energies

MDPI

Review

A Review of Solar Power Scenario Generation Methods with Focus on Weather Classifications, Temporal Horizons, and Deep Generative Models

Markos A. Kousounadis-Knousen [1], Ioannis K. Bazionis [1], Athina P. Georgilaki [1,2], Francky Catthoor [3,4] and Pavlos S. Georgilakis [1,*]

[1] School of Electrical and Computer Engineering, National Technical University of Athens, 15780 Athens, Greece; kousounadisknousen@mail.ntua.gr (M.A.K.-K.); gmpazionis@gmail.com (I.K.B.); ece01950@uowm.gr (A.P.G.)
[2] Department of Electrical and Computer Engineering, University of Western Macedonia, 50100 Kozani, Greece
[3] Interuniversity Microelectronics Centre (IMEC), 3001 Leuven, Belgium; francky.catthoor@imec.be
[4] Associated Division ESAT-INSYS (INSYS), Integrated Systems, KULeuven, Kapeldreef 75, 3001 Leuven, Belgium
* Correspondence: pgeorg@power.ece.ntua.gr; Tel.: +30-210-772-4378

Abstract: Scenario generation has attracted wide attention in recent years owing to the high penetration of uncertainty sources in modern power systems and the introduction of stochastic optimization for handling decision-making problems. These include unit commitment, optimal bidding, online supply–demand management, and long-term planning of integrated renewable energy systems. Simultaneously, the installed capacity of solar power is increasing due to its availability and periodical characteristics, as well as the flexibility and cost reduction of photovoltaic (PV) technologies. This paper evaluates scenario generation methods in the context of solar power and highlights their advantages and limitations. Furthermore, it introduces taxonomies based on weather classification techniques and temporal horizons. Fine-grained weather classifications can significantly improve the overall quality of the generated scenario sets. The performance of different scenario generation methods is strongly related to the temporal horizon of the target domain. This paper also conducts a systematic review of the currently trending deep generative models to assess introduced improvements, as well as to identify their limitations. Finally, several research directions are proposed based on the findings and drawn conclusions to address current challenges and adapt to future advancements in modern power systems.

Keywords: scenario generation; solar power generation; uncertainty; weather classification; stochastic optimization; deep generative models; photovoltaic forecasting

check for updates

Citation: Kousounadis-Knousen, M.A.; Bazionis, I.K.; Georgilaki, A.P.; Catthoor, F.; Georgilakis, P.S. A Review of Solar Power Scenario Generation Methods with Focus on Weather Classifications, Temporal Horizons, and Deep Generative Models. *Energies* **2023**, *16*, 5600. https://doi.org/10.3390/en16155600

Academic Editor: Nicu Bizon

Received: 3 July 2023
Revised: 21 July 2023
Accepted: 23 July 2023
Published: 25 July 2023

1. Introduction

Sustainability-oriented initiatives are growing increasingly crucial as the consequences of climate change have intensified in recent years. Transitioning away from fossil fuels is critical, as future global energy needs are expected to increase due to population, economic, and technological growth [1]. Renewable energy sources (RES), such as wind, solar, hydro, and geothermal, should occupy larger proportions of the total energy mix while simultaneously developing energy-efficient technologies to minimize greenhouse gas emissions and improve overall energy utilization.

Solar power is one of the most popular RES due to its abundant nature, wide availability, and strong diurnal and seasonal patterns. Furthermore, the installation of solar photovoltaics (PVs) is relatively simple. The global installed solar power capacity was approximately 942 GW by the end of 2021, with its annual increase rate surpassing that of onshore wind power [2]. The total installed solar capacity is expected to increase significantly due to the cost reduction in PVs production and continuous technological advancements. Specifically, it is expected that up to 69% of the electricity consumption in the European Union will be covered by PV power by 2050 [3]. Moreover, PVs are extremely flexible, as small-scale distribution-level PV panels can easily be installed on rooftops and other urban locations.

However, solar power is a variable RES, exclusively dependent on prevailing weather conditions. Dynamic cloud behavior, as well as other stochastic meteorological factors, contribute to the intermittent nature of solar power generation (SPG). Several problems may arise from the increasing integration of PVs into power systems, such as reverse power flow and unexpected voltage rises [4]. Accurately estimating future SPG is vital to ensure power quality standards in a cost-effective manner.

Deterministic solar power forecasting (SPF) has been studied comprehensively in recent years. Numerous studies have summarized, classified, and reviewed proposed deterministic SPF methods based on various aspects. A systematic review of SPF methods, evaluation metrics, optimization, and data pre-processing techniques, was provided in [5] and extended in [6] to include hybrid methods. In [2], a taxonomy of short-term SPF methods based on climatic conditions was introduced. In recent years, the focus of deterministic SPF has shifted toward machine learning. A comparative analysis of different machine learning methods for SPF was conducted in [7]. In [8], a similar comparative analysis was focused on deep learning methods. A comprehensive taxonomy of machine learning SPF methods based on various aspects, such as the machine learning technique used, the location, and the forecasting horizon, was introduced in [9]. Short-term SPF methods, spanning from several hours-ahead to day-ahead predictions, were reviewed in [10]. Further decreasing the forecasting horizon has become increasingly popular with the emergence of real-time operation and management of power systems. A review of very short-term (i.e., intra-hour) forecasting methods for wind and solar power was provided in [11]. In [12], very short-term SPF methods are comprehensively reviewed, with a focus on cloud modeling techniques. SPF using sky images is essential for such short forecasting horizons [13].

Deterministic methods issue forecasts in the form of point predictions, which do not provide any information regarding the forecasting uncertainty. On the other hand, probabilistic methods generate forecasts that quantify the uncertainty to some extent. Probabilistic forecasts are issued in the form of quantiles, prediction intervals (PIs), or probability density functions (PDFs) [14]. The consideration of the uncertainty of the stochastic input variables is crucial for the optimal operation and planning of power systems. While PDFs fully represent the uncertainty of the stochastic variables, they lead to a significant increase in computational cost [15]. On the other hand, PIs and quantiles contain limited information about the uncertainty, leading to overly conservative decisions via interval or robust optimization [16]. Furthermore, probabilistic forecasts fail to capture the temporal autocorrelation of the forecasting errors, as well as the spatiotemporal correlations of adjacent or geographically dispersed locations [17].

The interdependence structure of stochastic variables, such as SPG, carries significant weight with the planning, integration, and operation of stochastic time-dependent and multi-stage power system processes [18]. To address this important aspect, some researchers have suggested generating scenarios instead of point or probabilistic forecasts. Scenarios can be deterministic or stochastic, depending on the incorporated uncertainty of the model used to generate the scenarios. Deterministic scenarios are based on physics-based models with case-sensitive pre-determined parameters that map the output to the input. Stochastic scenarios are defined as possible discrete realizations of the probability distribution of stochastic variables, issued with a limited number of outcomes in the form of forecasted time-series or typical trajectories [19]. With the use of stochastic scenarios, the original distribution-based power system optimization problems become deterministic but still maintain the uncertainty and spatiotemporal interdependence aspects [20]. This paper focuses on stochastic scenario generation; thus, hereafter, stochastic scenarios will simply be referred to as scenarios.

Scenario generation methods (SGMs) have become increasingly popular in recent years, mainly due to their suitability for solving power system decision-making problems via stochastic optimization. Nevertheless, limited attempts have been made to systematically review and categorize SGMs in the context of RES-based power systems. In [21], a systematic categorization of SGMs proposed for wind power was provided, as well as a summary of evaluation metrics to efficiently assess the quality of generated scenarios. Furthermore, a comprehensive analysis of power system stochastic optimization problems (SOPs) and the corresponding SGMs were conducted, alongside a comparison between different SGMs for each application. In [22], three different methods of generating wind power scenarios (WPS) were evaluated based on their results of a day-ahead stochastic unit commitment (UC) problem. It was shown that traditional verification metrics failed to identify the obvious visual differences of the generated scenarios, indicating the importance of using performance-based evaluation metrics. In [23], four commonly used evaluation metrics were employed to assess the scenarios generated by three different deep generative models (DGMs) regarding wind power, solar power, and electricity prices. The results stressed the importance of using multiple evaluation metrics to effectively assess the quality of the generated scenarios. Wind and solar power SGMs were comprehensively reviewed in [24]. SGMs were classified into several categories and compared. Furthermore, a classification and detailed description of scenario reduction methods and evaluation metrics was provided.

Several aspects of SGMs in the context of integrated renewable energy systems remain unaddressed. None of the above studies have focused on reviewing SGMs specifically from the perspective of solar power to highlight the differences between wind and solar as stochastic processes. Classifications are based on SGMs, scenario reduction methods, evaluation metrics, and application domains of power systems, but not on the temporal horizon of the generated scenarios. Furthermore, important aspects of RES-related stochastic variables, such as weather conditions, are ignored. In recent years, generative methods have gained increasing momentum for scenario generation and have generated promising results. However, ref. [21] only presented a brief introduction to DGMs in the context of WPS generation as part of the machine learning category. In [24], DGMs were acknowledged as a popular choice for scenario generation; nevertheless, only a few related studies were briefly reviewed. Thus, both [21,24] only briefly referred to generative methods, which indicates the necessity of a more systematic assessment and comparison of the proposed DGMs, complementary to the existing literature.

This review paper surveys and evaluates SGMs in the context of SPG. The advantages and limitations of each method are highlighted, and overall conclusions are drawn. Dissimilarities between wind and solar power are identified, as well as the subsequent differences regarding the SGMs used for each stochastic variable. A taxonomy of solar power SGMs based on weather classification techniques is introduced. In addition, the SGMs are classified according to their temporal horizon. Furthermore, as DGMs emerge for long-term solar power scenario (SPS) generation, they are surveyed and compared in more detail. Future research directions for SPS generation are proposed based on identified research gaps and current advancements in the planning and operation of modern power systems.

The rest of this paper is organized as follows: an overview of SPS generation methods is provided in Section 2. Section 3 presents a taxonomy of studies incorporating weather classifications for SPS generation. In Section 4, a review of DGMs proposed for SPS generation is conducted. Future research directions are proposed in Section 5. Section 6 concludes the paper.

2. Solar Power Scenario Generation Overview

This section provides necessary definitions and presents an overview of scenario generation for solar power. Statistical properties are provided based on a bibliometric analysis and comparisons with scenario generation for wind power are made. SGMs are categorized and briefly analyzed. Furthermore, it presents a classification of SGMs according to their temporal horizon and the corresponding commonly used power system SOPs.

2.1. Definitions

Assume a stochastic process $\{Y_t\}$, such as SPG, for $t \in N^+$. A multivariate stochastic variable Z_t is then formulated as follows [25]:

$$Z_t = \{Y_{t+1}, Y_{t+2}, \ldots, Y_{t+K}\} \tag{1}$$

where t represents a reference time point, and $\{t+1, t+2, \ldots, t+K\}$ is a set of future time points, stretching over a temporal horizon K, beginning from $t+1$ with a constant step of one time unit. Y_{t+i}, with $i \in \{1, 2, \ldots, K\}$, represents all possible values of the stochastic process $\{Y_t\}$ at time point $t+i$, thus, Z_t includes all possible future realizations of $\{Y_t\}$ over the given temporal horizon K. A scenario $\hat{z}_t$, issued at time t, is defined as a possible realization of the predictive distribution of the stochastic variable Z_t:

$$\hat{z}_t^j = \left\{\hat{y}_{t+1|t}^j, \hat{y}_{t+2|t}^j, \ldots, \hat{y}_{t+K|t}^j\right\} \quad j = 1, 2, \ldots, J \tag{2}$$

where $\hat{y}_{t+i|t}^j$ is a possible realization of the stochastic variable Y_t at time $t+i$, issued at time t. Index j denotes the scenario number of a scenario set containing J scenarios in total [25]. Thus, scenarios $\hat{z}_t$ are trajectories formed by random realizations of the stochastic variable Y_t at each time point, which are sampled from the predictive distribution of the multivariate stochastic variable Z_t.

A general framework of the scenario generation process is presented in Figure 1. Depending on the occasion, probabilistic forecasts, forecasting errors, or historical observations can be used to formulate the multivariate stochastic variable Z_t, which is then sampled, discretized, clustered, or processed in some other way to generate the scenario trajectories. SGMs are described in Section 2.3. The final scenario set describes possible future paths of the stochastic process $\{Y_t\}$, while the realizations in each lead time depend on previously predicted realizations.

