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Evaluation of Distributed Generation and Electric Vehicles Hosting Capacity in Islanded DC Grids Considering EV Uncertainty

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Abstract: Current power systems are undergoing an energy transition, where technological elements such as distributed generation and electric vehicles through AC or DC microgrids are important elements to face this transition. This paper presents a methodology for quantifying distributed resource-based generation and the number of electric vehicles that can be connected to isolated DC grids without impacting the safe operation of these networks. The methodology evaluates the maximum capacity of distributed generation considering the uncertainty present in the electric vehicle charging of fleets composed of five types of electric vehicles. Specifically, the uncertainty is associated with the following variables: the home arrival time, home departure time, traveled distance, and battery efficiency. The methodology was applied to a 21-bus DC microgrid and a 33-bus DC network under different test conditions. The results show that higher penetrations of EVs and distributed resource-based generation can be introduced while guaranteeing a secure operation of the DC networks.

Keywords: DC power grids; distributed generation; electric vehicle modeling; hosting capacity; Monte Carlo simulation

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1. Introduction

1.1. Motivation

Due to the energy transition, power systems are facing challenges in the planning, operation and control of these systems. One of the major challenges is the penetration of several technological elements such as: non-conventional renewable energy sources (distributed generation (DG)) through AC and DC microgrids, the electrification of transportation and the incorporation of energy storage systems into these networks [1]. The use of these technologies provides important benefits to the grid, e.g., reducing the cost of generation and carbon emission, reducing the stress on transmission systems, and relieving the dependence of fossil fuels [1]. However, the high penetration of DGs in low-voltage (LV) and medium-voltage (MV) distribution networks can complicate the standard operation condition, including voltage violations, reverse power flows, overloading of distribution lines, and increasing losses [2]. On the other hand, the inclusion of electric vehicles (EVs) to the power grid is not only to fight against global warming; this penetration can also achieve efficient operation of the power grid (e.g., increasing the openness of electrical utilities to renewable generation, ancillary services, solving contingencies) [3]. This inclusion brings benefits to combat the aforementioned issues. Nevertheless, the penetration of EVs on a large scale introduces new challenges that must be considered [4]. For example, with this penetration, not only is an increased amount of the electricity consumption in the power network evident or the appearance of new load variations, but there are also clear impacts on transportation, manufacturing or the economy [5]. These repercussions will depend on when EVs are connected for charging, where EVs are connected and at which charging power [5]. Therefore, these factors must be contemplated in the operation, planning and analysis of the modern power grids such as active distribution networks or grid-connected microgrids [3].

With the above in mind and in order to prevent compromising the security and reliability in modern power grids, distribution system operators (DSOs) perform the EV and DG hosting capacity (HC), which is defined as the amount of new production or consumption, which can be connected to the grid without adversely impacting the reliability or voltage quality for other users [6,7]. Therefore, HC evaluation is considered an important tool for DSOs and DG investors. The HC should be calculated using indices such as voltage and frequency variations, thermal overload, power quality and protection problems. However, several authors have demonstrated that the voltage variation is the main performance indicator for HC calculations [8,9].

1.2. Literature Review

Different strategies have been proposed to analyze the hosting capacity in power grids considering the penetration of photovoltaic (PV) or wind turbine (WT)-based DG units. For example, in [8], the authors proposed a methodology to calculate the HC of 17 AC distributions feeders using the Monte Carlo simulation (MCS) based on a stochastic analysis. Munikoti et al. introduced a computationally efficient analytical approach to compute the probability distribution of voltage change due to random behaviors of randomly located multiple distributed PVs [1]. In [10], the HC of an AC distribution system is computed using a non-convex optimization problem with realistic constraints. The authors in [11] proposed a method based on iterative sweep load flow and affine arithmetic to calculate the hosting capacity of a rural distribution network considering PV and load uncertainties. In [12], the maximum WT-based DG capacity in an AC distribution network is computed using a cost–benefit analysis approach. Wang et al. [13] evaluated the maximum housing capacity for AC distribution networks and improved it using robust optimal operation considering load tap changers and static VAR compensators. In [14] proposed a convex optimization problem for computing the maximum hosting capacity of solar energy in an integrated energy AC distribution system based on the electrical–thermal units. In this way, many other methodologies have been proposed to determine hosting capacity in modern power systems with DG [15].

On the other hand, several studies have discussed how to evaluate the hosting capacity in MV/LV AC distribution networks considering the introduction of EVs. These methods can be classified into five groups, which include: deterministic [16], probabilistic [17–19], simulation-based approaches [4,20–22], optimization-based methods [7,23–27] and hybrid techniques [28–30]. For the deterministic approach, the authors assume unrealistic assumptions for EVs based on steady-state environments for the HC evaluation. In the second group, the EV charging demand is modeled by using random variables (e.g., daily distance traveled or the charging duration) that follow specific probability distributions. Then, the authors used a probabilistic power flow method to evaluate the number of EVs that can be plugged into an AC distribution network. For the simulation-based approaches, it is very common to find the use of MCS to determine the hosting capacity in AC distribution networks [4,20–22]. Despite providing accurate results, these MCS methods are computationally expensive. In the fourth group, the hosting capacity in power grids is computed based on metaheuristic methods [2,24], linear programming problems [23], mixed-integer linear programming models [25], stochastic optimization approaches [27], robust optimization methods [7] and Bayesian optimization problems [6]. In the last group, the combination of two of the above methods is considered a hybrid methodology. For example, [28] proposed to use interval and affine arithmetic, power flow computation and probability theory for calculating the hosting capacity of a radial AC distribution network. The authors in [29] solved an AC distribution network electric vehicle HC maximization problem using robust optimization and MCS. Finally, Calum et al. estimated the headroom available for domestic EV charging optimisation in LV AC networks based on both thermal and voltage limits using a linear programming approach and MCS [30].

From the above, it is shown that there has been considerable effort in determining the HC of the network by considering DG and EVs separately. A small number of studies have proposed the evaluation of network HC by simultaneously contemplating DG and EVs. In [31], the authors proposed a combined PV–EV grid integration and hosting capacity assessment for a residential LV AC distribution grid based on EV smart charging and PV curtailment. Specifically, the authors used an optimization problem to compute the optimal charging power of EVs and the optimal power of PV systems. Although it is a novel approach, the authors do not consider realistic scenarios for EV penetration and only analyzed one type of EV. The authors in [32] calculated the HC of an AC distribution system using a stochastic method (MCS) considering the random location of the EVs. However, the authors made unrealistic assumptions about the demand for EVs, and they only considered one type of EVs. Da Silva et al. [25] proposed using an optimization problem based on mixed integer linear programming to maximize PV generation considering network conditions and EVs. However, they did not take into account the uncertainty in the EVs. In [33], the authors performed the dispatch of distributed resources in such a way as to maximize the level of EVs and PVs. Although they considered the interaction of the AC transmission and AC distribution systems, they modeled the penetration of EVs as a ZIP load model (deterministic model) and did not take into account various types of EVs [34]. From the above, there is an evident need to propose discussion in the evaluation of HC in networks using simultaneously DG and EVs. On one hand, it is necessary to evaluate the HC for DC grids, since most studies focus on AC distribution networks or power transmission systems. As mentioned, these DC systems (microgrids, distribution or multi-terminal systems) have gained much interest and attention in the energy transition due to their efficiency, reliability and controllability [35]. On the other hand, it is essential to take into account realistic EV charging behaviors into the power grid, i.e., to consider the random behaviors of EV users in the EV charging demand such as the home arrival time, home departure time, traveled distance, the battery efficiency and different types of EVs.

