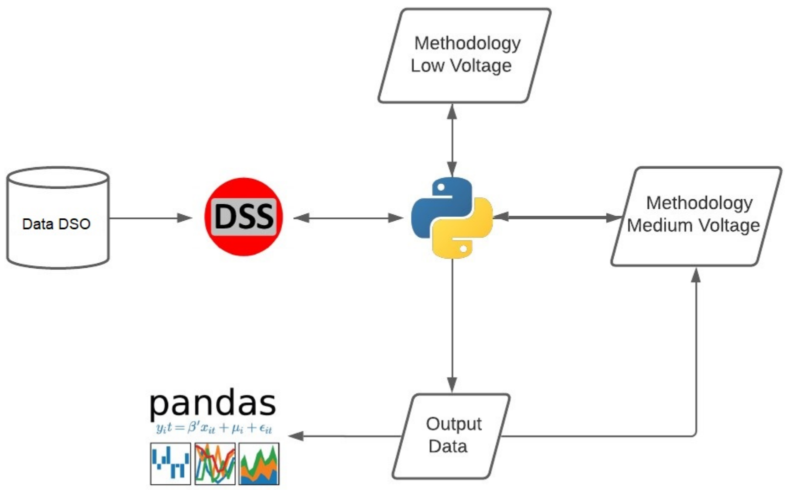

Figure 1. Flowchart of the proposed methodology.

OpenDSS is used to perform electrical system simulations for the obtainment of input data to evaluate the five performance criteria cited for evaluating the HC of the simulated grid. OpenDSS is a free software and is used by the National Electric Energy Agency to calculate losses in the distribution system in Brazil. Therefore, all the information of the DSO is in the DSS standard and can be accessed by the Geographical Database of the Distribution System Operator (in Portuguese, *Base de Dados Geográfica da Distribuidora* (BDGD)) [36]. OpenDSS is controlled by Python via Interface COM via the *py-dss-interface* package. The Python language was used in this work, as it allows for interaction with several visualization and data processing libraries and is an open language. Python is responsible for processing data generated from OpenDSS simulations, as well as managing the proposed methodology.

3.1. Methodology for Low Voltage

In the methodology for low voltage, deterministic and stochastic methodologies were used together in order to evaluate the capacity of hosting EVs by the secondary distribution grid.

The five performance criteria were composed using the deterministic method, with the user specifying the desired value. The deterministic methodology was used to select both the three-phase consumer units that receive the EV such as the fixed period for carrying out the slow recharge, normally over night, at the discretion of the user. Therefore, the load associated with the EV charger was added to a maximum load condition of the Customer User (CU), which corresponds to the worst-case scenario from a charging point of view. The period considered was that between 19:00 and 20:00, consistent with the peak hours of the distribution system; however, the user can select any other period.

When modeling LV distribution grids, the locations of the CU connections are known; however, it is unknown which customers will have EVs. EV location is a common source of uncertainty, and its loading can significantly affect the simulation results. Consequently, the stochastic methodology was used to select the CUs that will receive the EV, while producing a random draw, using a uniform distribution, without repetition, for the gradual allocation of the EVs. The maximum number of EVs that transformers can host was determined according to the following grid performance criteria:

- Undervoltage (UV);
- Conductor Thermal limit (CT);
- Transformer Overload (TO);
- Total Harmonic Distortion of Voltage (THDV);
- Voltage Unbalance (VU).

These criteria were selected according to the proposition of Prodist [37] and according to the BDGD (The BDGD contains various information concerning the DSO, from which the parameters for the simulation in OpenDSS were extracted. Among these parameters is the grouping of types of conductors existing in the distribution system, "SEGCON", which contains information on the gauge, insulation, resistance, nominal current, etc.), in accordance with Table 2.

Table 2. Evaluation criteria used.

Criteria	Values
Transformer Overload	$\leq$50%
Undervoltage	$\geq$0.93 pu
Voltage Unbalance	$\leq$3%
Total Harmonic Distortion	$\leq$10%
Conductor Thermal Limit	According to each section *

* The thermal limits of conductors are extracted from the BDGD from the maximum current.

According to the flowchart in Figure 2, the methodology applied to the low-voltage grid was divided into three stages.

In Step 1, the interaction between Python and the data entered by the user takes place, such as the type of charger, undervoltage limit, overload allowed in the transformer, power of the transformer, and the number of simulated scenarios. Next, Python commands the simulation of the power flow through the OpenDSS software for the low-voltage grid and obtains all the initial input data, such as active and reactive power, the number of buses (nodes), along with the maximum and minimum voltage, etc.

