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Review

State of the Art Monte Carlo Method Applied to Power System Analysis with Distributed Generation

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Abstract: Traditionally, electric power systems are subject to uncertainties related to equipment availability, topological changes, faults, disturbances, behaviour of load, etc. In particular, the dissemination of distributed generation (DG), especially those based on renewable sources, has introduced new challenges to power systems, adding further randomness to the management of this segment. In this context, stochastic analysis could support planners and operators in a more appropriate manner than traditional deterministic analysis, since the former is able to properly model the power system uncertainties. The objective of this work is to present recent achievements of one of the most important techniques for stochastic analysis, the Monte Carlo Method (MCM), to study the technical and operational aspects of electric networks with DG. Besides covering the DG topic itself, this paper also addresses emerging themes related to smart grids and new technologies, such as electric vehicles, storage, demand response, and electrothermal hybrid systems. This review encompasses more than 90 recent articles, arranged according to the MCM application and the type of analysis of power systems. The majority of the papers reviewed apply the MCM within stochastic optimization, indicating a possible trend.

Keywords: Monte Carlo Method; electric power systems; smart grids; distributed generation

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1. Introduction

One of the main objectives of the Electric Power System (EPS) is to provide electricity at the lowest possible cost to society, ensuring both an acceptable quality and reliability of the energy supply. However, regardless of how it is designed or operated, an EPS is subject to non-deterministic events that can compromise the regularity of service and power quality [1].

In the distribution system segment, operators need to contend with the new challenges imposed by distributed generation (DG), which changes the traditionally unidirectional flow, making distribution networks active and causing technical impacts associated with the occurrence of reverse flow. In addition, the location and size of DG units introduces uncertainties in distribution networks. Finally, there is also a randomness associated with electricity demand, especially within the context of new technologies—such as electric vehicles (EVs) and energy storage devices—and demand-side management [2].

For years, the impacts of DG on the EPS have been widely discussed in the literature. A review focused on the impacts of protection and regulation of distribution networks is presented in [3]. Conversely, [4] addresses photovoltaic (PV) DG allocation problems, including an overview of optimization algorithms and methodologies for assessing PV potential. References [5,6] present reviews on DG hosting capacity (HC), which is typically calculated in terms of power quality, protection, overvoltage, equipment overload, and losses. Finally, [7] provides a holistic review of how DG can affect the EPS in the future, covering several aspects such as environmental, geographical, regulatory, marketing, technological, infrastructural, and social.

The deterministic analysis of EPSs is limited, as it does not adequately model the various uncertainties associated with system operation, especially those related to the stochastic nature of load and generation. For example, extreme scenarios generally investigated by deterministic approaches may represent states that are unlikely to occur, leading to the rejection of viable proposals or to excessive investments and risks [8]. Alternatively, planning based on deterministic analysis of scenarios with a high probability of occurrence but with low severity may not provide the best performance in terms of reliability and adequacy of the system [1].

Recently, the randomness added by new technologies into the EPS has often been considered in planning and operation studies, especially in the distribution segment. Papers [9–14] are examples of recent reviews covering uncertainty modelling techniques and stochastic analysis of electrical networks. According to [9,12,14], uncertainty modelling techniques can be classified as probabilistic techniques, stochastic optimization, robust optimization, possibilistic techniques, hybrid probabilistic-possibilistic techniques, and information gap decision theory (IGDT). It is worth mentioning that probabilistic techniques include analytical and numerical methods, and that the Monte Carlo Method (MCM) is the most used numerical one. In fact, due to its relevance, the MCM is mentioned in the aforementioned reviews [9–14]. In [11,12,14], some variations of the MCM are discussed, such as the Sequential Monte Carlo (SMC)—which allows sampling chronological and temporally dependent data—and the Monte Carlo Markov Chain (MCMC)—used to sample a probability distribution from the construction of a Markov Chain. In particular, the present work focuses especially on the MCM, and proposes new categories to classify the reviewed papers.

Analytical probabilistic methods are statistical techniques that normally require simplifications in the formulation of the problem to allow calculating the moments and probability functions of the output variables. However, some problems can present such a high degree of complexity that it may be extremely difficult or even unfeasible to apply analytical methods [15]. According to [9], analytical methods can be classified as methods based on linearization (such as convolution, cumulants, Taylor series expansion, and first-order second moment) or based on the approximation of probability distributions (such as point estimation method (PEM) and unscented transformation).

The application of MCM is widely addressed in the literature, as it ensures greater flexibility and allows for the consideration of non-linear power flow relationships, operational strategies, as well as spatial and temporal correlations [2]. However, MCM requires a high computational effort, which can be improved by applying techniques such as sampling based variance control and high-performance computing. Furthermore, the current processing capacity of personal computers and the availability and accessibility of databases are no longer crucial restrictions for the application of MCM, unlike the technological context of past decades. This recent background favours the use of MCM to study emerging technologies in EPSs, including DG.

The objective of this work is to present the state of the art of MCM applied to electrical networks with DG, with an emphasis on the technical and operational aspects of the EPS. This review discusses the main stochastic simulation techniques related to the MCM that have been used in the literature recently, as well as the analyses conducted by the studies in question. The topic in question is pertinent, especially given the current context of transition of the electricity sector towards active and intelligent networks, subject to the randomness of renewable sources and emerging technologies.

The remainder of this paper is organized as follows: Section 1.1 presents the overall criteria considered in the literature review. Next, the basic concepts of the MCM are introduced in Section 2. Then, the proposed literature review is detailed in Sections 3 and 4. Finally, the conclusions are exposed in Section 5.

1.1. Criteria Adopted for the Literature Review

The scope of this work includes only papers focusing on technical impact analysis, operation, and planning of the EPS. In Section 3 the selected works are classified into different categories based on the type of simulation technique used, while in Section 4 the works are classified according to the area of analysis of electrical networks, technologies associated with DG, and the uncertainties observed in these papers.

The literature review has been carried out through the Web of Science database (Clarivate Analytics main collection), by searching for the conjunction of the keywords 'Monte Carlo' AND 'Distributed Generation', in the 'Topic' field (TS). Although other terms could have been included in the search process, especially to characterize the DG, the authors consider that the papers selected through the adopted criteria adequately cover the proposed theme of the review. The search process was carried out at the end of 2021, considering only recent papers from 2018 onwards. In all, 94 works have been selected.

2. The Monte Carlo Method

The name 'Monte Carlo' refers to the main district of Monaco, well known for its casino complex. The method was created at the end of the Second World War by physicists who were working with the atomic bomb. The development of the first digital computer, ENIAC (1946), allowed Jon Von Neuman to apply the MCM to solve thermonuclear and fission problems in 1947. The first paper on the method was published by Metropolis and Ulam in 1949. MCM has evolved over time along with computational advances. Currently, it has wide application in various areas such as engineering, finance, statistics, physics, biology, medicine, social sciences, etc. [16].

Figure 1 shows a simplified flowchart of the MCM. It consists of the following main steps: first, the computational model and the probability distributions of the random variables are defined. The developed model must be a valid representation of the studied system so that the computer simulations guarantee reliable results. Next, for each iteration, the model state is randomly sampled and, after that, the model behaviour is evaluated numerically. Finally, the results of each iteration are processed to obtain model statistics and its expected performance (or behaviour).

Through MCM, it is possible to calculate performance indexes to assess the computational model considering uncertainties. Therefore, stochastic simulations allow the evaluation of several characteristics of these indicators such as mean, variance, probabilities, confidence intervals, relative error, etc. For instance, suppose one wants to calculate a generic indicator ℓ through (1):

$$\ell = E[H(X)] = \int H(x)f(x)dx \tag{1}$$

where X is a random variable with probability density function (PDF) f, $H(X)$ is a generic real function, called performance indicator, and $E[H(X)]$ is the expectation of $H(X)$ with respect to the random variable X. Then, ℓ can be estimated using the MCM, by calculating the sample mean via (2):

$$\hat{\ell} = \frac{1}{n}\sum_{i=1}^{n} H(X_i) \tag{2}$$

where $X_1,\ X_2 \ldots X_n$ is a random sample of X from PDF f, and n is the sample size.

The estimator $\hat{\ell}$ is considered unbiased, since $E[\hat{\ell}] = \ell$. Furthermore, by the law of large numbers, $\hat{\ell}$ tends to ℓ for a sufficiently large n [15]. Another relevant observation is that the central limit theorem ensures that for a large n, $\hat{\ell}$ has an approximately normal PDF, even if $H(X)$ does not have a normal PDF [17].

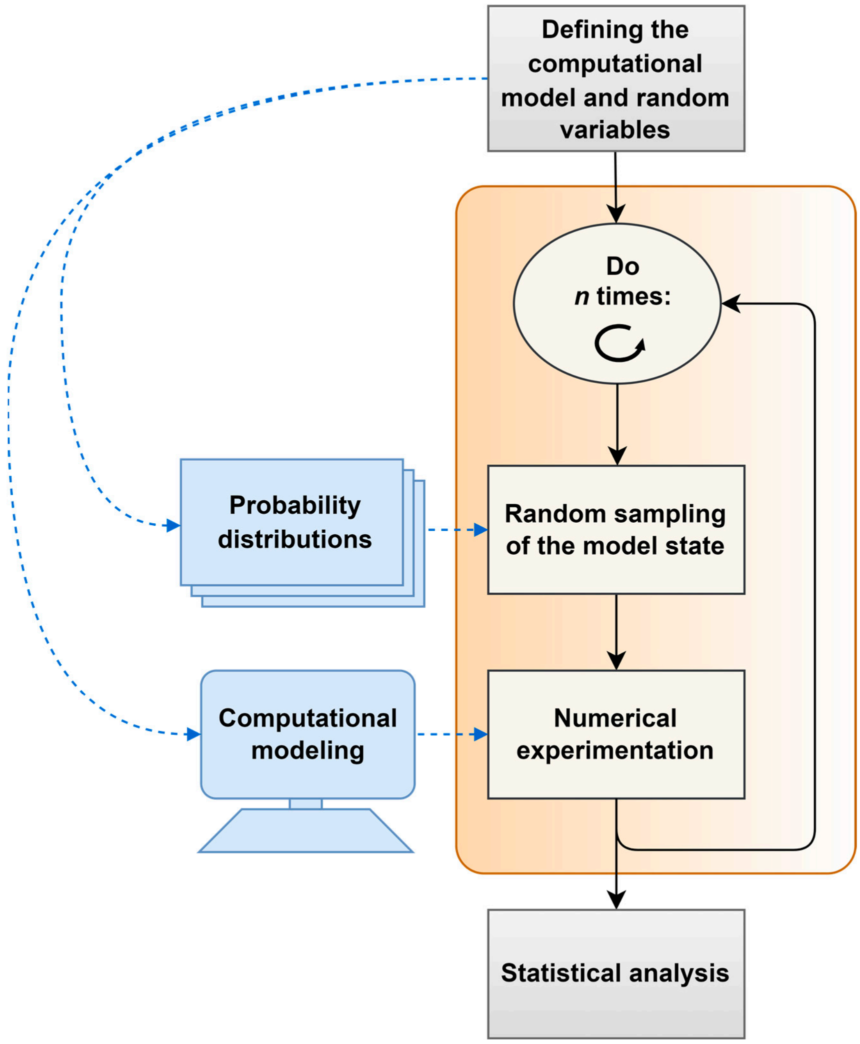

Figure 1. MCM flowchart.

Another important estimator is the sample variance S^2, which tends to the theoretical variance σ^2 for a sufficiently large n, according to the law of large numbers. Equation (3) presents the calculation of the sample variance, with respect to estimator $\hat{\ell}$. Once the variance is known, it is possible to calculate indicators, such as confidence intervals and relative error, which allows verifying the convergence of the MCM and the accuracy of the estimator.

$$S^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(H(X_i) - \hat{\ell}\right)^2 . \tag{3}$$

Next, in the remainder of this section, a practical example of the MCM is presented in Section 2.1, while some improvements and variations of the method are discussed in Section 2.2.