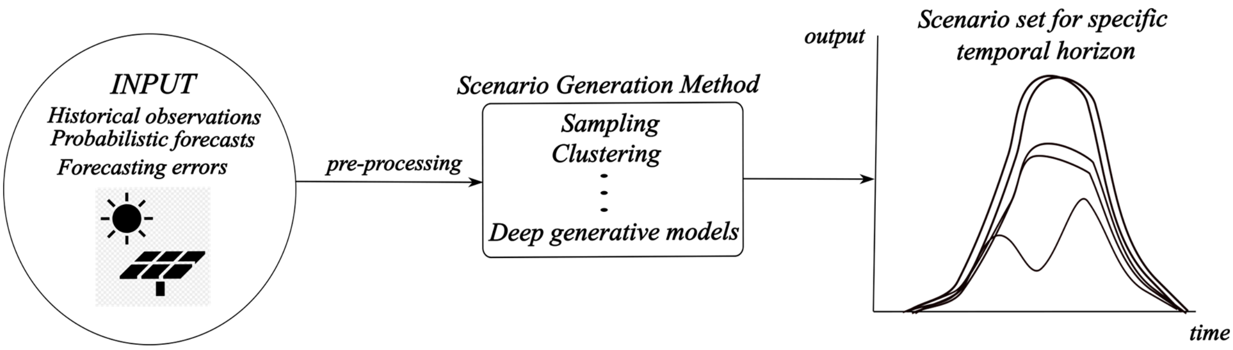


Figure 1. The general framework of the scenario generation process.

The temporal horizon for which scenarios are generated differs according to the context of the decision-making problem. Scenario forecasting usually refers to short-term forecasted scenarios for day-ahead operations, while scenario generation usually refers to representative (typical) scenarios for long-term resource and allocation planning. Scenario forecasting usually relies on point or probabilistic forecasts, while scenario generation exploits large datasets of historical observations [26]. For the remainder of this paper, both scenario generation and scenario forecasting will be referred to as scenario generation, while specific distinctions will be made when necessary. For some long-term power system planning problems, the temporal autocorrelation of scenarios is omitted, as its significance decreases with the horizon increase. All potential temporal horizons for scenario generation, i.e., from minutes to years-ahead, are considered in this paper.

2.2. Literature Overview

A comprehensive literature review in the solar power scenario generation field was conducted to provide an overview of the existing state-of-the-art and extract several statistics and insights. The studied literature contained research papers that either propose new solar power SGMs or use existing methods to generate scenarios that are used as input to SOPs. Only journal publications were considered since the related conference papers overlap in topic with the rest of the publications, and they provide only a subset. In all the research papers, scenarios are generated for either PV power output or solar irradiance, among other stochastic variables. Figure 2 presents the number of publications per year that satisfy these criteria. It is obvious that there is an increasing trend, which is a result of the increasing popularity of PVs and a shift towards uncertainty-integrated representations and stochastic optimization. Note that only the first two months of 2023 are considered in the bibliometric analysis; hence, the total number of journal publications in 2023 is expected to surpass those of 2021 and 2022.

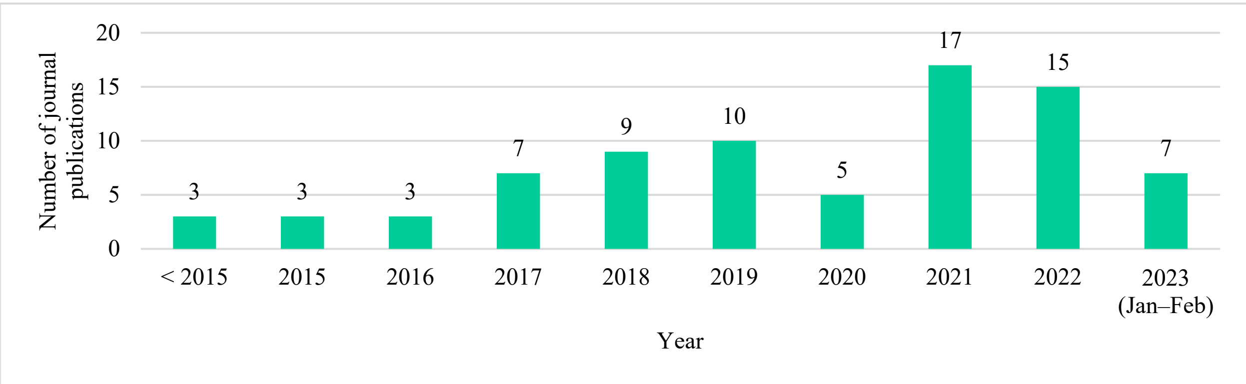
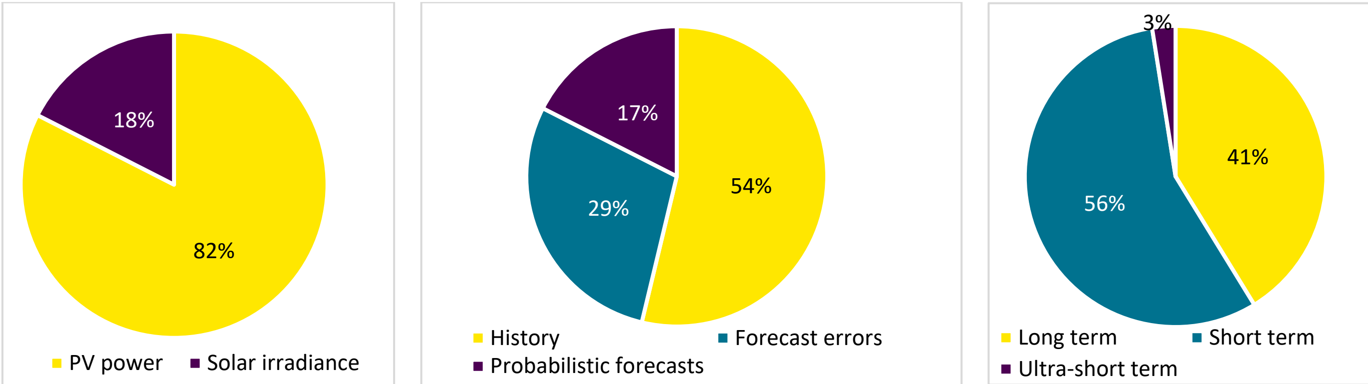


Figure 2. Journal publications per year related to solar power scenario generation.

As shown in Figure 3a, in 82% of the studied journal publications, scenarios were generated for PV power generation. In the remaining publications, scenarios were generated for solar irradiance. Historical observations were used to generate scenarios in 54% of the studied journal publications, as shown in Figure 3b. In the remaining publications, scenarios were generated based on previously issued forecasts; point forecasts with added error in 29% and probabilistic in 17% of the total cases, respectively. Typical scenarios were issued for long-term horizons in 41% of the studied journal publications, as shown in Figure 3c. The majority of the remaining cases generated scenarios for short-term horizons, mainly as day-ahead forecasts. Only 3% of the total studied publications generated scenarios for ultra-short-term horizons, i.e., up to 1 h ahead of forecasts. This is due to the high accuracy of deterministic forecasts for such small forecasting horizons, which makes scenario analysis and its inherent complexity unnecessary. The temporal horizons of the proposed SPS generation methods are further analyzed in Section 2.5.

Additional uncertainty sources were considered for scenario generation in several of the studied journal publications. As shown in Figure 4, wind, load, and electricity prices appear as additional uncertainty sources in 49, 39, and 12 research papers, respectively. In 6 cases, scenarios were generated for other additional uncertainty sources, such as temperature and run-of-river hydropower. In 17 out of 79 studied journal publications, scenarios were generated exclusively for PV power or solar irradiance.



(**a**) (**b**) (**c**)

Figure 3. Taxonomy of the studied journal publications related to solar power scenario generation. (**a**) Taxonomy based on stochastic variables for which scenarios are generated; (**b**) taxonomy based on data used as input for scenario generation; (**c**) taxonomy based on temporal horizon of scenario generation.

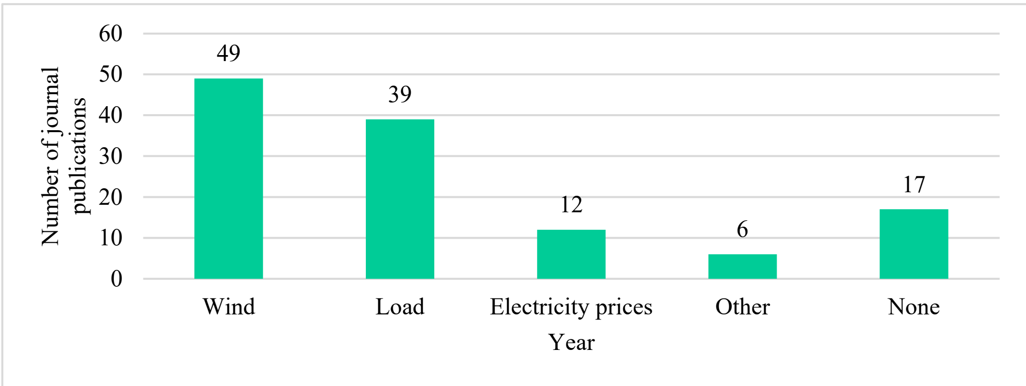


Figure 4. The number of studied journal publications in which each additional uncertainty source appeared.

2.3. Scenario Generation Methods

Several classifications of SGMs have been proposed in the related literature. In [21], SGMs were classified into three categories: sampling-based, forecasting-based, and optimization-based. Sampling-based methods rely on sampling PDFs to generate discrete scenarios. On the other hand, forecasting-based methods use statistical models or machine learning for scenario generation. Optimization-based methods use techniques, such as clustering, on large sets of historical observations to generate a reduced set of representative scenarios. In [24], SGMs were classified into parametric and non-parametric, depending on whether distribution assumptions regarding the uncertainty variable were necessary.

In this review paper, both classifications are considered to survey the SGMs for PV power and solar irradiance. In 39 out of the total 79 studied journal publications, scenarios are generated by a parametric sampling-based approach, as shown in Figure 5. Only a single parametric approach is optimization-based. On the other hand, the forecasting-based approaches constitute most of the non-parametric methods. The rest of the non-parametric methods are equally divided between sampling-based and optimization-based approaches. The general advantages and limitations of each SGM are summarized in Table 1. A comparison of SGMs on several important aspects is presented in Figure 6. Note that these comparisons are not exact, but rather rough approximations based on up-to-date research findings. Figure 6 is designed for facilitating purposes, to provide general guidelines rather than precise comparisons. Table 1 and Figure 6 are further analyzed in Sections 2.3.1–2.3.6.

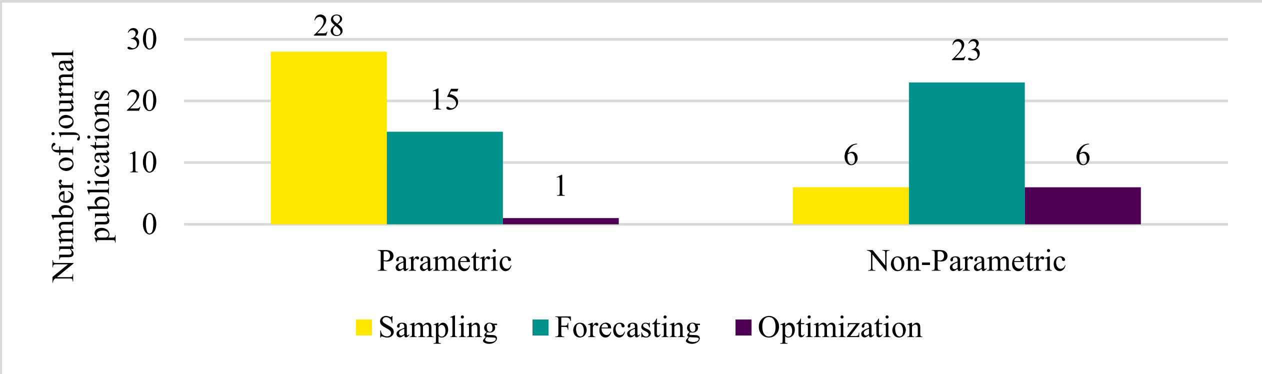


Figure 5. Classification of the studied publications based on SGM. The SGMs are divided into sampling, forecasting, and optimization methods [21], as well as parametric and non-parametric methods [24].