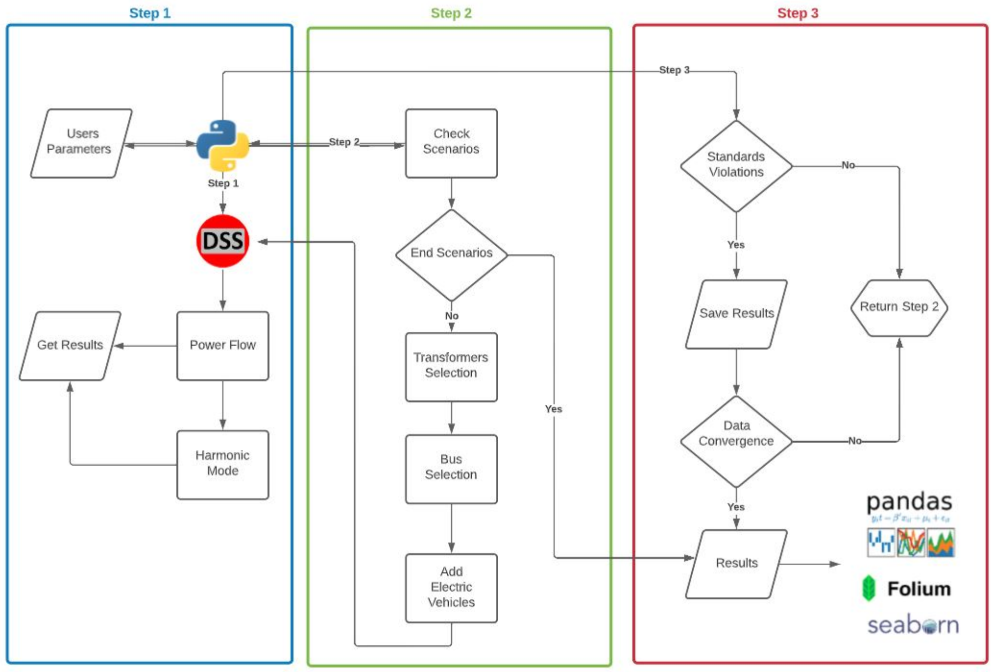

Figure 2. Low-voltage methodology flowchart.

In Step 2, with the initial data stored, a random draw is carried out among the transformers with the power previously selected by the user, and all possible scenarios are created, while performing the enumeration of states, which is combined with the data entered by the user. Subsequently, the selection of the three-phase CUs, which are able to receive the EV, begins. It was assumed in this work that these three-phase consumers would be in better financial conditions to acquire an EV.

In the low-voltage grid, the node and the connection phase of the VE have the same probability, allowing the LV allocation to be modeled as random. To define a two-phase EV allocation scenario in a node, on the three-phase grid, a customer connection point was selected by random sampling within a list of CUs. Therefore, the allocation of EVs in the CUs was carried out; however, for each CU drawn, the list was left without a replacement, and a new draw was carried out from among the remainder, while the distribution of the chargers was performed in a balanced way between the phases.

In Step 3, in each simulation of power flow at 60 Hz and its harmonic, the violation of the performance criteria already mentioned in low voltage is verified. Thus, the hosting capacity downstream of the transformer is defined until there is a violation of any of the five established criteria.

As the simulations generated a significant number of results, instead of saving all the variables for each repetition, only the final results were saved and recorded, highlighting as such the number of allocated vehicles, apparent power, reactive power, losses, voltage magnitudes, THD, and the bars (nodes) where the violations occurred. These data were stored and can be plotted and visualized together or individually through the Pandas in Python. Geo-referenced EVs and transformer location data (latitude and longitude) were plotted on the map and correlated with simulation data through the library Folium (Folium is a library for Python that facilitates the visualization of data that have been manipulated in an interactive map).

As the hosting capacity is directly related to the characteristics of each electrical system in which the EV will be installed, Python performs a new draw from among the selected

CUs and simulates the grid again until it reaches the number of scenarios established by the user. Accordingly, the number of EVs admitted to the grid is determined by calculating the mode of the set of simulations performed.

3.2. Methodology for Medium Voltage

The medium-voltage methodology aims at investigating the impact on the medium-voltage grid by loading the secondary transformer with the insertion of the EVs, which differs from all the methodologies presented in Item II. The proposed methodology uses the allocation of EVs on the secondary of the MV/LV transformers, from which the data were extracted from the results of the low-voltage methodology for evaluating the medium-voltage grid. The flowchart in Figure 3 presents the steps for simulating this methodology.

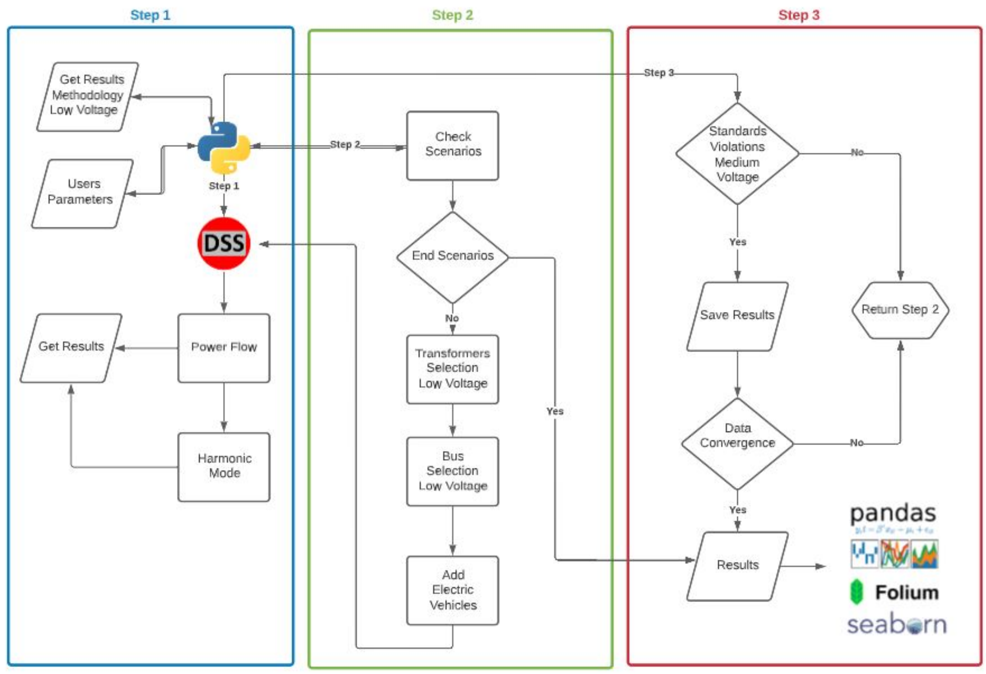

Figure 3. Medium-voltage methodology flowchart.