2.1. A Simple Example of MCM Application: π Value Estimation

As an illustrative example, the general MCM algorithm from Figure 1 could be applied to estimate π. Consider a circle with radius r inside a square with side length $2r$. Since the circle area (A_c) is πr^2 and the square area (A_s) is $4r^2$, π can be written as a function of the ratio of these areas, as indicated in (4):

$$\begin{gathered} \frac{A_c}{A_s} = \frac{\pi r^2}{4r^2} = \frac{\pi}{4} \\ \therefore \pi = 4 \times \frac{A_c}{A_s} . \end{gathered} \tag{4}$$

The MCM procedure is described as follows: Define $\boldsymbol{X}$ as the random vector of coordinates $[x_1, x_2]$ with uniform PDF in the interval $[-1, -1]$ to $[1, 1]$. In addition, define the performance indicator $H(\boldsymbol{X})$ as in (5):

$$H(\boldsymbol{X}) = 4 \times I_c \tag{5}$$

where I_c is an indicator function that denotes if a sample of coordinates falls within the circle, as in (6). Besides, note that the factor 4 in (5) comes from the ratio of areas in (4). Finally, the π estimated value $(\hat{\pi})$ can be computed through (7):

$$I_c = \begin{cases} 1, & \text{if } x_1^2 + x_2^2 \leq r^2 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

$$\hat{\pi} = \frac{1}{n} \sum_{i=1}^{n} H(\boldsymbol{X}_i) \tag{7}$$

Figure 2 exhibits some results of the proposed experiment. Figure 2b shows the convergence of π value estimation, indicating that the estimated value tends to the true value of π for a sufficiently large number of iterations.

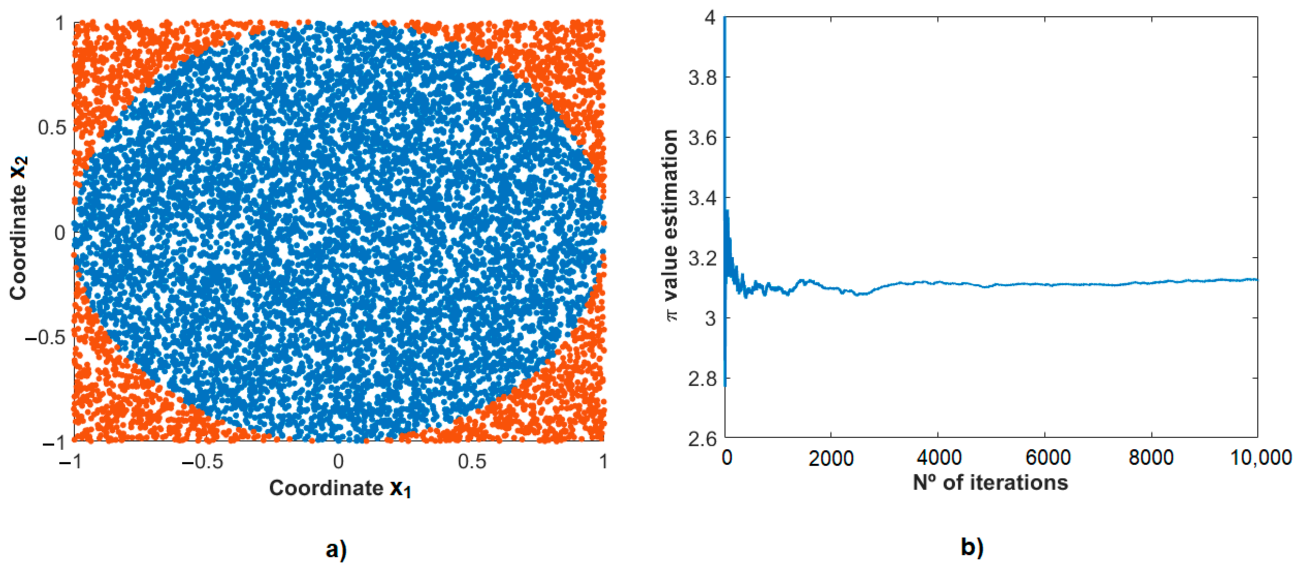

Figure 2. Application of the MCM to estimate π: (**a**) 10,000 pairs of coordinates randomly generated with uniform PDF; (**b**) convergence of π value estimation over MCM iterations.

2.2. Notable Advancements and Variations of the MCM

The simple approach described previously, represented in Figure 1 and applied in the example of Section 2.1, is often referred to as the Monte Carlo integration, due to its applicability on integration problems. This basic algorithm can be structured more efficiently, aiming to obtain a more reliable estimator and to reduce the computational effort. Besides this basic application, MCM encompasses a family of simulation-based algorithms that rely on random sampling. Some of the most well-known advancements or variations of the MCM are described below:

- Importance Sampling (IS)

IS is one of the most used techniques of variance reduction, and it can be applied to the simulation of rare events, i.e., the ones with a low probability of occurrence. The idea is favouring relevant events by changing the PDF used for sampling and then correcting the sample mean to match the one that would be obtained with the original PDF. Despite its effectiveness (which can overcome the order of millions in variance reduction when it comes to rare events [15]), the IS can be difficult to implement in comparison to other variance reduction techniques [12]. The process of choosing the importance sampling PDF—that is, the one that leads to the smallest variance possible, if used to sample instead of the original distribution—can be formulated as an optimization problem with the objective of minimizing the variance. A technique widely used to solve this problem is the Cross-Entropy (CE) method. In [2], for instance, the IS with CE is used to calculate the probability of line overload and bus undervoltage in IEEE test networks. For more details about IS and CE, the readers are referred to [15,18]. Besides the CE, the review paper [12] also mentions Adaptive Importance Sampling (AIS) and Sequential Importance Sampling (SIS) as relevant IS variations.

- Monte Carlo Markov Chain (MCMC)

MCMC is a sampling method that relies on both MCM and Markov Chain concepts. The idea is to draw samples from a target distribution based on the sequential process of a Markov Chain, such that the new generated random sample depends only on its direct predecessor. MCMC is often related to Bayesian inference, as the former allows for the predicting of the posterior distribution, which is a difficult task to be done analytically. According to [12], some of the main MCMC algorithms are Metropolis–Hastings, Gibbs sampling, and Differential Evolution. Metropolis-Hastings is simple and effective, but it is not recommended in the event of very strongly correlated parameters. Conversely, Gibbs sampling is more suitable to represent the correlation of multivariate problems by sampling from conditional distributions. Nonetheless, the computational efficiency of Gibbs sampling can be improved by using multiple chains, as in Differential Evolution algorithm. The advantages and disadvantages of these algorithms are covered in further details in [12,19]. For more information about MCMC, the readers are referred to [15,16].

- Quasi-Monte Carlo (QMC)

QMC methods are deterministic variations of the MCM. In other words, QMC follows the same general algorithm proposed by MCM, but uses deterministic low-discrepancy (or quasi-random) sequences rather than pseudo-random sampling. The reason behind using low-discrepancy sequences is to more uniformly cover the sampling domain by generating more equidistant samples, which can lead QMC to outperform MCM in terms of accuracy and faster rate of convergence [11]. Nevertheless, QMC performance can deteriorate in high-dimensional cases. Reference [20] discusses the implementation of QMC in high dimensions and explains why QMC can be superior to MCM and the variance reduction method Latin Hypercube Sampling (LHS). Some examples of quasi-random sequences are Halton, Sobol, Faure, and Niederreiter [20]. For more information about QMC, the readers are referred to [21,22].

- Sequential Monte Carlo (SMC)

SMC—also known as the particle method—allows representing temporal and chronological dependence of the system states, unlike the traditional Non-Sequential Monte Carlo (NSMC)—also known as the state sampling approach [9,14]. According to [23], SMC provides a flexible simulation-based procedure to calculate posterior distributions, which can handle high-dimensional, non-linear, and non-Gaussian models. This method is particularly useful to consider EPS component outage, failure, and repair time over a given period of service in reliability studies [11]. A popular improvement of SMC is the Pseudo-Sequential Monte Carlo (PSMC), which is easy to implement and faster than conventional SMC [14]. PSMC relies on the non-sequential sampling of system states and on the chronological simulation of only the sub-sequences associated with failed states [24]. SMC applications in reliability assessment of EPS are covered in further details in [1]. For general information about SMC, the readers are referred to [23].

The next section discusses the proposed literature review regarding the type of simulation techniques used. Note that some of the advancements and variations of the MCM addressed in Section 2.2 are also mentioned in Section 3.

3. Simulation Techniques

In this section, the reviewed papers are approached regarding the simulation techniques, according to the following classifications: *Crude Monte Carlo (CMC), Computational Efficiency Enhancement (CEE), Advanced Techniques for Uncertainty Modelling (ATUM), Stochastic Optimization (SO),* and *MCM as Benchmark (MCM-BK)*. Table 1 exhibits the selected works, organized according to the aforementioned categories of simulation techniques. Note that the same reference can be classified in more than one category.

Table 1. Classification of the reviewed papers—simulation techniques.

Simulation Techniques *	References	No. of References
CMC	[25–38]	14
CEE	[39–66]	28
ATUM	[39,45,47,48,51,53,54,59,61,62,67–79]	23
SO	[25,39–41,43–52,54–58,60,64,66–68,70,72–74,76,77,80–112]	63
MCM-BK	[70,71,75,77–79,86,112–118]	14

* Simulation Techniques: Crude Monte Carlo (CMC), Computational Efficiency Enhancement (CEE), Advanced Techniques for Uncertainty Modelling (ATUM), Stochastic Optimization (SO), and MCM as Benchmark (MCM-BK).

- Crude Monte Carlo (CMC)

CMC refers to MCM in its simplest form, which commonly requires a high computational effort. If a reference falls into any of the other categories, it should not be classified as CMC, since this reference proposes improvements in MCM or it uses the MCM as a secondary technique for comparison purposes (as for MCM-BK).

There are several works in this category focused on the analysis of power quality indices. Reference [29] for example, uses the MCM to consider the market influence (via Bass model) in the random locations of PV DGs, in order to analyse the DG impacts in terms of losses, voltage, consumption, and cable ampacity. In [37], the control of a Solid-State Transformer (SST) is implemented to improve the DG HC, in terms of voltage and current violation. In this sense, MCM is applied to calculate the HC considering uncertainties in the location and capacity of DG. Paper [26] analyses the magnitude and voltage unbalance when applying phase-to-ground faults (with random location) in LV networks, considering uncertainties in load and PV DG.

In terms of reliability analysis in EPSs, [31] proposes the allocation of DG based on the interruption duration index at the points of common coupling. Note that the allocation is not performed through an optimization algorithm, but qualitatively, based on the calculation of the indicator obtained via MCM. In addition, other well-known reliability indices are evaluated, such as Energy Not Supplied (ENS) and System Average Interruption Frequency Index (SAIFI). These indices are also calculated in [36], which assesses the impact of DG on the coordination of the protection system and on the reliability of distribution networks. This paper considers uncertainties on the failure rate and repair time of the network components (transformers, voltage regulators, and feeders). Reference [25] adopts the MCM to evaluate the robustness of the distribution network expansion planning, considering substation reinforcement as well as the allocation of EV charging stations, DG, and capacitor banks. That is, the MCM is only used to calculate the substation capacity failure rate for the solutions found in the planning, and not as a tool to solve the optimization problem itself—note that, while there is a robust optimization problem (in which the MCM is not applied), this article was exceptionally classified simultaneously in the categories SO and CMC, as there are two separate analyses.

- Computational Efficiency Enhancement (CEE)

CEE includes methods that aim to reduce the computational effort or improve the processing capacity, in order to decrease the MCM simulation time. It comprises techniques of variance reduction, scenario reduction, and high-performance computing, as indicated in Figure 3.

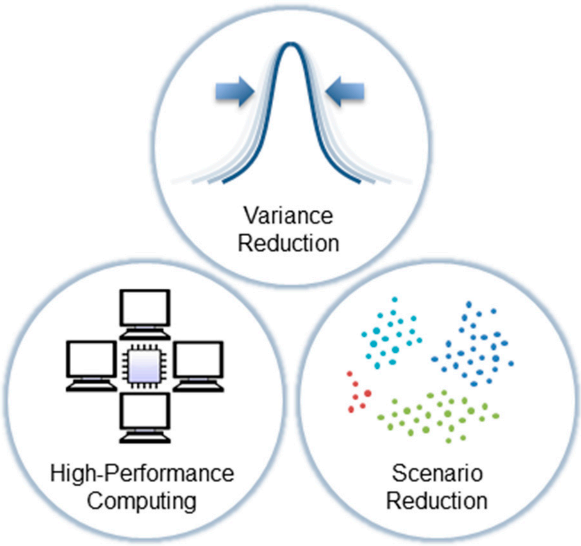

Figure 3. Types of techniques within CEE.

