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Review

Methods and Tools for PV and EV Hosting Capacity Determination in Low Voltage Distribution Networks—A Review

Vincent Umoh [1,*], Innocent Davidson [2], Abayomi Adebiyi [1] and Unwana Ekpe [3]

1 Department of Electrical Power Engineering, Durban University of Technology, Durban 4001, South Africa; abayomia@dut.ac.za
2 Department of Electrical, Electronic and Computer Engineering, Cape Peninsula University of Technology, Bellville 7535, South Africa; inno.davidson@gmail.com
3 Department of Electrical and Electronic Engineering, Akwa Ibom State University, Mkpat Enin 524106, Nigeria; unwanaekpe@aksu.edu.ng
* Correspondence: 22280333@dut4life.ac.za

Abstract: The increasing demand for electricity and the need for environmentally friendly transportation systems has resulted in the proliferation of solar photovoltaic (PV) generators and electric vehicle (EV) charging within the low voltage (LV) distribution network. This high penetration of PV and EV charging can cause power quality challenges, hence the need for hosting capacity (HC) studies to estimate the maximum allowable connections. Although studies and reviews are abundant on the HC of PV and EV charging available in the literature, there is a lack of reviews on HC studies that cover both PV and EVs together. This paper fills this research gap by providing a detailed review of five commonly used methods for quantifying HC including deterministic, time series, stochastic, optimization, and streamlined methods. This paper comprehensively reviews the HC concept, methods, and tools, covering both PV and EV charging based on a survey of state-of-the-art literature published within the last five years (2017–2022). Voltage magnitude, thermal limit, and loading of lines, cables, and transformers are the main performance indices considered in most HC studies.

Keywords: hosting capacity; solar PV; electric vehicle; distribution network; deterministic; stochastic; time series; streamlined; optimization

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1. Introduction

The existing power grid in many parts of the world is overloaded due to rapid urbanization and a corresponding increase in the number and magnitude of grid-connected loads. Environmental safety concerns make it imperative that alternative sources of electricity and transportation should be clean [1,2]. These concerns are progressively being alleviated by the rapid increase in the use of environmentally friendly solar photovoltaic (PV) systems and electric vehicles (EVs) [2,3]. The ongoing war between Russia and Ukraine has created shortages in gas supply and an energy crisis in parts of Europe [4,5], it is expected that the number of grid-connected PV systems will increase rapidly in the near future. However, a large amount of grid integration of solar PV and EVs can disrupt the standard operating condition by causing supply voltage violations, reverse power flow, transformer and lines overloading, and an increase in electrical losses [6]. As a result, distribution network operators perform PV and/or EV hosting capacity (HC) analysis to determine the amount of PV generation and EV charging that can be integrated into a particular distribution network.

Hosting capacity is defined as the amount of new production or consumption that can be connected to a network without degrading the quality of delivered power or reliability of service [2,7]. The HC calculation is performed using various performance indices such as voltage magnitude and frequency variations, thermal overload, and power quality, and defining practical limits for the indices as specified by national or international standards [8,9]. Using appropriate tools, an HC determination methodology can then be formulated to guide the choice of a maximum number of PVs and EVs that can be integrated into a distribution network without violating the operational limits of such a network. Considering the importance of this concept for the present and future grid, HC determination methods and tools must be well documented for ease of reference by researchers and industry practitioners. Studies such as [10–13] are the most recent reviews conducted on the different HC calculation methods while [14] reviewed the methods and tools. However, none of these studies have presented the five major HC calculation methods separately nor reviewed the HC of EV charging.

Considering the foregoing concerns, this paper provides the literature survey of the five commonly used HC calculation methods which include deterministic, time series, probabilistic, optimization, and streamlined methods. The paper discusses the HC concept, methods, and tools based on a survey of the state-of-the-art literature published within the last five years (2017–2022). The key contribution of this paper that distinguish it from other reviews is the review of solar PV and EV charging HC studies together considering how important these technologies are to the future power system.

The paper is structured as follows: Section 2 briefly discusses the hosting capacity concept and presents its various definitions. Section 3 examines the commonly adopted methods for HC quantification and reviews studies that have been conducted with these methods. Section 4 discusses EV charging HC and reviews recently published papers. Section 5 presents the tools available for HC calculation while Section 6 is the conclusion.

2. Definition and Concept of Hosting Capacity

The term, "hosting capacity" has already been used in other contexts such as the capacity of web servers, watermarking of images, and settlement of refugees [13,15], before its adoption as a term in distributed generation (DG). Hosting capacity (HC) as a concept in DG was first introduced by André Even in March 2004 during the integrated European EU-DEEP project discussion to examine the effects of high distributed generation integration in the distribution network [13,16,17]. This concept is illustrated in Figure 1. The theoretical application of the concept developed in [18], is now the widely adopted methodology by network operators, regulators, and researchers to determine HC.

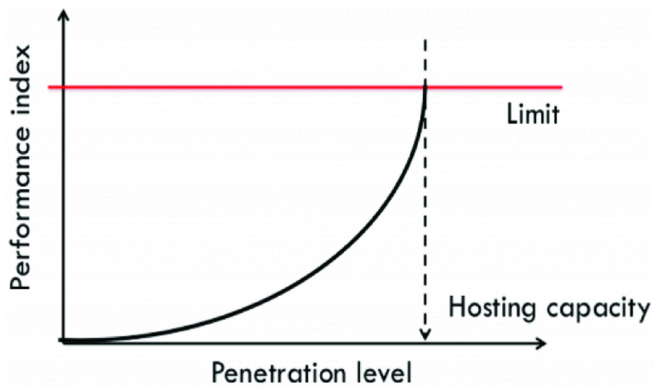

Figure 1. The HC concept.

This development brought the first official definition of HC available in the literature as the highest amount of distributed generation that can be integrated into a power system without the performance limit being violated [18]. This definition was further refined in [19] and subsequently, the growth in the utilization of electric vehicles (EVs) made the need to evaluate the HC of distribution networks a very important endeavor [20,21]. Thus, the definition of HC is further tilted to consider the amount of new production or consumption that can be connected without compromising the reliability or quality of power supplied to other users [15,21,22].

Furthermore, researchers and regulators have quantified HC in different ways depending on the different references adopted for each study, such as the proportion of customers that install PVs or the rated power from the installed PV as the percentage of the total connected load or transformer rating, or the present peak feeder load demand [23]. Table 1 lists the varying definitions of HC that have been presented in the literature depending on the different references adopted and a quantitative summary of various reference values showing that peak feeder load is the most adopted reference [12].

Table 1. Definitions of HC based on different references adopted for defining HC [12].

Ref	Reference Adopted	HC Definition	Quantitative Summary of Various References (%)
[24–34]	Peak feeder load	The proportion of the PV installation's maximum capacity to the feeder's peak load demand.	47
[35–43]	Transformer Rating	The proportion of the overall amount of PV output to the transformer's rated capacity.	20
[44–48]	Customer PVs	The proportion of households in the study area that install PVs to the total number of households there.	20
[49,50]	Active Power	The proportion of PV output to the load's active power.	5
[51]	Roof-space PVs	The possibilities for the connection and installation of solar PV panels on the roof space of the feeder-connected households.	2
[52–54]	Energy Consumption	the proportion of the total annual PV system energy production to total energy usage.	7

3. Hosting Capacity Determination Methodology

The general approach for HC determination is shown in Figure 2. It begins with the selection of at least one performance index (such as overvoltage, voltage unbalance, thermal overload, power quality, system losses, harmonics, or protection), defining a suitable limit for the index as specified by the national or international standards, and then applying HC determination methods to calculate the hosting capacity as a function of the amount of PV generation or EV charging [13,14]. During the load flow calculation, the amount of PV or EV is gradually increased until the result of a performance index exceeds the allowable limit. There are five major methods for HC quantification in the distribution networks found in the literature. They include; deterministic, time series, stochastic, streamlined-stochastic, and optimization-based methods [11,14]. Although these methods are unique in terms of actual implementation, they all use power flow calculations to find the values of the performance indices in the network and they all follow the same general approach shown in Figure 1. HC calculation can be handled from two viewpoints, customer-based and utility-based. From a customer-centric viewpoint, the HC calculation problem becomes a probabilistic one due to uncertainties since the distribution network operators do not have control over the location, size, or number of PV installations [14,55]. In this case, the stochastic method is mostly preferred for HC calculations. However, the utility-based HC calculation is often characterized as an optimization problem with the objective of maximizing PV or EV charging integration without endangering the technical operation of the distribution grid [14]. The next subsections discuss the different HC methods in the context of PV generation.

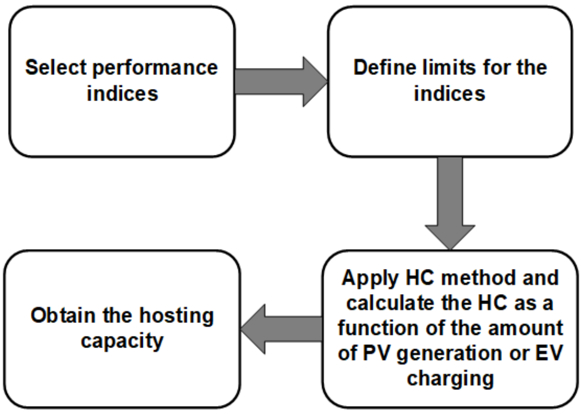

Figure 2. General hosting capacity approach.

3.1. The Deterministic Method

The deterministic method is the basic method for HC determination that begins with data collection of the distribution network followed by modeling of the network and load flow simulation, as shown in Figure 3. The deterministic method does not consider the uncertainty of the PV production, load consumption of consumers, and the size and location of the PV. Instead, these parameters are assumed to be known and assigned fixed input values before the HC calculation begins [11,14].

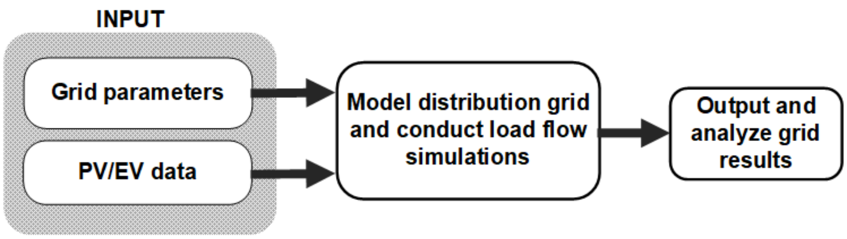

Figure 3. Deterministic method illustration.

The deterministic method generally adopts the constant PV generation approach, with the PV output as the independent variable assumed to be maximum and does not vary throughout the calculation [11,14]. This method evaluates the system in a scenario-based fashion by iteratively increasing the size of the PV unit until the first violation of a performance index is observed [43,56–61]. The deterministic method also considers the worst-case scenarios to determine the HC due to the extreme impact of uncertain parameters [60–62]. In this scenario, the PV is assumed to produce its maximum output while the load is assumed to draw a minimum amount of power. The PV size is then increased in steps until the first violation of an operational limit. This scenario is mostly set up to assess the voltage and overloading violations due to voltage rise and reverse power flow in the distribution network.

There is also a variation in the deterministic method where the rule-based analysis is applied. This approach allows iterative increment of the solar PV at the nodes of the grid realized using a forward, backward, and forward-backward method. In the end, three different hosting capacity values for the distribution network are obtained, and the actual grid HC is given as a range between these values [11,63].