In Step 1, Python reads the results obtained through the low-voltage methodology and stores these in a virtual database to be used during simulations. Then, the user input data are fixed, and a new parameter is added, i.e., the percentage of EVs loading on the secondary transformer. This parameter has the objective of verifying the variation in the number of EVs admitted through the secondary loading of the transformers in the medium-voltage grid. Therefore, the observation points of the performance criteria are inserted through monitors in the medium-voltage buses, thus ignoring the influence of the medium grid on the low-voltage grid, and the simulation of the power flow is performed through the OpenDSS software, which obtains the initial data of the medium-voltage grid.

In Step 2, the scenarios are formed, and the selection of the transformers is carried out through a random drawing, using a uniform distribution, without replacement. For each transformer selected, the number of EVs admitted is retrieved from the database, and the buses where the EVs were inserted in the low-voltage methodology are stored in a list. As the number of vehicles and the list of bars follows a statistical distribution, the scenario chosen to constitute the simulation is given by calculating the mode of these variables, as long as there is no violation of any of the five performance criteria used.

In Step 3, the medium-voltage grid is analyzed following the same procedure as for the low-voltage methodology. The transformers are allocated one by one, randomly, with their respective EVs, until there is a violation of any of the five performance criteria in the medium-voltage grid; in this way, the maximum hosting capacity is obtained.

In order to verify and compare the results obtained in the medium-voltage grid, the transformers are loaded with a percentage of vehicles defined by the user in the chosen scenario. In this way, the number of repetitions of the simulations is given by the combination of the number of scenarios and percentages chosen.

Finally, through the Pandas and Seaborn library, the obtained results were saved to a spreadsheet and plotted with an issuance of per-transformer hosting capacity report containing the main information.

4. Case Study

4.1. Feeder Data

For the case study, Feeder 16 was selected, which corresponds to the second-largest in number of CUs and represents 11% of the municipality of Poços de Caldas/MG. The feeder has a primary and secondary grid of approximately 39 and 58 km, respectively, with 9132 CUs. This feeder was chosen as it has a high purchasing power consumer class, with greater potential for buying EVs. In Figure 4, the main characteristics of the feeder are presented.

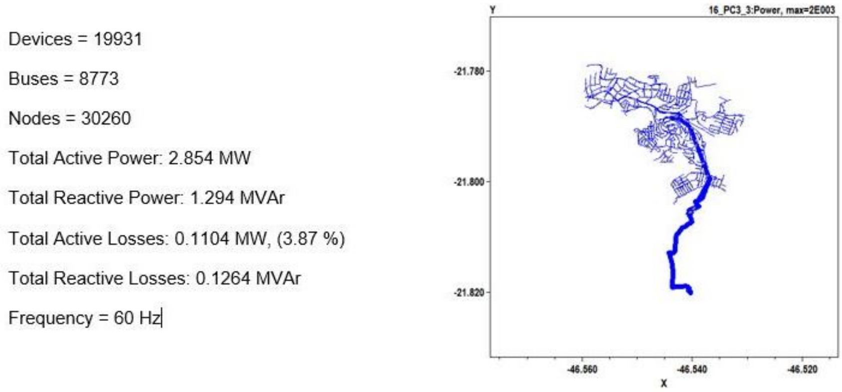

Figure 4. Feeder 16.

In the feeder, transformers with a capacity of 30, 45, and 75 kVA were selected, on which the powers represent 21%, 49%, and 30%, respectively, of all transformers in the feeder, as shown in Table 3.

Table 3. List of transformers for Feeder 16.

kVA	Quantity	Average CU	% Total
15	1	33	0.5%
25	1	39	0.5%
30	42	27	21.3%
45	96	39	48.7%
75	59	47	29.9%
112.5	8	53	4.1%
150	5	54	2.5%

4.2. Electric Vehicle

In the simulations, the two-phase residential charger model, 3.6 kW, and 7 kW, with a Type 2 connector, consistent with the JAC Motors vehicle, Model iEV40, was used.

Although public charging infrastructure is currently being installed in Poços de Caldas, most EV charging is expected to take place within residential environments. Vehicles are typically outside during the day, so the night window provides the best charging opportunity for the CU. Through this, using a deterministic approach, LV charging is defined between 19 and 20 h. The charging strategy that is expected from the EV owner is that, upon arriving home, he/she starts charging until reaching the rated capacity of the battery, so the period chosen for recharging coincides with the maximum charge period of the distribution system, which equates to the worst-case loading scenario.

In this study, the VE is defined as a constant load model and represented as a source of current harmonics. For harmonic analysis, the OpenDSS software uses the current injection method, and the EV load is modeled as a Norton equivalent circuit, in which the current source represents the harmonic currents injected by the non-linear portion of the load. Table 4 establishes the harmonics injected into the grid by the charger under consideration.

Table 4. Charger current harmonics [13].

Harmonic	Magnitude (%)	Angle (°)
1	100.00	−26.00
3	25.00	−94.00
5	17.00	−96.00
7	14.20	−72.00
9	9.69	−68.00
11	5.04	−49.00
13	1.80	−49.00
15	0.37	−46.00

5. Results and Discussions

5.1. Hosting Capacity—Low-Voltage Grid

The proposed methodology was applied in the evaluation of the HC of 197 transformers of Feeder 16 with the use of 3.6 and 7 kW chargers. These transformers, which range in power from 30, 45, to 75 kVA, account for 100% of the evaluation.