Most of the works in this category present scenario reduction techniques, which are widely used in stochastic optimization problems, so that the optimization is performed on the set of reduced scenarios, reducing the computational effort. The most used technique is k-means [43–46,51,53,66], but there are also k-medoid [39], k-means++ [49], fuzzy C-means [48], simultaneous backward reduction [41], Kantorovich distance scenario reduction [52], and Factor Analysis (FA) method [57]. Clustering techniques as k-means aims to group the generated scenarios in such a way that the main statistical characteristics of each group are preserved, while methods such as Kantorovich's select the reduced set of scenarios so that it presents a probability distribution close to the one of the original sets. Reference [42] combines k-means with metaheuristics—genetic algorithm (GA), particle swarm optimization (PSO), differential evolutionary (DE), harmony search (HS), and artificial bee colony (ABC)—to minimize the sum of the distances between each scenario and the centre of its respective cluster. Finally, there are also works that propose scenario reduction methods, but that do not have a well-defined name, as in [50,54].

Variance reduction techniques aim to reduce the variance of the samples, allowing it possible to increase the precision of the estimator without changing the number of samples. The variance reduction technique most found in this review is the LHS [46,53,55,64], which is a Stratified Sampling (SS), i.e., a sampling method applied independently in each population stratum. References [47,48] apply the QMC, which adopts a deterministic sequence of low discrepancy instead of the random or pseudo-random sampling used in the traditional MCM. Alternatively, [59,65] implement variations of the IS method called Latin Hypercube-Important Sampling Method (LHISM) and AIS, respectively. IS is one of the most effective methods of variance reduction, especially when estimating rare events (with a very small probability of occurrence) [15]. Nevertheless, choosing the appropriate importance sampling distribution can be an arduous task, making the implementation of IS much more complex than LHS and QMC, for example. The review paper [12] presents other examples of variance reduction techniques, such as Common Random Numbers (CRN), Antithetic Variates (AV), Control Variates (CV), and Dagger Sampling (DS).

There are also works that use advanced hardware and software resources to improve computational processing. Papers [56,60] implement Aris High Performance Computing to solve stochastic optimization problems using MCM as an optimization tool. Meanwhile, [63] applies the MCM with parallel processing as a tool for optimal allocation of DG, in order to reduce losses and improve the voltage profile. However, note that this last paper does not consider uncertainties in the optimization and, therefore, it is not classified in the SO category. Reference [58] implements high-performance computing—via OpenCL language—together with a metaheuristic to solve a multi-objective problem of DG allocation, using MCM for the dealing with load and renewable DG uncertainties. In general, the computational resources used in the works cited in this paragraph are hardly detailed, seeming that there is low complexity in the implementation of these tools.

Finally, there are also methods of CEE that have not been included in the categories of Figure 3. Paper [40], for example, uses a polynomial neural network (PNN) to consider uncertainties with a faster convergence than the traditional MCM, but the MCM is still considered in the initial part of the algorithm for training the neural network. In contrast, [61,62] propose the Accelerated Monte Carlo Method (AMCM) and the MCM with adaptive variable-step search, respectively, to improve the efficiency of the MCM algorithm.

- Advanced Techniques for Uncertainty Modelling (ATUM)

In basic applications of the MCM, well-known probability distributions are usually used to represent the uncertainties. Therefore, on the contrary, this category only comprises works that present more advanced modelling techniques. The idea is to use models that allow a more realistic representation of the analysed systems.

Instead of adopting simpler distributions, several works model the uncertainties through stochastic processes such as Brownian Motion [62] and Markov Chain [47,61,75,77], including MCMC [45]; autoregressive models such as autoregressive-moving-average (ARMA) [62,76] and autoregressive-integrated-moving-average (ARIMA) [68]; as well as through mixture models such as Gaussian Mixture Model [62,69] and Weibull Mixture Model [71]. For instance, [75] evaluates the contribution of storage systems in the reliability of distribution networks, using Markov Chain to model the operation of network components such as transformers, lines, DG, and storage system. Reference [76] adopts ARMA and the autoregressive process (AR) to model wind speed and irradiance, respectively.

Some works implement techniques for estimating probability distribution functions of the considered random variables, such as through Kernel density estimation (KDE) [39,51,73]. For example, [39] uses KDE to model irradiance uncertainties. In contrast, [67] proposes a new synthetic model for the generation of daily load profiles, which are validated from metrics such as the occupied bandwidth (OBW). Still in terms of modelling probability distributions, Copula is used in [51,73,77] to obtain joint distributions, allowing the consideration of the correlation of random variables. Reference [73] models the various uncertainties of residential load (use of computer, lighting, air conditioning, and EV charging) based on historical data, Gaussian Kernel, and Gaussian Copula. Furthermore, the representation of the correlation itself has been assumed in this review as an advanced uncertainty modelling. For example, [48,74,78] consider the correlations of random variables associated with wind, PV generation, and load.

- Stochastic Optimization (SO)

SO refers to optimization works that consider uncertainties in the formulation of the problem. In Table 1, this category presents the highest number of papers, with almost 70% of the total, indicating a possible trend in the theme of the review. Optimization problems can be solved through metaheuristics, mathematical programming, or by using the MCM itself as an optimization tool.

The most used metaheuristics are the Genetic Algorithm (GA) [47,51,98] and Particle Swarm Optimization (PSO) [43,76,91], including variations such as the Evolutionary Particle Swarm Optimization (EPSO) [40], Quantum-Behaved Particle Swarm Optimization (QPSO) [77], Multiobjective Particle Swarm Optimization (MOPSO) [89,104], and Nondominated Sorting Genetic Algorithm (NSGA-II [39,41,92] e NSGA-III [80]). Other examples of recently used metaheuristics are: Improved Bee Algorithm (IBA) [74], Biogeography Based Optimisation (BBO) [97], Backtracking Search Optimization (BSO) [103], Hybrid Whale Optimization Algorithm and Pattern Search (HWOA-PS) [106], β-Chaotic Sequence

Spotted Hyena Optimizer (β-SHO) [107], Algorithm of the Innovative Gunner (AIG) [108], Improved Sunflower Optimization Algorithm (ISFOA) [109], and Improved Bat Algorithm (MOIBA) [110].

Conversely, mathematical programming includes models such as mixed integer nonlinear programming (MINLP) [45,52,86], mixed integer linear programming (MILP), [55,73,96] and mixed-integer second-order cone programming (MISOCP) [46,72]. Some works implement techniques to simplify or decompose the optimization problem into simpler sub-problems. For example, this can be done through Bender's Decomposition [50,99] or as in [54], by applying a set of linearizations to transform a MINLP model into a MILP, so that it can be solved directly through commercial solvers. Some of the main computing environments for modelling optimization problems are GAMS [45,52,64,86], AMPL [72,112], and MATLAB [55,101], which support optimization packages such as CPLEX [46,54,73,96]—for integer, linear, and quadratic programming—and Artelys Knitro [52]—for non-linear programming. In addition, there has been found a recent paper that adopts the Interior Point (IP) optimization technique [102] and another that uses a hybrid optimization method, which includes Normal Boundary Intersection (NBI), Dynamic Niche Differential Evolution Algorithm (DNDEA), and Primal–dual Interior Point Method (PDIPM) [48].

Although it is more common to solve optimization problems through mathematical programming or heuristic techniques, this review also includes works that use MCM as an optimization tool. Due to its high computational cost, MCM as an optimization tool is usually applied in conjunction with some CEE technique, such as high-performance computing [56,60,63] or variance reduction techniques, such as LHS [55]. However, there are works that only employ the MCM for solving the optimization [95]. Furthermore, [100] proposes a variation of Monte Carlo Tree Search (MCTS), which is a heuristic search algorithm based on the MCM.

SO can be further classified according to the number of objectives to be optimized, such that the optimization can present a single objective or several conflicting ones. Reference [77] formulates a capacitor planning optimization problem (regarding capacitor capacity and location), with the single objective of minimizing losses in the network. Paper [108] aims to optimize a given voltage indicator, considering flexible loads with green hydrogen technology, which is capable of absorbing energy surplus from renewable sources to reduce voltage problems. Then again, [49,50,55,94] are examples of works with multilevel optimizations, all of them with a single objective. As for multi-objective optimization, [107] proposes a problem of optimal allocation and sizing of wind DG with the objectives of minimizing losses, maximizing the voltage profile, and maximizing the voltage stability index. Reference [80] solves a daily scheduling problem of an active distribution network (containing renewable and controllable DG; storage; switches; and demand response management) with three conflicting objectives: minimize operational costs, maximize the usage rate of renewable resources, and maximize user satisfaction. Unlike [107], which transforms the three objectives into one through the weight coefficient method, [80] employs the NSGA-III algorithm to calculate the set of solutions from Pareto front and applies a fuzzy decision-making method to filter this set. In [104], a clustering algorithm is implemented to reduce the size of a four-dimensional Pareto front.

SO also includes robust optimization, which is characterized by representing uncertainties through parametric bounds [9]. Papers [25,72,99] are examples of robust optimization. For instance, [99] proposes a problem of optimal allocation and sizing of storage devices and capacitor banks in a microgrid (MG), in order to minimize costs associated with DG, storage device, and reactive losses in the grid. The robust optimization is solved using PSO and GAMS, and the uncertainties of PV and wind DG are considered. Reference [25] formulates a chance-constraint programming, which is a type of robust optimization that contains stochastic constraints. In this work, the chance constraint considers the stochastic behaviour of the load (conventional demand and EV) and ensures that the substation capacity is satisfied within a certain confidence level.

- MCM as Benchmark (MCM-BK)

When searching for 'Monte Carlo' in the literature, it is possible to find several works focused on stochastic techniques not related to the MCM (such as analytical methods), but that use the MCM only as a reference for validating the results obtained. In general, the idea is to propose a method that presents a lower computational effort than the MCM, but without significantly compromising the accuracy of the results. The MCM-BK category has been created to cover this type of papers.

One of the analytical techniques most found in this review is the Point Estimate Method (PEM), which aims to obtain statistics of the output variable through point values of the input variable samples. Variations of the PEM include the Adaptive PEM [86], Hong's 2m + 1 PEM [115], Fast-specialized PEM [112] and Three PEM [78].

The methods based on cumulants—which are alternative quantities to the moments of the probability distributions—also stand out in the literature review. The Gram-Charlier Series [70] and Cornish-Fisher expansion [78,115] allow to approximate probability distributions in terms of their cumulants, while [79] proposes a non-linear method for reconstructing the PDF that maximizes Shannon entropy, based on cumulant arithmetic.

Other examples of stochastic techniques from works that fall into the MCM-BK category are Stochastic Response Surface Method (SRSM) [77], Convolution [118], Interval Arithmetic [116], Affine Arithmetic [114], Generalized Polynomial Chaos (gPC) method [117], State Enumeration Method (SEM) [113], and Taguchi's Ortogonal Arrays [71].

As an example of comparison with the MCM, [75] introduces a new analytical method (without a specific name) for reliability studies of distribution networks with storage devices, achieving values of indices such as SAIFI with a difference of about 2% compared to MCM, but with a simulation time up to 50 times faster. In [70], the proposed method based on cumulants is validated via MCM, such that the voltage averages present a deviation of less than 0.01% in relation to the MCM, however, requiring less than 0.04% of the MCM simulation time.

4. Areas of Analysis, Technologies, and Uncertainties

This section discusses the works selected according to the area of analysis of electrical networks, technologies associated with DG, and uncertainty modelling.

4.1. Areas of Analysis of Electrical Networks

The selected papers are divided into the following categories in terms of areas of analysis of electrical networks: *Power Quality, Reliability, Economic,* and *Energy Losses and Thermal Overload.* Figure 4 represents in a simplified way the main characteristics of the referred areas of analysis, while Table 2 shows the classification of the reviewed papers on this topic. Note that the same reference can be classified in more than one category.

Table 2. Classification of the reviewed papers—areas of analysis of electrical networks.