The deterministic method is often used to first obtain an estimated HC of a network. For example, [61,64] selected bus voltage, line overloading, and transformer overloading as performance indices to estimate the HC of a distribution feeder. The effect of load variability and split-phase transformer unbalance on three LV distribution networks by constantly increasing the PV generation is studied in [61]. In this paper, the size of the PV is increased by 1 kW for every iteration to assess the violation of different performance limits. The results obtained reveal that HC differs with the load when overvoltage, line overload, and transformer overload are the limiting factors. The authors in [64] developed and compared HC results with and without the shunt capacitances of the lines. They established that the HC is higher with the shunt capacitor. This is because the reactive power injected by the shunt capacitor lowers the bus voltages in the distribution network. In [65], the HC for a residential LV feeder is estimated using an analytical approach to the deterministic methods. The authors studied the impact of solar PV with unity or non-unity power factor and compared the result to that obtained using a power system software. Their result indicates an error of less than 0.7 V for all the tested scenarios.

The impact of PV location on the HC of distribution networks is evaluated in [57]. The study presents the location of PV as the major limiting factor of HC and proposes an index to quantify the impact of the location of PV units. In [66], the authors used a 16-bus distribution test network to assess the effect of high DG penetration levels on voltage rise and thermal limits. Their results show that the limit of penetration is significantly higher for DG located at the load center compared to other locations. Additionally, the deterministic HC method is found to be effective for performing sensitivity analysis of solar PV integration into the LV distribution networks similar to results obtained in [56,57]. Table 2 presents a summary of the studies that adopt the deterministic HC calculation method.

Table 2. Summary of studies that adopt the deterministic method for PV Hosting capacity determination.

Ref.	Performance Index	Study Summary
[56]	Harmonics distortion, losses	Conducted HC studies with harmonic distortion as the performance limit.
[57]	Voltage magnitude and transformer loading	proposed a new index to measure improved unit placement and generation power based on HC results proposed a new index to measure improved unit placement and generation power based on HC results
[58]	Over-voltage and thermal limits	Estimated the HC of a low voltage network in Yogyakarta.
[60]	Over-voltage and thermal limits	Determined a distribution network's solar PV HC while taking into account how MV and LV networks interact at various voltage levels.
[63]	Voltage magnitude and loading	Compared probabilistic techniques of HC capacity based on solar roof potential analysis with rule-based approaches at the distribution system level.
[66]	Voltage magnitude and loading	Investigated how different PV penetration levels would affect voltage rise and cable thermal limits considering different PV locations and loading scenarios.
[67]	Over-voltage and Harmonic distortion	Proposed PV HC using a performance index that considers voltage increase and harmonic voltage distortion at the point of common coupling while accounting for background harmonic distortion.
[68]	Voltage magnitude and current loading	Developed a technique for controlling voltage and current in sizable distribution grids with high penetration of solar PV.
[69]	Harmonic voltage and current	Identified and examined any potential resonance problems, harmonic distortion, and resonance at the LV distribution network where there is a high penetration of various solar PVs.
[70]	Voltage magnitude, loading, and losses	Presented a straightforward approach that may be used to determine the maximum allowable PV in a radial LV network while taking phase mutual inductance and line losses into account.
[71]	Voltage magnitude and loading	Proposed three methods aimed at utilizing solar roof potential analysis to calculate the PV HC on the MV feeder.
[72]	Voltage unbalance	Assessed how single-phase photovoltaic inverters contribute to voltage imbalance in three LV networks.

Merits and Limitations of the Deterministic HC Method

The deterministic method is very simple and useful for quick estimation and overview of the HC of electrical distribution networks [14]. The method is preferred for a single huge installation that requires less computational burden since uncertainties are not accounted for. However, for a huge number of small installations with several uncertainties that require large computations, the deterministic method becomes insufficient for HC quantification [11,73]. Additionally, the worst-case scenario often adopted in the deterministic method can easily underestimate the HC because the minimum load demand and maximum solar PV output are overestimated and unlikely to happen simultaneously [14,74].

3.2. The Time Series Method

The time series HC calculation method is an upgrade of the deterministic method. This method replaces the fixed values in the deterministic method with actual system measurements of load and PV generation for HC estimation [14]. The measurement data can be real or synthetic historical time series profiles with a long time scale and high resolution. Average values of these data on a small time scale are used for load flow calculations. During the load flow calculations, some uncertain parameters such as size, location, or the number of solar PV installations are varied until at least one of the performance indices is violated [31,40]. The time series profiles depend on the availability of requisite data, hence it typically uses 24-h generated time series data profiles based on average demand and generation values [31], least consumption and highest generation values [31], or some grid-dependent scenarios of PV generation and load consumption [29,75]. Alternatively, analytic time series data that span over a long period can be generated using techniques such as autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) [10,76–78].

Several studies have applied the time series method shown in Figure 4 to quantify the HC of real and test LV distribution grids. In [40,75], the time series method is used to study the effect of solar PV integration in existing electrical distribution grids. The authors in [40] looked at how high PV penetration affected an urban LV network in Sri Lanka considering network losses, active power flow, feeder voltage, secondary side power factor of transformers, and voltage unbalance as limiting factors. The results show overvoltage at the end of the feeder as the most violated performance limit. In [75], different PV placement and size scenarios were developed utilizing solar PV profiles based on actual data collected from a distribution network operator, as well as residential, commercial, and industrial demand profiles. The profiles were applied to an IEEE 69 bus network to assess the impact of solar PV integration on the current and voltage profile and the distribution network's system losses. Compared to residential and industrial load profiles, a higher reduction of losses was observed in the case of PV systems supplying commercial loads. This was mainly due to the coincidence of demand and PV generation.

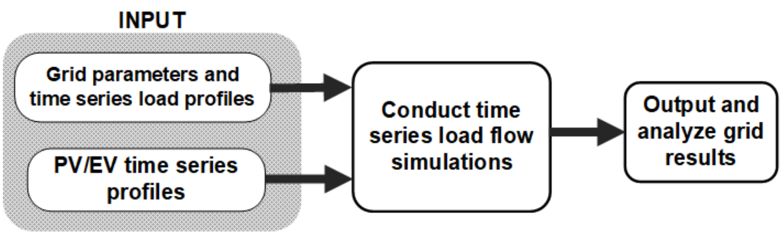

Figure 4. Time series method illustration.

High-resolution time series simulation was introduced in [79,80] to better account for the stochastic nature of solar PV generation and the load demand and to capture PV variations at smaller time frames. However, these simulation techniques are computationally complex, expensive, and time-consuming, and this has led to the development of faster methods to speed up the time series-based HC calculation simulations [81]. For example, Refs. [82,83] presented a fast scalable quasi-static time series (QSTS) simulation algorithm using a linear sensitivity model to perform time series analysis on a 3-phase unbalanced, non-radial distribution network with different discrete step control elements. The linear sensitivity model was further modified by [84] to assess the current-related PV impact on the distribution network including feeder loading and losses in the line. The results of these studies show more than a 99% reduction in computation time compared to the traditional time series method. Table 3 presents a summary of the studies that adopt the time series HC calculation method.

Table 3. Summary of studies that adopts the time series method for PV hosting capacity evaluation.

Ref.	Performance Index	Time Steps	Study Summary
[75]	Overvoltage and current magnitude	-	Studied the impact of distributed solar PV penetration using existing distribution network parameters and time-series analysis.
[76]	Voltage magnitude and loading	0.02-s for 301 min	Presented an analytic time series load flow considering the "time" sequential relation of system variables
[77]	Voltage magnitude	1-min for 1 year	Used PV and load profiles generated by the ARIMA simulator to examine the implications of various levels of penetration for a PV-wind hybrid system.
[83]	Voltage magnitude and protection	1-s for 1 year	Proposed a fast scalable quasi-static time series simulation algorithm that performs time series analysis of a 3-phase unbalanced, non-radial network 180 times faster than the traditional time series method.
[84]	Current magnitude, loading, and line losses	1-s for 1 year	Presented a rapid QSTS technique using a linear sensitivity model to evaluate current-related PV impact parameters.
[85]	Voltage magnitude	15-min for 1 year	Developed a framework that uses extreme combinations of PV production and loads time series data to study the HC of the distribution network
[86]	Voltage magnitude and loading	1-min for 24-h	Used load profile aggregation method to construct QSTS analysis of high PV penetration on the IEEE-123 distribution feeder.
[87]	Voltage magnitude	10-min for 1 week	Conducted a comparative HC study with storage deployment using time series and deterministic methods
[88]	Overvoltage and losses	1-h for 1 year	Presented a methodology to estimate the maximum PV penetration limit in an LV distribution network with regard to distribution losses by gradually increasing the PV penetration level.
[89]	Tap changer	10-min for one year	Investigated the HC at every bus in the CIGRE medium voltage electrical distribution grid.

Merits and Limitations of the Time Series HC Method

The time series method provides a more accurate estimate of the HC of distribution networks because it considers the time variation in the load demand and PV generation profiles [90]. Furthermore, the time series method can answer the when and how questions associated with HC calculations [91]. However, the method requires the availability of a huge amount of measurement data, which is a challenge to acquire. Additionally, the need for high-resolution simulations in this method is time-consuming and poses a huge computational burden [11,14].

3.3. The Stochastic Method

The stochastic method accounts for the uncertainties and unknown variables associated with the widespread connection of customer-owned solar PV systems. A primary uncertainty is the stochastic nature of the PV output that is heavily dependent on irradiation, which is influenced by changing weather conditions [11]. Similarly, other unknown variables include load consumption, the number of PV installations, and the location and size of PV installation [11]. The stochastic method considers the chance of occurrence of the unknown variables and uncertainties in the distribution network by using probabilistic load flow (PLF). To begin the PLF, random scenarios for the number, location, and/or size of PV are created as input in the distribution network using probability distribution functions (PDFs) [14]. This is followed by the load flow simulation of the network and the determination of the HC based on the performance indices whose operational limits are violated [92]. Figure 5 shows the general process of the stochastic method of HC determination for a distribution grid.

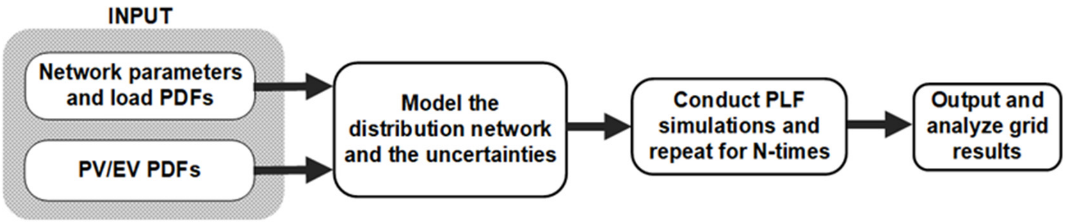

Figure 5. Stochastic method illustration.

The key part of the stochastic method is the classification and modeling of uncertainties. These uncertainties can be classified into two types, aleatory and epistemic uncertainties. Aleatory uncertainties are unknown variables that occur due to variability associated with PV generation and consumers' load consumption while epistemic uncertainties are unknown variables related to lack of information, such as the size of the PV or location of the PV on the distribution grid [11,91]. Several uncertainty modeling approaches exist in the literature including the probabilistic method, robust optimization, information gap decision theory, interval-based analysis, and hybrid probabilistic and possibilistic methods [11,93]. However, the probabilistic method is often used in the PLF with Monte Carlo Simulation (MCS) as the most common technique for generating random scenarios such as PV generation, location, size, and load profiles [55,94].