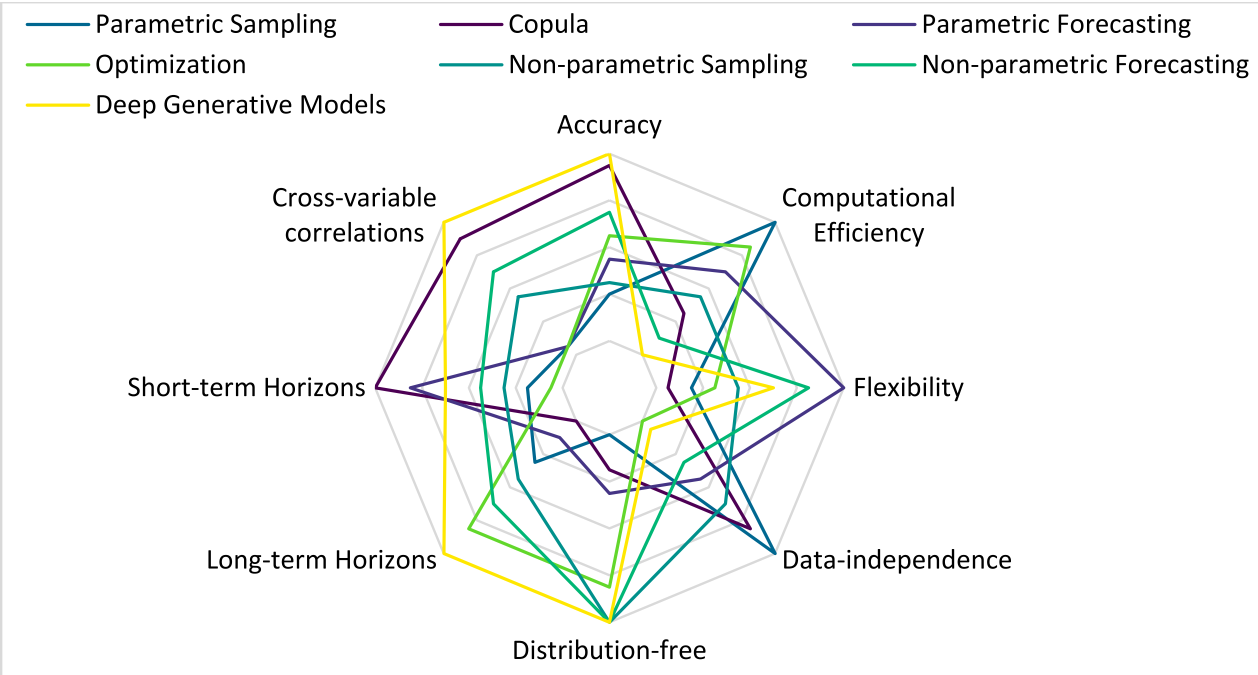


Figure 6. Qualitative comparison of different scenario generation methods for solar power.

2.3.1. Parametric Sampling-Based Methods

In parametric sampling-based methods, forecasting errors or historical data are fitted to a pre-determined distribution. The PDF is then discretized and sampled with a specific sampling technique. Parametric sampling-based methods are simple, computationally efficient, and generate quality scenarios when the distribution assumptions are accurate. However, stochastic variables, such as SPG, rarely follow a specific distribution, which leads to the generation of simplified scenarios that do not share the same statistical properties as the real observations.

Table 1. The main advantages and limitations of SGMs for solar power.

SGM	References	Advantages	Limitations
Parametric Sampling	[3,27–53]	• Simple implementation • Accurate when distribution shapes are known	• Distribution assumptions • Cross-variable correlations are not captured
Parametric Copula	[15,17,54–62]	• Cross-variable correlations are captured • Extreme events and tail dependencies are captured	• Unsuitable for long-term horizons • Complexity in higher dimensions
Parametric Forecasting	[63–66]	• High flexibility • Easy to use	• Distribution assumptions • Prone to overfitting
Parametric Optimization	[67]	• Computational efficiency	• Distribution assumptions • Cross-variable correlations • are not captured
Non-parametric Sampling	[19,68–72]	• Data-driven • Cross-variable correlations are captured	• Computational burden • Data reliance
Non-parametric Forecasting (non-DGMs)	[73–77]	• Data-driven • High flexibility	• Computational burden • Inability to distinguish from historical observations
Non-parametric Forecasting (DGMs)	[16,20,26,78–92]	• Data-driven • Generation of history-distinguishable samples • Cross-variable correlations are captured • Unsupervised learning	• Data reliance • Computational burden
Non-parametric Optimization	[4,93–97]	• Computational efficiency	• Data reliance • Cross-variable correlations are not captured

The most commonly used sampling technique is Monte Carlo sampling (MCS) [27–41]. In [33], MCS was used to sample the assumed error distribution of PV power curtailment forecasts generated by gated recurrent units (GRUs). In [34], MCS was used to sample forecasted PDFs of solar irradiance. The main disadvantage of traditional MCS is its complete randomness; thus, multiple scenarios are required to achieve a representative scenario set. Furthermore, the final scenario set usually includes many useless scenarios that are almost identical to others. Several traditional MCS improvements have been proposed. In [27], lattice MCS was used combined with roulette wheel selection (RWS) to efficiently generate scenarios. In [35], a seven-step distribution model was used to discretize the data distribution in order to generate less—but higher quality—scenarios. In both cases, the generated results were similar to those of traditional MCS, while maintaining a much smaller computational cost.

To overcome the limitations of MCS, several studies have used Latin hypercube sampling (LHS) [42–47]. LHS is a multi-dimensional stratified sampling method that divides the parameter space into equiprobable intervals. Compared to MCS, LHS is more efficient computationally and provides a better spread of the samples to include more extreme scenarios. In [42], LHS was used to generate scenarios from the error distribution of solar power point predictions. A multi-zone sampling method was adopted to better handle boundary scenarios. In [44], LHS was used to jointly sample PV power and load forecasting error distributions. Compared to MCS combined with scenario reduction, the proposed method generated scenarios with higher computational efficiency and included more low-probability extreme weather scenarios.

Other sampling techniques found in the literature for SPS generation include RWS [3,48–51], uniform random sampling [52], and Gibbs sampling [53]. RWS ensures proportional representation, as scenarios are sampled based on their probability of occurrence. Consequently, less data are needed for generating typical representative SPSs, compared to MCS. However, higher probability scenarios may be repetitively sampled while excluding low probability scenarios that represent extreme events. On the other hand, Gibbs sampling is particularly suitable for sampling in relatively higher dimensional spaces while capturing cross-variable correlations to some extent. However, Gibbs sampling depends on the availability of the conditional distributions of each variable.

SPF errors are usually assumed to follow the normal distribution, where the forecasted data are set as the mean values of the distribution [27,28,32,33,42,44]. The standard deviation of the distribution is directly related to the uncertainty band of the scenarios. A higher standard deviation increases the ability to capture extreme scenarios, often at the cost of scenario representativeness. On the other hand, several distributions are used to fit the historical observations of solar irradiance, such as beta [3,30,36], Weibull [41], normal [35,50,52], and lognormal [39,40]. Beta distribution has been the traditional choice in fitting solar irradiance data; however, in [41], better results were achieved with the Weibull distribution.

2.3.2. Parametric Copula-Based and Other Forecasting-Based Methods

The parametric sampling-based methods described in Section 2.3.1 heavily rely on the chosen distribution shape, which, in many cases, fails to accurately describe the behavior of a stochastic variable, such as SPG. Furthermore, these methods are incapable of modeling correlations between multiple variables. On the other hand, dependency structures between multiple variables can be captured efficiently by copulas. Copulas are multivariate distribution functions that link together the marginal distributions of stochastic variables. First, the marginal distribution of each stochastic variable is transformed to the uniform domain using its cumulative distribution function (CDF). After applying the inverse CDF transformation, the marginal distributions are combined into a joint multivariate distribution using a predetermined copula type. Unlike [21], in this paper, copula-based methods are distinguished from sampling-based methods, as significant distinctions appear between them. Copula-based methods depend more on generated forecasts and the necessary transformations to obtain the copulas rather than the sampling technique used for generating the scenarios. Significant forecasting information is needed to construct the CDFs of the variables. This information is sometimes unavailable or can be very difficult to obtain. Furthermore, copula-based methods are significantly more complex to develop compared to distribution-based methods and heavily depend on the performance of the probabilistic forecasting model. However, in the presence of quality probabilistic forecasts, once the copula is obtained, it is significantly faster in run-time during usage and better in describing the distributions of the variables, capturing cross-variable correlations, and generating higher-accuracy and time-efficient short-term scenarios.

A parametric copula-based method was first proposed in [18] to generate WPS for several spatially correlated wind power plants. No assumptions about the forecasting error distributions were necessary since the marginal distributions were obtained by non-parametric probabilistic forecasts generated with quantile regression. However, the proposed approach is not completely parametric-free since the type of copula needs to be pre-determined. A Gaussian copula was chosen in [18] to create the multivariate distribution function, which was then sampled to generate WPS. The approach proposed in [18] was first used in [17] for SPS generation, taking into consideration spatiotemporal dependencies. The approach proposed in [18] has also been used in [54,55]. Several improvements of [18] have also been proposed. In [15], the copula was set to capture temporal autocorrelations of SPSs, which were sampled using LHS. In [56], both temporal and other cross-variable correlations were captured using copulas. Multiple RES were considered for scenario generation using a Gaussian copula in [58]. In [57], Gibbs sampling was used to sample the copula-based joint distribution of several RES power plants.

In some cases, the Gaussian copula cannot sufficiently capture the interdependencies between variables. On the other hand, vine copulas efficiently capture the different types of dependencies while preserving outliers and limiting the additional computational burden. Vine copulas were used for solar, wind, and run-of-river hydropower scenario generation in [58] and for joint solar-wind scenarios in [59]. In [60], t-copulas were used to consider the data outliers while better capturing the tail dependencies. However, t-copulas can be time-consuming, especially for parameter determination. Other studies have proposed combining multiple copulas to capture highly complex dependencies. In [61], a self-organizing map was used to cluster PV and meteorological data. A different copula was used for each cluster to develop the joint distributions. In [62], the combined copulas comprised the Clayton copula, the Gumbel copula, and the Frank copula. However, combined copulas significantly increase the overall complexity and the risk of overfitting.

In non-copula parametric forecasting-based methods, scenarios are based on previously generated point forecasts. Distribution assumptions are made for the forecasting errors, which are then sampled and added to the corresponding point forecasts to generate scenarios. Parametric forecasting-based methods are usually based on simple statistical models or machine learning. In [63], an auto-regressive moving average (ARMA) model was used to generate the error distribution of previously generated forecasts, based on a Gaussian assumption. The generated distribution was then sampled with LHS to generate SPSs and WPSs. A machine learning method was first introduced in [64] to generate solar, wind, and load scenarios. In this method, point forecasts were generated utilizing artificial neural networks (ANNs) and exogenous variables as inputs. A forecasting error value assumed to follow a normal distribution was then added to the point forecast to generate a scenario trajectory. The generated scenarios of the proposed ANN-based method had superior characteristics compared to those of statistical-based methods, such as the seasonal auto-regressive integrated moving average (SARIMA). The method proposed in [64] was also used in [65] for solar irradiance scenario generation. In [66], scenarios were generated by transforming historical data and feeding them to a multivariate Vector ARMA to generate spatiotemporal forecasts which were assumed to follow a Gaussian distribution. Non-copula parametric forecasting-based methods are simple, flexible, and easily extendable to multiple locations and timeframes. On the other hand, they still rely on error distribution assumptions, which may lead to overly simplistic scenarios. Furthermore, they are prone to overfitting and heavily rely on the performance and finetuning of the forecasting model. Thus, while simpler and more flexible than copula-based methods, they fail to reach their high-accuracy performance.

2.3.3. Parametric Optimization-Based Methods

Optimization-based methods are usually non-parametric, as they rely on large sets of historical data to which they apply scenario reduction techniques based on pre-determined metrics. However, few studies have suggested parametric optimization-based approaches where the historical data are fitted to a known distribution. The distribution is then discretized, and the discrete realizations are clustered to form the final scenarios. In [67], the PV power output was assumed to follow the Beta distribution, which was discretized using the Wasserstein distance. The discrete scenarios were then clustered using K-medoid clustering to form the final set of scenarios. The generated scenarios were of higher accuracy compared to those generated by an ARMA model and parametric distribution-based approaches. While parametric optimization-based approaches generally outperform distribution-based approaches, they perform poorly when no assumed distribution can sufficiently characterize the stochastic variable.