In order for the information on the number of admitted EVs to be seen clearer, the results are presented in a group fashion according to the power of the transformers. Thus, Figure 5 depicts the location of 25% of the 45 kVA transformers; these transformers cover all feeder supply areas, allowing the EV charging load to be evaluated more evenly. Through the Seaborn and Pandas libraries, the results obtained for each transformer were compiled and plotted onto graphs for an enhanced visualization.

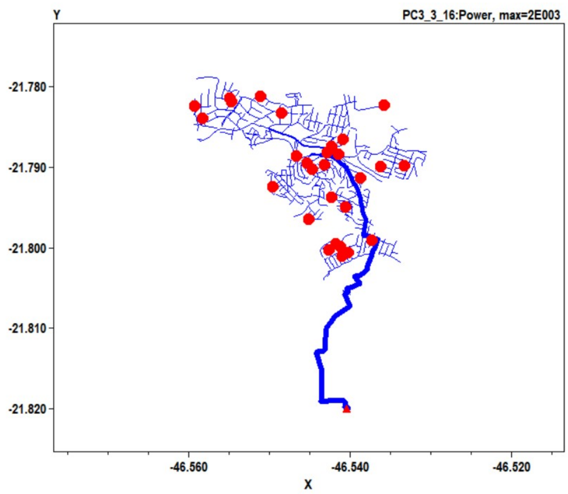

Figure 5. Location of 25% of the 45kVA transformers.

In Figure 6, one is able to identify through the graphs the number of EVs (nEV) admitted to the secondary of each transformer, its variability, as well as the minimum and maximum value represented by the black band in the columns. Transformers that have equal values for both chargers reached the maximum number of CUs that could receive EVs without any criteria being violated, examples of this being the transformers it1_5129, it1_6732, and it1_5558. Since both chargers could be inserted, the additional load from the EVs did not affect how the transformer or secondary network operated.

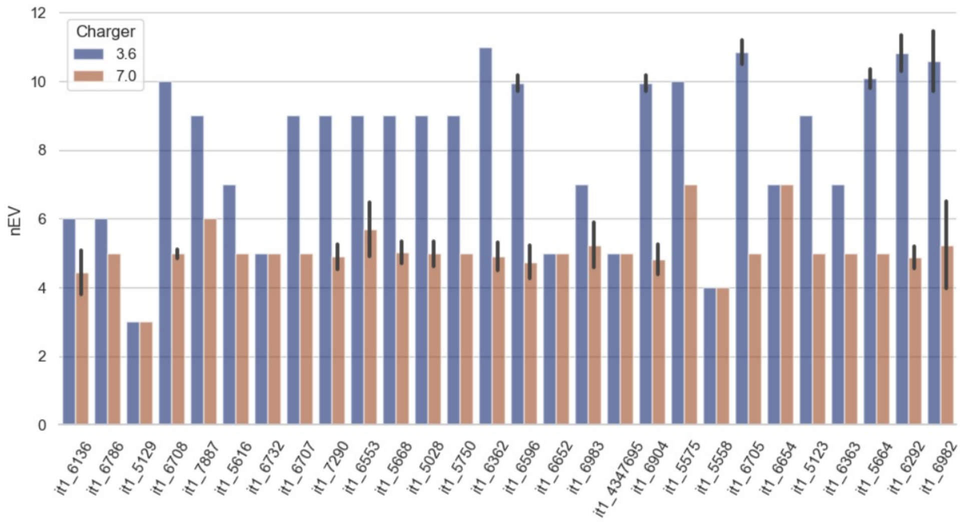

Figure 6. Hosting capacity for 25% of the 45kVA transformers.

The HC for the transformers presented varied from 3 to 11 EVs using the 3.6 kW charger, while for the 7 kW charger, there was a variation between 3 and 7 EVs. The increase in charger power caused the number of EVs to be smaller, as it increased the possibility of violating the criteria of conductor overload, undervoltage, and transformer overload.

Figure 7 shows the location of 25% of the 75 kVA transformers, or 15 out of a total of 59 units, as well as the representation of the 45 kVA transformers for the ease of visualization.

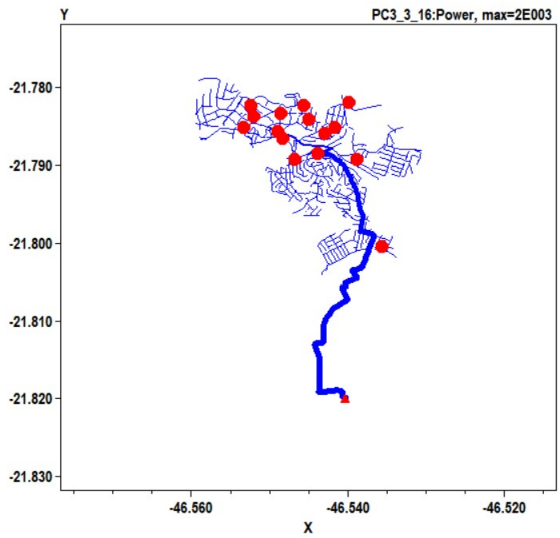

Figure 7. Location of 25% of the 75 kVA transformers.

In Figure 8, the HC for the transformers presented above is shown. For the 3.6 kW charger, there is a range from 3 to 19 EVs, and for the 7 kW charger, the HC of EVs is between 3 and 11 EVs. The introduction of EVs had a greater impact on the 45 kVA transformers than on the 75 kVA transformers. When compared to the 3.6 kW charger, charging the EV with the 7 kW charger resulted in more violations in the evaluated criteria.