Most stochastic HC studies typically include variables from both types of uncertainties without necessarily making a distinction between the two types of uncertainties [95–98]. However, the authors in [99] proposed a mixed aleatory-epistemic method of stochastic HC estimation approach that includes the two types of uncertainties but considers them distinctively. In [100], the authors presented improved modeling of PV using actual roof data of the building for the stochastic HC calculation. The result obtained show that the approach provides improved accuracy compared to other studies that mostly use the same installed power of the solar PV for all simulated PVs. Apart from MCS, studies such as [101,102] used other techniques to generate random scenarios for PLF simulation. In [101], a binary search-based stochastic simulation is used to determine the PV HC considering the influence of the number and location of PVs. The method is more accurate and reduces the computation time when compared to the traditional stochastic approach. Similarly, the authors in [102] present a risk assessment tool for determining the HC of a distribution network using the sparse grid technique for uncertainties computation. Table 4 presents a summary of studies that adopt the stochastic method for HC calculation.

Merits and Limitations of the Stochastic HC Method

The stochastic method considers uncertainties associated with Solar PV generation and load consumption and simulates realistic grid scenarios using appropriate PDFs. However, the major disadvantage of the stochastic method is that the relationship between the network variables over time can be lost. Moreover, as the number of uncertainties increases, the stochastic method may suffer from unrealistically too many scenarios. This will translate to a need for more measurement data leading to a tedious computational process [11,91].

Table 4. Summary of studies that adopt the stochastic method for PV hosting capacity determination.

Ref	Performance Index	Simulation Technique	Study Summary
[27]	Voltage magnitude	Monte Carlo Simulation	Presented a possibilistic method based on α-Cut that evaluates the PV HC of distribution networks while accounting for aleatory uncertainty without using a probability distribution function.
[35]	Voltage magnitude, voltage unbalance, thermal limit, and loading	Simplified Monte Carlo-based method	Applied risk-based analyses to 50,000 real low voltage systems to assess the characteristics of PV hosting capacity
[101]	Voltage magnitude and thermal limit	Binary search-based stochastic simulation	Proposed a stochastic approach for PV hosting capacity determination assessment based on binary search considering the impact of the number and location of PVs.
[102]	Overvoltage and thermal limit	Sparse grid technique	Presented a risk assessment tool for quantifying the HC of a distribution grid.
[103]	Harmonic distortion	Monte Carlo Simulation	Estimated the HC of an LV distribution network using the stochastic method together with the transfer-impedance matrix for harmonic frequencies.
[104]	Overvoltage and losses	Monte Carlo Simulation	Presented a stochastic HC determination method based on the Bass diffusion model customized for each customer.
[105]	Voltage magnitude and thermal limit	Quasi Monte-Carlo Simulation	Established a tool to enable distribution network operators in sizing the maximum permissible PV integration connections.
[106]	Voltage unbalance	Monte-Carlo Simulation and Gaussian distribution model	Developed a probabilistic multi-objective voltage unbalance factor to analyze the single-phase PV hosting capacity in 3-phase residential LV distribution networks.
[107]	Voltage unbalance	Monte Carlo Simulation	Estimated the HC of two rural distribution networks with 6 and 28 customers, respectively, taking into account the negative-sequence voltage unbalance brought on by the integration of a single-phase PV system.
[108]	Voltage unbalance	Monte Carlo Simulation	Determined the single-phase PV HC of rural distribution networks considering negative-sequence voltage unbalance and uncertainties.
[109]	Voltage magnitude	The random scenario created in MATLAB	Determined the HC of PV generations on an MV distribution network considering uncertainties in the size and location of PV.
[110]	Voltage magnitude	Monte Carlo Simulation	Used a stochastic planning approach to assess the impact of upgrading service and feeder cables on the HC
[111]	Overvoltage	Monte Carlo Simulation	Proposed an overvoltage risk-based PV HC assessment approach for LV distribution networks
[112]	Voltage magnitude	Monte Carlo Simulation	Presented a two-stage framework that combines deterministic and stochastic methods for estimating PV HC.

3.4. The Optimization-Based Method

The optimization-based HC determination methods generally consider PV integration as an optimization problem. This method uses the optimal power flow technique (OPF) with the objective of maximizing the PV installed capacity while meeting the grid operational constraints. Figure 6 shows the general process of the optimization method. The most common techniques used to solve this optimization problem are Particle Swarm Optimization [113], Artificial Bee Colony [114], Robust optimization [115,116], and Genetic Algorithm [117,118]. Some studies using the optimization method can define a single objective function to maximize the HC [119,120], while other studies can set up multiple objective functions to determine the HC that results in maximizing PV installations and minimizing the network losses or cost [55,113].

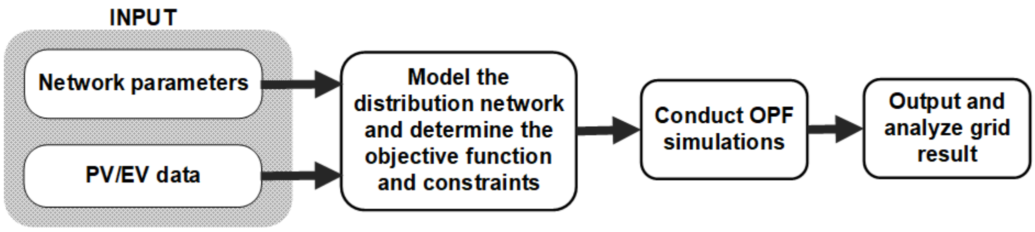

Figure 6. Optimization method illustration.

In [120], a simple power distance test tool based on OPF for HC assessment in a distribution network is presented. The studies adopted a single objective of maximizing the PV total output using voltage constraints. The results show that the developed tool can exploit more headroom of PV HC of the network compared to the existing analytical power distance tool. The authors in [119] proposed a two-stage approach to determine the maximum PV HC of a distribution network using the metaheuristics algorithm optimization technique. The method that was tested on the IEEE 123 node feeder, produced a more conservative HC value that is 13% higher when compared to the streamlined approach.

A multi-objective function optimization problem for the size and location of aggregated PV installations applied on a realistic distribution network is reported in [55]. The objective function of the study is to minimize total energy losses, voltage deviations, and voltage fluctuations. The study observed that for higher cumulative distribution functions, there was no significant difference in the probability of reverse power flow occurring. In [113], a multi-objective particle swarm optimization (PSO) algorithm with the Pareto dominance-based approach is used to optimally place an open unified power quality conditioner (UPQC-O) to maximize the PV HC and minimize distribution losses simultaneously. The results show that the addition of UPQC-O increases the PV HC and lowers the losses. However, this approach comes with an extra investment cost when compared to other approaches.

In a bid to tackle the challenge of the huge computational burden of the optimization method, several studies have utilized the linear programming technique [96,121–123]. This technique solves a set of linear power flow equations in one step without iteration. In [121], a linear power flow model which enabled a linear programming formulation was developed for HC calculation. The method was tested using the IEEE 33-bus system and the results obtained indicate that it can outperform traditional hosting capacity methods in terms of computation time but with a similar hosting capacity solution. Similarly, the authors in [122] used linear programming to determine the optimal loading capacity of a radial distribution network.

The optimization method provides a more conservative HC result for the defined constraints and covers several numbers of scenarios but requires several iterations to obtain an optimal solution. Table 5 shows a summary of the studies that adopt the optimization method. It is important to state that the deterministic, time-series or stochastic methods can be used in the optimization process. However, Table 5 is concerned with elaborating only on the optimization method used in the studies.

Table 5. Summary of studies that adopt the optimization-based method for PV hosting capacity determination.

Ref	Performance Index	Objective Function	Technique
[55]	Voltage magnitude and reverse power flow	Minimize energy losses, voltage deviation, and voltage fluctuation.	Improved particle swarm optimization
[96]	Voltage magnitude	Maximize the total PV generation.	Linear programming
[113]	Voltage magnitude and thermal limit	Maximize PV installations and minimize total network energy losses.	Particle swarm optimization.
[114]	Voltage magnitude	Minimize active power loss	Artificial bee colony
[115]	Voltage magnitude and thermal limit	Minimize total PV output	Robust comprehensive PV capacity assessment model (RC-CAM)
[116]	Voltage magnitude and thermal limit	Maximize the total PV output.	Robust optimization
[118]	Voltage magnitude, harmonic distortion, and thermal limit	Maximize the total PV output.	Genetic algorithm
[119]	Voltage magnitude	Maximize the total PV output.	Metaheuristics algorithm
[120]	Voltage magnitude, voltage unbalance, and thermal limit	Maximize the active power generation of the PV	-
[121]	Voltage magnitude and thermal limit	Minimize the power generation of PV over the uncertain variables while maximizing it over the primal variables	Linear programming
[123]	Voltage magnitude and thermal limit	Maximize the additional generation or load	Linear programming
[124]	Multiple DGs	Maximise DG output	Multistage analytical OPF algorithm
[125]	Voltage magnitude, Transformer rating, and reverse power flow	Maximise total PV output and Minimise total losses	Repeated particle swarm optimization
[126]	Voltage magnitude	Maximizing the PV generation	Linear programming
[127]	losses	Maximizing the PV generation	Particle swarm optimization.
[128]	Voltage magnitude	Maximize the total PV output.	Particle swarm optimization.

3.5. The Streamlined Method

The streamlined method uses algorithms and equations derived from thorough studies to perform HC calculations in a streamlined approach [129]. There are two types of streamlined methods in the literature, the first was developed by Electric Power Research Institute (EPRI) [10,130,131], while the other is the streamlined ICA (Integrated Capacity Analysis) method [11]. EPRI's streamlined method leverages the information taken from detailed PV HC studies of several unique distribution feeders. The trends from the initial set of power flow case studies are used to characterize the feeder response and derive a conservative, optimistic, and realistic range of HC values. The algorithm of the EPRI streamlined method is in the Distribution Resource Integration and Value Estimation (DRIVE) [132]. On the other hand, the streamlined ICA method applies a set of equations to assess the impact of distributed PV at each node of the distribution network without using a modeling tool or software. Similar to the EPRI's streamline method, the ICA method first performs a baseline power flow analysis to obtain the initial conditions of the network before evaluating the defined performance criteria [10]. The equations used for the HC calculation can be found in the PG&Es DEMO A/B report [130]. The main benefits of the streamlined methods are computational efficiency, the use of limited resources, and the ability to consider a wide range of possible PV locations. However, the streamlined HC may compromise accuracy for complex feeders with branch diversity [10,14,131]. Figure 7 shows the general process of the streamlined method while Table 6 summarizes the studies that have been conducted using the streamlined method. It is important to note that there are few studies openly available that use the streamlined method because the algorithm is mostly used by industries and regulators and is not open-sourced. Table 7 shows the merits and limitations of the different HC determination methods.

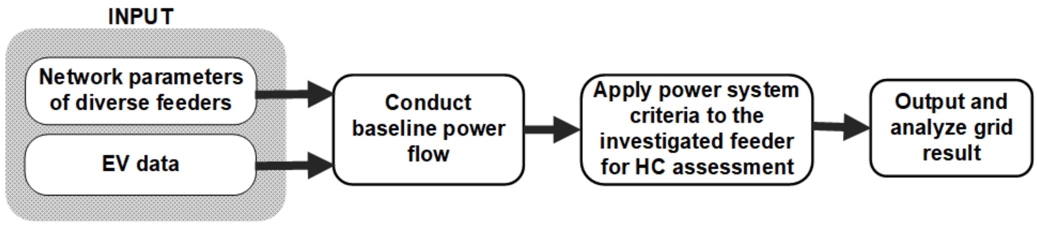

Figure 7. Streamlined method illustration.

Table 6. Summary of studies that adopt the streamlined method for PV hosting capacity determination.