2.3.4. Non-Parametric Sampling-Based Methods

Non-parametric sampling-based methods either rely on empirical distributions or generate distributions using techniques such as kernel density estimation (KDE). In [68,69], PIs generated for 19 different confidence levels were decomposed to quantiles to generate an empirical CDF. The CDF was then sampled with MCS to generate solar, wind, and load scenarios. In [70], the error distribution of PV power was estimated by calculating the error bounds and then using an epi-spline approximation. The probabilities of each scenario were calculated using a copula. The results indicated that the proposed methodology generated smoother scenarios compared to traditional copula-based approaches. In [19], KDE was used to generate the joint multivariate distribution of the forecasting errors. The distribution was then sampled with MCS to generate joint scenarios of solar, load, and electricity prices. In [71], KDE was applied to historical data to generate joint scenarios of PV power and load with MCS sampling. In [72], probabilistic graphical models were used to predict the distribution of the forecasting error of solar irradiance. While these models do not require any prior distribution assumption, they either require large amounts of data to build realistic empirical distributions or have substantial computational costs, making them less attractive for practical implementation. The overall scenario generation process is thus much more time-consuming compared to parametric methods while not providing particularly better results when sufficient distributions are known upfront.

2.3.5. Non-Parametric Forecasting-Based Methods

Non-parametric forecasting-based methods are completely data-driven and independent of any form of distribution assumption. Most methods are based on DGMs, which have gained increasing popularity in recent years for SPS generation [16,20,26,78–92]. DGMs are completely assumption-free and generate new synthetic data that highly resemble the training samples. They generate optimal long-term representative scenarios while still showing promising results in short-term temporal horizons. On the other hand, DGMs heavily rely on data availability and require massive computational resources as they are based on deep learning. A comprehensive review of DGMs proposed for SPS generation is provided in Section 4.

This subsection provides a brief description of proposed non-DGM methods for SPS generation. In [74], intra-hour PV power scenarios were generated by an ANN using a fuzzy inference framework. However, the proposed model generated only three scenarios, i.e., the upper and the lower bounds as well as a center scenario. In [75], synthetic sequences of solar irradiation were generated by applying non-parametric bootstrapping on historical data. The proposed method generated synthetic typical scenarios that were complementary to the historical observations. In [73], an autoregressive-to-anything statistical process was used combined with historical observations to generate solar, wind, and load scenarios. Non-DGM methods are less computationally demanding than DGM methods; however, the synthetic scenarios generated by them often fail to distinguish themselves from historical observations. Thus, they are not fully capable of capturing the behavior of stochastic variables, such as SPG. To overcome these limitations, week-ahead weather forecasts were combined with historical observations and fed to a combined GRU-convolutional neural network (CNN) [76] to generate PV power scenarios capturing spatiotemporal dependencies. The proposed model was compared to the DGM proposed in [78] and generated better scenarios while efficiently capturing spatiotemporal correlations. However, the proposed model heavily depends on the quality of the week-ahead forecasts, which are difficult to obtain. In [77], a long short-term memory auto-encoder (LSTM-AE) was set up to generate scenarios for a hybrid hydro-PV system. The proposed model is completely model-free, performs feature extraction, and captures spatiotemporal dependencies. Nevertheless, the SGMs proposed in [76,77] depend on complex deep learning structures to generate efficient forecasts without any distribution assumption, which leads to a significant increase in computational complexity. This increase in computational complexity is only cost-effective when efficient PV physical models are not available or when no known distribution can sufficiently characterize SPG.

2.3.6. Non-Parametric Optimization-Based Methods

As mentioned in Section 2.3.3, non-parametric optimization-based methods apply scenario reduction techniques to large sets of historical data to generate representative scenarios. In most cases, clustering is chosen for SPS generation [4,93–95]. K-means clustering is a commonly used clustering method. However, in [93], the fuzzy-C-means clustering method produced better results. In [94], clustering showed superior performance in generating solar, wind, and electricity price scenarios compared to the KDE-based non-parametric sampling method. In [96], clustering was applied to weather forecasts generated by a recurrent neural network (RNN) to generate solar irradiation, wind, and temperature scenarios. Moment matching was used in [97] to generate solar, wind, and electricity price scenarios. With moment matching, scenarios are generated such that they share the same statistical features with historical observations.

Non-parametric optimization-based methods are efficient SGMs that generate long-term representative SPSs. However, they heavily rely on historical data availability and fail to generate scenarios that distinguish them from already observed paths. Furthermore, the number of the generated scenarios needs to be pre-determined in certain optimization-based methods, such as clustering, which is not always possible.

2.4. Comparisons with Wind Power SGMs

Several distinctions appear between solar and wind power SGMs. In parametric sampling methods, the Weibull distribution is a commonly used distribution function to describe wind power [24]. On the other hand, the beta distribution, as well as the normal and lognormal distributions, have been used to describe SPG. Regarding copulas, the Gumbel and Gaussian copulas are suggested for the description of wind variations in low and high dimensions, respectively [17]. The Gaussian copula is commonly used for solar power; however, other types of copulas have not been comprehensively tested. Frank copulas are suitable for negative cross-variable correlations, such as wind and solar correlations [59]. Furthermore, in the proposed parametric forecasting-based approaches for SPS generation, the forecasting error is always assumed to follow a normal distribution.

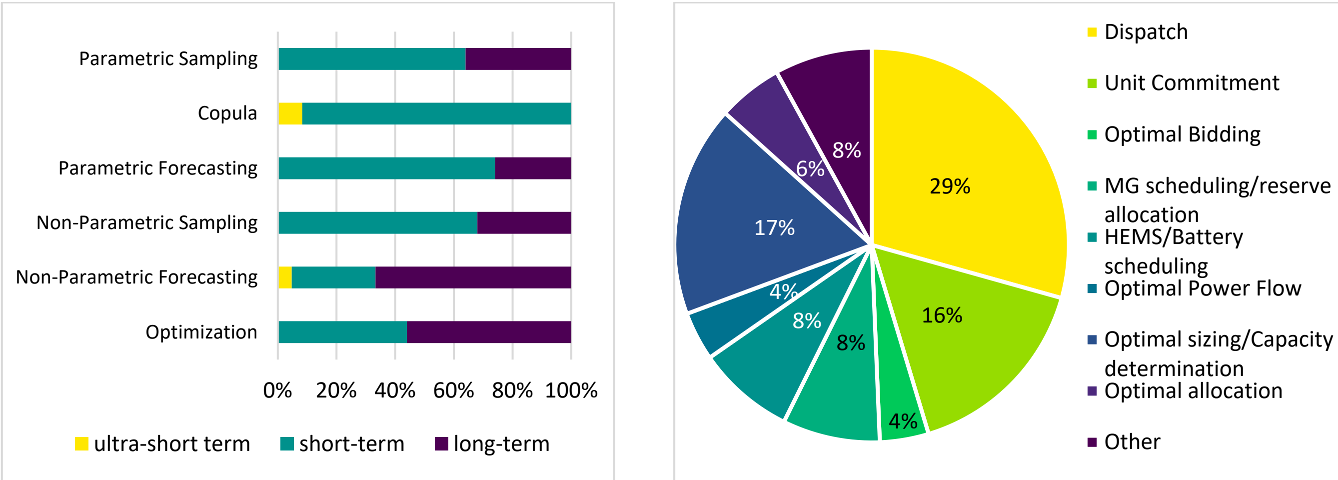
Most of the SGMs proposed for solar power are parametric sampling-based, as the characterization of solar power distributions is easier compared to that of wind. Furthermore, significantly fewer parametric forecasting-based and optimization-based methods are proposed for solar power compared to wind [21]. Solar power has become increasingly popular in recent years, which, combined with the shift towards DGMs, leads to the gradual abandonment of the more traditional forecasting-based and optimization-based SGMs. Moreover, DGMs are particularly popular for SPS generation, as the required training time is usually reduced compared to that for generating WPSs. This is due to the reduced complexity of SPG, which only occurs during the daytime.

2.5. Classification Based on Temporal Horizon

SGMs significantly differ in terms of the temporal horizon they are best suited for. A taxonomy of the studied research papers based on the temporal horizon for which the SPSs are generated is presented in Table 2. Figure 7a presents the share of different temporal horizons for each SGM. The most common power system target domains for which SPSs are generated are presented in Figure 7b. Long-term temporal horizons span from several days to years ahead and are used for power system planning tasks, such as optimal allocation of RES and capacity determination. Short-term temporal horizons span from several hours to day-ahead decision-making tasks, such as UC, economic dispatch, and optimal bidding strategies. Ultra-short-term temporal horizons refer to intra-hour forecasting aimed at real-time operations of microgrids and home energy management systems (HEMS).

Table 2. Classification of proposed solar power SGMs based on temporal horizon.

Temporal Horizon	References
Ultra-short-term	[61,74]
Short-term	[3,6,15,17,27,31,32,34,35,37,41–46,48–52,54–60,62,64–70,72,80,81,83,86,89,90,95,97]
Long-term	[4,19,20,26,28–30,33,36,38–40,47,53,63,71,73,75–79,82,84,85,87,88,91–94,96]



(**a**) (**b**)

Figure 7. (**a**) Temporal horizon used for each scenario generation method; (**b**) share of each power system target domain for which solar power scenarios are generated.

Parametric sampling-based methods can be used for both short-term and long-term temporal horizons, with a slight preference towards short-term horizons, where the available execution times are shorter and require simpler SGMs. On the other hand, optimization-based methods are slightly more used for long-term temporal horizons, as they rely on large sets of historical data that are capable of representing long-term trends of SPG. Non-parametric sampling-based methods are used both for short-term and long-term temporal horizons, depending on whether they rely on forecasts or historical data to generate the empirical distributions. However, as their complexity is significantly increased, they are best suited for long-term planning tasks. Non-parametric forecasting-based methods are mainly destined for long-term temporal horizons, owing to their increased computational complexity and their ability to infer complex, deeply rooted relationships between data. The only exception is in [74], where a simple fuzzy ANN was used to generate three scenarios for intra-hour forecasting. Copula-based methods are exclusively designed for short-term temporal horizons, where they are extremely accurate. As the temporal horizon increases, they fail to capture cross-variable and interdependent temporal correlations. Similarly, non-copula parametric forecasting-based methods are better suited for short-term temporal horizons as they rely on the accuracy of previously generated point forecasts.

3. Taxonomy Based on Weather Classifications

3.1. Weather Classifications

SPG is directly related to the prevailing weather conditions, especially to the cloud coverage of the sky. Different weather conditions can significantly alter the power curve of solar generation. Generating SPSs for different weather conditions can significantly improve the accuracy of the scenarios and reduce the overall computational cost, as fewer scenarios are necessary to describe the uncertainty of SPG. A simple typical SPG scenario set, comprising nine scenarios, is depicted in Figure 8a. The variance of the initial scenario set is relatively big, indicating an increased complexity and difficulty in obtaining these initial scenarios. However, considering simple different weather types, e.g., sunny, cloudy, and overcast sky conditions, the initial scenario set can be divided into three typical scenario sets (Figure 8b–d), each corresponding to a specific weather type. The variance of each scenario set is significantly reduced, leading to an increase in both computational efficiency and accuracy.