1.3. Main Contributions

This paper proposes a hybrid methodology to evaluate the HC in networks considering simultaneously DG and EVs. To do so, an optimization problem is used to maximize the participation of the DG, and the penetration of EVs is evaluated by simulation. In the optimization problem, power balance constrains, operational limits of DG, voltages and currents are considered. The EV integration was performed using the modeling presented by [36], which was modified to include five types of EVs used in [5]. This study intends to model the EV penetration using a MCS-based procedure and employ a heterogeneous fleet of EVs; i.e., five types of EVs were used to calculate the HC in these grids: private EV, commercial EV, utility EV, goods trucks and bus. The proposed modeling for EV integration takes into account the state of charge of the batteries and their efficiency, and the random behaviors of EV users in terms of the home arrival time, home departure time and the traveled distance. Another noteworthy element of this paper is the analysis of HC in two isolated DC networks: a 21-bus DC microgrid and a 33-bus DC distribution system, since there are few studies that provide interesting discussion on this type of networks. The main contributions of this paper include the following:

- A hybrid methodology to evaluate the HC in networks considering simultaneously DG and EVs based on genetic algorithms and MCS is proposed.
- The methodology to evaluate the HC is applied in isolated DC networks.
- Five types of EVs and random behaviors of EV users were contemplated in the methodology to calculate the HC in DC grids.

The rest of this article is organized as follows. Section 2 presents the description of the DC grid model. Section 3 shows how to model the EV charging considering user realistic behavior. In addition, this section also shows how to use MCS to calculate the demand for EVs. In Section 4, the proposed methodology for determining the HC of DC networks considering DG and EVs is explained. An analysis of the results obtained when applying the proposed methodology to two isolated DC networks is shown in Section 5. Finally, conclusions and future works are presented in Section 6.

2. DC Grid Model

A DC grid is a network that includes renewable energy generation, energy storage systems, electric vehicles and controlled loads; see Figure 1. Aside from AC networks, the DC microgrids and multi-terminal high-voltage DC transmission are modern and attractive electric technologies due to their efficiency, reliability and controllability [35]. These three properties are the result of considerable advances in power electronics. Nonetheless, it is not only because of these three properties that one may decide to use and implement DC grids but also because many of the renewable energy sources, energy storage systems and residential loads are naturally DC. The penetration of these technologies to power systems is a sustainable solution to many non-interconnected areas (rural areas or remote regions) to have electricity supplies [37]. These networks can operate in island mode or be connected to the AC network through a bidirectional AC/DC converter. Although DC networks can be considered unaffected by power frequency variations and harmonics (due to their operation [38]), it is necessary to analyze issues related to the stability of the integration of these microgrids to conventional AC systems through converters [39] and disturbances associated to the voltage in the DC networks due to transient behaviors when these networks are connected to the AC network. However, these dynamic analyses will not be addressed in this study. Another possible disadvantage of DC networks is the joint operation with the AC network. Nevertheless, as explained in [35], by means of a master–slave operation, it is possible to maintain the voltages at the interaction points of both networks. That is, the slack node imposes the voltage, and the nodes of the microgrid are adjusted to the voltage value of the slack node due to their operation.

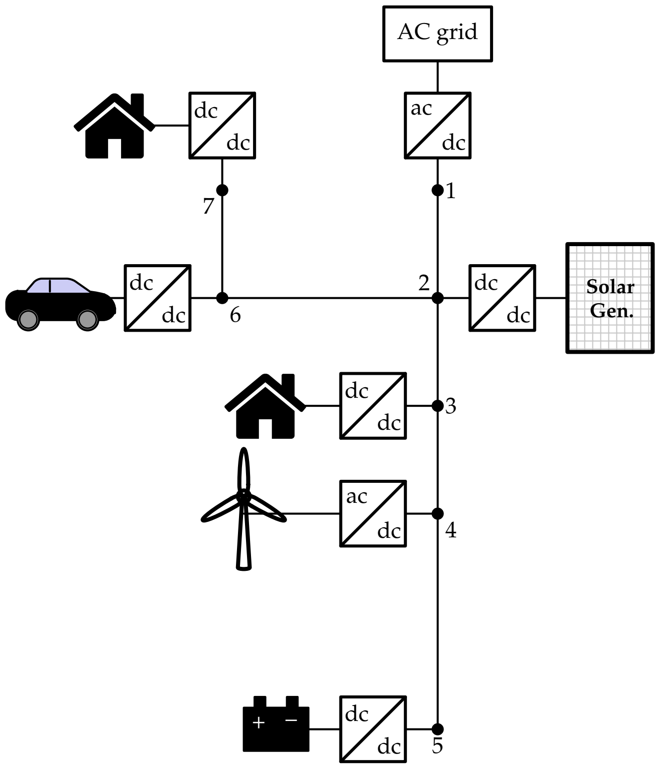

Figure 1. Example of a seven-bus DC Microgrid that allows the incorporation of distributed generation based on renewable sources, energy storage elements and EVs.

According to Zuluaga and Guarnizo in [37], DC grids have gained attention in the research context, but there is also evidence that it is a key element to support power systems. For example, two DC systems were installed in the NASA International Space Station [40]. The Duke Energy data center in Charlotte [41] and the Datacenter of the University of California [42] operate using DC distribution systems. Therefore, it is important to analyze these technologies incorporated into power systems.

Let us consider a DC grid with master–slave operation, which can be modeled as follows [37],

$$\mathbf{I} = V_0\mathbf{G}_0 + \mathbf{G}\mathbf{V}, \tag{1}$$

where $\mathbf{G}_0 \in \mathbb{R}^{n\times 1}$ and $\mathbf{G} \in \mathbb{R}^{n\times n}$ are nodal admittance matrices; V_0 corresponds to the voltage value at the Master Terminal, which is known; $\mathbf{V} \in \mathbb{R}^{n\times 1}$ and $\mathbf{I} \in \mathbb{R}^{n\times 1}$ are the nodal voltages and currents, respectively. For the DC grids analyzed here, we consider that: the graph is connected ($\mathbf{G}$ is not singular), and the system is represented in per-unit [35]. From the model shown in (1), the power injected to the DC grid can be computed as the product between the nodal voltages and currents, that is

$$\begin{aligned} \mathbf{P} &= \mathbf{I} \odot \mathbf{V}, \\ \mathbf{P} &= \mathbf{f}(\mathbf{V}) = V_0\mathbf{G}_0 \odot \mathbf{V} + \mathbf{G}\mathbf{V} \odot \mathbf{V}, \end{aligned} \tag{2}$$

where $\mathbf{P} \in \mathbb{R}^{n\times 1}$ includes all the injected active powers, and $\odot$ is the Hadamard product (i.e., the element-wise product of matrices). In the island mode operation of these networks, the master terminal is disconnected. In this case, the reference voltage must be provided by a secondary control stage [35].

3. EV Charging Probabilistic Modeling

The penetration of EVs in power network analysis studies has been widely addressed [3], and it has been introduced by following several charging opportunities: unidirectional charging, bidirectional charging, uncontrolled charging, external charging strategies, and individual charging strategies [43]. Uncontrolled charging (UCC) represents EV users traveling and parking as they choose to, and they connect their EVs when there is a need to recharge the battery. External charging strategies are based on that the charging may somewhat be controlled externally based on information of the power grid operator. The individual charging strategies are considered as an UCC approach, but also that individuals may adjust their charging decisions based on economic incentives. These individual charging intentions are widely known as grid-to-vehicle (G2V) charging strategies, which consider power flows in the grid to vehicle direction. The external charging strategies could be based on either unidirectional charging or bidirectional charging, which consider power flows in the vehicle-to-grid (V2G) direction. In this article, EV penetration was considered as a G2V strategy using MCS-based modeling.