Areas of Analysis *	References	No. of References
PQ	[26,28,29,32–35,37–40,49,52,53,56,59,60,63,65–67,69–71,74,76–82,84,85,89,90,92–94,97,99,102,107–109,112–117]	51
REL	[25,27,30,31,36,42,43,47,48,51,57,61,62,68,72,75,76,84,87–89,92,96,98,100,101,104,105,110,111,118]	31
ECO	[25,29,34,38,40,41,44–46,48–52,54,55,57,58,64,66,70,72,73,75,76,80,82,83,85–89,91,92,94,95,98–100,103–106,109,110]	46
ELTO	[25,28,29,32,34,35,37–41,46,48,49,53,56,58,63,67,70,72,74,76,77,80,82,84,85,90,93–95,97–99,107–109,112,115,117]	41

* Areas of Analysis: Power Quality (PQ), Reliability (REL), Economic (ECO), and Energy Losses and Thermal Overload (ELTO).

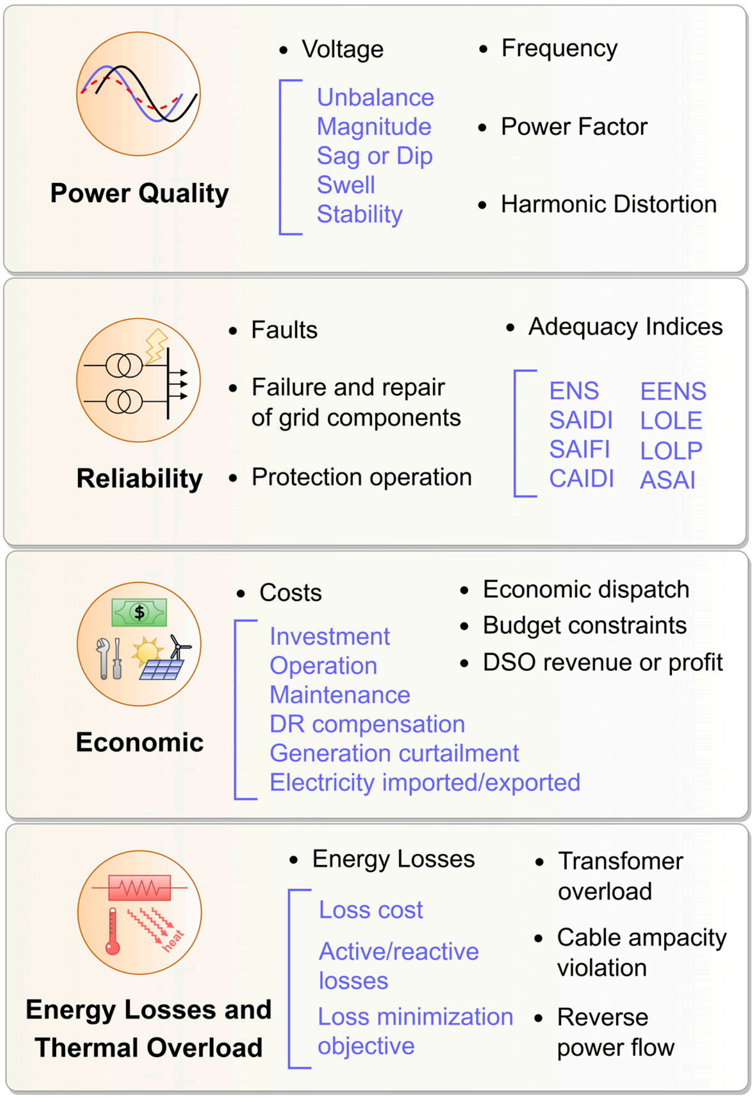

Figure 4. Representation of the main indices and characteristics of the areas of analysis of electrical networks.

- Power Quality

Power Quality comprehends voltage indices—such as dips or sags [26,65,81,84,113], voltage unbalance [26,34,71,117], voltage magnitude [29,32,52,53], and voltage stability index [66,74,78,107] (note that voltage stability is also related to reliability or security in the literature)—frequency [33,69,70], power factor [74,79,90], and total harmonic distortion [90,102]. In [90] for example, a C-type harmonic filter is designed to maximize the probabilistic HC of PV DG, subject to constraints of total and individual harmonic distortion, power factor, voltage, and thermal capacity of the lines. Reference [67] analyses indices associated with voltage (deviation, fluctuation, flicker, and voltage violation), reverse power flow, and losses. In [69], the impact of renewable energy (wind and solar) on the dynamic stability of an islanded MG is evaluated in terms of power and frequency. Paper [65] estimates voltage dips through the Bayesian Inference, based on the pre-fault and fault conditions of the network.

- Reliability

Reliability usually refers to the continuity of energy supply, measured through indices such as Energy Not Supplied (ENS) [27,36,87,89,104], Expected Energy Not Supplied (EENS) [43,88,92,98,118], System Average Interruption Duration Index (SAIDI) [30,31,76,100,110], System Average Interruption Frequency Index (SAIFI) [36,75,92,98,104], Average

Service Availability Index (ASAI) [36,47,76], Customer Average Interruption Duration Index (CAIDI) [31,36,98], Loss of Load Expectation (LOLE) [30,42,62], and Loss of Load Probability (LOLP) [30,42]. For instance, [92] formulates a multi-period and multi-objective expansion planning problem, aiming to minimize costs and maximize system reliability (in terms of SAIDI, LOLC, and EENS), considering the allocation of DG, capacitors, switches, and branches (including self-healing branches). Reference [96] determines the optimal tripping characteristics for overcurrent relays in radial distribution systems in order to minimize the expected value of load and generation disconnected by relay operation. Papers [42,118] evaluate 'well-being' indices, which indicate how 'healthy' the system is in terms of energy reserve availability concerning the demand.

- Economic

The third area of analysis is the economic one, characterized by the calculation of economic indices and the consideration of costs associated with investment, maintenance, and operation of electrical networks—note that the costs associated with indices of power quality or reliability in optimization problems have not been considered as economic values. Almost every paper in this category contends with optimization problems, including economic dispatch, daily scheduling, component allocation, islanding, and restoration of MGs with the objective of minimizing costs. For example, [83,88] define optimal configurations of AC-DC hybrid networks, aiming to minimize the costs associated with the installation of lines, Voltage Source Converters (VSCs) and generators (AC and DC). Papers [25,64,104,109,110] investigate allocation problems of DG, capacitors, charging stations, and other technologies, considering economic objectives. For instance, [110] analyses the allocation problem of a Cascaded H bridge short-circuit limiter, including among the objectives the minimization of the limiter capital cost. This work economically evaluates the limiter technology through Life Cycle Cost (LCC) and Net Present Value (NPV) indices. Alternatively, [64] is a long-term planning study of an isolated MG for the optimal sizing of a battery and the definition of its ideal year of installation, with the objective of minimizing the NPV of battery costs (installation and operation) and network costs (dispatchable DG operational cost and load shedding) in the considered horizon.

In addition to cost minimization, some studies such as [45,46,49,95] aim to maximize the distributor's revenue or profit. In [46], profit is defined as the difference between revenue and costs, including the cost of purchasing electricity from the upstream grid, cost of energy losses, cost of demand response, and cost due to DG reduction.

There are also a few works included in the economic category that do not carry out any type of optimization, such as [29,34,38,75]. For example, [29] builds different PV penetration scenarios through an economic analysis, using the Bass diffusion model, which allows predicting the dissemination of new technologies from a marketing perspective. Reference [38] calculates the expected NPV from the monetization of impacts (voltage, peak demand, and losses) due to the integration of battery storage systems associated with PV DG.

- Energy Losses and Thermal Overload

The category of energy losses and thermal overload covers the indices of losses, overload (in feeders, transformers and conductors), and reverse power flow, with losses being the most addressed topic—note that energy losses refer to the amount of heat dissipated by the Joule effect and not to the loss of load due to the disconnection of sections of the network as in [62,92]. An adequate allocation of DG, for example, can supply the local demand, reducing losses and overload in the equipment, while the excessive installation of DG can cause reverse power flow and worsen the mentioned indices. In [32], the integration of PV DG in a real distribution network of almost 500 feeders is analysed in terms of voltage magnitude, losses, peak demand, and reverse power flow. Paper [34] estimates the PV HC based on technical constraints of voltage magnitude/unbalance, conductor ampacity, and transformer overload, as well as through an economic limit, defined by the cost of losses. Reference [28] investigates the impact of PV DG on voltage stability and uses losses (active and reactive) to define the maximum PV penetration in the network.

Moreover, several optimization works include loss minimization among their objectives, as in [39,58,77,97,107]. Reference [109] proposes a problem of capacitor allocation in distribution networks with DG, aiming to minimize the costs of losses and the costs associated with capacitors. In [41], a multi-objective optimization model is formulated to minimize the demand and energy losses of the network via Conservation Voltage Reduction (CVR), as well as to reduce the number of operations of the following voltage regulator devices: On-Load Tap Changer (OLTC), Step Voltage Regulator (SVR), and Switched Shunt Capacitor (SC).

4.2. Technologies Associated with DG

Figure 5 represents the main technologies covered within the topic of smart grids. Besides, in the literature review there have been found different terms related to smart grids, such as Smart Residential Community [73], Energy Clusters [30], Virtual Power Plants [94], District Energy Systems [91], Smart Buildings [101], Residential Energy Hubs [44], and Hybrid-Energy Microgrid [51]. In particular, [44,51,55,91,101] analyse electrothermal hybrid smart grids, as shown in Figure 6. Thermal technologies cover equipment such as boilers, heat pumps, heat storage systems, chillers, and cogeneration units—combined heat and power (CHP). Note that the CHP unit is represented in Figure 6 as a common link between the electrical and thermal (heating) grids, since it can generate electricity and heat simultaneously.

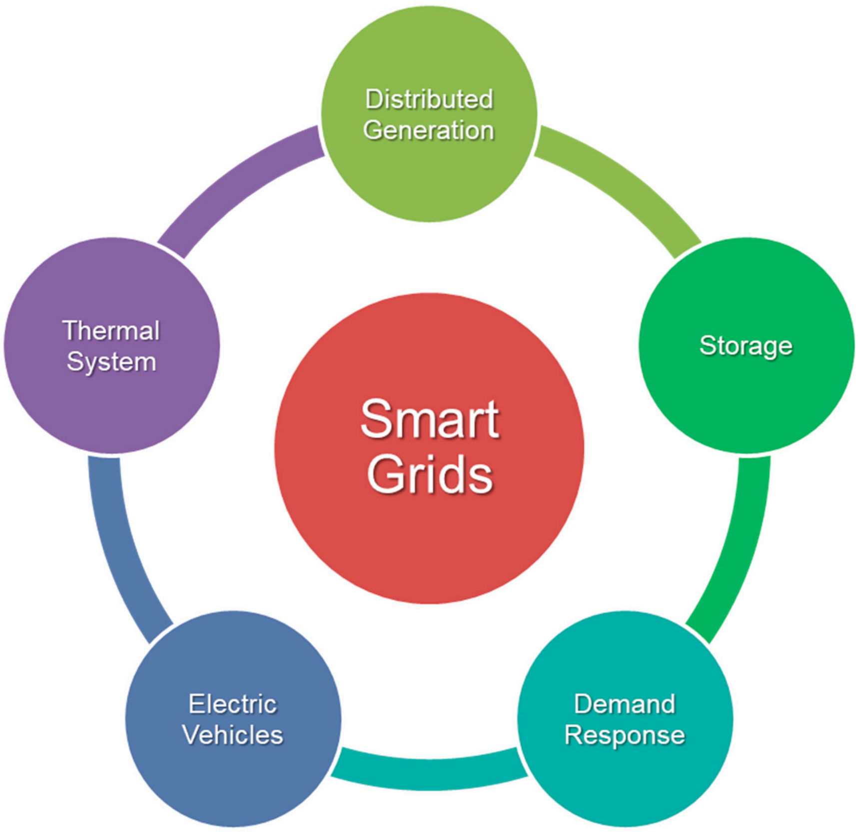

Figure 5. Main technologies related to smart grids.