Ref	Performance Index	Study Summary
[131]	Voltage magnitude, thermal limit, transformer rating, protection and reverse power flow	Outlined the streamlined method's technique by calculating the PV HC of a distribution network.
[133]	Voltage magnitude, thermal limit, transformer rating, protection, fault current, and reverse power flow	Outlined the streamlined method's technique by calculating the PV HC of a distribution network.
[134]	Voltage magnitude, thermal limit transformer rating, protection, and fault current	Provided a summary of how to use the streamlined method to assess the impacts of distributed PV integration on a distribution network.

Table 7. Merits and limitations of the HC determination methods.

Methods	Merits	Limitations
Deterministic	• Very simple, fast, and easy to implement with a less computational burden • Requires few inputs parameters • Useful for quick estimation and overview of the HC • Preferred for a single large installation	• Underestimates the HC due to overestimation of the worst-case scenario • It does not consider uncertainties • Assumes fixed input values
Time series	• Provides a more realistic HC value because it • Considers the time variation in the load consumption and PV generation profiles • Answers the 'when' and 'how' questions associated with HC calculations	• Time-consuming due to the need for high-resolution simulations • This poses a huge computational and simulation burden • A large amount of measurement data is required
Stochastic	• Considers uncertainties associated with solar PV generation and load consumption • Ability to simulate realistic grid scenarios • Presents a more realistic overview of grid performance based on PDFs	• Relationships between the network variables over time can be lost. • May suffer from unrealistically too many scenarios as the number of uncertainties increases. • The need for more measurement data leads to a tedious computation • Analyzing and interpreting HC results is difficult

Table 7. *Cont.*

Methods	Merits	Limitations
Optimization	• Provides a more conservative HC result for the defined constraints • Covers several numbers of scenarios	• Requires several iterations to obtain an optimal solution • Requires huge measurement data
Streamlined	• Computational efficiency • Uses limited resources • Ability to consider a wide range of possible PV locations	• This poses a huge computational burden • Provides approximate HC values, especially with complex feeders

4. EV Hosting Capacity Studies

The growing sales of plug-in electric vehicles (EVs) [3] imply that EV charging in the distribution network is increasing, and this translates to a corresponding increase in peak power consumption and changes in consumption patterns [135,136]. Large-scale integration and simultaneous charging of multiple EVs are identified to have a high impact on the network, creating several technical challenges for the grid. This makes the HC a useful planning tool for estimating the amount of EV charging that is possible on a distribution feeder. In this case, HC is defined as the amount of new consumption that can be connected to the network without risking the reliability or power quality of other customers [15].

The general approach for EV charging HC calculation is shown in Figure 2 only that PV is replaced by EV and in some cases, both PV and EV are combined. There are several unknowns and uncertainties associated with EV charging such as charging patterns (the key determining factor of EV impact), phase connection (single-phase or three-phase), type of charging, location of EV on the feeder, and time and duration of charging. Moreover, connecting single-phase or three-phase EVs on the distribution network causes violations of various performance limits including thermal limits and transformer overload due to increased demand, harmonics, voltage magnitude, and voltage unbalance [2,137,138].

The deterministic [139], time series [140], stochastic [141], and optimization-based [142] HC calculation methods can be used to estimate the HC of EV in the distribution network. Similar to the PV HC calculations, the uncertainties associated with EV charging can be addressed using the time series or stochastic method. The deterministic method is suitable for worst-case scenarios, while utilities can also view the EV HC as an optimization problem. A simple deterministic method is used to assess the impact of either average or peak load consumption from survey and measurement data in [139]. The limiting factors were applied for the charging cycle occurring between 6 p.m. and 10 p.m. Similarly, a deterministic method is used in [143] to estimate the HC of EV charging in a real LV network containing 13 detached single-family houses. Cable loading and voltage drop were used as the limiting factor for four case studies. The results show that a maximum of 6–11 (46% to 85%) customers can charge their EVs with 11 kW simultaneously before a violation occurs.

In [2], a stochastic approach to single-phase and three-phase EV charging HC for two existing distribution networks including aleatory and epistemic uncertainties is presented. Background voltage and under-voltage are the limiting factors, with the 10th percentile of the worst-case voltage distribution as the performance index and 90% of the nominal voltage as a limit. The results show that EV charging HC is sensitive to the lowest background voltage and highest power consumption. The method can be used at any time without detailed knowledge of the charging patterns. A stochastic approach to determine the single-phase and three-phase EV charging HC considering both aleatory and epistemic uncertainties is developed in [2], while [15] applied a simplified MCS using limited input data to determine the EV charging HC. To quantify the risk of overloading in the network, [144,145] capture the uncertainty of EV and customer loading using Poisson and Gaussian distribution models respectively.

Furthermore, different HC determination methods can be applied to EV HC studies as presented in [140]. The authors applied stochastic and time series methods to study the power quality problems of electric transportation charging of EVs on distribution systems. Stochastic measured data of EVs are used to develop stochastic harmonic analysis models and usage scenario models. The study shows transformer loading as the most violated performance limit. Furthermore, studies such as [7,146] assessed the combined effect of PV and EV integration in the distribution network. In the investigative study reported in [146], the authors used a stochastic method based on Monte Carlo simulations to assess the unified effect of solar PV and EV connections on a Brazilian LV network. The results show overvoltage as the most limiting factor in the distribution network.

It is necessary for key uncertainties such as charging patterns and types of charging to be considered in EV HC. Therefore, [142] introduced a voltage-constrained-based approach to calculate the HC of EVs under uncontrolled charging scenarios while the authors in [144] considered both uncontrolled and controlled charging schemes. Similarly, [143] developed an EV HC tool for extremely fast charging hosting options. Table 8 shows a summary of the EV charging HC studies highlighting different methods and performance indices, while Table 9 compares the different HC determination methods.

Table 8. Summary of EV charging HC studies highlighting the method and performance indices.

Ref	Performance Indices	HC Method	Study Summary
[2]	Voltage magnitude	Stochastic	Developed a method for single-phase and three-phase EV charging charge HC for two existing distribution networks including aleatory and epistemic uncertainties.
[15]	Voltage magnitude	Stochastic	Presented a method of determining the HC of EV in an LV distribution network using limited input data and simplified MCS.
[123]	Voltage magnitude and thermal limit	Optimization	Presented a mathematical model for determining a distribution network node's marginal EV charging hosting capacity.
[140]	Harmonics, low voltage, voltage unbalance, and transformer loading	Stochastic	Studied the power quality impact of electric transportation charging including EVs on distribution systems.
[142]	Voltage magnitude, thermal limits, and losses	Optimization	Proposed a rule-based algorithm based on a holistic approach to determine the EV HC of two interlinked systems.
[143]	Voltage drop and cable overloading	Deterministic	Estimated the HC of EV charging in a Swedish LV network consisting of 13 detached single-family houses.
[144]	Transformer loading	Stochastic	Proposed a model that captures the EV charging and customer load uncertainties with Poisson and Gaussian distribution models respectively.
[145]	Transformer loading and Cable loading	Stochastic	Presented a user-defined, data-driven risk assessment method to evaluate the impact of high levels of EV charging and solar PV penetration.
[146]	Voltage magnitude, voltage unbalance, and cable and transformer loading.	Stochastic	Investigated how a Brazilian LV distribution network is affected by a combination of both PV and EV connections.
[147]	Losses	Stochastic and optimization method	Presented an approach to determine the HC of a distributed resource-based generation and the number of EVs in isolated DC grids.

Table 8. *Cont.*

Ref	Performance Indices	HC Method	Study Summary
[148]	Total harmonic distortion	Stochastic	Presented the HC result on a mixture of electric vehicles from diverse brands under different states of charge and background distortion.
[149]	Voltage magnitude and voltage unbalance	Time series and stochastic	Formulated the EV HC assessment of two real Australian MV-LV networks by exploring multiple EV penetrations.
[150]	Voltage magnitude and thermal limit	Optimization	Proposed the concept of "EV chargeable region" to determine the EV HC for each node.
[151]	Voltage magnitude, voltage unbalance, and transformer loading	Time series and stochastic	Introduced a voltage-constrained-based approach to calculate the HC EVs under an uncontrolled charging scenario.
[152]	Voltage magnitude and thermal limit	Deterministic	Developed an EV HC tool for an extremely fast charging hosting option.
[153]	-	Time series and stochastic	Used additional available power (AAP) as an indicator in the hybrid algorithm to determine the EV HC during controlled and uncontrolled charging.
[154]	Voltage magnitude, and transformer and cable loading	Deterministic and stochastic	Carried out a wide-scale study to estimate EV HC using data readily available to utility engineers.
[155]	Voltage magnitude	Time series and stochastic	Compared how much impact the different types of EV charging can contribute to PV HC.

Table 9. Comparison of the different HC determination methods.

Features	Deterministic	Time Series	Stochastic	Optimization	Streamlined
Data requirements	Low	Huge	Moderate	Moderate	Moderate
Consideration of uncertainties	None	Few	Various	Various	Various
Computation time	Short	Moderate	Huge	Huge	Moderate
Complexity	Simple	Moderate	Complex	Complex	Complex
No. of scenarios considered	Few	Few	Many	Various	Various
Correctness of Results	Approximate	Correct	Correct	Precise (based on the chosen constraint)	Approximate

5. Hosting Capacity Determination Tools

This section presents software applications that offer off-the-counter HC calculation tools and functions. The information presented in this section is primarily based on what is available online on the website of the software providers and the user manuals. A broader range of other power system tools that can be used for HC determination is listed in [156].

5.1. PowerFactory

PowerFactory is a power system modeling and simulation software application developed by DIgSILENT. The software application can easily be used for analyzing generation, transmission, distribution, and industrial systems. Recent versions of the software have an HC calculation tool for a distribution network considering voltage, thermal, protection, and power quality limits. Moreover, there are quasi-dynamic simulation and scripting functions that are useful for time series and stochastic impact assessment of PV and EV integration. PowerFactory uses an iterative method (stochastic method) for HC determination and detailed information about the software and its functions can be found in [157].

5.2. PSS Sincal ICA

PSS Sincal ICA (Integrated Capacity Analysis) module developed by Siemens automatically determines the maximum PV generation or load capacity that can be independently installed at a respective node of the distribution network without violating user-given constraints. The ICA is a module for HC calculation in the PSS Sincal software. The software has a wide variety of functions for the analysis of power system operation, planning, and modeling of distribution, transmission, industrial, and renewable energy systems. The ICA HC analysis uses the time series fully iterative method to evaluate criteria such as thermal loading, protection, reverse power flow, voltage limits, voltage fluctuations, and short-circuit persistence of network equipment. More information about the PSS Sincal and its ICA module can be found in [158,159].

5.3. Synergi Electric

Synergi Electric is a power distribution system analysis and electrical simulation software developed by DNV GL. The tool provided in the software uses five different methods for HC calculation in the distribution network, which are stochastic, feeder rating, feeder maximum demand, incremental, and sectional incremental. A detailed procedure of how these methods work within the software and the description of the software itself can be seen in [160,161].

5.4. NEPLAN

NEPLAN is an electrical power system analysis software tool that is used for network planning, simulation, optimization, and analysis. It provides a module within the software that can model PVs and EVs for stochastic evaluation of the HC of the distribution network. The stochastic method adopted in NEPLAN is based on Monte Carlo simulation and considers limiting factors such as voltage violations, equipment overloading, and other performance indices [162].