The EV Charging Probabilistic (EVCP) model is based on the study presented by Ahmadian et al. in [36], which was modified to include a specific EV fleet with five types of EVs: private EV, commercial EV, utility EV, goods trucks and buses [3]. For this model, the home arrival time t_a, home departure time t_d, and traveled distance d are Gaussian random variables, and battery efficiency is uniformly distributed. The state of charge (SOC) after a daily travel distance can be computed as:

$$\mathrm{SOC}_{ij_0} = 1 - \frac{d}{D\eta}, \tag{3}$$

where D is the average daily travel distance; η is the efficiency of battery power in driving cycles in EV; i represents the type of EV and j is the scenario in the MCS. The rated charging power P_c is modeled as a nonlinear function of the SOC, where the SOC is recursively calculated as follows:

$$\mathrm{SOC}_t = \mathrm{SOC}_{t-1} + \frac{100 P_c \eta}{\mathrm{Cap}}, \tag{4}$$

where η represents the efficiency of the EV during driving; and Cap is the full battery capacity. Considering the random variables mentioned before and Equation (4), the total EV power is calculated as,

$$P_{\mathrm{EV}} = \sum_{i=1}^{5} \sum_{j=1}^{N} P_{\mathrm{EV}_{ij}}, \tag{5}$$

where

$$P_{\mathrm{EV}_{ij}} = \begin{cases} P_c, & t_d \leq t \quad and \quad \mathrm{SOC}_t = 100\%, \\ 0, & \text{other} \quad \text{time}. \end{cases}$$

From Equations (3)–(5) and through a repetitive process (MCS), the random variables considered above are propagated in order to calculate the probability distributions of the charging of the set of electric vehicles connected to the power network. This MCS-based model follows the procedure shown in Figure 2. In the EV input data block, the battery capacity, EV types, charging power and full endurance mileages are sampled from probability distributions (see Table 1) to generate a specific EV charging scenario [3,5]. For the sampling block, the previous samples feed the MCS-based EVCP model to compute the total EV power. This procedure is repeated $N = 1000$ times in order to obtain statistics and generated samples for the total EV power. Different EV types and assumptions about how to compute the total EV power are used as shown in [5]. For example, private EVs, commercial EVs, utility EVs, good trucks and buses are contemplated. In addition, it has been considered that 80% of private EVs are plugged into the power grid from 18:00 to 07:00, and the remaining 20% is recharged during working hours, that is, from 09:00 to 17:00. Likewise, it was assumed that the commercial EVs have three working shifts per day (see Table 1 for more details). To determine the number of EVs, a Poisson distribution with expected value λ is used [3]. For each level of penetration, 60% of private EVs are privately owned, 20% of EVs are utility vehicles, 10% of EVs are taxies, 5% of EVs are electric goods trucks, and the remaining 5% are electric buses. From Figure 2, the modeling of EV penetration is achieved by means of an MCS-based procedure. However, as explained in [3], it is possible to take into account the integration of these elements considering deterministic approaches [44], stochastic process [45] or data-driven methods such as k-Nearest Neighbors [46], linear regression [47] and random forest [48]. With deterministic methods, a low computational cost methodology can be achieved but does not contain the random behaviors of EV users. In contrast, methods that support the variability of these behaviors, as stochastic processes, MCS-based approaches and data-driven methods, seek to incorporate realistic scenarios for the calculation of EV power demand. However, these latter methodologies are computationally expensive; see [3] for more information.

Table 1. Charging EV parameters for probabilistic modeling [3,5]. $\mathcal{N}(\mu, \sigma)$ is a Gaussian distribution with parameters μ (mean) and σ (standard deviation); $\mathcal{LN}(\mu, \sigma)$ is the log normal distribution, and $\mathcal{U}(a, b)$ is a uniform distribution with parameters a and b.

EV Type	Period	Mode	Prob.	d	η	t_a	t_d
Private	9–17 h	Slow	10	$\mathcal{LN}(3.2, 0.92)$	$\mathcal{U}(0.88, 0.9)$	$\mathcal{N}(9, 0.9)$	$\mathcal{N}(7, 2)$
	18–7 h	Slow	80			$\mathcal{N}(18.5, 1)$	
	9–17 h	Fast	10			$\mathcal{N}(9, 0.9)$	
Utility	9–17 h	Fast	30	$\mathcal{LN}(3.2, 0.92)$	$\mathcal{U}(0.88, 0.9)$	$\mathcal{N}(18.5, 1)$	$\mathcal{N}(17, 2)$
	18–7 h	Slow	70			$\mathcal{N}(12, 0.9)$	$\mathcal{N}(6, 2)$
Commercial	0–9 h	Fast	70	$\mathcal{N}(195.49, 49.99)$	$\mathcal{U}(0.73, 0.9)$	$\mathcal{N}(4, 2.5)$	$\mathcal{N}(16, 2)$
	9–16 h	Fast	20			$\mathcal{N}(12, 2.5)$	$\mathcal{N}(0, 2)$
	16–24 h	Fast	10			$\mathcal{N}(18.5, 1)$	$\mathcal{N}(9, 0.9)$
Good Trucks	0–9 h	Fast	60	$\mathcal{N}(201.8, 94.42)$	$\mathcal{U}(0.73, 0.9)$	$\mathcal{N}(3, 1.5)$	$\mathcal{N}(12, 2)$
	9–24 h	Fast	40			$\mathcal{N}(14.5, 2.8)$	$\mathcal{N}(4, 2)$
Bus	22–7 h	Fast	100	$\mathcal{N}(155, 10)$	$\mathcal{U}(0.73, 0.9)$	$\mathcal{N}(22, 0.5)$	$\mathcal{N}(5, 2)$

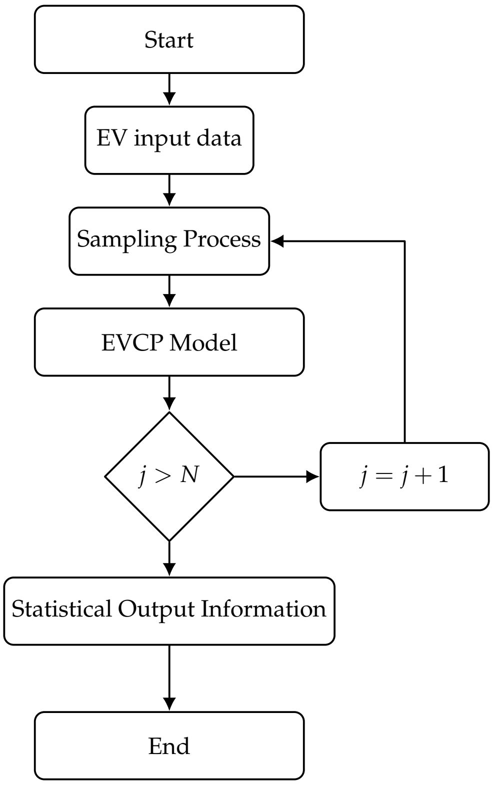

Figure 2. Flowchart for the EV charging probabilistic modeling.

4. DG and EV Hosting Capacity Evaluation

Keeping in mind the DC network model (see Equation (2)) and the computation of the total demand of the EVs (see Equation (5)), the idea in this section is to determine the maximum capacity of the DGs in some nodes of the system without incurring operational problems through an optimization approach. Therefore, the objective is to maximize distributed generation at some points in the grid, that is, DGHC $= \max \sum_{i=1}^{m} P_i^{\text{DG}}$, where P_i^{DG} represents the active power contribution of the distributed generator connected at node i; and m is the number of DGs that can be incorporated into the power grid. To ensure the safe operation of the network, the following optimization problem has been proposed,

$$\text{DGHC} = \max \sum_{i=1}^{m} P_i^{\text{DG}}, \tag{6}$$

$$s.t,$$

$$\mathbf{P}\left(\mathbf{P}^{\text{DG}}, \mathbf{P}_{\text{EV}}\right) - V_0\mathbf{G}_0 \odot \mathbf{V} - \mathbf{G}\mathbf{V} \odot \mathbf{V} = 0, \tag{7}$$

$$0 \leq \mathbf{P}^{\text{DG}} \leq \mathbf{P}_{max}^{\text{DG}}, \tag{8}$$

$$\mathbf{V}_{min} \leq \mathbf{V} \leq \mathbf{V}_{max}, \tag{9}$$

$$|I_{ij}| \leq I_{ij,max}, \quad \text{for all branches}, \tag{10}$$

where $\mathbf{V}_{min} \in \mathbb{R}^{n\times1}$ and $\mathbf{V}_{max} \in \mathbb{R}^{n\times1}$ are vectors that contain the lower and the upper permitted voltages at each node, respectively. I_{ij} is the current between node i and node j. $I_{ij,max}$ is the maximum value of I_{ij}. $\mathbf{P}^{\text{DG}} \in \mathbb{R}^{m\times1}$ is vector that contains all contributions from DG units. $\mathbf{P}_{max}^{\text{DG}} \in \mathbb{R}^{m\times1}$ represents the maximum generation capacity of the DG units. $\mathbf{P}(\mathbf{P}^{\text{DG}}, \mathbf{P}_{\text{EV}})$ is the active power injected into the grid, which depends on the total power of the EVs and the DG contribution. The expression $\mathbf{P}(\mathbf{P}^{\text{DG}}, \mathbf{P}_{\text{EV}}) - V_0\mathbf{G}_0 \odot \mathbf{V} - \mathbf{G}\mathbf{V} \odot \mathbf{V} = 0$ represents all power balance constrains.