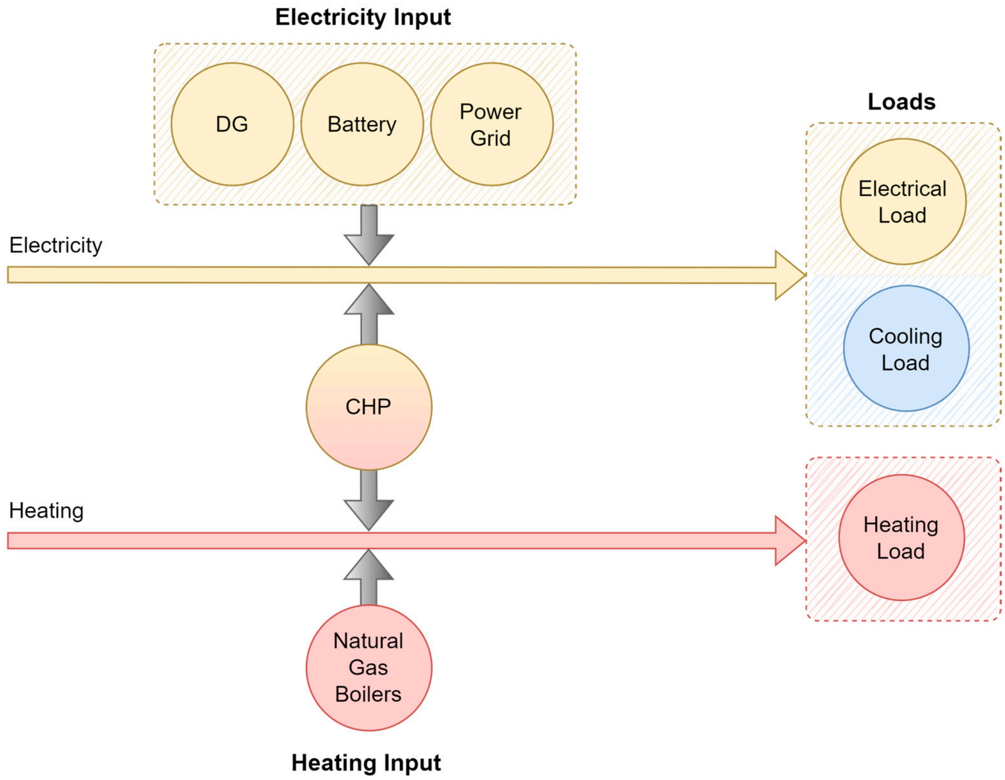

Figure 6. Example of an electrothermal diagram of a hybrid smart grid (based on [91]).

The most common types of DG addressed in the literature are PV and wind. For example, [48,58,97,98,107] propose PV and/or wind DG allocation problems. However, in the review there have been found other DG technologies such as microturbines [103,106], fuel cells [103,106], CHPs [51,55,101], synchronous distributed generators [81,84], biomass [87], and tidal energy [76]. Reference [27] studies a reconfiguration problem of a MG with the ability to operate in islanding mode, including generation sources such as geothermal, waste-to-energy (W2E), and mobile generation/storage—transported in trucks.

Smart grids are generally related to concepts of sustainable development and the reduction of environmental impacts. For instance, [49,51] proposes optimization problems that include objectives of maximizing renewable generation and reducing emissions of polluting gases. However, although several works prioritize renewable sources, fossil DG is often used to meet the grid demand in problems of economic dispatch, daily operation scheduling, and reliability, due to the ease of dispatching this type of generation, as in [43,52,118].

In addition to DG, smart grids can use other resources to assist in energy management, in order to meet the electrical demand within the appropriate standards of quality and energy supply. Storage systems and demand response, for example, provide greater flexibility to network operation, assisting in the adjustment of generation and load profiles. Reference [57] introduces the concept of Storage-to-Storage (S2S), which occurs when a 'generation source with memory' (such as a battery bank) feeds a 'load with memory' (such as a plug-in EV), providing even greater flexibility for the network. Paper [38] analyses the technical and financial impacts of the integration of individual storage systems associated with PV DG in a distribution network, considering different strategies for controlling energy prices. In addition to this type of control, other examples of demand response measures include load shedding, curtailment, and shifting [42,52,54,73,87]; energy supply via Vehicle-to-Grid (V2G) technology [44,45,93]; and flexible loads with Power-to-Gas (P2G) technology [108].

4.3. Uncertainty Modelling

One of the key elements of stochastic analysis is uncertainty modelling. Figure 7 illustrates the main uncertainties observed in this review, in which the size of each circumference represents the frequency of occurrence of the respective type of randomness.

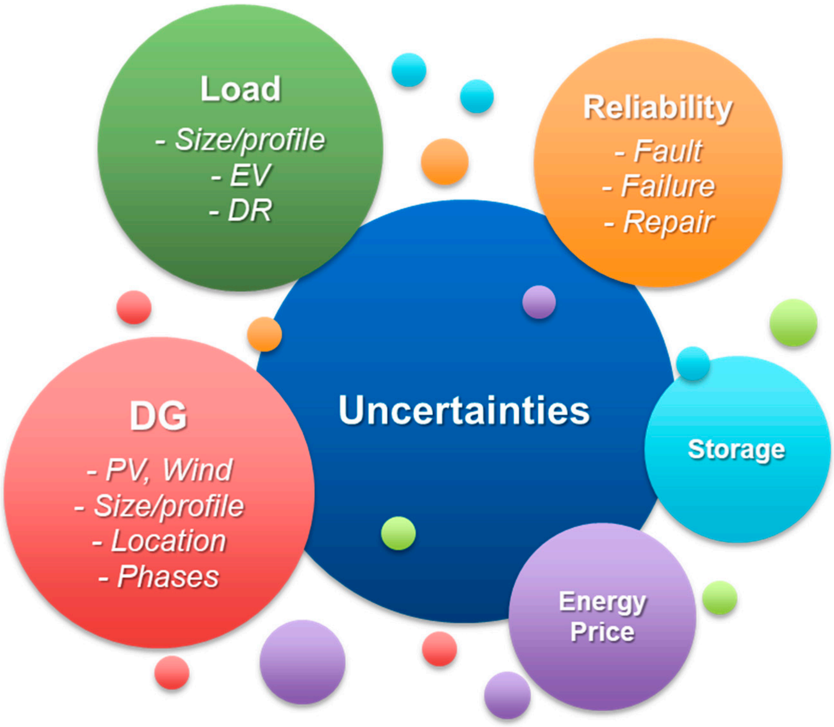

Figure 7. Main uncertainties observed in the literature review.

According to [119], the two most relevant types of uncertainties associated with DG are due to the variation of the primary energy source and the unavailability of the generation unit. Most of the selected papers consider uncertainties related to renewable generation, especially wind and PV. Typically, uncertainties related to the PV and wind generation profile are modelled via probability distributions such as Beta [42,43,78,118] and Weibull [107,109,112,118], respectively, but they can also be represented by other distributions as normal [64,82], by sampling based on real data [40,87], or by advanced modelling techniques such as MCMC [45] and KDE [39] (see ATUM in Section 3). Besides the uncertainties of the generation profile, the selected papers often consider uncertainties in the DG installed power [113,116], in the DG location [32,37,38] and in the phases of the electrical network connected to DG [29,34].

The second most observed type of uncertainty refers to the load. Load profiles are frequently modelled through normal distribution [41,65,79,107,112], but similar to DG, they can also be sampled from real data [29,38,40,87] or by using more advanced modelling techniques such as copula [73] and the ARIMA model [68] (see ATUM in Section 3). In special, works such as [35,49,103,118] model uncertainties related to plug-in EVs in terms of charging start time, charging duration, distance travelled, state of charge (SOC), charging station location, etc. Some studies still consider uncertainties associated with consumer behaviour in demand response programs, such as [62,80].

Reliability studies usually consider uncertainties associated with faults, failure, and/or repair of network components to evaluate the quality of power supply. In [89], the analysed grid is divided into two zones, each with different failure rates and times. In [81], random variables with normal and uniform distributions represent the duration of voltage dip and the fault characteristics—including fault location, type (three-phase, two-phase, two-phase-to-ground, or phase-to-ground), and impedance. Reference [98] considers failure rates of network equipment, including the following protection devices: circuit breakers, fuses, and sectionalizers. Papers [101,105] model the randomness of natural disasters—characterized as catastrophic events of low probability, but with extremely high impact—in order to analyse the reliability and resilience of the electric grid.

Storage uncertainties are often modelled in terms of capacity, location, SOC, and availability or equipment failure, as in papers such as [38,40,61,75,87]. For instance, [61] proposes a two-dimensional multistage storage model to stochastically represent the SOC and the maximum storage capacity, using the Markov Chain. In [87], SOC is randomly sampled from historical data.

Studies such as [44,50,52,85] model electric energy price uncertainties, which can influence the behaviour of demand response strategies, daily operation scheduling and the calculation of economic indices. In [44,85], these uncertainties follow a normal distribution, while in [50,52] they are represented by several scenarios with different price curves.

4.4. Detailed Classification of the Reviewed Papers from 2021

Table 3 shows a detailed classification of the most recent papers in the review, from 2021, totalling 22 references. Each work is categorized according to the simulation techniques and areas of analysis of electrical networks, discussed in Sections 3 and 4.1, respectively. Besides, this table addresses key features on the following topics: uncertainties, DG type, and other relevant technologies considered in these studies.

Table 3. Detailed classification of the reviewed papers from 2021.

Reference	Title	Simulation Techniques [a]	Areas of Analysis [b]	Uncertainties	DG Type	Other Technologies
[39]	Stochastic investigation for solid-state transformer integration in distributed energy resources integrated active distribution network	-CEE -ATUM -SO	-PQ -ELTO	-PV and wind DG -Load	-PV -Wind	-Battery -Solid-State Transformer
[33]	Robust Controller Synthesis and Analysis in Inverter-Dominant Droop-Controlled Islanded Microgrids	-CMC	-PQ	-Voltage fluctuation -Phase difference among DGs	-Undefined type	-MI-synthesis robust controller for inverters
[106]	Hybrid whale optimization and pattern search algorithm for day-ahead operation of a microgrid in the presence of electric vehicles and renewable energies	-SO	-ECO	-PV and wind DG -Load -EV -Electric energy price	-PV -Wind -Microturbine -Fuel cell	-EV -Battery
[34]	Comparison of Economical and Technical Photovoltaic Hosting Capacity Limits in Distribution Network	-CMC	-PQ -ELTO -ECO	-PV DG -Load	-PV	-
[35]	Simulating the Impacts of Uncontrolled Electric Vehicle Charging in Low Voltage Grids	-CMC	-PQ -ELTO	-PV DG -Load -EV	-PV	-EV
[40]	Mixed-integer stochastic evaluation of battery energy storage system integration strategies in distribution systems	-CEE -SO	-PQ -ELTO -ECO	-PV and wind DG -Load -EV -Battery -Electric energy price	-PV -Wind	-EV -Battery
[36]	Evaluation of service quality of distribution systems with critically located generators	-CMC	-REL	-Fault -Equipment failure rate and repair time	-Wind	-Recloser -Fuse -Overcurrent relay

Table 3. *Cont.*

Reference	Title	Simulation Techniques [a]	Areas of Analysis [b]	Uncertainties	DG Type	Other Technologies
[107]	Deterministic and probabilistic multi-objective placement and sizing of wind renewable energy sources using improved spotted hyena optimizer	-SO	-PQ -ELTO	-Wind DG -Load	-Wind	-
[108]	Voltage Optimization in MV Network with Distributed Generation Using Power Consumption Control in Electrolysis Installations	-SO	-PQ -ELTO	-DG (undefined type) -Load	-Undefined type	-OLTC -DG reactive control -Power-to-Gas (P2G) technology for green hydrogen production
[37]	Hosting Capacity Improvement Method Using MV–MV Solid-State-Transformer	-CMC	-PQ -ELTO	-PV DG	-PV	-Solid-State Transformer
[41]	Operation planning and decision-making approaches for Volt/Var multiobjective optimization in power distribution systems	-CEE -SO	-ELTO -ECO	-PV DG -Load	-PV	-OLTC -SVR -Capacitor
[38]	Technical and Financial Impacts on Distribution Systems of Integrating Batteries Controlled by Uncoordinated Strategies	-CMC	-PQ -ELTO -ECO	-PV DG -Load -Battery	-PV	-Battery
[109]	An Improved Sunflower Optimization Algorithm-Based Monte Carlo Simulation for Efficiency Improvement of Radial Distribution Systems Considering Wind Power Uncertainty	-SO	-PQ -ELTO -ECO	-Wind DG	-Wind	-Capacitors
[110]	Pareto Optimal Allocation of Flexible Fault Current Limiter Based on Multi-Objective Improved Bat Algorithm	-SO	-REL -ECO	-Fault	-PV	-Cascaded H bridge fault current limiter
[111]	A Novel Method for Islanding in Active Distribution Network Considering Distributed Generation	-SO	-REL	-Wind DG	-Wind	-Controllable loads -Circuit breaker
[112]	A fast-specialized point estimate method for the probabilistic optimal power flow in distribution systems with renewable distributed generation	-SO -MCM-BK	-PQ -ELTO	-PV and wind DG -Load	-PV -Wind -Dispatchable DG	-
[118]	Investigation of impacts of plug-in hybrid electric vehicles' stochastic characteristics modeling on smart grid reliability under different charging scenarios	-MCM-BK	-REL	-PV and wind DG -EV -Failure in network segments	-PV -Wind -Diesel	-Capacitor -Protection devices -Circuit breaker -EV