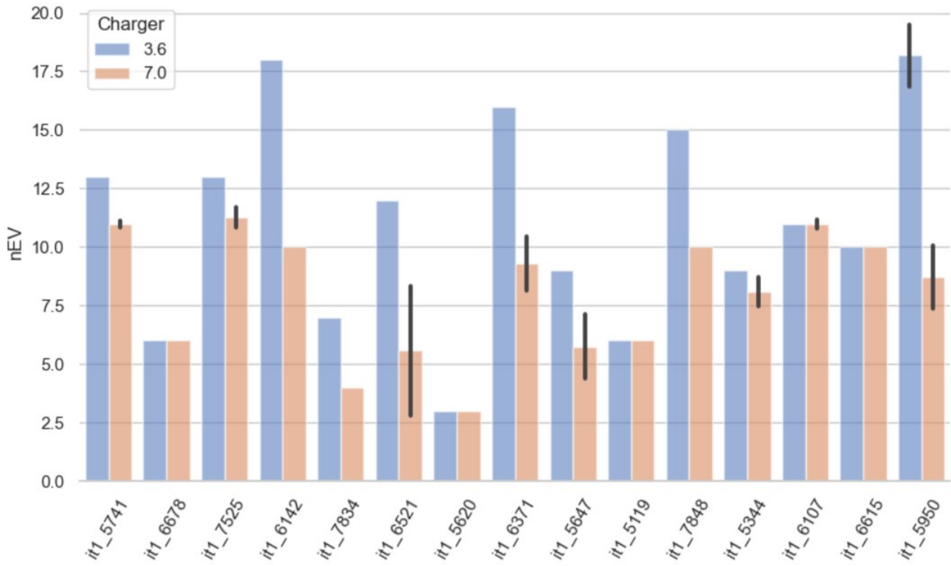

Figure 8. Hosting capacity for 25% of the 75 kVA transformers.

The transformers it1_6678, it1_5620, and it1_5119 have a limited number of three-phase CUs that can receive VE. As a result, without violating any of the evaluated criteria, these transformers can accommodate 3.6 and 7 kW chargers in their secondary network.

Table 5 summarizes, in percentage values, the violations that occurred during the simulations for the transformers of Feeder 16. The purpose of the table is to determine what the restrictive factors for the widespread implementation of EVs are, along with subsidizing the DSO for mitigating action.

According to the methodology used, there was no violation of voltage imbalance at any time, as the methodology equally distributes the chargers between the phases. The table shows the increase in transformer overload violations and conductor overload; the values go from 1.88% to 7.54%, due to the use of a charger with a higher power of 7 kW.

For the 3.6 kW charger, the conductor overload criterion (CT) represents 36.69% of the violations that occurred. In this case study, 50.96% of the simulations did not violate any of the performance criteria evaluated. By lowering the charging power, the number of EVs is more evenly distributed along the feeder, covering more transformers without concentrating the current in the conductors at a single point. The conclusion was thus reached that the secondary circuits of these transformers were, for the most part, able to host the quantity of EVs using this type of charger.

The insertion of the 7 kW charger shows that the overload of the conductors (CT) is a limiting factor for the grid and represents 52.14% of the violations that occurred. Then, with 12.18%, the Transformer Overload (TO) can be verified, which becomes the second restrictive factor for connecting the charger with the highest level of power. In this evaluation scenario, 18.40% of the simulations did not violate any of the performance criteria used. In this case, the EV charging power increased proportionally to the current in the conductors, causing this criterion to be violated and, as a result, increasing the overload on the transformers.

Table 5. Summary of violations in Feeder 16.

UV	CT	TO	VU	THDV1	THDV2	THDV3	3.6 kW (%)	7 kW (%)
FALSE	**FALSE**	**FALSE**	**FALSE**	**FALSE**	**FALSE**	**FALSE**	50.968	18.400
					TRUE	**FALSE**	0.102	0.000
						TRUE	0.051	0.000
				TRUE	**FALSE**	**FALSE**	0.102	0.204
						TRUE	0.000	0.102
					TRUE	**FALSE**	0.000	0.510
						TRUE	0.000	0.561
		TRUE	**FALSE**	**FALSE**	**FALSE**	**FALSE**	9.735	12.181
					TRUE	**FALSE**	0.000	0.153
						TRUE	0.000	0.051
				TRUE	**FALSE**	**FALSE**	0.000	0.866
					TRUE	**FALSE**	0.000	1.121
						TRUE	0.000	1.070
	TRUE	**FALSE**	**FALSE**	**FALSE**	**FALSE**	**FALSE**	36.697	52.141
				TRUE	**FALSE**	**FALSE**	0.000	0.153
					TRUE	**FALSE**	0.000	0.255
						TRUE	0.000	0.051
		TRUE	**FALSE**	**FALSE**	**FALSE**	**FALSE**	1.886	7.543
				TRUE	**FALSE**	**FALSE**	0.000	1.427
						TRUE	0.000	0.051
					TRUE	**FALSE**	0.000	0.051
						TRUE	0.000	0.051
TRUE	**FALSE**	**FALSE**	**FALSE**	**FALSE**	**FALSE**	**FALSE**	0.459	1.631
					TRUE	**TRUE**	0.000	0.102
				TRUE	**FALSE**	**FALSE**	0.000	0.102
						TRUE	0.000	0.051
					TRUE	**FALSE**	0.000	0.765
						TRUE	0.000	0.408

Because the methodology assumes that EV charging always occurs at the highest load time of the distribution system, the criteria of conductor overload and transformer overload were the ones most violated in the two charger powers.

Through the Folium library, the latitude and longitude data are used to map the critical locations for the insertion of EVs through heat maps and clusters. In Figure 9, one notes the areas with the most-suitable characteristics to allocate the EVs in Feeder 16. The heat map shows how the HC varies along the secondary grid using an appropriate color code concerning the load percentage of each grid segment. The strongest colors (yellow, orange, and red) represent the places where EVs were allocated in greater quantity and did not violate the established performance criteria; therefore, they represent more favorable places for the insertion of EV charging equipment. In contrast, the cooler colors (purple, blue, and green) represent locations that violated the performance criteria.