From the model shown by Equations (6)–(10), it is possible to discuss the following: Equation (6) presents the objective function which quantifies the total distributed generation contribution of the grid. It is important to note that the objective function is convex and concave (unrestricted) because it is a plane in several variables. Two main challenges can be highlighted from the above model: the variability due to EV user behaviors and that the optimal solution must guarantee the energy balance of the grid. For these two reasons, it was decided to use heuristic solution methodologies. From this model, it is also possible to carry out planning studies in these power networks. For this case, a multi-objective optimization problem should be considered, where on the one hand, the investment and operating cost in the proposed new DG units is minimized, and on the other hand, the capacity of these units is maximized. It is also necessary to add constraints to ensure the optimal placement of distributed resources. For more information, see [49].

With the solution of the problem shown in Equation (6), it is possible to find the maximum contribution of the DG in the network for a single scenario of EVs. Therefore, an MCS was performed to determine the number of EVs on average that can have the solution of the model presented in (6). This process is shown in Figure 3. In the input data block, the network parameters, the characteristics of the EVs, and the operating conditions of the DGs are imported. Then, in the initial conditions calculation block, the initial operating conditions of the network are obtained through a power flow based on Newton's method [50]. Then, the total power demanded by the EVs is obtained using the procedure in Figure 2. Using the above information, the problem of Equation (6) is solved. Recall that lambda is the average number of EVs associated with the Poisson distribution.

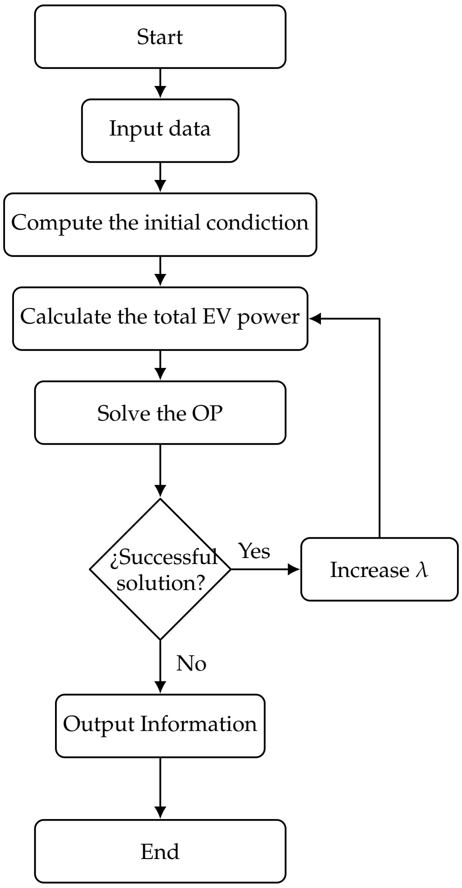

Figure 3. Flowchart for the DG and EV hosting capacity evaluation. OP represents the optimization problem shown in Equation (6).

Solving HC Optimization Problem

The model expressed in Equation (6) has a linear objective function, nonlinear restrictions and is in the presence of uncertainty. It is possible to find a set of methods to solve this model. For example, among the main methodologies for solving this type of problem are: robust optimization [13] and stochastic optimization or stochastic programming [27,33,34]. Within the stochastic optimization can be found: MCS-based optimization [6,21] and randomized search approaches [24,34], among others. In this paper, genetic algorithms (GA) were used as the search engine for the optimal solution to the problem presented in Equation (6). GA have been widely used in the solution of optimization problems in several engineering fields, for example: power transformer design problems [51], energy efficiency in industrial refrigeration systems [52], and magnetic gears optimal designs [53] just to mention a few applications. This search algorithm is based on the generation of new populations from existing ones by emulating biological evolution. The most important steps of this method are: selection, crossover, mutation and elimination. In the first step, the best possible options are set aside as high-quality solutions. In the next step, a crossover of the best DG contributions is performed. The new DG contributions are then altered by the mutation of 1 bit to help maintain the change in the process. Finally, the least feasible contributions are eliminated from the solution set. Figure 4 shows how to apply the above steps to solve the optimization problem shown in Equation (6).

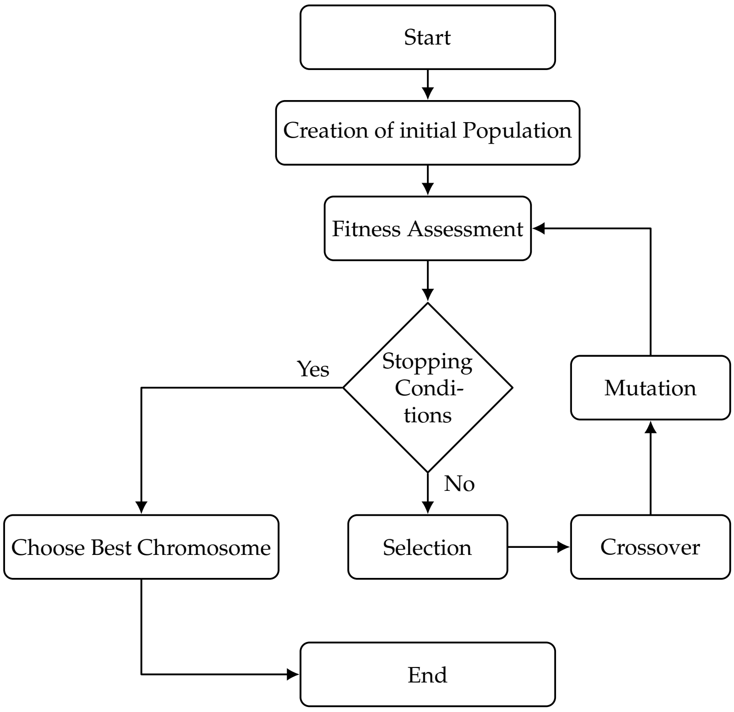

Figure 4. Flowchart of GA applied to solve the optimization problem in Equation (6).

From Figure 3, the contribution of the DGs at a predefined location is determined when considering an EV penetration scenario. If the solution is successful, the EV penetration is increased. This process is repeated until no solution to the optimization problem is found. Since there are a number of solutions due to the uncertainty of EV introduction, the best quality solution is retained. From the above and due to the use of the GA, it is necessary to perform an exhaustive search for global solutions, since this solution methodology does not guarantee these solutions. However, this study does not want to focus on the solution methodology. In other words, the solutions found by the GA will be assumed to be of good quality. It is more important to know what occurs with the inclusion of the DG and EVs in DC networks. Therefore, the solution methodology was conceived as a tool for our analysis.

5. Results and Discussion

In this section, the performance of the methodology when considering the penetration of EVs and DG simultaneously is presented. For this purpose, the proposed methodology has been applied to two DC power networks, one with 21 nodes (proposed by [35]) and the other one with 33 nodes, which was proposed in [54]. In both networks, five types of EVs have been considered with different operating conditions represented by random variables such as the home arrival time t_a, home departure time t_d, traveled distance d and the battery efficiency.