5.5. CYME

CYME power engineering simulation tool developed by EATON has two modules that use streamlined methods to determine the hosting capacity of a distribution grid: EPRI DRIVE module and the Integration Capacity Analysis module [163]. The Distribution Resource Integration and Value Estimation (DRIVE) module developed by the EPRI is used in the CYME software to calculate the HC for PV and other DER technologies using performance limits such as protection, power quality, voltage, thermal, and reliability/safety [164]. The Integration Capacity Analysis (ICA) module in CYME uses a streamlined iterative method based on the constant source technique to determine how much generation or load can be independently added to a distribution network node. Voltage change, thermal loading, steady-state voltages, protection, reverse power flow, and sympathetic tripping are the limiting criteria for the HC quantification available in the software [165]. Table 10 presents a summary of the HC evaluation software tools, their HC calculation method, and the performance indices that can be assessed.

Table 10. Summary of HC evaluation Software tools.

Software	Method	Limits
PowerFactory	Stochastic (Based on Standard binomial search method)	Voltage Power quality Thermal Protection
PSS Sincal ICA	Time series	Voltage Short-circuit Thermal Protection Voltage fluctuations Reverse power flow
Synergi Electric	Stochastic (Based on Random placement method) iterative time series	Overvoltage Thermal Reverse power flow
NEPLAN	Stochastic (Based on Monte Carlo Simulation)	Voltage Thermal Other performance indices
CYME (ICA)	Streamlined (Iterative constant source)	Voltage Voltage fluctuations Thermal Protection Reverse power flow Sympathetic tripping
CYME (EPRI DRIVE)	Streamlined	Voltage Power quality Thermal Protection Reliability/Safety

6. Conclusions

Due to the importance of hosting capacity studies in modern electrical power systems, this paper has conducted a comprehensive review of the HC concept, methods, and tools based on a survey of state-of-the-art literature published within the last five years (2017–2022). It presents five HC calculation methods; deterministic, time series, stochastic, optimization-based, and streamlined, commonly used for PV and EV HC studies.

In summary, the deterministic HC determination method is simple, does not consider uncertainties, and can be used to quickly estimate the HC. The time series method uses actual system measurements of load and PV generation historical time series profiles with a long time scale and high resolution for HC calculation. The stochastic method considers the chance of occurrence of the unknown variables and uncertainties associated with solar PV and EV charging integration in the distribution network by using probabilistic load flow. The optimization-based method views the HC as an optimization problem with the goal of maximizing PV output and EV charging through the use of optimal power flow strategies. The streamlined method uses algorithms and equations derived from trends obtained from thorough studies to estimate the HC in a streamlined approach. It is important to note that no particular method or tool is most suitable for HC determination since the characteristics of each LV network are not homogenous. This is why some studies adopt hybrid HC determination methods for robustness and to maximize the advantages of the different methods. It is observed from the survey that most of the HC studies of PV and EV charging in the LV distribution network consider voltage magnitude, line loading, and transformer loading as performance indices. The selection of the performance indices, the definition of their acceptable limits, and the non-homogeneity of distribution networks affect the outcome of the HC for a particular distribution grid.

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References

1. Haque, M.; Wolfs, P. A review of high PV penetrations in LV distribution networks: Present status, impacts and mitigation measures. *Renew. Sustain. Energy Rev.* **2016**, *62*, 1195–1208. [CrossRef]
2. Mulenga, E.; Bollen, M.; Etherden, N. Adapted Stochastic PV Hosting Capacity Approach for Electric Vehicle Charging Considering Undervoltage. *Electricity* **2021**, *2*, 387–402. [CrossRef]
3. EV Sales. Available online: https://cleantechnica.com/tag/ev-sales/ (accessed on 11 November 2022).
4. 3 Charts that Show the State of Europe's Energy Crisis Right Now. Available online: https://www.weforum.org/agenda/2022/10/europe-energy-crisis-gas-report-iea/ (accessed on 29 November 2022).
5. IEA. Europe Needs to Take Immediate Action to Avoid Risk of Natural Gas Shortage Next Year. Available online: https://www.iea.org/news/europe-needs-to-take-immediate-action-to-avoid-risk-of-natural-gas-shortage-next-year (accessed on 29 November 2022).
6. Ogunboyo, P.T.; Tiako, R.; Davidson, I.E. Effectiveness of Dynamic Voltage Restorer for Unbalance Voltage Mitigation and Voltage Profile Improvement in Secondary Distribution System. *Can. J. Electr. Comput. Eng.* **2018**, *41*, 105–115. [CrossRef]
7. 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]
8. *NRS 097-2-1*; Grid Interconnection of Embedded Generation. 2017. Available online: https://www.sseg.org.za/wp-content/uploads/2017/01/NRS-097-2-1-2017-Edition-2.1-published-2020-07-20.pdf (accessed on 26 February 2023).
9. *EN 50160:2010*; Voltage Characteristic of Electricity Supplied by Public Electricity Networks. European Commitee for Electrotechnical Standardization (CENELEC). 2010. Available online: https://standards.iteh.ai/catalog/standards/clc/18a86a7c-e08e-405e-88cb-8a24e5fedde5/en-50160-2010 (accessed on 26 February 2023).
10. Rajabi, A.; Elphick, S.; David, J.; Pors, A.; Robinson, D. Innovative approaches for assessing and enhancing the hosting capacity of PV-rich distribution networks: An Australian perspective. *Renew. Sustain. Energy Rev.* **2022**, *161*, 112365. [CrossRef]
11. Mulenga, E.; Bollen, M.H.J.; Etherden, N. A review of hosting capacity quantification methods for photovoltaics in low-voltage distribution grids. *Int. J. Electr. Power Energy Syst.* **2020**, *115*, 105445. [CrossRef]
12. Fatima, S.; Püvi, V.; Lehtonen, M. Review on the PV hosting capacity in distribution networks. *Energies* **2020**, *13*, 4756. [CrossRef]
13. Ismael, S.M.; Aleem, S.H.E.A.; 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]
14. Abideen, M.Z.; Ellabban, O.; Al-Fagih, L. A review of the tools and methods for distribution networks' hosting capacity calculation. *Energies* **2020**, *13*, 2758. [CrossRef]
15. Bollen, M.H.; Rönnberg, S.K. Hosting capacity of the power grid for renewable electricity production and new large consumption equipment. *Energies* **2017**, *10*, 1325. [CrossRef]
16. Hatziargyriou, N.; Karfopoulos, E.; Tsitsimelis, A.; Koukoula, D.; Rossi, M.; Giacomo, V. On the der hosting capacity of distribution feeders. In Proceedings of the CIRED 23rd International Conference on Electricity Distribution, Lyon, France, 15–18 June 2015.
17. Deuse, J.; Benintendi, D.; Agrell, P.; Bogetoft, P. Power system and market integration of der, the eu-deep approach. In Proceedings of the CIRED 2005-18th International Conference and Exhibition on Electricity Distribution, Turin, Italy, 6–9 June 2005; IET: Stevenage, UK, 2005; pp. 1–4.
18. Bollen, M.; Yang, Y.; Hassan, F. Integration of distributed generation in the power system-a power quality approach. In Proceedings of the 2008 13th International Conference on Harmonics and Quality of Power, Wollongong, NSW, Australia, 28 September–1 October 2008; IEEE: Piscataway, NJ, USA, 2008; pp. 1–8.
19. Bollen, M.H.; Hassan, F. *Integration of Distributed Generation in the Power System*; John Wiley & Sons: Hoboken, NJ, USA, 2011.
20. Rodriguez-Calvo, A.; Cossent, R.; Frías, P. Integration of PV and EVs in unbalanced residential LV networks and implications for the smart grid and advanced metering infrastructure deployment. *Int. J. Electr. Power Energy Syst.* **2017**, *91*, 121–134. [CrossRef]
21. Cundeva, S.; Mateska, A.K.; Bollen, M.H. Hosting capacity of LV residential grid for uncoordinated EV charging. In Proceedings of the 2018 18th International Conference on Harmonics and Quality of Power (ICHQP), Ljubljana, Slovenia, 13–16 May 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–5.

22. Avila-Rojas, A.E.; Oliveira-De Jesus, M.D. Alvarez Distribution network electric vehicle hosting capacity enhancement using an optimal power flow formulation. *Electr. Eng.* **2022**, *104*, 1337–1348. [CrossRef]
23. Fatima, S.; Püvi, V.; Lehtonen, M. Lehtonen Comparison of Different References When Assessing PV HC in Distribution Networks. *Clean Technol.* **2021**, *3*, 123–137. [CrossRef]
24. Kikuchi, S.; Machida, M.; Tamura, J.; Imanaka, M.; Baba, J.; Iioka, D.; Miura, K.; Takagi, M.; Asano, H. Hosting capacity analysis of many distributed photovoltaic systems in future distribution networks. In Proceedings of the 2017 IEEE Innovative Smart Grid Technologies-Asia (ISGT-Asia), Auckland, New Zealand, 4–7 December 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–5.
25. Saber, A.Y.; Khandelwal, T.; Srivastava, A.K. Srivastava Fast feeder PV hosting capacity using swarm based intelligent distribution node selection. In Proceedings of the 2019 IEEE Power & Energy Society General Meeting (PESGM), Atlanta, GA, USA, 4–8 August 2019; IEEE: Piscataway, NJ, USA, 2019.
26. Asano, M.; Wong, F.; Ueda, R.; Moghe, R.; Rahimi, K.; Chun, H.; Tholomier, D. On the interplay between svcs and smart inverters for managing voltage on distribution networks. In Proceedings of the 2019 IEEE Power & Energy Society General Meeting (PESGM), Atlanta, GA, USA, 4–8 August 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–5.
27. Yao, H.; Qin, W.; Jing, X.; Zhu, Z.; Wang, K.; Han, X.; Wang, P. Possibilistic evaluation of photovoltaic hosting capacity on distribution networks under uncertain environment. *Appl. Energy* **2022**, *324*, 119681. [CrossRef]
28. Haghi, H.V.; Pecenak, Z.; Kleissl, J.; Peppanen, J.; Rylander, M.; Renjit, A.; Coley, S. Feeder impact assessment of smart inverter settings to support high PV penetration in California. In Proceedings of the 2019 IEEE Power & Energy Society General Meeting (PESGM), Atlanta, GA, USA, 4–8 August 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–5.
29. Essackjee, I.A.; King, R.T.A. King Maximum Rooftop Photovoltaic Hosting Capacity with Harmonics as Limiting Factor–Case Study for Mauritius. In Proceedings of the 2019 International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD), Winterton, South Africa, 5–6 August 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–6.
30. Padullaparti, H.V.; Jothibasu, S.; Santoso, S.; Todeschini, G. Increasing feeder PV hosting capacity by regulating secondary circuit voltages. In Proceedings of the 2018 IEEE Power & Energy Society General Meeting (PESGM), Portland, OR, USA, 5–10 August 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–5.
31. Steyn, A.F.; Rix, A.J. Modelling the technical influence of randomly distributed solar PV uptake on electrical distribution networks. In Proceedings of the 2019 International Conference on Clean Electrical Power (ICCEP), Otranto, Italy, 2–4 July 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 690–698.
32. Ding, F.; Mather, B. On distributed PV hosting capacity estimation, sensitivity study, and improvement. *IEEE Trans. Sustain. Energy* **2016**, *8*, 1010–1020. [CrossRef]
33. Mohammadi, P.; Mehraeen, S. Challenges of PV Integration in Low-Voltage Secondary Networks. *IEEE Trans. Power Deliv.* **2017**, *32*, 525–535. [CrossRef]
34. Gaunt, C.; Namanya, E.; Herman, R. Voltage modelling of LV feeders with dispersed generation: Limits of penetration of randomly connected photovoltaic generation. *Electr. Power Syst. Res.* **2017**, *143*, 1–6. [CrossRef]
35. Torquato, R.; Salles, D.; Pereira, C.O.; Meira, P.C.M.; Freitas, W. A comprehensive assessment of PV hosting capacity on low-voltage distribution systems. *IEEE Trans. Power Deliv.* **2018**, *33*, 1002–1012. [CrossRef]
36. Singh, N.K.; Wanik, M.; Jabbar, A.A.; Sanfilippo, A. Enhancing PV hosting Capacity of a Qatar Remote Farm Network using Inverters Ability to Regulate Reactive Power-a Case Study. In Proceedings of the 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), Bucharest, Romania, 29 September–2 October 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–5.
37. Arshad, A.; Püvi, V.; Lehtonen, M. Monte Carlo-based comprehensive assessment of PV hosting capacity and energy storage impact in realistic finnish low-voltage networks. *Energies* **2018**, *11*, 1467. [CrossRef]
38. Rahman, M.M.; Arefi, A.; Shafiullah, G.; Hettiwatte, S. A new approach to voltage management in unbalanced low voltage networks using demand response and OLTC considering consumer preference. *Int. J. Electr. Power Energy Syst.* **2018**, *99*, 11–27. [CrossRef]
39. Martin, W.; Stauffer, Y.; Ballif, C.; Hutter, A.; Alet, P.-J. Automated quantification of PV hosting capacity in distribution networks under user-defined control and optimisation procedures. In Proceedings of the 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Sarajevo, Bosnia and Herzegovina, 21–25 October 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
40. Chathurangi, D.; Jayatunga, U.; Rathnayake, M.; Wickramasinghe, A.; Agalgaonkar, A.; Perera, S. Potential power quality impacts on LV distribution networks with high penetration levels of solar PV. In Proceedings of the 2018 18th International Conference on Harmonics and Quality of Power (ICHQP), Ljubljana, Slovenia, 13–16 May 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
41. Pukhrem, S.; Basu, M.; Conlon, M.F.; Sunderland, K. Enhanced network voltage management techniques under the proliferation of rooftop solar PV installation in low-voltage distribution network. *IEEE J. Emerg. Sel. Top. Power Electron.* **2016**, *5*, 681–694. [CrossRef]
42. Rahman, M.M.; Shafiullah, G.; Arefi, A.; Pezeshki, H.; Hettiwatte, S. Improvement of voltage magnitude and unbalance in LV network by implementing residential demand response. In Proceedings of the 2017 IEEE Power & Energy Society General Meeting, Chicago, IL, USA, 16–20 July 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–5.