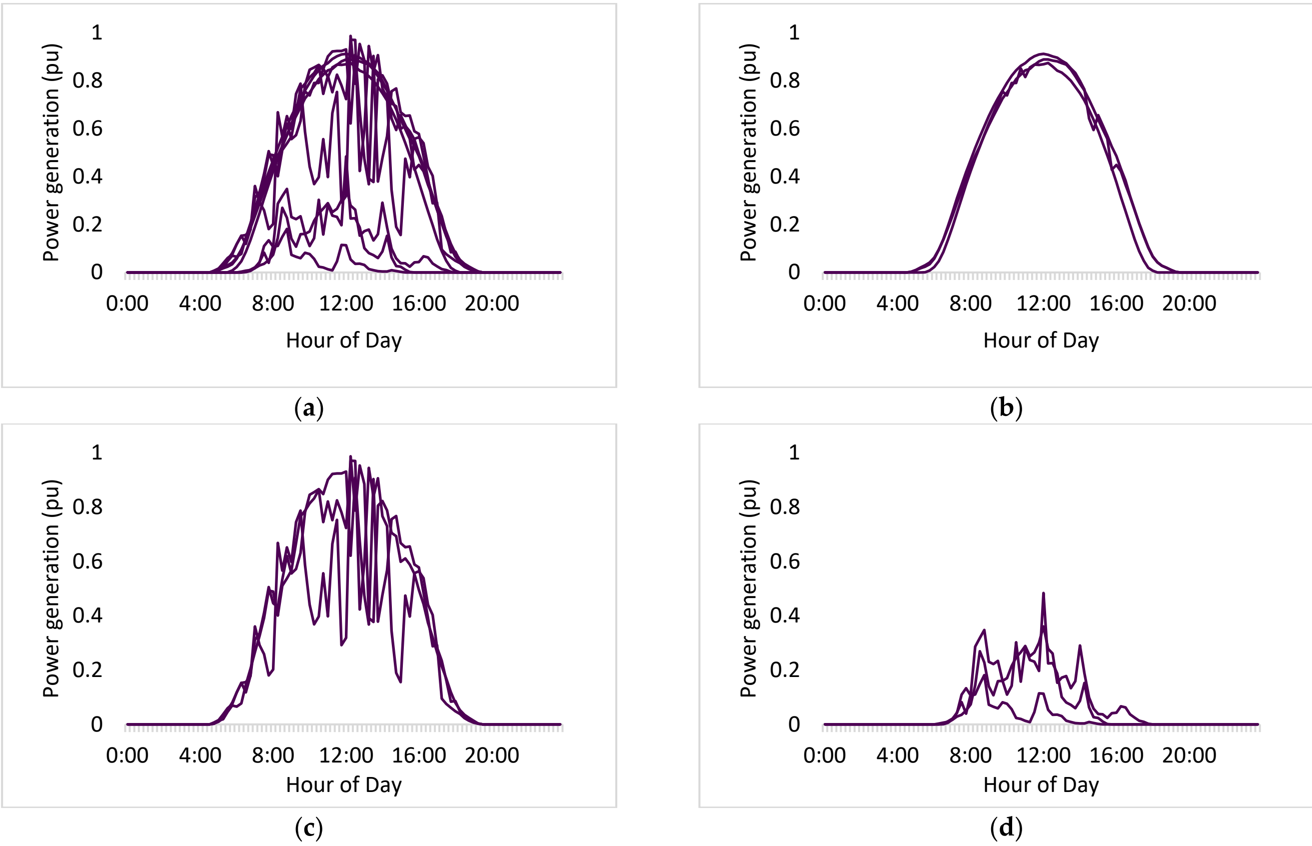


Figure 8. Typical scenario sets of SPG. (**a**) Nine scenarios without weather classification; (**b**) sunny day scenario set; (**c**) cloudy day scenario set; (**d**) overcast day scenario set.

Several weather classification strategies have been proposed for SPS generation. A taxonomy of the proposed solar power SGMs that introduce weather classifications is presented in Table 3. Table 3 also includes seasonal classifications wherever they appear. The simplest weather classification for SPS generation is based on sky conditions and includes two weather types, i.e., sunny and cloudy [61]. A slightly more detailed and commonly used classification includes rainy as a weather type [36,42]. As shown in Figure 8b, sunny days are characterized by a bell-shaped SPG curve, while overcast days are those with a significantly lower peak in the daily generation. Cloudy days are the most dynamic due to frequent changes in sky conditions, leading to high fluctuations in the generated solar power. Other studies have included more classifications, such as partly/mostly cloudy [89], as well as classifications based on temperature (hot/cold sunny, hot/cold cloudy) [51] and duration of meteorological phenomena (short-term/continuous rainfall, short-term/continuous snowfall) [76].

Table 3. Taxonomy of reviewed solar power SGMs, based on weather classifications and seasonality analysis.

References	Seasonality	Weather Classification
[26]	4 seasons (summer, winter, shoulder A, shoulder B)	2 weather types (normal, abnormal)
[36]	4 seasons (summer, autumn, winter, spring)	3 weather types (sunny, rainy, cloudy)
[42]	–	3 weather types (sunny, rainy, cloudy)
[79]	2 seasons (heating, non-heating)	2 weather types for heating season 4 weather types for the non-heating season
[89]	12 months	4 weather types (sunny, partly cloudy, mostly cloudy, rainy/snowy)
[91]	–	5 weather types (sunny, cloudy, rainy, snowy, windy)
[51]	–	4 weather types (hot sunny, hot cloudy, cold sunny, cold cloudy)
[61]	2 seasons (summer, winter)	2 weather types (sunny, cloudy)
[72]	–	8 weather types based on precipitation PDF (from sunny to rainy)
[76]	4 seasons (summer, autumn, winter, spring)	6 weather types (sunny dominant, cloudy dominant, short-term rainfall, continuous rainfall, short-term snowfall, continuous snowfall)

Besides sunny and cloudy, which are the two most essential weather types, additional weather types should be included, depending on their effect on SPG, the prevailing weather conditions of the region, the decision-making problem, and the computational complexity constraints. Cloud conditions can be further divided into several classes based on cloud motion, height, and shape. Wind fields have also been proven to significantly affect the PV power output, as the airflow over a PV module unevenly distributes its temperature [98,99]. In [91], the windy weather condition was considered as one of the five determined weather types. However, the optimal choice of weather conditions depends on the correlation of SPG to different meteorological parameters. Some weather conditions do not significantly affect SPG; thus, their consideration should depend on the decision-making problem and its computational complexity constraints. For example, in regions with low precipitation levels throughout the year, the rainy weather type may not be necessary, as it will increase the computational cost without significantly changing the overall quality of the SPG scenarios. However, if the power system optimization problem is sensitive to extreme, low-probability scenarios, the decision-maker should consider including rainy or other low-probability weather types. Multiple weather classifications can significantly increase the quality of the generated scenarios, as the variance of each scenario set decreases, and fewer scenarios are needed to accurately quantify the uncertainty of SPG. On the other hand, too many weather classifications can lead to complex frameworks with insignificant uncertainty, in which scenarios have no use.

Multiple methodologies have been proposed to derive classifications of weather from historical data or weather forecasts. A simple, efficient, and common method for classifications is based on constructing solar irradiance profiles, which are directly related to SPG [42,51]. However, classifications based on solar irradiance are coarse-grained; thus, obtaining other weather types besides sunny, cloudy, and overcast is difficult. In [79], clustering on historical data was used to obtain different weather types. Clustering was based on temperature values, as temperature showed the highest correlation with both solar irradiance and load. The proposed methodology is particularly useful when scenarios are generated for multiple stochastic variables and historical meteorological data are available. In [72], eight atmospheric conditions were deduced by considering two precipitation probabilities in each of four sky conditions (sunny, mostly sunny, mostly cloudy, and cloudy). The atmospheric conditions represented sky conditions from sunny with a low probability of rain, to cloudy with a high probability of rain. Deep learning methods have also been used to determine weather classifications based on historical data by specifying different weather types in the labels of DGMs. In [26], a data-driven method was proposed to divide weather types into normal and abnormal days. The classification was based on an advanced time-series distance metric called dynamic time warping (DTW). DTW was measured between all historic daily time series and a reference representative daily time series. The daily time series were then sorted and plotted based on their DTW values to identify the slope change. The days beyond the slope change were considered abnormal. The proposed methodology is completely data-driven and magnifies abnormal days that are less frequent. Thus, higher quality SPSs were generated for the abnormal days, in which the uncertainty is at the highest level. Data-hidden information regarding geography characteristics and prevailing weather conditions of the target region are fully exploited when sophisticated data mining techniques are used. On the other hand, data-driven approaches require huge amounts of data to perform the classifications efficiently.

Weather classifications significantly improve the overall quality of the generated SPSs. The accuracy of the SPG scenarios is increased, while the variance of each scenario set is limited; thus, fewer scenarios are necessary to describe the uncertainty of SPG, leading to a reduction in computational complexity. However, little focus has been given to weather classification techniques. It is essential to consider finer weather classifications, such as finer divisions of cloud conditions, depending on cloud formation and motion, as well as new classifications based on other parameters that affect SPG, such as wind fields and regional climatic phenomena. The optimal number of weather conditions should be determined based on the prevailing climatic conditions of the target region while achieving an accuracy–computational efficiency tradeoff. Furthermore, greater focus should be placed on data-driven techniques for deriving weather classifications, as the availability of longer and more detailed meteorological datasets increases.

3.2. Seasonality Analysis

Besides weather classifications, several studies have proposed generating SPSs independently for different seasons. Seasonal classifications are based on temporal divisions of the year. Such divisions are calendar-based or meteorological-based. Calendar-based classifications are usually monthly or seasonal (winter, spring, summer, and autumn). Seasonality analysis on a calendar basis facilitates energy management optimization tasks that incorporate time-series variables with seasonal labeling, such as wholesale gas price, seasonal water inflow, and seasonal load profiles. On the other hand, with meteorological-based classifications, seasons are determined based on factors such as temperature, load type, and general sky conditions. Meteorological-based seasonality analysis resembles the weather classifications described in Section 3.1 and deduces finer seasonal characteristics, that adapt more to the geographical and meteorological characteristics of the target region.

SPG has strong diurnal and seasonal characteristics. Typical PV power generation curves differ depending on the time of the year, as solar power is directly linked to factors such as temperature, daylight duration, solar zenith angle, precipitation, and prevailing sky conditions. Throughout each season, SPG is mainly affected in terms of daily peaks and duration of generation. However, these distinctions are highly predictable, and deterministic forecasting models can sufficiently capture seasonal variations of SPG. On the other hand, meteorological-based seasonal classifications are difficult to efficiently deduce, as seasonal variations significantly differ depending on the geographical location, which leads to an increase in computational complexity. Furthermore, there is no guarantee that seasonal characteristics will be sufficiently consistent throughout each season. Thus, it is suggested to put more focus on weather classifications rather than meteorological-based seasonal divisions. On the other hand, calendar-based seasonality analysis is beneficial whenever SOPs contain seasonal-labeled stochastic variables.

4. Review of Deep Generative Models for Solar Power Scenario Generation

In recent years, DGMs have emerged as alternatives for generating SPSs, owing to their data-driven nature and their ability to generate new synthetic data that resemble historical observations. Furthermore, DGMs are based on deep learning, thus enabling the identification of complex, non-linear relationships, cross-variable correlations, and data labeling. DGMs include models such as generative adversarial networks (GANs), variational auto-encoders (VAEs), flow-based models, and deep Boltzmann machines. Further information about DGMs can be found in [100]. The number of journal publications per year regarding DGM-based SPS generation is shown in Figure 9. It is evident that there is an increasing trend of DGM-based models, especially since only publications from January and February are considered for 2023. However, to the authors' knowledge, no systematic review of DGM-based scenario generation exists in the context of power systems and RES. Hence, this section reviews proposed DGMs for SPS generation.

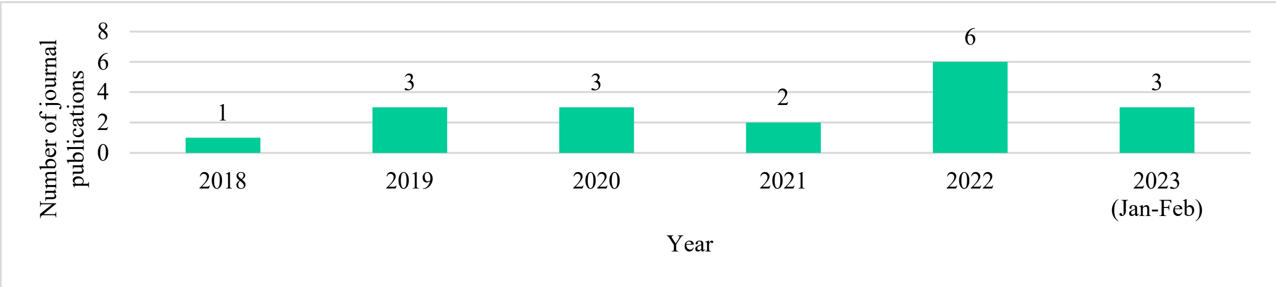


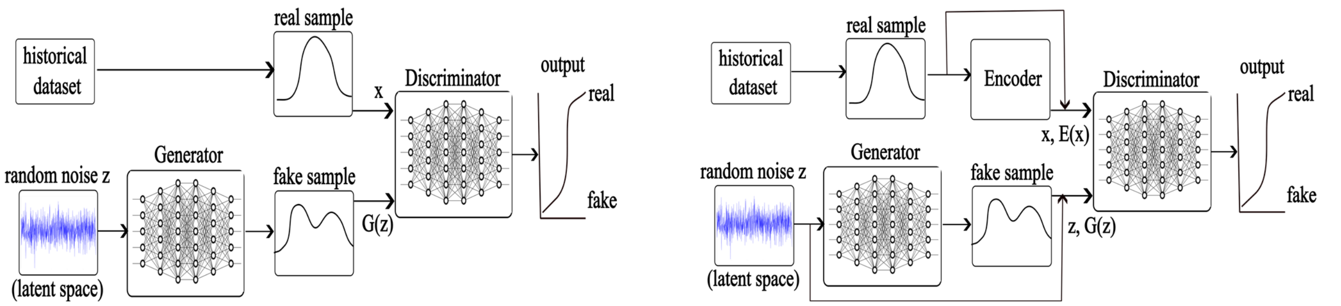
Figure 9. Journal publications per year related to solar power scenario generation with deep generative models.