5.1. HC Evaluation for a 21-Bus DC Microgrid

In order to illustrate the penetration of EVs and DG in DC power grids, the behavior of these two technological elements in a 21-bus DC microgrid [35] was analyzed. This microgrid is shown in Figure 5. This microgrid is composed of multiple controlled constant power loads, 21 lines that connect five charging stations and 11 DG units to the main grid. The parameters of this network can be found in [35]. The charging stations were located at nodes 8, 9, 17, 20 and 21 and the possible DG locations were placed at nodes 2–5, 7, 8, 10, 14, 16, 18 and 20. The maximum contribution of the DGs is 2 pu, that is, $P^{DG}_{max} = 2$ pu. The minimum and maximum limits of the voltages at the microgrid nodes are 0.95 pu and 1.05 pu, respectively. That is, the voltage has to be maintained within 5% of the base voltage based on the recommendation provided by the American National Standards Institute. The thermal capacity (maximum current) of the branches was set at 1.05 pu. For the charging station locations, EVs were increased as follows: 10, 20, 50, 100, 200, ... etc., until the stop criteria established in Section 4 were satisfied. For the application of the GA, a crossover fraction of 0.8 was used, a population size of 30, and a maximum number of generations (or iterations) of 100 were also considered. All tests and simulations were conducted on an Intel Core i7 PC with a 2.1 GHz processor.

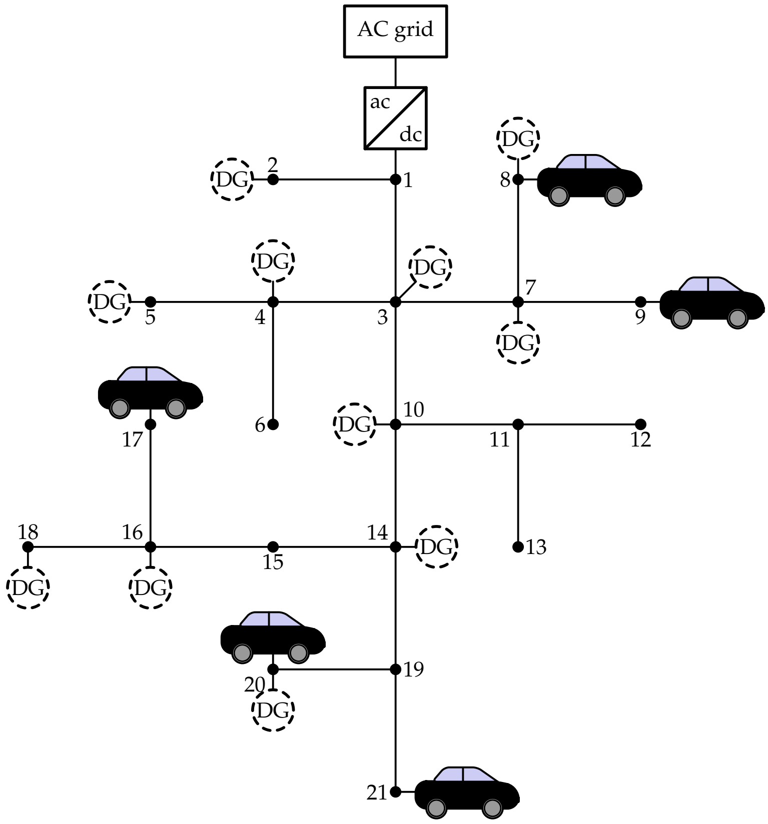

Figure 5. A 21-bus DC microgrid proposed in [35].

Figure 6 shows the application of the proposed methodology (see Figure 3) to the 21-bus DC microgrid. On one hand, Figure 6a shows the contribution of all DG units present in the microgrid considering the penetration of EVs. From this figure, note that for this network, it was only possible to introduce on average 250 EVs with a contribution of 5.3164 pu of DG without violating voltage, current and power generation limits. In order to validate this scenario, the experiment was repeated considering sequential quadratic programming (SQP) and particle swarm optimization (PSO). To apply the PSO algorithm, c_1 and c_2, which are constants that influence the local and global best solutions, were both fixed in 2, and the inertia weight constant $\omega = 5$. From this additional experiment, the SQP had convergence problems and did not obtain feasible solutions. On the contrary, using PSO, it was possible to introduce 250 EVs on average with a total contribution of 4.7505 pu of the distributed resources. On the other hand, Figure 6b shows the contribution of each DG unit separately considering EVs by means of a color map. This color map reflects by shades the contribution present in each EV penetration scenario. The shades range from white to magenta, with white being 0 pu and magenta being 2 pu.

From this color map, the contributions of units at nodes 7, 8, 10, 14 and 18 in all scenarios are reflected. For the 250 EVs scenario, note that the generation unit of node 14 made a considerable contribution, which was 1.6 pu in the HC assessment. It should also be noted that the units at nodes 3, 4, 5 and 16 did not supply significantly in the power generation in the three scenarios. Therefore, it would be interesting to investigate the number of these units and its optimal location in order to take full advantage of the distributed resources. On the other hand, note that when EVs are not considered, i.e., when the HC of the network is calculated only considering DG, the units connected at nodes 2, 3 and 16 provided generation in this scenario. In other words, the penetration of EVs means that more DG units must be added (see the units at nodes 7, 8, 10, 14 and 18) to ensure the safe operation of the network. Finally, Figure 7 shows the behavior of the microgrid losses with the proposed methodologies and without considering it.

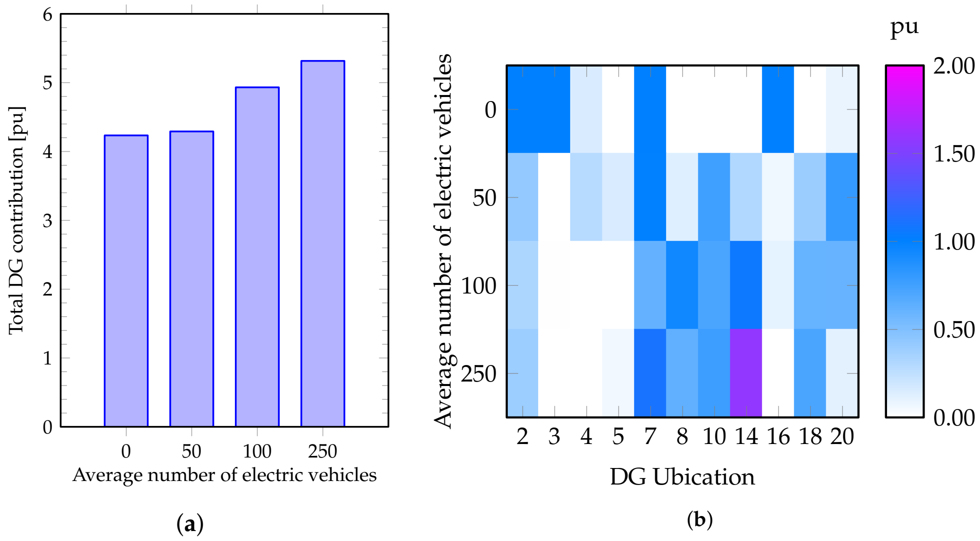

Figure 6. HC evaluation considering different penetration of EVs in the 21-bus DC microgrid. The shades range from white to magenta, with white being 0 pu and magenta being 2 pu. (**a**) DG Contrubition; (**b**) Color map of DG contribution.

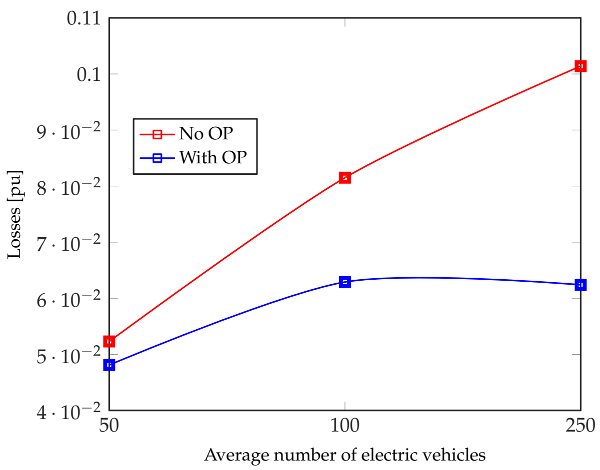

Figure 7. Loss behavior considering optimal HC management in a 21-bus DC microgrid.