43. Guevara, D.P.; Correa-Florez, C.A.; Ordóñez-Plata, G. Assessment of harmonic distortion associated with pv penetration in a low voltage distribution network. In *2020 IEEE PES Transmission & Distribution Conference and Exhibition-Latin America (T&D LA)*; IEEE: Piscataway, NJ, USA, 2020; pp. 1–6.
44. Chathurangi, D.; Jayatunga, U.; Perera, S.; Agalgaonkar, A.; Siyambalapitiya, T.; Wickramasinghe, A. Connection of Solar PV to LV Networks: Considerations for Maximum Penetration Level. In Proceedings of the 2018 Australasian Universities Power Engineering Conference (AUPEC), Auckland, New Zealand, 27–30 November 2018; pp. 1–6. [CrossRef]
45. Procopiou, A.T.; Ochoa, L.F. Voltage control in PV-rich LV networks without remote monitoring. *IEEE Trans. Power Syst.* **2016**, *32*, 1224–1236. [CrossRef]
46. Long, C.; Ochoa, L.F. Voltage control of PV-rich LV networks: OLTC-fitted transformer and capacitor banks. *IEEE Trans. Power Syst.* **2015**, *31*, 4016–4025. [CrossRef]
47. Sarmiento, D.A.; Vergara, P.P.; Da Silva, L.C.; De Almeida, M.C. Increasing the PV hosting capacity with OLTC technology and PV VAr absorption in a MV/LV rural Brazilian distribution system. In Proceedings of the 2016 17th International Conference on Harmonics and Quality of Power (ICHQP), Belo Horizonte, Brazil, 16–19 October 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 395–399.
48. Aziz, T.; Ketjoy, N. PV penetration limits in low voltage networks and voltage variations. *IEEE Access* **2017**, *5*, 16784–16792. [CrossRef]
49. Yan, R.; Saha, T.K. Investigation of voltage stability for residential customers due to high photovoltaic penetrations. *IEEE Trans. Power Syst.* **2012**, *27*, 651–662. [CrossRef]
50. Alam, M.; Muttaqi, K.; Sutanto, D. Distributed energy storage for mitigation of voltage-rise impact caused by rooftop solar PV. In Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 1–8.
51. Heinrich, C.; Fortenbacher, P.; Fuchs, A.; Andersson, G. PV-integration strategies for low voltage networks. In Proceedings of the 2016 IEEE International Energy Conference (ENERGYCON), Leuven, Belgium, 4–8 April 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1–6.
52. Divshali, P.H.; Soder, L. Improving hosting capacity of rooftop PVs by quadratic control of an LV-central BSS. *IEEE Trans. Smart Grid* **2017**, *10*, 919–927. [CrossRef]
53. Divshali, P.H.; Soder, L. Improving PV hosting capacity of distribution grids considering dynamic voltage characteristic. In Proceedings of the 2018 Power Systems Computation Conference (PSCC), Dublin, Ireland, 11–15 June 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–7.
54. Weisshaupt, M.J.; Schlatter, B.; Korba, P.; Kaffe, E.; Kienzle, F. Evaluation of measures to operate urban low voltage grids considering future PV expansion. *IFAC-PapersOnLine* **2016**, *49*, 336–341. [CrossRef]
55. Sadeghian, H.; Wang, Z. A novel impact-assessment framework for distributed PV installations in low-voltage secondary networks. *Renew. Energy* **2020**, *147*, 2179–2194. [CrossRef]
56. Braga, M.D.; Machado, S.D.; Oliveira, I.C.; De Oliveira, T.E.C.; Ribeiro, P.F.; Lopes, B.I.L. Lopes Harmonic hosting capacity approach in a radial distribution system due to pv integration using opendss. In Proceedings of the 2018 13th IEEE International Conference on Industry Applications (INDUSCON), Sao Paulo, Brazil, 12–14 November 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 222–228.
57. Quintero-Molina, V.; Romero, M.; Pavas, A. Pavas Assessment of the hosting capacity in distribution networks with different DG location. In Proceedings of the 2017 IEEE Manchester PowerTech, Manchester, UK, 18–22 June 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
58. Putranto, L.M. Study on Photovoltaic Hosting in Yogyakarta Electric Distribution Network. In Proceedings of the 2018 5th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE), Semarang, Indonesia, 27–28 September 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 240–244.
59. Hartvigsson, E.; Odenberger, M.; Chen, P.; Nyholm, E. Estimating national and local low-voltage grid capacity for residential solar photovoltaic in Sweden, UK and Germany. *Renew. Energy* **2021**, *171*, 915–926. [CrossRef]
60. Navarro, B.B.; Navarro, M.M. A comprehensive solar PV hosting capacity in MV and LV radial distribution networks. In Proceedings of the 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Torino, Italy, 26–29 September 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
61. Soukaina, N.; Hassane, E.; Tijani, L. Hosting capacity estimation of underground distribution feeder in Urbain Areas. In Proceedings of the International Conference on Wireless Technologies, Embedded and Intelligent Systems (WITS), Fez, Morocco, 3–4 April 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–5.
62. Kharrazi, A.; Sreeram, V.; Mishra, Y. Assessment techniques of the impact of grid-tied rooftop photovoltaic generation on the power quality of low voltage distribution network—A review. *Renew. Sustain. Energy Rev.* **2020**, *120*, 109643. [CrossRef]
63. Ebe, F.; Idlbi, B.; Morris, J.; Heilscher, G.; Meier, F. Evaluation of PV hosting capacity of distribuion grids considering a solar roof potential analysis—Comparison of different algorithms. In Proceedings of the 2017 IEEE Manchester PowerTech, Manchester, UK, 18–22 June 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
64. Peppanen, J.; Bello, M.; Rylander, M. Service entrance hosting capacity. In Proceedings of the 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC)(A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC), Waikoloa Village, HI, USA, 10–15 June 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1451–1456.