4.1. Generative Adversarial Networks

4.1.1. Definition

GANs are the most popular DGMs used for SPS generation. The main advantages of GANs are their scalability, unsupervised training, and data-driven nature, as well as their ability to infer cross-variable correlations. The general structure of GANs is shown in Figure 10a. GANs are based on two deep learning structures, the generator G and the discriminator D. During training, random noise z is sampled from the latent space and provided as input to the generator, which tries to transform it to create fake samples $G(z)$ that resemble real historical observations. The discriminator takes as its input either generated samples $G(z)$ or real observations x, sampled from a historical dataset. The objective of the discriminator is to be able to identify whether its input is a real or a generated observation. The higher the output of the discriminator, the closer the input sample is to a real observation.

Wasserstein GANs (WGANs) have been introduced as an improved version of traditional GANs. WGANs employ the Wasserstein distance metric to measure the resemblance between the generated and the historical samples. The higher the output of the discriminator, the closer the generated samples are to the historical observations. For the remainder of this paper, WGANs will be simply referred to as GANs.



(**a**) (**b**)

Figure 10. GAN structures. (**a**) Traditional GAN; (**b**) GAN-VI.

The loss function of GANs is formed as a two-player minimax game. The objective of the generator is to minimize the difference between generated and real samples. The higher the output of the discriminator, the closer the generated sample is to a real observation; thus, the generator should be updated to maximize the expectation of $D[G(z)]$ (or minimize the additive inverse of $D[G(z)]$):

$$minL_G = -\mathbb{E}_Z[D(G(z))] \tag{3}$$

where L_G represents the loss function of the generator, $D(G(z))$ is the output of the discriminator when provided a generated sample $G(z)$, and $\mathbb{E}_Z$ is the mean expectation over different random noise samples z. On the other hand, the objective of the discriminator is to be able to fully differentiate between real and generated samples. Thus, the discriminator should be updated to maximize its output when provided with real samples, and minimize it when provided with generated samples:

$$minL_D = -\mathbb{E}_X[D(x)] + \mathbb{E}_Z[D(G(z))] \tag{4}$$

where L_D represents the loss function of the discriminator, $D(x)$ is the output of the discriminator when provided with a real sample x, and $\mathbb{E}_X$ is the mean expectation over different real samples x. The two-player minimax game is then formulated as follows:

$$\min_G \max_D V(G, D) = \mathbb{E}_X[D(x)] - \mathbb{E}_Z[D(G(z))] \tag{5}$$

where $V(G,\ D)$ is the combined loss function of the GAN, consisting of the loss functions described in (4) and (5). The GAN is trained to simultaneously satisfy both objectives, i.e., generate realistic scenarios and discriminate between the real and the synthetic scenarios, until a Nash equilibrium is reached. More information about GANs can be found in [101].

4.1.2. Literature Review

Several different GANs have been proposed for SPS generation. Table 4 summarizes their respective advantages and limitations. A GAN was first proposed for SPS generation in [78], considering conditionality. With conditional GANs (CGANs), conditions are incorporated in the training procedure to allow event-based scenario generation by assigning user-defined labels to the outputs of the generator. The generated scenarios shared the same statistical properties with historical samples and successfully captured spatiotemporal correlations between multiple sites. Monthly labels were given to the CGAN to generate SPSs for each month. The results showed that monthly variations of SPG were successfully captured, with a small difference in average daily production between historical and generated scenarios. A similar CGAN was proposed in [85] with risk-averse labels to generate PV power generation scenarios used for the planning of a hybrid ESS. In [91], a combined weighting method (CWM) was proposed for CGANs. However, the proposed approach is heavily dependent on the availability of weather data.

Traditional GANs, as well as CGANs proposed in [78,85,87,90,91], suffer training instability and mode collapse. To address mode collapse, a GAN with variational inference (GAN-VI) was proposed in [80]. GAN-VI includes an encoder to map historical samples x to the hidden space by generating variables $E(x)$. Unlike traditional GANs, the input to the discriminator of GAN-VI is two-dimensional. The real input batch consists of the pair $(x, E(x))$, while the fake batch consists of the pair $(z, G(z))$. The structure of GAN-VI is shown in Figure 10b. GAN-VI was used to generate spatiotemporal WPSs and SPSs for the optimal operation of a hybrid hydro-wind-solar energy system. In general, variational inference allows for more complex representations of distributions; however, the proposed GAN-VI was not compared to the CGAN proposed in [78].

Table 4. Advantages and limitations of proposed GAN-based methods for solar power scenario generation.

Reference	Date of Publication	Model	Advantages	Limitations
[78]	May 2018	CGAN	• Seasonal classification	• Training instability • Mode collapse • Unclear latent space
[85]	April 2019	CGAN	• Risk-averse classification	• Same as [78]
[80]	September 2019	GAN-VI	• Complex representations • Training stability	• Unclear latent space • Uncontrollable generation
[81]	November 2019	GAN-GP	• Training stability	• Mode collapse • Unclear latent space
[84]	August 2020	ctrl-GAN	• Training stability • Controllable generation • Seasonality	• Computational cost • Data dependence
[83]	December 2020	GAN-GP	• Same as [81]	• Same as [81]
[20]	July 2021	Fed-LSGAN	• Decentralized method • Training stability	• Unrealistic circumstances • Unclear latent space
[88]	February 2022	ctrl-GAN	• Same as [84]	• Same as [84]
[91]	February 2022	CWM-CGAN	• Weather classification	• Same as [78] • Weather data dependency
[89]	April 2022	C-StyleGAN2-SE	• Weather classification • Training stability • Controllable generation • Complex representations	• Computational cost • Difficult fine-tuning • Weather data dependency
[87]	November 2022	CGAN	• Same as [78]	• Same as [78]
[90]	January 2023	GAN	• GAN advantages	• Same as [78]
[16]	January 2023	StyleGAN-ADA-ESR	• Parallel scenarios • Training stability • Controllable generation • Complex representations	• Computational cost • Difficult fine-tuning
[26]	February 2023	CCRGAN	• Weather classification • Captures long-term temporal correlations	• Same as [78] • Does not capture spatiotemporal correlations

A common method to address training instability issues, such as exploding or vanishing gradients, is to add regulation terms in the objective functions of the generator and the discriminator. For example, in [81], a gradient penalty (GP) term was added to the objective function of the discriminator. The improved GAN-GP was used to generate extended datasets of integrated energy systems' rare control and operation data. Other proposed regularization terms can be found in [80,83].

Another drawback of traditional GANs is the inability to control the generation process. The relationship of the latent space, i.e., the low-dimensional space where the random input noise is generated and the output data are unclear. This issue is addressed to some extent with CGANs, however, the maximum number of conditions that can be used is limited. Furthermore, it is impossible to add new features without retraining. A controllable GAN with transparent latent space (ctrl-GAN) was proposed in [84] for WPS and SPS generation. In ctrl-GAN, an extra feature extraction model F, e.g., a CNN, is added to the overall framework to find relationships between output labels y and the latent space variables z. It is proven that understanding the behavior of the latent space can lead to controllable scenario generation. The feature extraction model was coupled with the generator and was first trained with sample pairs (x, y). Then, each generated scenario was assigned a label, which was mapped to the latent space using a generalized linear regression model to create sample pairs (z, y). Schmidt orthogonalization was employed to un-correlate the features and enable moving independently in each feature axis. Furthermore, regularization terms and spectral normalization were employed to avoid training instabilities. The proposed ctrl-GAN was compared to a simple GAN and GAN-GP. It was shown that the proposed method converged faster and better while generating the highest-quality scenarios. Seasonal scenarios can be generated with ctrl-GAN; however, the proposed model was not tested against CGAN to compare their conditionality capabilities. Furthermore, scenario generation can be controlled based on features, e.g., duration of daily SPG; however, to fully exploit the advantages of controllable generation, massive amounts of historical data are needed. The additional computational cost of the proposed method is unclear. Nevertheless, the proposed ctrl-GAN is highly accurate and flexible, making it ideal for SPS generation for stochastic power system applications. Latent space transparency in the context of RES scenario generation was further investigated in [88].

A framework for SPS forecasting with GANs was first proposed in [83]. Unlike previous studies, which simply exploited GANs to generate SPS sets, the proposed framework exploited meteorological point forecasts $\hat{p}$ to generate scenario forecasts for a specific lead time. The point forecasts were transformed to latent space variables z, which were then fed to a pre-trained generator to generate scenario forecasts. The proposed methodology is characterized by high flexibility, as scenario forecasts can be generated for multiple sites and temporal horizons.

Generating SPSs with GANs for multiple sites in a centralized way can lead to several data-related problems, such as demand for excessive computational resources, data overhead, and data security threats. In [20], a federated learning framework was proposed to generate WPSs and SPSs for multiple sites in a decentralized manner. Furthermore, to address training instability issues and mode collapse, a least square GAN (LSGAN) was used. The results showed that the proposed Fed-LSGAN model generated higher-quality scenarios than traditional GAN models while maintaining data privacy and security. However, ideal conditions were considered regarding data losses, communication delays, and available computational resources, which indicate that in more realistic circumstances, the generated scenarios would be of lower quality.

An attempt to overcome all GAN-related limitations mentioned above was made in [89]. The StyleGAN2 architecture was proposed to enhance the representation of complex distributions and improve the transparency of the latent space to enable controllable scenario generation. Conditionality was implemented to generate scenarios for different weather types in each month. A mini-batch standard deviation layer and regularization terms were added to the discriminator and the generator, respectively, to ensure training stability. Furthermore, a sequence encoder (SE) comprising convolutional LSTMs was added to generate day-ahead WPS and SPS forecasts. The proposed C-StyleGAN2-SE model generated scenarios with superior characteristics based on a variety of different evaluation metrics and effectively solved the day-ahead stochastic UC problem. On the other hand, the significant complexity of the model hindered the optimal configuration of its parameters. Nevertheless, the proposed model was sufficiently scalable with a relatively reasonable training duration.

The StyleGAN architecture was also used in [16] for SPS forecasting. The proposed model implemented Gramian angular field transformations to generate scenarios for multiple sources in parallel. Training stability was significantly improved by adaptive discriminator augmentation (ADA), a technique to dynamically challenge the training procedure of the discriminator as it becomes better at discriminating real and generated scenarios. Furthermore, enhanced super-resolution (ESR) was introduced for feature extraction and construction of multi-model ensembles. The proposed StyleGAN-ADA-ESR improved the controllability of the latent space and generated high-quality short-term scenario forecasts. As in [89], the computational complexity of the model was significant; however, the overall computational time was acceptable for day-ahead forecasting horizons.

Studies [16,20,78,80,81,83–85,87–91] implemented generators and discriminators as a combination of multiple CNNs and MLPs (convolutional GANs). Other deep learning structures have also been proposed for SPS generation with GANs. In [26], a cross-correlated conditional recurrent GAN (CCRGAN) was proposed for seasonal solar and load scenario generation. Both the generator and the discriminator comprised three LSTM layers to capture long-term temporal dependencies. The proposed model generated efficient solar and load scenarios that captured temporal dependencies. However, the proposed model was not tested against other state-of-the-art DGM-based SGMs.

4.2. Other Deep Generative Models

Besides GANs, other types of DGMs have been proposed for SPS generation. In [79,82], modular denoising VAEs (MDVAEs) were proposed for SPS generation. The structure of VAEs is depicted in Figure 11a. With VAEs, historical samples are encoded into distributions to regularize the latent space and avoid overfitting. The latent space is then sampled, and new samples are generated with variational inference. Encoding and decoding are done probabilistically. It was found that MDVAEs were able to capture complex data interdependencies and cross-variable correlations. Furthermore, MDVAEs were able to generate extreme-case scenarios with fewer data compared to other conventional SGMs.