Table 3. *Cont.*

Reference	Title	Simulation Techniques [a]	Areas of Analysis [b]	Uncertainties	DG Type	Other Technologies
[42]	Reliability evaluation of smart grid using various classic and metaheuristic clustering algorithms considering system uncertainties	-CEE	-REL	-PV and wind DG -Load -Equipment failure rate and repair time	-PV -Wind -Diesel	-Consider load curtailment -Recloser -Circuit breaker -Load break switch -Fuse -Capacitor
[43]	Optimal stochastic scenario-based allocation of smart grids' renewable and non-renewable distributed generation units and protective devices	-CEE -SO	-REL	-PV and wind DG -Failure in network segments, load points and protection devices	-PV -Wind -Diesel	-Consider load curtailment -Circuit breaker -Protection devices -Capacitor
[78]	Probabilistic Steady State Voltage Stability Assessment Method for Correlated Wind Energy and Solar Photovoltaic Integrated Power Systems	-ATUM -MCM-BK	-PQ	-PV and wind DG -Load	-PV -Wind	-
[44]	Optimal Scenario-based Operation and Scheduling of Residential Energy Hubs Including Plug-in Hybrid Electric Vehicle and Heat Storage System Considering the Uncertainties of Electricity Price and Renewable Distributed Generations	-CEE -SO	-ECO	-PV DG -Electric energy price	-PV	-Heat storage system -EV with V2G -Micro-combined heat and power -Thermal load
[45]	An optimal resource allocation for future parking lots with charger assignment considering uncertainties	-CEE -ATUM -SO	-ECO	-PV DG -Load	-PV	-EV withV2G

[a] Simulation Techniques: Crude Monte Carlo (CMC), Computational Efficiency Enhancement (CEE), Advanced Techniques for Uncertainty Modelling (ATUM), Stochastic Optimization (SO), and MCM as Benchmark (MCM-BK). [b] Areas of Analysis: Power Quality (PQ), Reliability (REL), Economic (ECO), and Energy Losses and Thermal Overload (ELTO).

5. Conclusions

This work presents the state of the art of MCM applied to electrical networks with DG. The proposed literature review comprises over 90 recent papers from pertinent journals and conferences, with emphasis on the technical, operational, and planning aspects of the EPS. The search process has been performed using transparent criteria, such that it can be easily replicated. The works have been approached according to the simulation techniques, area of analysis of electrical networks, technologies associated with DG, and uncertainty modelling.

MCM allows for considering with flexibility the various uncertainties associated with load, renewable generation, and random events such as equipment failures and power grid faults. Therefore, given the current context of increasing dissemination of renewable generation sources, and other related technologies; personal computers with high processing capacity; and huge availability of data; the area of stochastic simulations applied to EPS is expected to remain relevant in the coming years.

Regarding the simulation techniques, the works have been divided into five categories: CMC, CEE, ATUM, SO, and MCM-BK. The literature review reveals a preponderance of SO papers, indicating a possible trend. Alternatively, since MCM has been widely applied as the benchmark to validate other stochastic techniques, the MCM-BK category has been created specifically to include this type of work in the review. As a secondary benefit, this allows the reader to learn about other alternative techniques to the MCM, which can be used for the same type of stochastic analysis.

The areas of analysis of electrical networks have been divided into four categories: Power Quality, Reliability, Economic, and Energy Losses and Thermal Overload. In particular, reliability works often consider uncertainties associated with faults, failure, and/or repair of network components. However, in general, the uncertainties most found in the review refer to DG (PV or wind power) and loads. Given the ability of the MCM to represent randomness with relative ease and versatility, this method is expected to be further applied in EPS analysis, increasingly modelling the uncertainties of emerging technologies such as storage, EV, demand response, and electrothermal hybrid systems.

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References

1. Billinton, R.; Li, W. *Reliability Assessment of Electric Power Systems Using Monte Carlo Methods*; Springer: Boston, MA, USA, 1994; ISBN 978-1-4899-1348-7.
2. Leite da Silva, A.M.; de Castro, A.M. Risk Assessment in Probabilistic Load Flow via Monte Carlo Simulation and Cross-Entropy Method. *IEEE Trans. Power Syst.* **2019**, *34*, 1193–1202. [CrossRef]
3. Razavi, S.-E.; Rahimi, E.; Javadi, M.S.; Nezhad, A.E.; Lotfi, M.; Shafie-khah, M.; Catalão, J.P.S. Impact of Distributed Generation on Protection and Voltage Regulation of Distribution Systems: A Review. *Renew. Sustain. Energy Rev.* **2019**, *105*, 157–167. [CrossRef]
4. Bawazir, R.O.; Cetin, N.S. Comprehensive Overview of Optimizing PV-DG Allocation in Power System and Solar Energy Resource Potential Assessments. *Energy Rep.* **2020**, *6*, 173–208. [CrossRef]
5. 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]
6. Ismael, S.M.; Abdel Aleem, S.H.E.; 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]
7. Mehigan, L.; Deane, J.P.; Gallachóir, B.P.Ó.; Bertsch, V. A Review of the Role of Distributed Generation (DG) in Future Electricity Systems. *Energy* **2018**, *163*, 822–836. [CrossRef]
8. Lopes, J.A.P.; Hatziargyriou, N.; Mutale, J.; Djapic, P.; Jenkins, N. Integrating Distributed Generation into Electric Power Systems: A Review of Drivers, Challenges and Opportunities. *Electr. Power Syst. Res.* **2007**, *77*, 1189–1203. [CrossRef]
9. Ehsan, A.; Yang, Q. State-of-the-Art Techniques for Modelling of Uncertainties in Active Distribution Network Planning: A Review. *Appl. Energy* **2019**, *239*, 1509–1523. [CrossRef]
10. Tan, W.; Shaaban, M.; Ab Kadir, M.Z.A. Stochastic Generation Scheduling with Variable Renewable Generation: Methods, Applications, and Future Trends. *IET Gener. Transm. Distrib.* **2019**, *13*, 1467–1480. [CrossRef]
11. Hasan, K.N.; Preece, R.; Milanović, J.V. Existing Approaches and Trends in Uncertainty Modelling and Probabilistic Stability Analysis of Power Systems with Renewable Generation. *Renew. Sustain. Energy Rev.* **2019**, *101*, 168–180. [CrossRef]
12. Zakaria, A.; Ismail, F.B.; Lipu, M.S.H.; Hannan, M.A. Uncertainty Models for Stochastic Optimization in Renewable Energy Applications. *Renew. Energy* **2020**, *145*, 1543–1571. [CrossRef]
13. Talari, S.; Shafie-khah, M.; Osório, G.J.; Aghaei, J.; Catalão, J.P.S. Stochastic Modelling of Renewable Energy Sources from Operators' Point-of-View: A Survey. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1953–1965. [CrossRef]
14. Zubo Rana, H.A.; 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]
15. Rubinstein, R.Y.; Kroese, D.P. *Simulation and the Monte Carlo Method*, 3rd ed.; Wiley Series in Probability and Statistics; Wiley: Hoboken, NJ, USA, 2017; ISBN 978-1-118-63220-8.
16. Brooks, S.; Gelman, A.; Jones, G.; Meng, X.-L. (Eds.) *Handbook of Markov Chain Monte Carlo*; Chapman and Hall/CRC: Boca Raton, FL, USA, 2011; ISBN 978-0-429-13850-8.
17. Ross, S.M. *An Elementary Introduction to Mathematical Finance*, 3rd ed.; Cambridge University Press: New York, NY, USA, 2011; ISBN 978-0-521-19253-8.

18. Rubinstein, R.Y.; Kroese, D.P. *The Cross-Entropy Method: A Unified Approach to Combinatorial Optimization, Monte-Carlo Simulation and Machine Learning*; Springer: New York, NY, USA, 2011; ISBN 978-1-4419-1940-3.
19. Van Ravenzwaaij, D.; Cassey, P.; Brown, S.D. A Simple Introduction to Markov Chain Monte–Carlo Sampling. *Psychon. Bull. Rev.* **2018**, *25*, 143–154. [CrossRef]
20. Singhee, A.; Rutenbar, R.A. Why Quasi-Monte Carlo Is Better Than Monte Carlo or Latin Hypercube Sampling for Statistical Circuit Analysis. *IEEE Trans. Comput. Aided Des. Integr. Circuits Syst.* **2010**, *29*, 1763–1776. [CrossRef]
21. Niederreiter, H. *Random Number Generation and Quasi-Monte Carlo Methods*; CBMS-NSF Regional Conference Series in Applied Mathematics; Society for Industrial and Applied Mathematics: Philadelphia, PA, USA, 1992; ISBN 978-0-89871-295-7.
22. Lemieux, C. *Monte Carlo and Quasi-Monte Carlo Sampling*, 1st ed.; Springer: New York, NY, USA, 2010; ISBN 978-1-4419-2676-0.
23. Doucet, A.; Freitas, N.; Gordon, N. *Sequential Monte Carlo Methods in Practice*; Springer: New York, NY, USA, 2001; ISBN 978-1-4757-3437-9.
24. Mello, J.C.O.; Pereira, M.V.F.; Leite da Silva, A.M. Evaluation of Reliability Worth in Composite Systems Based on Pseudo-Sequential Monte Carlo Simulation. *IEEE Trans. Power Syst.* **1994**, *9*, 1318–1326. [CrossRef]
25. Banol Arias, N.; Tabares, A.; Franco, J.F.; Lavorato, M.; Romero, R. Robust Joint Expansion Planning of Electrical Distribution Systems and EV Charging Stations. *IEEE Trans. Sustain. Energy* **2018**, *9*, 884–894. [CrossRef]
26. 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]
27. De Quevedo, P.M.; Contreras, J.; Mazza, A.; Chicco, G.; Porumb, R. Reliability Assessment of Microgrids with Local and Mobile Generation, Time-Dependent Profiles, and Intraday Reconfiguration. *IEEE Trans. Ind. Appl.* **2018**, *54*, 61–72. [CrossRef]
28. Rawat, M.S.; Vadhera, S. Impact of Photovoltaic Penetration on Static Voltage Stability of Distribution Networks: A Probabilistic Approach. *Asian J. Water Environ. Pollut.* **2018**, *15*, 51–62. [CrossRef]
29. Abud, T.P.; Maciel, R.S.; Borba, B.S.M.C. Influence of Local Market Economic Analysis on PV Generation Stochastic Approach in LV Distribution Networks. *Int. J. Electr. Power Energy Syst.* **2019**, *112*, 178–190. [CrossRef]
30. Andruszkiewicz, J.; Lorenc, J.; Weychan, A. Distributed generation as efficient measure to improve power generation adequacy. *Arch. Electr. Eng.* **2019**. [CrossRef]
31. Muhammad Ridzuan, M.I.; Roslan, N.N.R.; Mohd Fauzi, N.F.; Rusli, M.A.Z. Reliability-Based DG Location Using Monte-Carlo Simulation Technique. *SN Appl. Sci.* **2020**, *2*, 145. [CrossRef]
32. Stecanella, P.A.J.; Vieira, D.; Vasconcelos, M.V.L.; Ferreira Filho, A.D.L. Statistical Analysis of Photovoltaic Distributed Generation Penetration Impacts on a Utility Containing Hundreds of Feeders. *IEEE Access* **2020**, *8*, 175009–175019. [CrossRef]
33. Azizi, S.M. Robust Controller Synthesis and Analysis in Inverter-Dominant Droop-Controlled Islanded Microgrids. *IEEECAA J. Autom. Sin.* **2021**, *8*, 1401–1415. [CrossRef]
34. Fatima, S.; Püvi, V.; Arshad, A.; Pourakbari-Kasmaei, M.; Lehtonen, M. Comparison of Economical and Technical Photovoltaic Hosting Capacity Limits in Distribution Networks. *Energies* **2021**, *14*, 2405. [CrossRef]
35. Haider, S.; Schegner, P. Simulating the Impacts of Uncontrolled Electric Vehicle Charging in Low Voltage Grids. *Energies* **2021**, *14*, 2330. [CrossRef]
36. Abreu, P.S.E.; Martins, A.G. Evaluation of Service Quality of Distribution Systems with Critically Located Generators. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e12852. [CrossRef]
37. Song, J.-S.; Kim, J.-S.; Mather, B.; Kim, C.-H. Hosting Capacity Improvement Method Using MV–MV Solid-State-Transformer. *Energies* **2021**, *14*, 622. [CrossRef]
38. Camargos, R.S.C.; Stecanella, P.A.J.; Vieira, D.; Raggi, L.M.D.R.; Melo, F.C.; Domingues, E.G.; Filho, A.D.L.F. Technical and Financial Impacts on Distribution Systems of Integrating Batteries Controlled by Uncoordinated Strategies. *IEEE Access* **2021**, *9*, 91361–91376. [CrossRef]
39. Gantayet, A.; Dheer, D.K. Stochastic Investigation for Solid-state Transformer Integration in Distributed Energy Resources Integrated Active Distribution Network. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e13056. [CrossRef]
40. Sepúlveda Rangel, C.A.; Canha, L.N.; Sperandio, M.; Miranda, V. Mixed-integer Stochastic Evaluation of Battery Energy Storage System Integration Strategies in Distribution Systems. *IET Gener. Transm. Distrib.* **2022**, *16*, 641–655. [CrossRef]
41. Vitor, T.S.; Vieira, J.C.M. Operation Planning and Decision-Making Approaches for Volt/Var Multi-Objective Optimization in Power Distribution Systems. *Electr. Power Syst. Res.* **2021**, *191*, 106874. [CrossRef]
42. Memari, M.; Karimi, A.; Hashemi-Dezaki, H. Reliability Evaluation of Smart Grid Using Various Classic and Metaheuristic Clustering Algorithms Considering System Uncertainties. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e12902. [CrossRef]
43. Yaghoubi-Nia, M.-R.; Hashemi-Dezaki, H.; Halvaei Niasar, A. Optimal Stochastic Scenario-Based Allocation of Smart Grids' Renewable and Non-Renewable Distributed Generation Units and Protective Devices. *Sustain. Energy Technol. Assess.* **2021**, *44*, 101033. [CrossRef]
44. Emrani-Rahaghi, P.; Hashemi-Dezaki, H. Optimal Scenario-Based Operation and Scheduling of Residential Energy Hubs Including Plug-in Hybrid Electric Vehicle and Heat Storage System Considering the Uncertainties of Electricity Price and Renewable Distributed Generations. *J. Energy Storage* **2021**, *33*, 102038. [CrossRef]
45. Abdelwahab, O.M.; Shalaby, A.A.; Shaaban, M.F. An Optimal Resource Allocation for Future Parking Lots with Charger Assignment Considering Uncertainties. *Electr. Power Syst. Res.* **2021**, *200*, 107455. [CrossRef]