From Figure 7, the continuous growth of losses when DG penetration is not considered is evident, which is not the case when considering the proposed methodology. This is largely due to the fact that some of the DG units coincide with the locations of EV charging stations. On the other hand, because it is being calculated from optimal DG contribution, this is reflected in the bidirectional power flows of the grid. The above results validate the optimal management of the distributed resource when considering the penetration of EVs while guaranteeing a secure operation of the DC networks. However, it is necessary to point out that the proposed methodology is computationally expensive. The EV power calculation step increases as EV penetration increases. This is due to the fact that the modeling performed in this study collects daily EV user aspects as reported by Su et al. in [5] in order to reflect realistic behaviors in DC power networks. In addition, the solution of the optimization problem takes an average of 6 s per scenario considering this microgrid. In order to overcome this drawback, Zuluaga et al. in [3] recommend using gamma probability distributions for low penetration (less than 2000 EVs) of EVs and a normal probability distribution for high penetration of EVs. On the other hand, the behavior of the proposed methodology, as shown in the above figures, can be substantially limited due to the thermal restriction of the conductors or the ampacity of the main microgrid feeder, as stated by Lamedica et al. in [55] in the case of AC networks. Finally, the impact of the number of DG units and their maximum capacity on this microgrid was also analyzed. For the above, the experiments shown in Figure 6a were repeated but considering 7 and 16 DGs units, and the capacity of these units was reduced to 1 pu ($P_{max}^{DG} = 1$ pu). Considering the above, a relationship between the HC of the network and P_{max}^{DG} is observed. That is, if the capacity of the DGs is reduced, the HC of the network is also reduced, and vice versa. On the other hand, if more DG units are added, the HC of the network increases and more EVs can be introduced, and vice versa.

5.2. HC Evaluation for a 33-Bus DC Grid

After examining the behavior of the proposed methodology in a small-scale network, the performance of the methodology was analyzed when the number of nodes is increased. Specifically, a 33-bus DC network proposed by [54] was considered. All variables and constraints from the previous experiment were taken into consideration; only the properties of the network and its parameters were changed. The location of the DG was established at nodes 2, 4, 6, 8, 11, 14, 17, 20, 22, 25, 26, 27, 30 and 32. On the other hand, five charging stations for EVs were considered, which are located at nodes 6, 13, 20, 26 and 33. Figure 8 shows the behavior of the methodology after considering a penetration of 50 EVs up to 50k EVs on average.

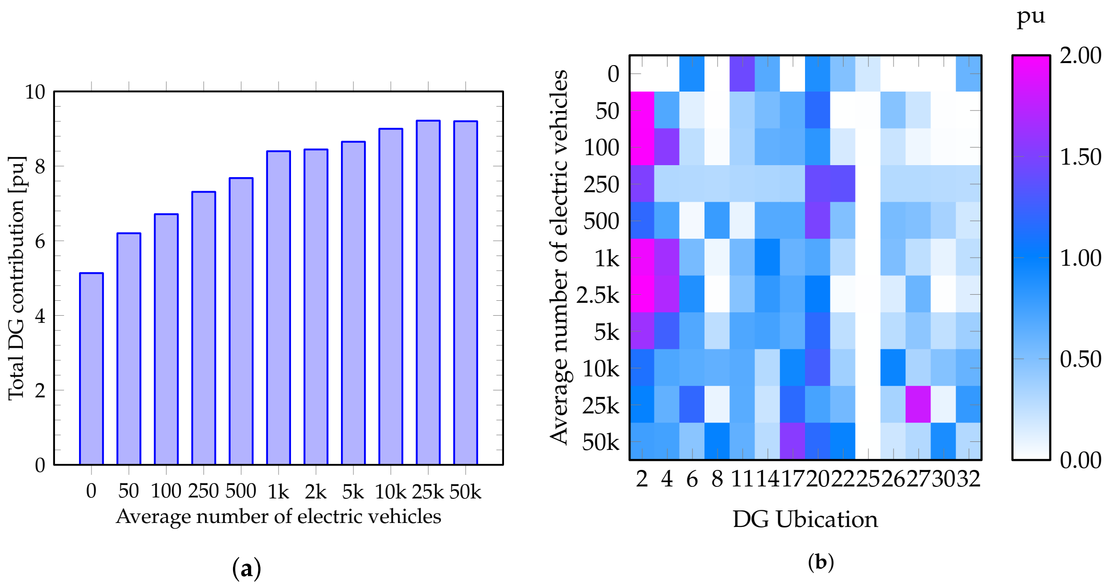

Figure 8. HC evaluation considering different penetration of EVs in the 33-bus DC grid. The shades range from white to magenta, with white being 0 pu and magenta being 2 pu. (**a**) DG Contrubition; (**b**) Color map of DG contribution.

From Figure 8a, note that the optimal HC evaluation was of 9.2 pu and 50k EVs on average for this network, ensuring a safe operation of this DC grid. From Figure 8b, it can be seen that the vast majority of the units provide power to the grid. However, the generation unit at node 25 did not provide power when considering the penetration of EVs. From the above graph, it can also be mentioned that the DG units at nodes 2, 4, 17, 20 and 27 make a significant power contribution in the scenarios considered. Finally, Figure 9 shows the behavior of the DC network losses when only EVs are considered and when the proposed methodology is applied. As in the microgrid, the behavior of losses when considering the proposed methodology shows the improvement compared to when only the penetration of EVs is considered. This constant behavior of the losses was for the following reasons: firstly, with the solution of the optimization problem, it is being ensured that the voltages are between 0.95 and 1.05 pu, which does not happen when the proposed methodology is not considered. Secondly, several DG units coincide with the locations of EV charging stations. This makes the relationship between the penetration of EVs and the contribution of DGs units proportional, i.e., As the penetration of EVs increases, so does the contribution of DG units. Therefore, currents on the main branches are reduced.

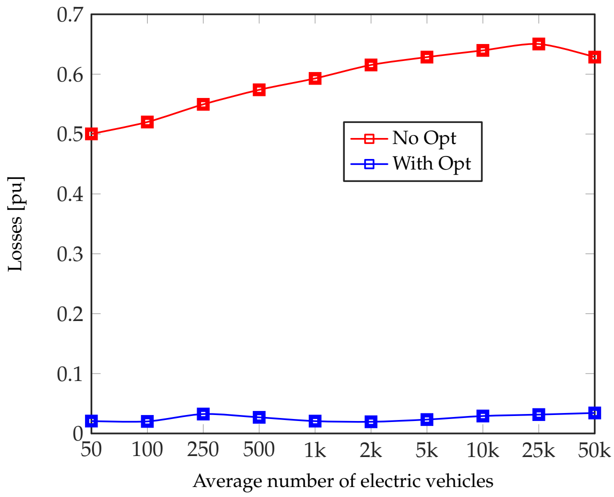

Figure 9. Loss behavior considering optimal HC management in a 33-bus DC distribution network.

6. Conclusions

This paper presented a hybrid methodology for estimating the hosting capacity of isolated DC networks considering DG and EVs. This hybrid methodology was performed by combining an optimization approach and an MCS process. EV charging in estimating DC network hosting capacity was through MCS-based modeling, which incorporated random variables such as home arrival time, home departure time, traveled distance and the battery efficiency from a fleet of five types of EVs. The maximum capacity of the DGs was performed by solving an optimization problem considering the EV charging probabilistic model. The methodology was applied to two isolated DC networks: a 21-bus DC microgrid and a 33-bus DC grid. From the results, we demonstrated the possible penetration of DG and EVs in isolated DC networks, and it is also possible to reduce the active power losses without violating the operational limits of these networks. It is necessary to emphasize that this hybrid methodology, which is based on MCS, is computationally expensive when increasing the number of nodes of the grid and the number of EVs. As future work, it is necessary to include the number of DG units, the locations of these units and the charging stations in the optimization approach to make the best use of distributed resources. It is also possible to improve the proposed methodology by considering the charger efficiency of EV charging stations.