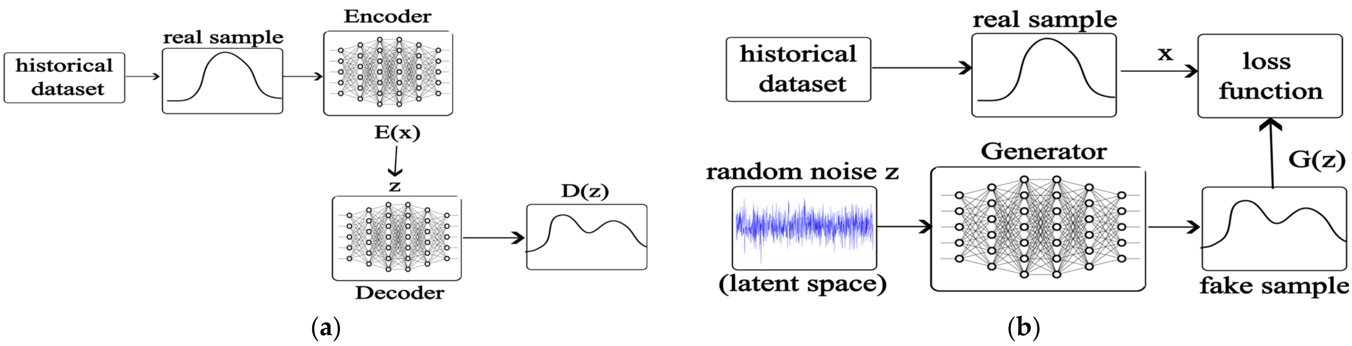


Figure 11. Other DGM structures. (**a**) VAE; (**b**) IMLE-based model structure.

In [92], solar, wind, and load scenarios were generated using implicit maximum likelihood estimation (IMLE). IMLE-based models distinguish themselves from other DGMs by incorporating a simple minimization-based training procedure. IMLEs do not explicitly estimate the PDF of the data and are characterized by high training stability. While the loss function of IMLE-based models ensures that the generated samples resemble the historical samples, the training procedure is not based on minimizing the difference between generated and historical samples. The general structure of an IMLE-based model is depicted in Figure 11b. Convolutional layers were used in [92] to generate scenarios that highly resembled historical scenarios. However, conditionality was not introduced in the overall procedure.

In [86], normalizing flows (NFs) were proposed for solar, wind, and load scenario generation. NFs significantly differ from other DGMs, as they are basically a sequence of transformations that transform a known distribution into a complex target distribution. The proposed NF-based model generated promising scenarios, and its performance was compared with the performances of simple GANs and VAEs. Each method exhibited several advantages and limitations, which are discussed in Section 4.3.

4.3. Summary

Even though DGMs are still in a relatively early stage of development, their increasing rate of utilization for SPS generation, combined with the extreme advancements in deep learning, indicated the necessity of a literature review to summarize up-to-date findings and provide possible future research directions. For long-term temporal horizons, it has been proven that DGMs generate higher accuracy SPSs compared to copula-based and parametric sampling-based SGMs [78]. Furthermore, in [80], DGMs outperformed a copula-based SGM for a short-term temporal horizon. However, the copula used as a benchmark was simple, and further comparisons are necessary to prove that DGMs are more efficient than copulas for short-term temporal horizons. Nevertheless, for long-term temporal horizons, in which copula-based methods lose their efficiency, DGMs seem to be the optimal choice as long as the necessary computational resources are available.

The choice of the optimal DGM depends on several factors, such as the temporal horizon, available computational resources, and target domain. GANs are the most popular DGMs, as they provide the most diverse SPSs. The main disadvantages of GANs are their training instability and mode collapse, which are overcome by the improvements described in Section 4.1.2. VAEs are efficient choices for SPS generation, with simple implementation and training procedures. However, VAEs can easily result in over-simplistic scenarios due to the assumptions made regarding the latent space. Improved GANs were compared to VAEs in [80] and generated higher-quality SPSs for short-term temporal horizons. IMLE-based and NF-based methods have also shown promising results. Once NFs are built, they are easier to fine-tune and generate scenarios that highly differ from those generated by GANs and VAEs. In [92], the proposed IMLE-based method outperformed a GAN and a VAE in generating SPSs. Similarly, in [86], the proposed NF-based method showed superior performance compared to the GAN and VAE used as benchmarks. However, only simple versions of GANs and VAEs were used in both studies. It is evident that more comprehensive comparisons are needed to draw safe conclusions. Furthermore, non-GAN DGMs lack systematic research compared to GANs.

Regarding GANs, some general conclusions can be drawn: GANs with convolutional layers are able to generate high-quality SPSs that capture spatiotemporal and other cross-variable correlations. To minimize the possibility of training instabilities and mode collapse, it is suggested to integrate GANs with techniques such as variational inference and GP, as the additional computational cost is insignificant. Furthermore, it is highly beneficial to control the scenario generation process by using latent space transparency techniques. If the necessary amount of data is not available, or the computational complexity ought to be limited, CGANs could be used as alternatives to partially control the scenarios with data labeling. Improvements, such as StyleGANs and ADA, further increase the quality of the generated scenarios while simultaneously adding to the overall computational complexity.

5. Discussion and Future Research

Scenario generation has become increasingly attractive in recent years due to its applicability to a wide range of power system decision-making problems through stochastic optimization. At the same time, the share of SPG in the total energy mix has significantly increased and is expected to grow further due to the rapid development of PV technologies, cost reductions, and the transition towards more flexible, distribution-level power generation. SPS generation has been implemented in many studies in various forms during the last decade; however, it is safe to say that scenario analysis in the context of power systems is still at an early stage. It is essential to address certain aspects of SPS generation in future research efforts, to further adapt to solar power characteristics and improve existing models in terms of accuracy, versatility, and computational complexity.

5.1. Hybrid Models and Other Deep Learning Techniques

Deep learning has been excessively used recently for SPS generation, especially in the form of DGMs. Thus, it is essential to systematically assess different network structures, as well as compare and standardize suitable regularization terms. Furthermore, little focus has been given to developing hybrid models comprising multiple deep learning methods, data pre-processing techniques, and optimization algorithms. As discussed in Section 4, each individual method comes with certain advantages and limitations. Hybrid models combine several different methods (components) that complement each other in a way that the limitations of each component are mitigated as much as possible. Furthermore, other deep learning techniques, such as deep reinforcement learning, should be incorporated in SPS generation models and tested against the existing state-of-the-art.

5.2. Computational Complexity

DGMs, and especially GANs, have been proven effective for SPS generation owing to their various advantages, listed in Section 4. However, several DGM-related issues need to be addressed, such as computational complexity and parameter configuration. DGMs incorporate complex deep-learning models that require certain computational resources and excessive training durations. Furthermore, parameter fine-tuning becomes challenging as the number of parameters increases significantly in complex multi-layered models and high-dimensionality optimization problems. Advanced, fully adaptive models, specifically developed for the corresponding target domain, could address these issues, as their parameters are dynamically determined during training according to the state of the optimization procedure.

5.3. Global Searching

All models reviewed in Section 4 are optimized by traditional back-propagation algorithms, which are prone to local optimum entrapment. More complex optimization algorithms, e.g., metaheuristics and hill-climbing algorithms, could be coupled with DGMs to enhance global searching or even decrease the overall training time.

5.4. Copula-Based Solar Power Scenario Forecasting

While the focus on scenario generation methods has shifted towards DGMs, it is essential to further develop existing copula-based forecasting approaches. Copulas are particularly efficient for short-term scenario forecasting as long as quality probabilistic forecasts can be obtained. However, unlike wind power, where multiple copula types have been investigated, there is a lack of systematic evaluation of copula types for the description of SPG.

5.5. Complex Physical PV Models

Research efforts should also be directed towards further adapting scenario forecasting to the specific characteristics of SPG. Complex physical PV models, such as the one used in [102], could be incorporated into hybrid methodologies, as they have proven to better capture solar power characteristics and obtain more realistic distributions for sampling. These models will enable deterministic scenario generation and, as a result, facilitate other aspects of SPG, such as control of PV power output via different maximum power point tracking techniques [103]. Thus, deterministic scenario generation will further increase the compatibility of SPG with power system target domains.

5.6. Weather Classifications

More focus should be given to weather classifications, which can significantly improve the quality of the generated scenarios, as discussed in Section 3. For example, finer weather classes could be derived from different cloud types, defined by cloud formation and movement. Days with dynamic cloud conditions are the most challenging in terms of forecasting uncertainty; thus, it is essential to better exploit existing meteorological classifications used in other scientific fields to reduce the stochasticity of SPG. Airflows also significantly affect PV power, as they unevenly distribute the temperature on the surface of the PV module [98,99]. Furthermore, climatic phenomena such as El Niño and La Niña, monsoons, and variations of the warm Gulf Stream, are usually neglected in weather classifications for SPS generation. Such phenomena can significantly affect the prevailing weather conditions of a region; thus, taking them into consideration would improve the quality of the derived weather classes.

5.7. Applicability to Power System Decision-Making Problems

Increasing the applicability of SPSs to power system decision-making problems is also important. Forecasting horizons are constantly decreasing as power systems are becoming more flexible to allow higher penetrations of variable RES. Furthermore, forecasting uncertainty is considered in more optimization stages, even with intra-hour lead times. Thus, it is essential to develop simple and effective solar power SGMs to increase their implementation in short-term forecasting horizons, such as intra-day or even intra-hour forecasting. Ultra-short-term forecasting is becoming increasingly relevant in power systems for energy loss minimization via real-time control of grid stability, load demand, and storage management [104,105]. Furthermore, exploiting sky images for SPF in such small forecasting horizons is essential, as sky images capture the dynamic real-time motion of clouds [104]. Sky images are excessively used in ultra-short-term deterministic SPF and should also be introduced to scenario forecasting to reduce forecasting horizons and enhance weather classifications.

6. Conclusions

This paper presents an overview of the current state-of-the-art methods used for SPS generation, compares different SGMs on several key aspects, and introduces taxonomies based on weather classifications and temporal horizons. It compares the current state of solar power scenario generation to that of wind power and highlights differences between the stochasticity of solar and wind power while also investigating existing gaps and limitations. Furthermore, it comprehensively reviews DGMs proposed for SPS generation and provides several possible research directions to enhance the efficiency and applicability of scenarios.

The main insights are summarized again now. The choice of the optimal SGM for solar power depends on several aspects, such as the temporal horizon, computational complexity restrictions, data availability, and flexibility issues. Copula-based SGMs are suited for short-term temporal horizons, where they seem to be the optimal choice as long as realistic copulas can be effectively obtained. Parametric sampling-based methods are the simplest and can be sufficiently accurate if good distributions are known upfront, and cross-variable correlations do not necessarily need to be captured. DGMs are the most popular choice for long-term scenario generation while still showing promising results in shorter temporal horizons. However, they can be computationally demanding and difficult to handle, especially when improvements such as regularization terms and latent space controllability are added to optimize the training procedure. Nevertheless, the development of DGMs is still at an early stage, and significant advancements are expected to be made in terms of learning techniques, global searching, adaptivity, and computational efficiency.

SPS generation based on weather classifications can significantly improve the accuracy of the scenarios while reducing the variance of each weather class scenario set. However, the most common sunny/cloudy classification is relatively coarse-grained and fails to uncover the full potential of weather classification analysis. It is essential to introduce finer-grain weather classes, mainly based on sky conditions and different cloud types, but also on other parameters closely correlated to SPG, such as temperature and wind flow. Furthermore, more sophisticated data-driven classification techniques would result in optimal weather classes and thus enable higher-level scenario generation.

The continuous advancements in solar power technology and integration will significantly affect the overall power system uncertainty, increasing the necessity of uncertainty modeling and stochastic optimization. The applicability of SPSs needs to be improved with the introduction of advanced models, shorter temporal horizons, and data such as sky images. Nevertheless, the current status and development rate of SPS generation indicates that significant advancements will be made in the near future, capable of mitigating the challenges derived from the increasing integration of uncertainty sources in electric power systems.