46. Yang, J.; Gao, H.; Ye, S.; Lv, L.; Liu, Y.; Liu, J. Applying Multiple Types of Demand Response to Optimal Day-ahead Stochastic Scheduling in the Distribution Network. *IET Gener. Transm. Distrib.* **2020**, *14*, 4509–4519. [CrossRef]
47. Yan, F.; Chen, X.; Tang, W.; Yan, R.; Wu, H. Reliability and Power Supply Capability Evaluation of Active Distribution Networks with Four-terminal Soft Open Points. *IET Smart Grid* **2020**, *3*, 657–666. [CrossRef]
48. Liu, J.; Zeng, P.; Li, Y.; Xing, H. Coordinated Optimal Allocation of Distributed Generations in Smart Distribution Grids Considering Active Management and Contingencies. *J. Electr. Eng. Technol.* **2020**, *15*, 1969–1983. [CrossRef]
49. Liu, L.; Zhang, Y.; Da, C.; Huang, Z.; Wang, M. Optimal Allocation of Distributed Generation and Electric Vehicle Charging Stations Based on Intelligent Algorithm and Bi-level Programming. *Int. Trans. Electr. Energy Syst.* **2020**, *30*, e12366. [CrossRef]
50. Abdi-Siab, M.; Lesani, H. Two-stage Scenario-based DEP Incorporating PEV Using Benders' Decomposition. *IET Gener. Transm. Distrib.* **2020**, *14*, 1508–1520. [CrossRef]
51. Luo, Y.; Yang, D.; Yin, Z.; Zhou, B.; Sun, Q. Optimal Configuration of Hybrid-energy Microgrid Considering the Correlation and Randomness of the Wind Power and Photovoltaic Power. *IET Renew. Power Gener.* **2020**, *14*, 616–627. [CrossRef]
52. Prudhviraj, D.; Kiran, P.B.S.; Pindoriya, N.M. Stochastic Energy Management of Microgridwith Nodal Pricing. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 102–110. [CrossRef]
53. Rezaeian-Marjani, S.; Masoumzadehasl, S.; Galvani, S.; Talavat, V. Probabilistic Assessment of D-STATCOM Operation Considering Correlated Uncertain Variables. *Int. Trans. Electr. Energy Syst.* **2020**, *30*, e12522. [CrossRef]
54. Vergara, P.P.; López, J.C.; Rider, M.J.; Shaker, H.R.; da Silva, L.C.P.; Jørgensen, B.N. A Stochastic Programming Model for the Optimal Operation of Unbalanced Three-Phase Islanded Microgrids. *Int. J. Electr. Power Energy Syst.* **2020**, *115*, 105446. [CrossRef]
55. Rigo-Mariani, R.; Chea Wae, S.O.; Mazzoni, S.; Romagnoli, A. Comparison of Optimization Frameworks for the Design of a Multi-Energy Microgrid. *Appl. Energy* **2020**, *257*, 113982. [CrossRef]
56. Vita, V.; Lazarou, S.; Christodoulou, C.A.; Seritan, G. On the Determination of Meshed Distribution Networks Operational Points after Reinforcement. *Appl. Sci.* **2019**, *9*, 3501. [CrossRef]
57. Ahmadian, A.; Sedghi, M.; Fgaier, H.; Mohammadi-ivatloo, B.; Golkar, M.A.; Elkamel, A. PEVs Data Mining Based on Factor Analysis Method for Energy Storage and DG Planning in Active Distribution Network: Introducing S2S Effect. *Energy* **2019**, *175*, 265–277. [CrossRef]
58. Abdelaziz, M.; Moradzadeh, M. Monte-Carlo Simulation Based Multi-Objective Optimum Allocation of Renewable Distributed Generation Using OpenCL. *Electr. Power Syst. Res.* **2019**, *170*, 81–91. [CrossRef]
59. Li, Q.; Wang, X.; Rong, S. Probabilistic Load Flow Method Based on Modified Latin Hypercube-Important Sampling. *Energies* **2018**, *11*, 3171. [CrossRef]
60. Lazarou, S.; Vita, V.; Christodoulou, C.; Ekonomou, L. Calculating Operational Patterns for Electric Vehicle Charging on a Real Distribution Network Based on Renewables' Production. *Energies* **2018**, *11*, 2400. [CrossRef]
61. Yan, T.; Tang, W.; Wang, Y.; Zhang, X. Reliability Assessment of a Multi-state Distribution System with Microgrids Based on an Accelerated Monte-Carlo Method. *IET Gener. Transm. Distrib.* **2018**, *12*, 3221–3229. [CrossRef]
62. Feng, J.; Zeng, B.; Zhao, D.; Wu, G.; Liu, Z.; Zhang, J. Evaluating Demand Response Impacts on Capacity Credit of Renewable Distributed Generation in Smart Distribution Systems. *IEEE Access* **2018**, *6*, 14307–14317. [CrossRef]
63. Grisales-Noreña, L.; Gonzalez Montoya, D.; Ramos-Paja, C. Optimal Sizing and Location of Distributed Generators Based on PBIL and PSO Techniques. *Energies* **2018**, *11*, 1018. [CrossRef]
64. Alharbi, H.; Bhattacharya, K. Stochastic Optimal Planning of Battery Energy Storage Systems for Isolated Microgrids. *IEEE Trans. Sustain. Energy* **2018**, *9*, 211–227. [CrossRef]
65. Ye, G.; Nijhuis, M.; Cuk, V.; Cobben, J.F.G. Incorporating Network Uncertainties in Voltage Dip State Estimation. *Int. J. Electr. Power Energy Syst.* **2019**, *113*, 888–896. [CrossRef]
66. Karim, M.A.; Currie, J.; Lie, T.-T. A Machine Learning Based Optimized Energy Dispatching Scheme for Restoring a Hybrid Microgrid. *Electr. Power Syst. Res.* **2018**, *155*, 206–215. [CrossRef]
67. 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]
68. Sharma, A.; Srinivasan, D.; Trivedi, A. A Decentralized Multi-Agent Approach for Service Restoration in Uncertain Environment. *IEEE Trans. Smart Grid* **2018**, *9*, 3394–3405. [CrossRef]
69. Krismanto, A.U.; Mithulananthan, N.; Kamwa, I. Oscillatory Stability Assessment of Microgrid in Autonomous Operation with Uncertainties. *IET Renew. Power Gener.* **2018**, *12*, 494–504. [CrossRef]
70. Liu, Z.; Yang, J.; Zhang, Y.; Ji, T.; Zhou, J.; Cai, Z. Multi-Objective Coordinated Planning of Active-Reactive Power Resources for Decentralized Droop-Controlled Islanded Microgrids Based on Probabilistic Load Flow. *IEEE Access* **2018**, *6*, 40267–40280. [CrossRef]
71. Carpinelli, G.; Rizzo, R.; Caramia, P.; Varilone, P. Taguchi's Method for Probabilistic Three-Phase Power Flow of Unbalanced Distribution Systems with Correlated Wind and Photovoltaic Generation Systems. *Renew. Energy* **2018**, *117*, 227–241. [CrossRef]
72. Giraldo, J.S.; Castrillon, J.A.; Lopez, J.C.; Rider, M.J.; Castro, C.A. Microgrids Energy Management Using Robust Convex Programming. *IEEE Trans. Smart Grid* **2019**, *10*, 4520–4530. [CrossRef]
73. Nan, S.; Zhou, M.; Li, G.; Xia, Y. Optimal Scheduling Approach on Smart Residential Community Considering Residential Load Uncertainties. *J. Electr. Eng. Technol.* **2019**, *14*, 613–625. [CrossRef]