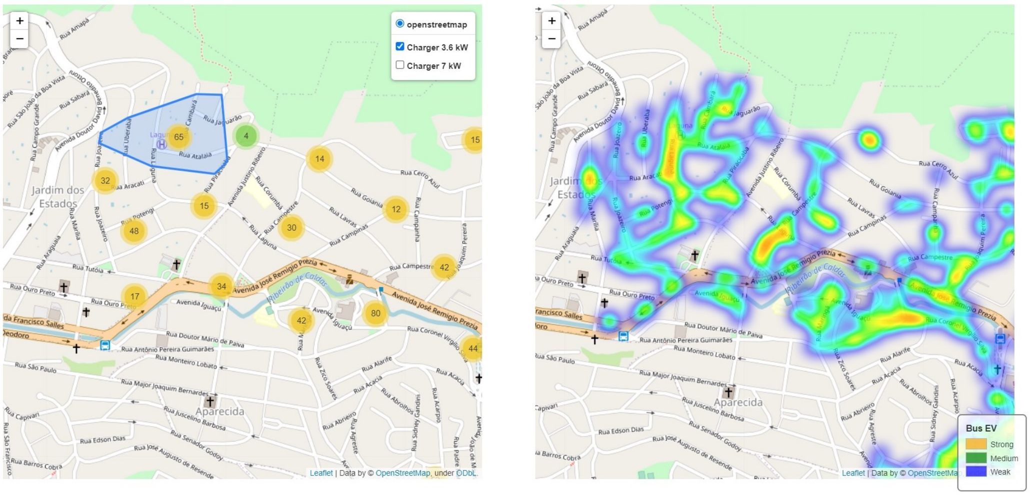

Figure 9. HC map—Feeder 16.

5.2. Hosting Capacity—Medium-Voltage Grid

With the data generated by the methodology at hand for low voltage, an evaluation of the hosting capacity of medium-voltage feeders was executed considering the same established performance criteria. For this study, transformers were loaded with 10%, 50%, and 100% of the number of vehicles admitted to their secondary in relation to the mode. According to Figure 10, the medium-voltage grid associated with Feeder 16 has limited hosting capacity when considering the percentage of 100% for the loading of the number of EVs on the secondary transformer. The number of EVs allocated when considering this charging scenario is 380 EVs for the 3.6 kW charger and 159 EVs for the 7 kW charger. On the other hand, when using a load of 50% the number of EVs, the result represents a considerable increase in the number of EVs that the medium-voltage grid can support. With this percentage, a greater number of transformers can be served until there is a violation of some criterion.

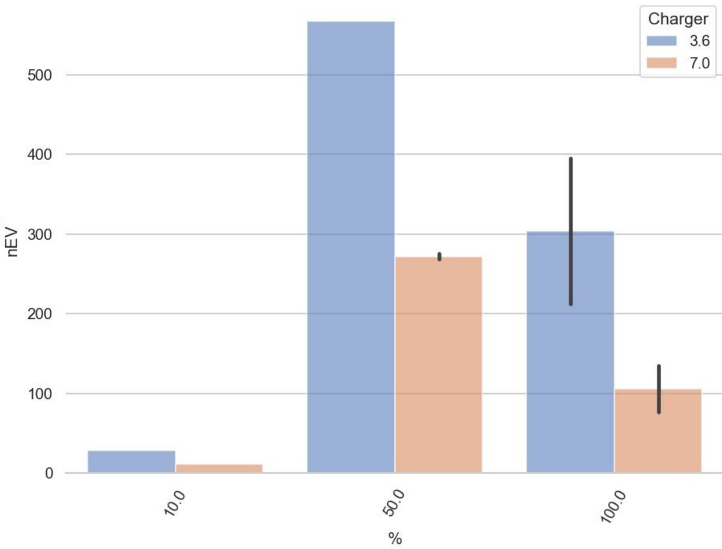

Figure 10. Medium voltage HC—Feeder 16.

The results showed that the medium-voltage network suffered the most with 100% EV loading in the transformers. In other words, it is preferable to distribute EV values throughout the network, in this case 50%, rather than using the transformer's total hosting capacity, to increase the values of EVs in the network.

In Figure 11, one obtains a detailed view of the number of EVs that were admitted by the number of transformers that were included in the simulations. Note here that, when considering a loading of 50% on the secondary transformers with a 3.6 kW charger, the hosting capacity reached a maximum value of 567 EVs for 197 transformers. When considering the 7 kW charger, this number was 277 EVs for 172 transformers. These numbers represent an additional power of 2 MW in the medium-voltage network, or more than 40% of the feeder's initial power. The number of transformers demonstrates that, in general, using the 3.6 kW charger had less of an impact on the network, increasing hosting capacity by 100%.