65. Heslop, S.; MacGill, I.; Fletcher, J. Maximum PV generation estimation method for residential low voltage feeders. *Sustain. Energy Grids Netw.* **2016**, *7*, 58–69. [CrossRef]
66. Ampofo, D.O.; Otchere, I.K.; Frimpong, E.A. An investigative study on penetration limits of distributed generation on distribution networks. In Proceedings of the 2017 IEEE PES PowerAfrica, Accra, Ghana, 27–30 June 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 573–576.
67. de Oliveira, T.E.C.; Carvalho, P.M.S.; Ribeiro, P.F.; Bonatto, B.D. Bonatto PV hosting capacity dependence on harmonic voltage distortion in low-voltage grids: Model validation with experimental data. *Energies* **2018**, *11*, 465. [CrossRef]
68. Luthander, R.; Lingfors, D.; Widén, J. Large-scale integration of photovoltaic power in a distribution grid using power curtailment and energy storage. *Sol. Energy* **2017**, *155*, 1319–1325. [CrossRef]
69. Deng, Z.; Rotaru, M.D.; Sykulski, J.K. Harmonic Analysis of LV distribution networks with high PV penetration. In Proceedings of the 2017 International Conference on Modern Power Systems (MPS), Cluj-Napoca, Romania, 6–9 June 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
70. Fan, S.; Li, C.; Wei, Z.; Pu, T.; Liu, X. Method to determine the maximum generation capacity of distribution generation in low-voltage distribution feeders. *J. Eng.* **2017**, *2017*, 944–948. [CrossRef]
71. Heilscher, G.; Ebe, F.; Idlbi, B.; Morris, J.; Meier, F. Evaluation of PV Hosting Capacities of Distribution Grids with Utilization of Solar-Roof-Potential-Analyses. In Proceedings of the 2017 IEEE 44th Photovoltaic Specialist Conference (PVSC), Washington, DC, USA, 25–30 June 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 2996–3001.
72. Schwanz, D.; Möller, F.; Rönnberg, S.K.; Meyer, J.; Bollen, M.H. Stochastic assessment of voltage unbalance due to single-phase-connected solar power. *IEEE Trans. Power Deliv.* **2017**, *32*, 852–861. [CrossRef]
73. Deboever, J.; Grijalva, S.; Reno, M.J.; Broderick, R.J. Fast quasi-static time-series (QSTS) for yearlong PV impact studies using vector quantization. *Sol. Energy* **2018**, *159*, 538–547. [CrossRef]
74. Abad, M.S.S.; Ma, J.; Zhang, D.; Ahmadyar, A.S.; Marzooghi, H. Sensitivity of hosting capacity to data resolution and uncertainty modeling. In Proceedings of the 2018 Australasian Universities Power Engineering Conference (AUPEC), Auckland, New Zealand, 27–30 November 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
75. Athari, M.H.; Wang, Z.; Eylas, S.H. Time-series analysis of photovoltaic distributed generation impacts on a local distributed network. In Proceedings of the 2017 IEEE Manchester PowerTech, Manchester, UK, 18–22 June 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
76. Samet, H.; Khorshidsavar, M. Analytic time series load flow. *Renew. Sustain. Energy Rev.* **2018**, *82*, 3886–3899. [CrossRef]
77. Behravesh, V.; Keypour, R.; Foroud, A.A. Stochastic analysis of solar and wind hybrid rooftop generation systems and their impact on voltage behavior in low voltage distribution systems. *Sol. Energy* **2018**, *166*, 317–333. [CrossRef]
78. Lamprianidou, I.S.; Papadopoulos, T.A.; Kryonidis, G.C.; Papagiannis, G.K.; Bouhouras, A.S. Impact of Data-Driven Modelling Approaches on the Analysis of Active Distribution Networks. In Proceedings of the 2019 54th International Universities Power Engineering Conference (UPEC), Bucharest, Romania, 3–6 September 2019; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
79. Deboever, J.; Grijalva, S.; Peppanen, J.; Rylander, M.; Smith, J. Practical data-driven methods to improve the accuracy and detail of hosting capacity analysis. In Proceedings of the 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC) (A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC), Waikoloa Village, HI, USA, 10–15 June 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 3676–3681.
80. Qureshi, M.U.; Kumar, A.; Grijalva, S.; Deboever, J.; Peppanen, J.; Rylander, M. Fast Hosting Capacity Analysis for Thermal Loading Constraint Using Sensitivity-based Decomposition Method. In Proceedings of the 2020 52nd North American Power Symposium (NAPS), Tempe, AZ, USA, 11–13 April 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 1–5.
81. Broderick, R.J.; Reno, M.J.; Lave, M.S.; Azzolini, J.A.; Blakely, L.; Galtieri, J.; Mather, B.; Weekley, A.; Hunsberger, R.; Chamana, M.; et al. *Rapid QSTS Simulations for High-Resolution Comprehensive Assessment of Distributed PV*; Sandia National Lab.(SNL-CA): Livermore, CA, USA, 2021.
82. Qureshi, M.U.; Grijalva, S.; Reno, M.J. A fast quasi-static time series simulation method for pv smart inverters with var control using linear sensitivity model. In Proceedings of the 2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC) (A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC), Waikoloa Village, HI, USA, 10–15 June 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1614–1619.
83. Qureshi, M.U.; Grijalva, S.; Reno, M.J.; Deboever, J.; Zhang, X.; Broderick, R.J. A fast scalable quasi-static time series analysis method for PV impact studies using linear sensitivity model. *IEEE Trans. Sustain. Energy* **2018**, *10*, 301–310. [CrossRef]
84. Qureshi, M.U.; Grijalva, S.; Reno, M.J. A Rapid Quasi-Static Time Series Method for Evaluating Current-Related Distributed PV Impacts including Feeder Loading and Line Losses. In Proceedings of the 2019 IEEE Power & Energy Society General Meeting (PESGM), Atlanta, GA, USA, 4–8 August 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–5.
85. Liu, D.; Wang, C.; Tang, F.; Zhou, Y. Probabilistic Assessment of Hybrid Wind-PV Hosting Capacity in Distribution Systems. *Sustainability* **2020**, *12*, 2183. [CrossRef]
86. Wang, J.; Zhu, X.; Lubkeman, D.; Lu, N.; Samaan, N.; Werts, B. Load aggregation methods for quasi-static power flow analysis on high PV penetration feeders. In Proceedings of the 2018 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), Denver, CO, USA, 16–19 April 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–5.
87. Bartecka, M.; Barchi, G.; Paska, J. Time-series PV hosting capacity assessment with storage deployment. *Energies* **2020**, *13*, 2524. [CrossRef]

88. Abideen, M.Z.U.; Ellabban, O.; Refaat, S.S.; Abu-Rub, H.; Al-Fagih, L. A novel methodology to determine the maximum PV penetration in distribution networks. In Proceedings of the 2019 2nd International Conference on Smart Grid and Renewable Energy (SGRE), Doha, Qatar, 19–21 November 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–6.
89. Do, M.T.; Bruyere, A.; Francois, B. Sensitivity analysis of the CIGRE distribution network benchmark according to the large scale connection of renewable energy generators. In Proceedings of the 2017 IEEE Manchester PowerTech, Manchester, UK, 18–22 June 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
90. de Oliveira, T.E.C.; Bollen, M.; Ribeiro, P.F.; de Carvalho, P.M.S.; Zambroni, A.C.; Bonatto, B.D. The concept of dynamic hosting capacity for distributed energy resources: Analytics and practical considerations. *Energies* **2019**, *12*, 2576. [CrossRef]
91. Mulenga, E.; Bollen, M.H.; Etherden, N. Solar PV hosting capacity methods and industrial application gaps. In Proceedings of the CIRED 2021-The 26th International Conference and Exhibition on Electricity Distribution, Online, 20–23 September 2021; IET: Stevenage, UK, 2021; Volume 2021, pp. 1757–1761.
92. Rossi, M.; Viganò, G.; Moneta, D.; Clerici, D. Stochastic evaluation of distribution network hosting capacity: Evaluation of the benefits introduced by smart grid technology. In Proceedings of the 2017 AEIT International Annual Conference, Cagliari, Italy, 20–22 September 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
93. Zubo, R.H.; Mokryani, G.; Rajamani, H.S.; Aghaei, J.; Niknam, T.; Pillai, P. Operation and planning of distribution networks with integration of renewable distributed generators considering uncertainties: A review. *Renew. Sustain. Energy Rev.* **2017**, *72*, 1177–1198. [CrossRef]
94. Koirala, A.; Van Acker, T.; D'hulst, R.; Van Hertem, D. Uncertainty quantification in low voltage distribution grids: Comparing Monte Carlo and general polynomial chaos approaches. *Sustain. Energy Grids Netw.* **2022**, *31*, 100763. [CrossRef]
95. Arshad, A.; Lehtonen, M. A stochastic assessment of PV hosting capacity enhancement in distribution network utilizing voltage support techniques. *IEEE Access* **2019**, *7*, 46461–46471. [CrossRef]
96. Abad, M.S.S.; Ma, J.; Zhang, D.; Ahmadyar, A.S.; Marzooghi, H. Probabilistic assessment of hosting capacity in radial distribution systems. *IEEE Trans. Sustain. Energy* **2018**, *9*, 1935–1947. [CrossRef]
97. Pukhrem, S.; Basu, M.; Conlon, M.F. Probabilistic risk assessment of power quality variations and events under temporal and spatial characteristic of increased PV integration in low-voltage distribution networks. *IEEE Trans. Power Syst.* **2018**, *33*, 3246–3254. [CrossRef]
98. Deakin, M.; Crozier, C.; Apostolopoulou, D.; Morstyn, T.; McCulloch, M. Stochastic Hosting Capacity in LV Distribution Networks. In Proceedings of the 2019 IEEE Power & Energy Society General Meeting (PESGM), Atlanta, GA, USA, 4–8 August 2019; IEEE: Piscataway, NJ, USA, 2019.
99. Mulenga, E.; Bollen, M.H.J.; Etherden, N. Solar PV stochastic hosting capacity in distribution networks considering aleatory and epistemic uncertainties. *Int. J. Electr. Power Energy Syst.* **2021**, *130*, 106928. [CrossRef]
100. Grabner, M.; Souvent, A.; Suljanović, N.; Košir, A.; Blažič, B. Probabilistic Methodology for Calculating PV Hosting Capacity in LV Networks Using Actual Building Roof Data. *Energies* **2019**, *12*, 4086. [CrossRef]
101. Chen, C.; Li, W.; Yu, B.; Wu, L. An improved stochastic approach for PV's hosting capacity assessment based on binary search. In Proceedings of the 10th Renewable Power Generation Conference (RPG 2021), Online, 1–2 March 2021; IET: Stevenage, UK, 2021; Volume 2021, pp. 539–545.
102. 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]
103. Schwanz, D.; Busatto, T.; Bollen, M.; Larsson, A. A stochastic study of harmonic voltage distortion considering single-phase photovoltaic inverters. In Proceedings of the 2018 18th International Conference on Harmonics and Quality of Power (ICHQP), Ljubljana, Slovenia, 13–16 May 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
104. Abud, T.P.; Cataldo, E.; Maciel, R.S.; Borba, B.S. A modified Bass model to calculate PVDG hosting capacity in LV networks. *Electr. Power Syst. Res.* **2022**, *209*, 107966. [CrossRef]
105. Al-Saadi, H.; Zivanovic, R.; Al-Sarawi, S.F. Probabilistic analysis of maximum allowable PV connections across bidirectional feeders within a distribution network. In Proceedings of the 2017 Asian Conference on Energy, Power and Transportation Electrification (ACEPT), Singapore, 24–26 October 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
106. Hung, D.Q.; Mishra, Y. A Multiobjective Voltage Unbalance Factor for PV Hosting Capacity with Probabilistic ZIP Load Models. In Proceedings of the 2018 IEEE Power & Energy Society General Meeting (PESGM), Portland, OR, USA, 5–10 August 2018; IEEE: Piscataway, NJ, USA, 2018.
107. Schwanz, D.; Rönnberg, S.K.; Bollen, M. Hosting capacity for photovoltaic inverters considering voltage unbalance. In Proceedings of the 2017 IEEE Manchester PowerTech, Manchester, UK, 18–22 June 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
108. Schwanz, D.; Rönnberg, S.; Bollen, M. Voltage unbalance due to single-phase photovoltaic inverters. *CIRED-Open Access Proc. J.* **2017**, *2017*, 906–910. [CrossRef]
109. Liu, Y.J.; Tai, Y.H.; Huang, C.Y.; Su, H.J.; Lan, P.H.; Hsieh, M. Assessment of the PV hosting capacity for the medium-voltage 11.4 kV distribution feeder. In Proceedings of the 2018 IEEE International Conference on Applied System Invention (ICASI), Chiba, Japan, 13–17 April 2018; pp. 381–384.
110. Mulenga, E.; Bollen, M.H.J. Impact of service and feeder cable upgrade on hosting capacity for single phase connected photovoltaics. In Proceedings of the 2018 18th International Conference on Harmonics and Quality of Power (ICHQP), Ljubljana, Slovenia, 13–16 May 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6. [CrossRef]