74. Naghdi, M.; Shafiyi, M.-A.; Haghifam, M.-R. A Combined Probabilistic Modeling of Renewable Generation and System Load Types to Determine Allowable DG Penetration Level in Distribution Networks. *Int. Trans. Electr. Energy Syst.* **2019**, *29*, e2696. [CrossRef]
75. Escalera, A.; Prodanović, M.; Castronuovo, E.D. Analytical Methodology for Reliability Assessment of Distribution Networks with Energy Storage in Islanded and Emergency-Tie Restoration Modes. *Int. J. Electr. Power Energy Syst.* **2019**, *107*, 735–744. [CrossRef]
76. Recalde, A.A.; Alvarez-Alvarado, M.S. Design Optimization for Reliability Improvement in Microgrids with Wind-Tidal-Photovoltaic Generation. *Electr. Power Syst. Res.* **2020**, *188*, 106540. [CrossRef]
77. Fu, X.; Guo, Q.; Sun, H. Statistical Machine Learning Model for Stochastic Optimal Planning of Distribution Networks Considering a Dynamic Correlation and Dimension Reduction. *IEEE Trans. Smart Grid* **2020**, *11*, 2904–2917. [CrossRef]
78. Rawat, M.S.; Vadhera, S. Probabilistic Steady State Voltage Stability Assessment Method for Correlated Wind Energy and Solar Photovoltaic Integrated Power Systems. *Energy Technol.* **2021**, *9*, 2000732. [CrossRef]
79. Sui, B.; Hou, K.; Jia, H.; Mu, Y.; Yu, X. Maximum Entropy Based Probabilistic Load Flow Calculation for Power System Integrated with Wind Power Generation. *J. Mod. Power Syst. Clean Energy* **2018**, *6*, 1042–1054. [CrossRef]
80. Yong, C.; Kong, X.; Chen, Y.; Chen, E.Z.; Cui, K.; Wang, X. Multiobjective Scheduling of an Active Distribution Network Based on Coordinated Optimization of Source Network Load. *Appl. Sci.* **2018**, *8*, 1888. [CrossRef]
81. Eslami, A.; Hamedani Golshan, M.E. Index-Based Voltage Dip Consideration in Optimal Planning of SDGs by Applying a Modified Monte Carlo Simulation Method. *Int. Trans. Electr. Energy Syst.* **2018**, *28*, e2478. [CrossRef]
82. Hemmati, R.; Ghiasi, S.M.S.; Entezariharsini, A. Power Fluctuation Smoothing and Loss Reduction in Grid Integrated with Thermal-Wind-Solar-Storage Units. *Energy* **2018**, *152*, 759–769. [CrossRef]
83. Ahmed, H.M.A.; Eltantawy, A.B.; Salama, M.M.A. A Planning Approach for the Network Configuration of AC-DC Hybrid Distribution Systems. *IEEE Trans. Smart Grid* **2016**, *9*, 2203–2213. [CrossRef]
84. Eslami, A.; Hamedani Golshan, M.E. Monte-Carlo Based Approach to Consider the Cost of Voltage Dip and Long Duration Interruption in Optimal Planning of SDGs. *IET Gener. Transm. Distrib.* **2018**, *12*, 1856–1865. [CrossRef]
85. Malee, R.K.; Chundawat, A.S.; Maliwar, N.; Sharma, A.K. DG Integrated Distribution System Expansion Planning with Uncertainties. *J. Intell. Fuzzy Syst.* **2018**, *35*, 4997–5006. [CrossRef]
86. Ghaljehei, M.; Ahmadian, A.; Golkar, M.A.; Amraee, T.; Elkamel, A. Stochastic SCUC Considering Compressed Air Energy Storage and Wind Power Generation: A Techno-Economic Approach with Static Voltage Stability Analysis. *Int. J. Electr. Power Energy Syst.* **2018**, *100*, 489–507. [CrossRef]
87. Mo, H.; Sansavini, G. Impact of Aging and Performance Degradation on the Operational Costs of Distributed Generation Systems. *Renew. Energy* **2019**, *143*, 426–439. [CrossRef]
88. Ahmed, H.M.A.; Eltantawy, A.B.; Salama, M.M.A. A Reliability-Based Stochastic Planning Framework for AC-DC Hybrid Smart Distribution Systems. *Int. J. Electr. Power Energy Syst.* **2019**, *107*, 10–18. [CrossRef]
89. Bakhshi Yamchi, H.; Shahsavari, H.; Taghizadegan Kalantari, N.; Safari, A.; Farrokhifar, M. A Cost-Efficient Application of Different Battery Energy Storage Technologies in Microgrids Considering Load Uncertainty. *J. Energy Storage* **2019**, *22*, 17–26. [CrossRef]
90. Ismael, S.; Abdel Aleem, S.; Abdelaziz, A.; Zobaa, A. Probabilistic Hosting Capacity Enhancement in Non-Sinusoidal Power Distribution Systems Using a Hybrid PSOGSA Optimization Algorithm. *Energies* **2019**, *12*, 1018. [CrossRef]
91. Tran, T.; Smith, A. Stochastic Optimization for Integration of Renewable Energy Technologies in District Energy Systems for Cost-Effective Use. *Energies* **2019**, *12*, 533. [CrossRef]
92. Pinto, R.S.; Unsihuay-Vila, C.; Fernandes, T.S.P. Multi-objective and Multi-period Distribution Expansion Planning Considering Reliability, Distributed Generation and Self-healing. *IET Gener. Transm. Distrib.* **2019**, *13*, 219–228. [CrossRef]
93. Cheng, S.; Li, Z. Multi-Objective Network Reconfiguration Considering V2G of Electric Vehicles in Distribution System with Renewable Energy. *Energy Procedia* **2019**, *158*, 278–283. [CrossRef]
94. Liu, Y.; Yang, J.; Tang, Y.; Xu, J.; Sun, Y.; Chen, Y.; Peng, X.; Liao, S. Bi-Level Fuzzy Stochastic Expectation Modelling and Optimization for Energy Storage Systems Planning in Virtual Power Plants. *J. Renew. Sustain. Energy* **2019**, *11*, 014101. [CrossRef]
95. Parol, M.; Rokicki, Ł.; Parol, R. *Bulletin of the Polish Academy of Sciences: Technical Sciences*; Polska Akademia Nauk: Warsaw, Poland, 2019. [CrossRef]
96. Lwin, M.; Guo, J.; Dimitrov, N.B.; Santoso, S. Stochastic Optimization for Discrete Overcurrent Relay Tripping Characteristics and Coordination. *IEEE Trans. Smart Grid* **2019**, *10*, 732–740. [CrossRef]
97. Suliman, M.S.; Hizam, H.; Othman, M.L. Determining Penetration Limit of Central PVDG Topology Considering the Stochastic Behaviour of PV Generation and Loads to Reduce Power Losses and Improve Voltage Profiles. *IET Renew. Power Gener.* **2020**, *14*, 2629–2638. [CrossRef]
98. Afzal, M.; Alvarez-Alvarado, M.S.; Khan, Z.A.; Alghassab, M. Composition Assessment of a Power Distribution System with Optimal Dispatching of Distributed Generation. *Int. J. Renew. Energy Dev.* **2020**, *9*, 455–466. [CrossRef]
99. Rajamand, S. Loss Cost Reduction and Power Quality Improvement with Applying Robust Optimization Algorithm for Optimum Energy Storage System Placement and Capacitor Bank Allocation. *Int. J. Energy Res.* **2020**, *44*, 11973–11984. [CrossRef]
100. Shang, Y.; Wu, W.; Liao, J.; Guo, J.; Su, J.; Liu, W.; Huang, Y. Stochastic Maintenance Schedules of Active Distribution Networks Based on Monte-Carlo Tree Search. *IEEE Trans. Power Syst.* **2020**, *35*, 3940–3952. [CrossRef]

101. Zeng, B.; Li, X.; Fang, W.; Zhu, Z.; Zhao, C. Evaluating Potential Benefits of Distributed Energy Resources for Improvement of Distribution System Resiliency. *J. Electr. Syst.* **2020**, *16*, 320–331.
102. Barutcu, I.C.; Karatepe, E.; Boztepe, M. Impact of Harmonic Limits on PV Penetration Levels in Unbalanced Distribution Networks Considering Load and Irradiance Uncertainty. *Int. J. Electr. Power Energy Syst.* **2020**, *118*, 105780. [CrossRef]
103. Li, Y.; Mohammed, S.Q.; Nariman, G.S.; Aljojo, N.; Rezvani, A.; Dadfar, S. Energy Management of Microgrid Considering Renewable Energy Sources and Electric Vehicles Using the Backtracking Search Optimization Algorithm. *J. Energy Resour. Technol.* **2020**, *142*, 052103. [CrossRef]
104. Yahaya, A.A.; AlMuhaini, M.; Heydt, G.T. Optimal Design of Hybrid DG Systems for Microgrid Reliability Enhancement. *IET Gener. Transm. Distrib.* **2020**, *14*, 816–823. [CrossRef]
105. Lagos, T.; Moreno, R.; Espinosa, A.N.; Panteli, M.; Sacaan, R.; Ordonez, F.; Rudnick, H.; Mancarella, P. Identifying Optimal Portfolios of Resilient Network Investments against Natural Hazards, with Applications to Earthquakes. *IEEE Trans. Power Syst.* **2020**, *35*, 1411–1421. [CrossRef]
106. Tao, H.; Ahmed, F.W.; Abdalqadir kh Ahmed, H.; Latifi, M.; Nakamura, H.; Li, Y. Hybrid Whale Optimization and Pattern Search Algorithm for Day-Ahead Operation of a Microgrid in the Presence of Electric Vehicles and Renewable Energies. *J. Clean. Prod.* **2021**, *308*, 127215. [CrossRef]
107. Naderipour, A.; Nowdeh, S.A.; Saftjani, P.B.; Abdul-Malek, Z.; Bin Mustafa, M.W.; Kamyab, H.; Davoudkhani, I.F. Deterministic and Probabilistic Multi-Objective Placement and Sizing of Wind Renewable Energy Sources Using Improved Spotted Hyena Optimizer. *J. Clean. Prod.* **2021**, *286*, 124941. [CrossRef]
108. Pijarski, P.; Kacejko, P. Voltage Optimization in MV Network with Distributed Generation Using Power Consumption Control in Electrolysis Installations. *Energies* **2021**, *14*, 993. [CrossRef]
109. Shaheen, A.M.; Elattar, E.E.; El-Sehiemy, R.A.; Elsayed, A.M. An Improved Sunflower Optimization Algorithm-Based Monte Carlo Simulation for Efficiency Improvement of Radial Distribution Systems Considering Wind Power Uncertainty. *IEEE Access* **2021**, *9*, 2332–2344. [CrossRef]
110. Shu, Z.; Chen, Y.; Deng, C.; Zheng, F.; Zhong, H. Pareto Optimal Allocation of Flexible Fault Current Limiter Based on Multi-Objective Improved Bat Algorithm. *IEEE Access* **2021**, *9*, 12762–12778. [CrossRef]
111. Wang, J.; Wang, X.; Di, B.; Sun, C.; Zheng, W. A Novel Method for Islanding in Active Distribution Network Considering Distributed Generation. *J. Power Technol.* **2021**, *101*, 11–21. [CrossRef]
112. Gallego, L.A.; Franco, J.F.; Cordero, L.G. A Fast-Specialized Point Estimate Method for the Probabilistic Optimal Power Flow in Distribution Systems with Renewable Distributed Generation. *Int. J. Electr. Power Energy Syst.* **2021**, *131*, 107049. [CrossRef]
113. Baptista, J.E.R.; Rodrigues, A.B.; da Guia da Silva, M. Probabilistic Analysis of PV Generation Impacts on Voltage Sags in LV Distribution Networks Considering Failure Rates Dependent on Feeder Loading. *IEEE Trans. Sustain. Energy* **2019**, *10*, 1342–1350. [CrossRef]
114. Raj, V.; Kumar, B.K. A Modified Affine Arithmetic-Based Power Flow Analysis for Radial Distribution System with Uncertainty. *Int. J. Electr. Power Energy Syst.* **2019**, *107*, 395–402. [CrossRef]
115. Rawat, M.S.; Vadhera, S. Maximum Penetration Level Evaluation of Hybrid Renewable DGs of Radial Distribution Networks Considering Voltage Stability. *J. Control Autom. Electr. Syst.* **2019**, *30*, 780–793. [CrossRef]
116. Alves, H.d.N. An Interval Arithmetic-Based Power Flow Algorithm for Radial Distribution Network with Distributed Generation. *J. Control Autom. Electr. Syst.* **2019**, *30*, 802–811. [CrossRef]
117. Gruosso, G.; Maffezzoni, P. Data-Driven Uncertainty Analysis of Distribution Networks Including Photovoltaic Generation. *Int. J. Electr. Power Energy Syst.* **2020**, *121*, 106043. [CrossRef]
118. Hariri, A.-M.; Hejazi, M.A.; Hashemi-Dezaki, H. Investigation of Impacts of Plug-in Hybrid Electric Vehicles' Stochastic Characteristics Modeling on Smart Grid Reliability under Different Charging Scenarios. *J. Clean. Prod.* **2021**, *287*, 125500. [CrossRef]
119. Keane, A.; Ochoa, L.F.; Borges, C.L.T.; Ault, G.W.; Alarcon-Rodriguez, A.D.; Currie, R.A.F.; Pilo, F.; Dent, C.; Harrison, G.P. State-of-the-Art Techniques and Challenges Ahead for Distributed Generation Planning and Optimization. *IEEE Trans. Power Syst.* **2013**, *28*, 1493–1502. [CrossRef]