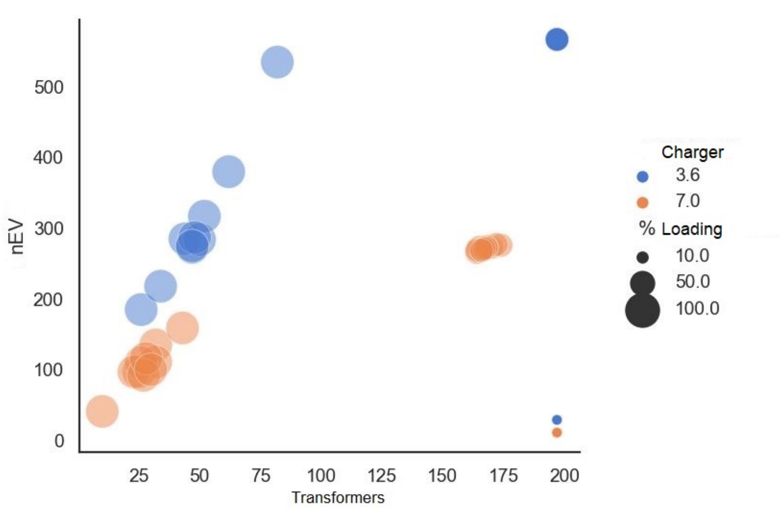

Figure 11. Detailed medium-voltage HC—Feeder 16.

5.3. Time Process

To show the benefits of using a high-level programming language (Python) together with the power flow simulation software (OpenDSS), in the proposed methodology, the times of all power flow and harmonic simulations were compiled, using Feeder 16 with the fully modeled medium-voltage system as an example. Figure 12 shows the processing times for transformers with powers of 30, 45, and 75 kVA at low voltage.

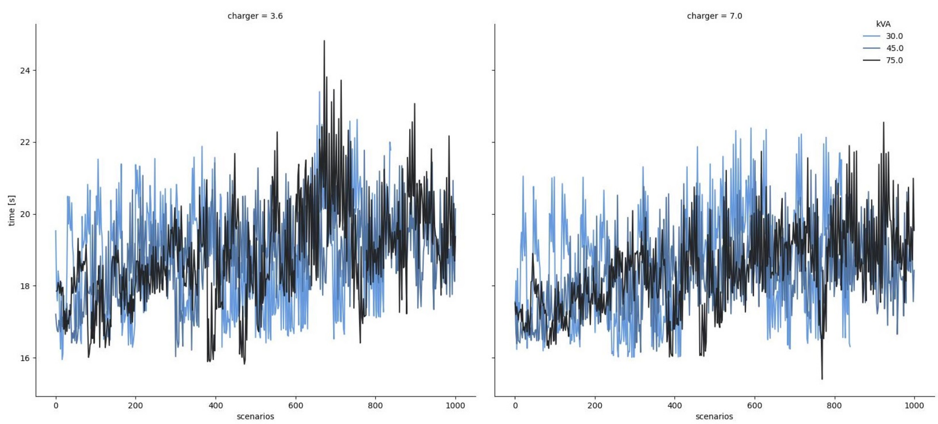

Figure 12. Computational time results for low voltage—Feeder 16.

Processing time may vary depending on the number of EVs each transformer can support and the type of charger used. In Figure 13, note that the simulation time increases proportionally with the number of EVs that were inserted on the transformer for the 3.6 and

7 kW charger. The 75 kVA transformer has a greater number of CUs that can receive the EV according to the selection criterion used; thus, the processing time was longer according to the increase in EVs inserted on the grid.

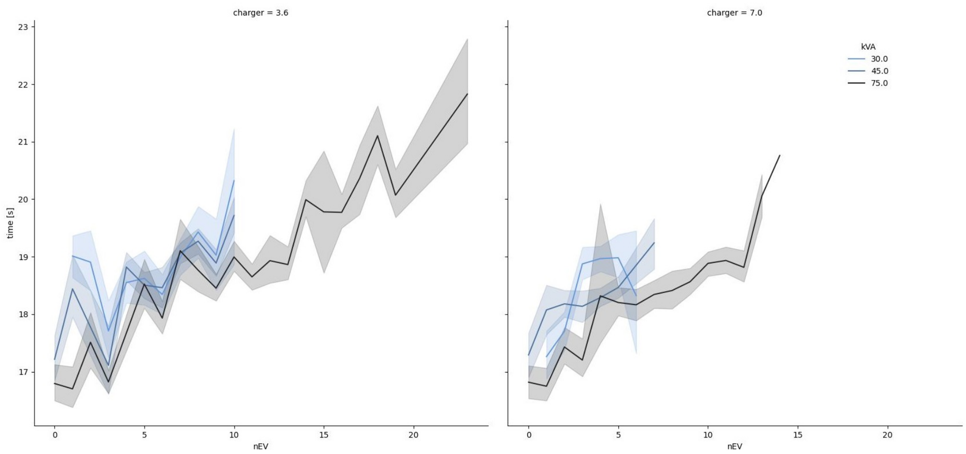

Figure 13. Processing time results for the number of EVs—Feeder 16.

The reduced simulation time is an advantage that highlights the proposed methodology, through the use of low-cost conventional hardware and open-source software. The choice of hardware is also directly linked to the processing time of the proposed methodology. The simulations were performed on a laptop with the following settings:

- Processor—Intel(R) *Core*(TM) i7-7700HQ CPU 2.80 GHz;
- RAM memory—16 GB DDR4 type;
- HD storage—1TB 5400 rpm;
- Dedicated graphics card—NVIDIA GeForce GTX 1050 with 4 GB gDDR5.

Ultimately, as noted in the report of [35] report, "computing power" is a significant determinant of computational efficiency. Solutions such as parallel and cloud computing can help lessen the computational barrier, although there may be other challenges associated with adopting such additional options, as in including built-in restrictions on the use of cloud computing solutions or the need to obtain software licenses.

5.4. Projection

The projection of EV growth for 2030, according to [38], considers three scenarios: conservative (0.1%), moderate (3%), and aggressive (20%).

DME Distribuição S.A. possesses around 78,863 CUs, and Feeder 16 represents 11.58%, that is 9132 CUs. According to the data [1], the municipality of Poços de Caldas/MG has 72,735 motor vehicles registered in its database. For calculation purposes, when equating the ratio of CUs in the system with the number of vehicles, Feeder 16 supplies 8422 CUs with vehicles.