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draft, C.D.Z.-R. and S.D.S.-Z.; Writing—review and editing, S.D.S.-Z., C.D.Z.-R. and A.V.-J. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Alternating Current
DC	Direct Current
DG	Distributed Generation
DSOs	Distribution System Operators
EV	Electric Vehicle
EVCP	Electric Vehicle Charging Probabilistic model
GA	Genetic Algorithms
G2V	Grid-to-Vehicle
HC	Hosting Capacity
LV	Low Voltage
MV	Medium Voltage
MCS	Monte Carlo Simulation
NASA	National Aeronautics and Space Administration
PSO	Particle Swarm Optimization
PV	Photovoltaic
SOC	State-of-Charge
SQP	Sequential Qquadratic Programming
UCC	Uncontrolled charging
V2G	Vehicle-to-Grid
WT	Wind Turbine

References

1. Munikoti, S.; Abujubbeh, M.; Jhala, K.; Natarajan, B. A novel framework for hosting capacity analysis with spatio-temporal probabilistic voltage sensitivity analysis. *Int. J. Electr. Power Energy Syst.* **2022**, *134*, 107426. [CrossRef]
2. Ali, A.; Mahmoud, K.; Lehtonen, M. Maximizing Hosting Capacity of Uncertain Photovoltaics by Coordinated Management of OLTC, VAr Sources and Stochastic EVs. *Int. J. Electr. Power Energy Syst.* **2021**, *127*, 106627. [CrossRef]
3. Zuluaga-Ríos, C.D.; Florián-Ceballos, D.F.; Ángel Rojo-Yepes, M.; Saldarriaga-Zuluaga, S.D. Review of Charging Load Modeling Strategies for Electric Vehicles: A Comparison of Grid-to-Vehicle Probabilistic Approaches. *Tecnura* **2021**, *25*, 108–125. [CrossRef]
4. Dimas, C.; Ramos, G.; Caro, L.; Luna, A.C. Parallel Computing and Multicore Platform to Assess Electric Vehicle Hosting Capacity. *IEEE Trans. Ind. Appl.* **2020**, *56*, 4709–4717. [CrossRef]
5. Su, J.; Lie, T.; Zamora, R. Modelling of large-scale electric vehicles charging demand: A New Zealand case study. *Electr. Power Syst. Res.* **2019**, *167*, 171–182. [CrossRef]
6. Geng, X.; Tong, L.; Bhattacharya, A.; Mallick, B.; Xie, L. Probabilistic Hosting Capacity Analysis via Bayesian Optimization. In Proceedings of the 2021 IEEE Power & Energy Society General Meeting (PESGM), Washington, DC, USA, 26–29 July 2021; pp. 1–5. [CrossRef]
7. Alturki, M.; Khodaei, A. Marginal Hosting Capacity Calculation for Electric Vehicle Integration in Active Distribution Networks. In Proceedings of the 2018 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), Denver, CO, USA, 16–19 April 2018; pp. 1–9. [CrossRef]

8. Ding, F.; Mather, B. On Distributed PV Hosting Capacity Estimation, Sensitivity Study, and Improvement. *IEEE Trans. Sustain. Energy* **2017**, *8*, 1010–1020. [CrossRef]
9. Walla, T. Hosting Capacity for Photovoltaics in Swedish Distribution Grids. Master's Thesis, Uppsala University, Uppsala, Sweden, 2012.
10. Yuan, J.; Weng, Y.; Tan, C.W. Determining maximum hosting capacity for PV systems in distribution grids. *Int. J. Electr. Power Energy Syst.* **2022**, *135*, 107342. [CrossRef]
11. Wang, S.; Dong, Y.; Wu, L.; Yan, B. Interval Overvoltage Risk Based PV Hosting Capacity Evaluation Considering PV and Load Uncertainties. *IEEE Trans. Smart Grid* **2020**, *11*, 2709–2721. [CrossRef]
12. Nursebo Salih, S.; Chen, P.; Carlson, O.; Tjernberg, L.B. Optimizing Wind Power Hosting Capacity of Distribution Systems Using Cost Benefit Analysis. *IEEE Trans. Power Deliv.* **2014**, *29*, 1436–1445. [CrossRef]
13. Wang, S.; Chen, S.; Ge, L.; Wu, L. Distributed Generation Hosting Capacity Evaluation for Distribution Systems Considering the Robust Optimal Operation of OLTC and SVC. *IEEE Trans. Sustain. Energy* **2016**, *7*, 1111–1123. [CrossRef]
14. Luo, F.; Jiao, Z.; Wei, W. Maximum Hosting Capacity Evaluation Method of Solar Energy in Integrated Energy Distribution System based on enhanced-SOCP. In Proceedings of the 2021 IEEE Power & Energy Society General Meeting (PESGM), Washington, DC, USA, 26–29 July 2021; pp. 1–5. [CrossRef]
15. Ismael, S.M.; Abdel Aleem, S.H.; Abdelaziz, A.Y.; Zobaa, A.F. State-of-the-art of hosting capacity in modern power systems with distributed generation. *Renew. Energy* **2019**, *130*, 1002–1020. [CrossRef]
16. Awadallah, M.A.; Singh, B.N.; Venkatesh, B. Impact of EV Charger Load on Distribution Network Capacity: A Case Study in Toronto. *Can. J. Electr. Comput. Eng.* **2016**, *39*, 268–273. [CrossRef]
17. Al-Saadi, H.; Zivanovic, R.; Al-Sarawi, S.F. Probabilistic Hosting Capacity for Active Distribution Networks. *IEEE Trans. Ind. Inform.* **2017**, *13*, 2519–2532. [CrossRef]
18. Ramadan, H.; Ali, A.; Farkas, C. Assessment of plug-in electric vehicles charging impacts on residential low voltage distribution grid in Hungary. In Proceedings of the 2018 6th International Istanbul Smart Grids and Cities Congress and Fair (ICSG), Istanbul, Turkey, 25–26 April 2018; pp. 105–109. [CrossRef]
19. Wang, S.; Li, C.; Pan, Z.; Wang, J. Probabilistic Method for Distribution Network Electric Vehicle Hosting Capacity Assessment based on Combined Cumulants and Gram-Charlier Expansion. *Energy Procedia* **2019**, *158*, 5067–5072. [CrossRef]
20. Kamruzzaman, M.; Benidris, M. A Smart Charging Strategy for Electric Vehicles to Increase their Hosting Capacity in Distribution Systems. In Proceedings of the 2019 North American Power Symposium (NAPS), Wichita, KS, USA, 13–15 October 2019; pp. 1–6. [CrossRef]
21. Kamruzzaman, M.; Bhusal, N.; Benidris, M. Determining Maximum Hosting Capacity of Electric Distribution Systems to Electric Vehicles. In Proceedings of the 2019 IEEE Industry Applications Society Annual Meeting, Baltimore, MD, USA, 29 September–3 October 2019; pp. 1–7. [CrossRef]
22. Paudyal, P.; Ghosh, S.; Veda, S.; Tiwari, D.; Desai, J. EV Hosting Capacity Analysis on Distribution Grids. In Proceedings of the 2021 IEEE Power & Energy Society General Meeting (PESGM), Washington, DC, USA, 26–29 July 2021; pp. 1–5. [CrossRef]
23. Kamruzzaman, M.; Zhang, X.; Abdelmalak, M.; Benidris, M.; Shi, D. A Method to Evaluate the Maximum Hosting Capacity of Power Systems to Electric Vehicles. In Proceedings of the 2020 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Liege, Belgium, 18–21 August 2020; pp. 1–6. [CrossRef]
24. Kamruzzaman, M.; Benidris, M.; Elsaiah, S.; Tian, Y. A Method for Maximizing the Hosting Capacity to Electric Vehicles using Feeder Reconfiguration. In Proceedings of the 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, QC, Canada, 2–6 August 2020; pp. 1–5. [CrossRef]
25. Da Silva, E.C.; Melgar-Dominguez, O.D.; Romero, R. Assessment of Distributed Generation Hosting Capacity in Electric Distribution Systems by Increasing the Electric Vehicle Penetration. In Proceedings of the 2021 IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), Espoo, Finland, 18–21 October 2021; pp. 1–5. [CrossRef]
26. Belonogova, N.; Honkapuro, S.; Partanen, J.; Simolin, T.; Rautiainen, A.; Heine, P.; Lepistö, J. Assessment of EV Hosting Capacity in a Workplace Environment in Different Charging Strategies. In Proceedings of the CIRED 2020 Berlin Workshop (CIRED 2020), Berlin, Germany, 22–23 September 2020; Volume 2020, pp. 444–447. [CrossRef]
27. Najafi, A.; Pourakbari-Kasmaei, M.; Contreras, J.; Lehtonen, M.; Leonowicz, Z. Optimal Bilevel Operation-Planning Framework of Distributed Generation Hosting Capacity Considering Rival DISCO and EV Aggregator. *IEEE Syst. J.* **2021**, *16*, 5023–5034. [CrossRef]
28. Kim, T.H.; Kim, D.; Moon, S.I. Evaluation of Electric Vehicles Hosting Capacity Based on Interval Undervoltage Probability in a Distribution Network. *IEEE Access* **2021**, *9*, 140147–140155. [CrossRef]
29. Zhao, J.; Wang, J.; Xu, Z.; Wang, C.; Wan, C.; Chen, C. Distribution Network Electric Vehicle Hosting Capacity Maximization: A Chargeable Region Optimization Model. *IEEE Trans. Power Syst.* **2017**, *32*, 4119–4130. [CrossRef]
30. Edmunds, C.; Galloway, S.; Dixon, J.; Bukhsh, W.; Elders, I. Hosting capacity assessment of heat pumps and optimised electric vehicle charging on low voltage networks. *Appl. Energy* **2021**, *298*, 117093. [CrossRef]
31. Fachrizal, R.; Ramadhani, U.H.; Munkhammar, J.; Widén, J. Combined PV–EV hosting capacity assessment for a residential LV distribution grid with smart EV charging and PV curtailment. *Sustain. Energy Grids Netw.* **2021**, *26*, 100445. [CrossRef]