111. Yao, D.; Lu, Y.; Zhang, D.; Shi, S.; Zhu, M.; Zhang, B. PV hosting capacity evaluation method in distribution network considering overvoltage risk. *J. Phys. Conf. Ser.* **2022**, *2351*, 012032. [CrossRef]
112. Esau, Z.; Ryoichi, H.; Hiroyuki, K. A flexible stochastic PV hosting capacity framework considering network over-voltage tolerance. *Energy Rep.* **2023**, *9*, 529–538. [CrossRef]
113. Lakshmi, S.; Ganguly, S. Simultaneous optimisation of photovoltaic hosting capacity and energy loss of radial distribution networks with open unified power quality conditioner allocation. *IET Renew. Power Gener.* **2018**, *12*, 1382–1389. [CrossRef]
114. Mmary, E.R.; Marungsri, B. Optimal Hybrid Renewable Generator for Techno-Economic Benefits in Smart Distribution Network. In Proceedings of the 2018 International Electrical Engineering Congress (iEECON), Krabi, Thailand, 7–9 March 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–4.
115. Chen, X.; Wu, W.; Zhang, B. Robust capacity assessment of distributed generation in unbalanced distribution networks incorporating ANM techniques. *IEEE Trans. Sustain. Energy* **2017**, *9*, 651–663. [CrossRef]
116. Chen, X.; Wu, W.; Zhang, B.; Lin, C. Data-driven DG capacity assessment method for active distribution networks. *IEEE Trans. Power Syst.* **2016**, *32*, 3946–3957. [CrossRef]
117. Vatani, M.; Solati Alkaran, D.; Sanjari, M.J.; Gharehpetian, G.B. Multiple distributed generation units allocation in distribution network for loss reduction based on a combination of analytical and genetic algorithm methods. *IET Gener. Transm. Distrib.* **2016**, *10*, 66–72. [CrossRef]
118. Sakar, S.; Balci, M.E.; Aleem, S.H.A.; Zobaa, A.F. Increasing PV hosting capacity in distorted distribution systems using passive harmonic filtering. *Electr. Power Syst. Res.* **2017**, *148*, 74–86. [CrossRef]
119. Xu, X.; Gunda, J.; Dowling, R.; Djokic, S. A Two-stage Approach for Renewable Hosting Capacity Assessment. In Proceedings of the 2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), Bucharest, Romania, 29 September–2 October 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–5.
120. Wang, Z.; Wang, X.; Tang, L. Practical power distance test tool based on OPF to Assess Feeder DG Hosting Capacity. In Proceedings of the 2017 IEEE Electrical Power and Energy Conference (EPEC), Saskatoon, SK, Canada, 22–25 October 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
121. Alturki, M.; Khodaei, A.; Paaso, A.; Bahramirad, S. Optimization-based distribution grid hosting capacity calculations. *Appl. Energy* **2018**, *219*, 350–360. [CrossRef]
122. Alturki, M.T. Hosting Capacity Optimization in Modern Distribution Grids. Ph.D. Thesis, University of Denver, Denver, CO, USA, 2018.
123. 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; IEEE: Piscataway, NJ, USA, 2018; pp. 1–9.
124. Hassan, S.J.U.; Gush, T.; Kim, C.-H. Maximum Hosting Capacity Assessment of Distribution Systems With Multitype DERs Using Analytical OPF Method. *IEEE Access* **2022**, *10*, 100665–100674. [CrossRef]
125. Abideen, M.Z.U.; Ellabban, O.; Ahmad, F.; Al-Fagih, L. An Enhanced Approach for Solar PV Hosting Capacity Analysis in Distribution Network. *IEEE Access* **2022**, *10*, 120563–120577. [CrossRef]
126. Jothibasu, S.; Santoso, S.; Dubey, A. Optimization methods for evaluating PV hosting capacity of distribution circuits. In Proceedings of the 2019 IEEE 46th Photovoltaic Specialists Conference (PVSC), Chicago, IL, USA, 16–21 June 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 0887–0891.
127. Alghamdi, Y.; Al-Mehizia, A.A.; Al-Ismail, F. PV Hosting Capacity Calculation Using Particle Swarm Optimization. In Proceedings of the 2021 North American Power Symposium (NAPS), College Station, TX, USA, 14–16 November 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 1–6.
128. Liu, Y.J.; Lee, C.Y.; Liu, W.M.; Lee, Y.D.; Cheng, C.C.; Chen, Y.-F. Optimization-Based Stochastic Analysis Method for the Assessment of PV Hosting Capacity. In *Proceedings of the 2022 8th International Conference on Applied System Innovation (ICASI)*; Nantou, Taiwan, 22–23 April 2022, IEEE: Piscataway, NJ, USA, 2022; pp. 33–36.
129. Molefyane, B.; Mbatha, L.; Rampokanyo, M. Development of a feeder Hosting Capacity Tool for South African municipalities. Available online: https://cigresa-events.co.za/cigre_2021_regional_conference/cigre10thfiles/03-Technical-Papers-Presentations/Session%203/19%20S3P6%2091%20Development%20of%20a%20feeder%20hosting%20-%20B%20Molefyane.pdf (accessed on 23 December 2022).
130. Rylander, M.; Smith, J.; Rogers, L. Impact Factors, Methods, and Considerations for Calculating and Applying Hosting Capacity. Electric Power Research Institute, 3002011009, 2018. Available online: https://www.epri.com/research/products/000000003002011009 (accessed on 21 December 2022).
131. Rylander, M.; Smith, J.; Sunderman, W. Streamlined method for determining distribution system hosting capacity. *IEEE Trans. Ind. Appl.* **2015**, *52*, 105–111. [CrossRef]
132. EPRI. Distribution Resource Integration and Value Estimation (DRIVE) Tool User Group. Available online: https://www.epri.com/research/products/000000003002020018 (accessed on 23 November 2022).
133. Rylander, M.; Smith, J.; Sunderman, W. Streamlined Method for Determining Distribution System Hosting Capacity. In Proceedings of the 2015 IEEE Rural Electric Power Conference, Savannah, GA, USA, 19–21 April 2015; pp. 3–9. [CrossRef]

134. Rylander, M.; Smith, J.; Sunderman, W.; Smith, D.; Glass, J. Application of new method for distribution-wide assessment of Distributed Energy Resources. In Proceedings of the 2016 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), Dallas, TX, USA, 3–5 May 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1–5.
135. Ping, J.; Yan, Z.; Chen, S. A two-stage autonomous EV charging coordination method enabled by blockchain. *J. Mod. Power Syst. Clean Energy* **2020**, *9*, 104–113. [CrossRef]
136. Shepero, M.; Munkhammar, J.; Widén, J.; Bishop, J.D.; Boström, T. Modeling of photovoltaic power generation and electric vehicles charging on city-scale: A review. *Renew. Sustain. Energy Rev.* **2018**, *89*, 61–71. [CrossRef]
137. Khalid, M.R.; Alam, M.S.; Sarwar, A.; Asghar, M.J. A Comprehensive review on electric vehicles charging infrastructures and their impacts on power-quality of the utility grid. *ETransportation* **2019**, *1*, 100006. [CrossRef]
138. Guo, C.; Zhu, K.; Chen, C.; Xiao, X. Characteristics and effect laws of the large-scale electric Vehicle's charging load. *ETransportation* **2020**, *3*, 100049. [CrossRef]
139. Leou, R.C.; Su, C.L.; Lu, C.-N. Stochastic analyses of electric vehicle charging impacts on distribution network. *IEEE Trans. Power Syst.* **2013**, *29*, 1055–1063. [CrossRef]
140. Leou, R.; Teng, J.; Lu, H.; Lan, B.; Chen, H.; Hsieh, T.; Su, C. Stochastic analysis of electric transportation charging impacts on power quality of distribution systems. *IET Gener. Transm. Distrib.* **2018**, *12*, 2725–2734. [CrossRef]
141. Zou, Y.; Zhao, J.; Gao, X.; Chen, Y.; Tohidi, A. Experimental results of electric vehicles effects on low voltage grids. *J. Clean. Prod.* **2020**, *255*, 120270. [CrossRef]
142. Fadi, A.K.; Bruno, F. Holistic approach for prioritizing emergency EV charging in an existing distribution network. In Proceedings of the CIRED Porto Workshop 2022: E-Mobility and Power Distribution Systems, Hybrid Conference, Porto, Portugal, 2–3 June 2022.
143. Sandström, M.; Bales, C.; Dotzauer, E. Hosting Capacity of the Power Grid for Electric Vehicles-A Case Study on a Swedish Low Voltage Grid. In *IOP Conference Series: Earth and Environmental Science*; IOP Publishing: Bristol, UK, 2022; Volume 1050, p. 012008.
144. Palomino, A.; Parvania, M. Probabilistic impact analysis of residential electric vehicle charging on distribution transformers. In Proceedings of the 2018 North American Power Symposium (NAPS), Fargo, ND, USA, 9–11 September 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
145. Palomino, A.; Parvania, M. Data-driven risk analysis of joint electric vehicle and solar operation in distribution networks. *IEEE Open Access J. Power Energy* **2020**, *7*, 141–150. [CrossRef]
146. e Silva, L.E.S.; Vieira, J.P.A. Combined PV-PEV Hosting Capacity Analysis in Low-Voltage Distribution Networks. *Electr. Power Syst. Res.* **2022**, *206*, 107829. [CrossRef]
147. Zuluaga-Ríos, C.D.; Villa-Jaramillo, A.; Saldarriaga-Zuluaga, S.D. Evaluation of Distributed Generation and Electric Vehicles Hosting Capacity in Islanded DC Grids Considering EV Uncertainty. *Energies* **2022**, *15*, 7646. [CrossRef]
148. Nakhodchi, N.; Bakhtiari, H.; Bollen, M.H.; Rönnberg, S.K. Including uncertainties in harmonic hosting capacity calculation of a fast EV charging station. *Electr. Power Syst. Res.* **2023**, *214*, 108933. [CrossRef]
149. Zhu, J.; Nacmanson, W.J.; Ochoa, L.F.; Hellyer, B. Assessing the EV Hosting Capacity of Australian Urban and Rural MV-LV Networks. *Electr. Power Syst. Res.* **2022**, *212*, 108399. [CrossRef]
150. 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]
151. 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; IEEE: Piscataway, NJ, USA, 2019; pp. 1–7.
152. 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; IEEE: Piscataway, NJ, USA, 2021; pp. 1–5.
153. Zeng, B.; Zhu, Z.; Zhu, X.; Qin, L.; Liu, J.; Zhang, M. Estimation of Distribution System Capability for Accommodating Electric Vehicles. *J. Electr. Syst.* **2020**, *16*, 131–141.
154. Barbosa, T.; Andrade, J.; Torquato, R.; Freitas, W.; Trindade, F.C. Use of EV hosting capacity for management of low-voltage distribution systems. *IET Gener. Transm. Distrib.* **2020**, *14*, 2620–2629. [CrossRef]
155. Henrique, L.F.; Bitencourt, L.A.; Borba, B.S.M.C.; Dias, B.H. Impacts of EV residential charging and charging stations on quasi-static time-series PV hosting capacity. *Electr. Eng.* **2022**, *104*, 2717–2728. [CrossRef]
156. Power Engineering Software. Available online: https://en.wikipedia.org/wiki/Power_engineering_software (accessed on 28 November 2022).
157. Digsilent. Powerfactory Applications. Available online: https://www.digsilent.de/en/powerfactory.html (accessed on 29 November 2022).
158. Siemens. PSS®SINCAL—Simulation Software for Analysis and Planning of Electric and Pipe Networks. Available online: https://new.siemens.com/global/en/products/energy/energy-automation-and-smart-grid/pss-software/pss-sincal.html (accessed on 28 November 2022).
159. Siemens. Maximal Hosting Capacity (ICA). Available online: https://assets.new.siemens.com/siemens/assets/api/uuid:d30d49557176528d935ec035d8499ac26d083822/version:1516636173/11-ica-module-datasheet-sincal-ag.pdf (accessed on 21 November 2022).

160. DNV. Power Distribution System and Electrical Simulation Software—Synergi Electric. Available online: https://www.dnv.com/services/power-distribution-system-and-electrical-simulation-software-synergi-electric-5005 (accessed on 28 November 2022).
161. Smarter Grid Solutions (SGS) Enhanced Hosting Capacity Analysis. 2018. Available online: http://mnsolarpathways.org/wp-content/uploads/2018/10/mn-solar-pathways_pv-hosting-capacity-report.pdf (accessed on 2 December 2022).
162. NEPLAN. Target Grid Planning. Available online: https://www.neplan.ch/description/target-grid-planning/ (accessed on 20 November 2022).
163. EATON. CYME Power Engineering Software. Available online: https://www.cyme.com/software/cymeica/ (accessed on 29 November 2022).
164. EATON. EPRI Drive. Available online: https://www.cyme.com/software/cymeepri/ (accessed on 29 November 2022).
165. EATON. CYME-Integration Capacity Analysis. Available online: https://www.cyme.com/software/cymeica/BR917066EN-ICA.pdf (accessed on 29 November 2022).