Following the projection of [38], in 2030, Feeder 16 will supply 8 EVs (conservative), 253 EVs (moderate), and 1684 EVs (aggressive).

In Figure 14, a comparison is made between the scenarios and the maximum number of EVs (nEV) that the Feeder can host according to the simulations carried out for the medium-voltage grid. If one considers chargers with a power of 3.6 and 7 kW, for the 3.6 kW charger, the maximum number allowed is 567 units and for the 7 kW charger, 277 units.

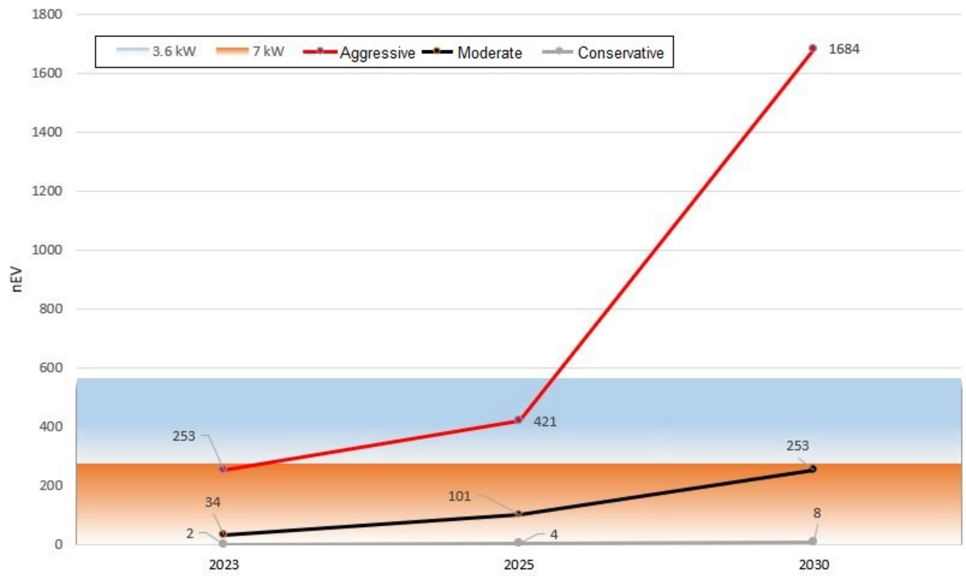

Figure 14. Projection—Feeder 16.

According to the evaluated projections, Feeder 16 will be able to accommodate the growth of EVs in any of the scenarios until 2025 for the 3.6 kW charger. However, the aggressive scenario for 2030 foresees the replacement of 1684 vehicles, which are beyond the hosting capacity of the feeder. Concerning the 7kW charger, the aggressive scenario exceeds the EVs values between 2023 and 2025, causing the inserted chargers to affect transformers, cables, and switches (circuit breakers and fuses).

It is important to note that, when considering the moderate scenario, all projections for the replacement of combustion vehicles with EVs support growth in both chargers until 2030.

6. Conclusions

The aim of the present paper was the proposal of a new methodology for the evaluation of the hosting capacity of EVs on the distribution grid, combining deterministic and stochastic methods. The proposed methodology takes into account five grid performance criteria in order to determine the hosting capacity of low- and medium-voltage grids.

One of the intrinsic characteristics of the allocation of EVs is that it is not possible to predict when, and at which points in the grid, they will be installed. Therefore, the stochastic method was used to model some uncertainties inherent to the process.

In addition to the random variables considered, the hosting capacity depends on the intrinsic characteristics of the analyzed distribution grid, where the number of allocated vehicles does not result in a single value, but in a range of values.

The allocation of EVs on the distribution system is different for each region. At the local level, downstream of the transformer, EV charging can cause impacts on the distribution grid, such as overloading of conductors and undervoltage observed in the simulations performed. Undervoltage and overload violations in conductors are significantly more common at high penetration levels; however, despite this, for the vast majority of simulations with the 3.6 kW charger, there were no violations even with 100% penetration on the secondary grid of Feeder 16. Overload in the transformers and overcurrent in the conductors can be seen primarily in simulations with the 7 kW charger. The voltage unbalance criterion was not violated in any of the simulated scenarios because the methodology works with an equitable distribution of chargers across the distribution network's phases.

The projections made for future scenarios show that the primary grid of Feeder 16 is able to host the EVs until 2025, provided that the secondary transformers are not loaded with 100% of their hosting capacity.

The methodology proposed in this work can be used to identify weaknesses in the grid where the established performance criteria are violated and, consequently, support the distribution planning sector in the definition of mitigating measures. Therefore, the conclusion was reached that the proposed methodology, associated with the script developed, represents an important resource for the distribution system planning engineers in the context of smart grids.

The proposed methodology was applied to other distribution system operator feeders, and the results revealed similar behavior, allowing Feeder 16 to be chosen for the development of the article.

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Abbreviations

The following abbreviations are used in this manuscript:

ANEEL	Brazilian National Agency of Electrical Energy
DER	Distributed Energy Resources
DG	Distributed Generation
DSO	Distribution System Operator
EV	Electric Vehicle
HC	Hosting Capacity
IFSULDEMINAS	Brazilian Federal Institute of Education, Science and Technology
MG	Brazilian State of Minas Gerais
CU	Customer User
UNIFEI	Federal University of Itajubá
UV	Undervoltage
CT	Conductor Thermal limit
TO	Transformer Overload
THDV	Total Harmonic Distortion of Voltage
VU	Voltage Unbalance

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