32. Bhusal, N.; Kamruzzaman, M.; Benidris, M. Photovoltaic Hosting Capacity Estimation Considering the Impact of Electric Vehicles. In Proceedings of the 2019 IEEE Industry Applications Society Annual Meeting, Baltimore, MD, USA, 29 September–3 October 2019; pp. 1–6. [CrossRef]
33. Rabiee, A.; Keane, A.; Soroudi, A. Enhanced Transmission and Distribution Network Coordination to Host More Electric Vehicles and PV. *IEEE Syst. J.* **2022**, *16*, 2705–2716. [CrossRef]
34. Da Silva, E.C.; Melgar-Dominguez, O.D.; Romero, R. Simultaneous Distributed Generation and Electric Vehicles Hosting Capacity Assessment in Electric Distribution Systems. *IEEE Access* **2021**, *9*, 110927–110939. [CrossRef]
35. Garcés, A. On the Convergence of Newton's Method in Power Flow Studies for DC Microgrids. *IEEE Trans. Power Syst.* **2018**, *33*, 5770–5777. [CrossRef]
36. Ahmadian, A.; Sedghi, M.; Aliakbar-Golkar, M. Stochastic modeling of Plug-in Electric Vehicles load demand in residential grids considering nonlinear battery charge characteristic. In Proceedings of the 2015 20th Conference on Electrical Power Distribution Networks Conference (EPDC), Zahedan, Iran, 28–29 April 2015; pp. 22–26. [CrossRef]
37. Zuluaga-Ríos, C.D.; Guarnizo-Lemus, C. Stochastic voltage estimation for islanded DC grids. *Electr. Power Syst. Res.* **2022**, *210*, 108074. [CrossRef]
38. Jithin, K.; Haridev, P.P.; Mayadevi, N.; Kumar, R.H.; Mini, V.P. A Review on Challenges in DC Microgrid Planning and Implementation. *J. Mod. Power Syst. Clean Energy* **2022**, 1–21. [CrossRef]
39. Hatziargyriou, N.; Milanovic, J.; Rahmann, C.; Ajjarapu, V.; Canizares, C.; Erlich, I.; Hill, D.; Hiskens, I.; Kamwa, I.; Pal, B.; et al. Definition and Classification of Power System Stability—Revisited & Extended. *IEEE Trans. Power Syst.* **2021**, *36*, 3271–3281. [CrossRef]
40. Elsayed, A.T.; Mohamed, A.A.; Mohammed, O.A. DC microgrids and distribution systems: An overview. *Electr. Power Syst. Res.* **2015**, *119*, 407–417. [CrossRef]
41. Kintner, D. *Duke Energy–EPRI DC Powered Data Center Demonstration Executive Summary*; Technical Report; Duke Energy Data Center: Charlotte, NC, USA, 2011.
42. AlLee, G.; Tschudi, W. Edison Redux: 380 Vdc Brings Reliability and Efficiency to Sustainable Data Centers. *IEEE Power Energy Mag.* **2012**, *10*, 50–59. [CrossRef]
43. Grahn, P.; Rosenlind, J.; Hilber, P.; Alvehag, K.; Söder, L. A Method for Evaluating the Impact of Electric Vehicle Charging on Transformer Hotspot Temperature. In Proceedings of the 2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies, Manchester, UK, 5–7 December 2011; pp. 1–8. [CrossRef]
44. Gil-Aguirre, J.; Perez-Londoño, S.; Mora-Flórez, J. A measurement-based load modelling methodology for electric vehicle fast-charging stations. *Electr. Power Syst. Res.* **2019**, *176*, 105934. [CrossRef]
45. Jiang, H.; Ren, H.; Sun, C.; Watts, D. The Temporal-Spatial Stochastic Model of Plug-in Hybrid ElectricVehicles. In Proceedings of the 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Torino, Italy, 26–29 September 2017; pp. 1–6. [CrossRef]
46. Li, X.; Zhang, Q.; Peng, Z.; Wang, A.; Wang, W. A data-driven two-level clustering model for driving pattern analysis of electric vehicles and a case study. *J. Clean. Prod.* **2019**, *206*, 827–837. [CrossRef]
47. Frendo, O.; Graf, J.; Gaertner, N.; Stuckenschmidt, H. Data-driven smart charging for heterogeneous electric vehicle fleets. *Energy AI* **2020**, *1*, 100007. [CrossRef]
48. Gerossier, A.; Girard, R.; Kariniotakis, G. Modeling and Forecasting Electric Vehicle Consumption Profiles. *Energies* **2019**, *12*, 1341. [CrossRef]
49. Xu, X.; Li, J.; Xu, Z.; Zhao, J.; Lai, C.S. Enhancing photovoltaic hosting capacity—A stochastic approach to optimal planning of static var compensator devices in distribution networks. *Appl. Energy* **2019**, *238*, 952–962. [CrossRef]
50. Zuluaga R., C.D. Probabilistic Analysis in DC Grids. In *Modeling, Operation, and Analysis of DC Grids*; Garcés, A., Ed.; Academic Press: Cambridge, MA, USA, 2021; pp. 175–191. [CrossRef]
51. Orosz, T. FEM-Based Power Transformer Model for Superconducting and Conventional Power Transformer Optimization. *Energies* **2022**, *15*, 6177. [CrossRef]
52. Nedjah, N.; de Macedo Mourelle, L.; Lizarazu, M.S.D. Evolutionary Multi-Objective Optimization Applied to Industrial Refrigeration Systems for Energy Efficiency. *Energies* **2022**, *15*, 5575. [CrossRef]
53. Mao, Y.; Yang, Y. Optimization of Magnetic Gear Patterns Based on Taguchi Method Combined with Genetic Algorithm. *Energies* **2022**, *15*, 4963. [CrossRef]
54. Montoya, O.D.; Gil-González, W.; Garces, A. Numerical methods for power flow analysis in DC networks: State of the art, methods and challenges. *Int. J. Electr. Power Energy Syst.* **2020**, *123*, 106299. [CrossRef]
55. Lamedica, R.; Geri, A.; Gatta, F.M.; Sangiovanni, S.; Maccioni, M.; Ruvio, A. Integrating Electric Vehicles in Microgrids: Overview on Hosting Capacity and New Controls. *IEEE Trans. Ind. Appl.* **2019**, *55*, 7338–7346. [CrossRef]