Author Contributions: Conceptualization, M.A.K.-K., I.K.B., F.C. and P.S.G.; methodology, M.A.K.-K., I.K.B. and P.S.G.; validation, M.A.K.-K., I.K.B., F.C. and P.S.G.; formal analysis, M.A.K.-K.; investigation, M.A.K.-K., I.K.B. and A.P.G.; data curation, M.A.K.-K., I.K.B. and A.P.G.; writing—original draft preparation, M.A.K.-K., I.K.B. and A.P.G.; writing—review and editing, M.A.K.-K., I.K.B., F.C. and P.S.G.; visualization, M.A.K.-K., I.K.B. and A.P.G.; supervision, F.C. and P.S.G.; project administration, F.C. and P.S.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Halkos, G.E.; Gkampoura, E.-C. Reviewing Usage, Potentials, and Limitations of Renewable Energy Sources. *Energies* **2020**, *13*, 2906. [CrossRef]
2. Bazionis, I.K.; Kousounadis-Knousen, M.A.; Georgilakis, P.S.; Shirazi, E.; Soudris, D.; Catthoor, F. A Taxonomy of Short-term Solar Power Forecasting: Classifications Focused on Climatic Conditions and Input Data. *IET Renew. Power Gener.* **2023**, *17*, 2411–2432. [CrossRef]
3. Buonanno, A.; Caliano, M.; Di Somma, M.; Graditi, G.; Valenti, M. A Comprehensive Tool for Scenario Generation of Solar Irradiance Profiles. *Energies* **2022**, *15*, 8830. [CrossRef]
4. Hashemi, S.; Ostergaard, J.; Yang, G. A Scenario-Based Approach for Energy Storage Capacity Determination in LV Grids with High PV Penetration. *IEEE Trans. Smart Grid* **2014**, *5*, 1514–1522. [CrossRef]
5. Ahmed, R.; Sreeram, V.; Mishra, Y.; Arif, M.D. A Review and Evaluation of the State-of-the-Art in PV Solar Power Forecasting: Techniques and Optimization. *Renew. Sustain. Energy Rev.* **2020**, *124*, 109792. [CrossRef]
6. Wu, Y.-K.; Huang, C.-L.; Phan, Q.-T.; Li, Y.-Y. Completed Review of Various Solar Power Forecasting Techniques Considering Different Viewpoints. *Energies* **2022**, *15*, 3320. [CrossRef]
7. Wang, H.; Liu, Y.; Zhou, B.; Li, C.; Cao, G.; Voropai, N.; Barakhtenko, E. Taxonomy Research of Artificial Intelligence for Deterministic Solar Power Forecasting. *Energy Convers. Manag.* **2020**, *214*, 112909. [CrossRef]
8. Kumari, P.; Toshniwal, D. Deep Learning Models for Solar Irradiance Forecasting: A Comprehensive Review. *J. Clean. Prod.* **2021**, *318*, 128566. [CrossRef]
9. Alcañiz, A.; Grzebyk, D.; Ziar, H.; Isabella, O. Trends and Gaps in Photovoltaic Power Forecasting with Machine Learning. *Energy Rep.* **2023**, *9*, 447–471. [CrossRef]
10. Gaboitaolelwe, J.; Zungeru, A.M.; Yahya, A.; Lebekwe, C.K.; Vinod, D.N.; Salau, A.O. Machine Learning Based Solar Photovoltaic Power Forecasting: A Review and Comparison. *IEEE Access* **2023**, *11*, 40820–40845. [CrossRef]
11. Tawn, R.; Browell, J. A Review of Very Short-Term Wind and Solar Power Forecasting. *Renew. Sustain. Energy Rev.* **2022**, *153*, 111758. [CrossRef]
12. Barbieri, F.; Rajakaruna, S.; Ghosh, A. Very Short-Term Photovoltaic Power Forecasting with Cloud Modeling: A Review. *Renew. Sustain. Energy Rev.* **2017**, *75*, 242–263. [CrossRef]
13. Lin, F.; Zhang, Y.; Wang, J. Recent Advances in Intra-Hour Solar Forecasting: A Review of Ground-Based Sky Image Methods. *Int. J. Forecast.* **2023**, *39*, 244–265. [CrossRef]
14. Bazionis, I.K.; Georgilakis, P.S. Review of Deterministic and Probabilistic Wind Power Forecasting: Models, Methods, and Future Research. *Electricity* **2021**, *2*, 13–47. [CrossRef]
15. Bhavsar, S.; Pitchumani, R.; Ortega-Vazquez, M.A. Machine Learning Enabled Reduced-Order Scenario Generation for Stochastic Analysis of Solar Power Forecasts. *Appl. Energy* **2021**, *293*, 116964. [CrossRef]
16. Wu, Y.; Wang, B.; Yuan, R.; Watada, J. A Gramian Angular Field-Based Data-Driven Approach for Multiregion and Multisource Renewable Scenario Generation. *Inf. Sci.* **2023**, *619*, 578–602. [CrossRef]

17. Golestaneh, F.; Gooi, H.B.; Pinson, P. Generation and Evaluation of Space-Time Trajectories of Photovoltaic Power. *Appl. Energy* **2016**, *176*, 80–91. [CrossRef]
18. Pinson, P.; Madsen, H.; Nielsen, H.; Papaefthymiou, G.; Klöckl, B. From Probabilistic Forecasts to Statistical Scenarios of Short-Term Wind Power Production. *Wind. Energy* **2009**, *12*, 51–62. [CrossRef]
19. Liang, J.; Shirsat, A.; Tang, W. Sustainable Community Based PV-Storage Planning Using the Nash Bargaining Solution. *Int. J. Electr. Power Energy Syst.* **2020**, *118*, 105759. [CrossRef]
20. Li, Y.; Li, J.; Wang, Y. Privacy-Preserving Spatiotemporal Scenario Generation of Renewable Energies: A Federated Deep Generative Learning Approach. *IEEE Trans. Ind. Inf.* **2022**, *18*, 2310–2320. [CrossRef]
21. Li, J.; Zhou, J.; Chen, B. Review of Wind Power Scenario Generation Methods for Optimal Operation of Renewable Energy Systems. *Appl. Energy* **2020**, *280*, 115992. [CrossRef]
22. Rachunok, B.; Staid, A.; Watson, J.P.; Woodruff, D.L. Assessment of Wind Power Scenario Creation Methods for Stochastic Power Systems Operations. *Appl. Energy* **2020**, *268*, 114986. [CrossRef]
23. Cramer, E.; Gorjao, L.R.; Mitsos, A.; Schafer, B.; Witthaut, D.; Dahmen, M. Validation Methods for Energy Time Series Scenarios From Deep Generative Models. *IEEE Access* **2022**, *10*, 8194–8207. [CrossRef]
24. Li, H.; Ren, Z.; Fan, M.; Li, W.; Xu, Y.; Jiang, Y.; Xia, W. A Review of Scenario Analysis Methods in Planning and Operation of Modern Power Systems: Methodologies, Applications, and Challenges. *Electr. Power Syst. Res.* **2022**, *205*, 107722. [CrossRef]
25. Pinson, P.; Girard, R. Evaluating the Quality of Scenarios of Short-Term Wind Power Generation. *Appl. Energy* **2012**, *96*, 12–20. [CrossRef]
26. Dalal, D.; Bilal, M.; Shah, H.; Sifat, A.I.; Pal, A.; Augustin, P. Cross-Correlated Scenario Generation for Renewable-Rich Power Systems Using Implicit Generative Models. *Energies* **2023**, *16*, 1636. [CrossRef]
27. Niknam, T.; Azizipanah-Abarghooee, R.; Narimani, M.R. An Efficient Scenario-Based Stochastic Programming Framework for Multi-Objective Optimal Micro-Grid Operation. *Appl. Energy* **2012**, *99*, 455–470. [CrossRef]
28. Safdarian, A.; Fotuhi-Firuzabad, M.; Aminifar, F. Compromising Wind and Solar Energies from the Power System Adequacy Viewpoint. *IEEE Trans. Power Syst.* **2012**, *27*, 2368–2376. [CrossRef]
29. Dolatabadi, A.; Ebadi, R.; Mohammadi-Ivatloo, B. A Two-Stage Stochastic Programming Model for the Optimal Sizing of Pv/Diesel/Battery in Hybrid Electric Ship System. *J. Oper. Autom. Power Eng.* **2019**, *7*, 16–26. [CrossRef]
30. Gazijahani, F.S.; Salehi, J. Stochastic Multi-Objective Framework for Optimal Dynamic Planning of Interconnected Microgrids. *IET Renew. Power Gener.* **2017**, *11*, 1749–1759. [CrossRef]
31. Biswas, P.P.; Suganthan, P.N.; Mallipeddi, R.; Amaratunga, G.A.J. Optimal Reactive Power Dispatch with Uncertainties in Load Demand and Renewable Energy Sources Adopting Scenario-Based Approach. *Appl. Soft Comput. J.* **2019**, *75*, 616–632. [CrossRef]
32. Hossain, M.A.; Pota, H.R.; Squartini, S.; Zaman, F.; Guerrero, J.M. Energy Scheduling of Community Microgrid with Battery Cost Using Particle Swarm Optimisation. *Appl. Energy* **2019**, *254*, 113723. [CrossRef]
33. Shams, M.H.; Niaz, H.; Na, J.; Anvari-Moghaddam, A.; Liu, J.J. Machine Learning-Based Utilization of Renewable Power Curtailments under Uncertainty by Planning of Hydrogen Systems and Battery Storages. *J. Energy Storage* **2021**, *41*, 103010. [CrossRef]
34. Zhang, Z.; Qin, H.; Li, J.; Liu, Y.; Yao, L.; Wang, Y.; Wang, C.; Pei, S.; Zhou, J. Short-Term Optimal Operation of Wind-Solar-Hydro Hybrid System Considering Uncertainties. *Energy Convers. Manag.* **2020**, *205*, 112405. [CrossRef]
35. Xiong, Z.; Huang, Y.; Wang, W.; Zhang, Y.; Xu, X.; Sun, X. A Day-Ahead Chance Constrained Volt/Var Control Scheme with Renewable Energy Sources by Novel Scenario Generation Method in Active Distribution Networks. *IEEE Access* **2021**, *9*, 64033–64042. [CrossRef]
36. Lv, S.; Li, J.; Guo, Y.; Shi, Z. A Typical Distributed Generation Scenario Reduction Method Based on an Improved Clustering Algorithm. *Appl. Sci.* **2019**, *9*, 4262. [CrossRef]
37. Li, Z.; Xie, X.; Cheng, Z.; Zhi, C.; Si, J. A Novel Two-Stage Energy Management of Hybrid AC/DC Microgrid Considering Frequency Security Constraints. *Int. J. Electr. Power Energy Syst.* **2023**, *146*, 1017–1024. [CrossRef]
38. Sheidaei, F.; Ahmarinejad, A.; Tabrizian, M.; Babaei, M. A Stochastic Multi-Objective Optimization Framework for Distribution Feeder Reconfiguration in the Presence of Renewable Energy Sources and Energy Storages. *J. Energy Storage* **2021**, *40*, 102775. [CrossRef]
39. Ramadan, A.; Ebeed, M.; Kamel, S.; Agwa, A.M.; Tostado-véliz, M. The Probabilistic Optimal Integration of Renewable Distributed Generators Considering the Time-Varying Load Based on an Artificial Gorilla Troops Optimizer. *Energies* **2022**, *15*, 1302. [CrossRef]
40. Riaz, M.; Hanif, A.; Hussain, S.J.; Memon, M.I.; Ali, M.U.; Zafar, A. An Optimization-Based Strategy for Solving Optimal Power Flow Problems in a Power System Integrated with Stochastic Solar and Wind Power Energy. *Appl. Sci.* **2021**, *11*, 6883. [CrossRef]
41. Afzaal, M.U.; Sajjad, I.A.; Awan, A.B.; Paracha, K.N.; Khan, M.F.N.; Bhatti, A.R.; Zubair, M.; ur Rehman, W.; Amin, S.; Haroon, S.S.; et al. Probabilistic Generation Model of Solar Irradiance for Grid Connected Photovoltaic Systems Using Weibull Distribution. *Sustainability* **2020**, *12*, 2241. [CrossRef]
42. Yang, Z.; Li, K.; Niu, Q.; Xue, Y. A Comprehensive Study of Economic Unit Commitment of Power Systems Integrating Various Renewable Generations and Plug-in Electric Vehicles. *Energy Convers. Manag.* **2017**, *132*, 460–481. [CrossRef]
43. Fu, X.; Guo, Q.; Sun, H.; Pan, Z.; Xiong, W.; Wang, L. Typical Scenario Set Generation Algorithm for an Integrated Energy System Based on the Wasserstein Distance Metric. *Energy* **2017**, *135*, 153–170. [CrossRef]

44. Liu, Z.; Liu, S.; Li, Q.; Zhang, Y.; Deng, W.; Zhou, L. Optimal Day-Ahead Scheduling of Islanded Microgrid Considering Risk-Based Reserve Decision. *J. Mod. Power Syst. Clean. Energy* **2021**, *9*, 1149–1160. [CrossRef]
45. Xu, M.; Li, W.; Feng, Z.; Bai, W.; Jia, L.; Wei, Z. Economic Dispatch Model of High Proportional New Energy Grid-Connected Consumption Considering Source Load Uncertainty. *Energies* **2023**, *16*, 1696. [CrossRef]
46. Liu, C.; Wang, X.; Guo, J.; Huang, M.; Wu, X. Chance-Constrained Scheduling Model of Grid-Connected Microgrid Based on Probabilistic and Robust Optimisation. *IET Gener. Transm. Distrib.* **2018**, *12*, 2499–2509. [CrossRef]
47. Cao, X.; Cao, T.; Gao, F.; Guan, X. Risk-Averse Storage Planning for Improving RES Hosting Capacity under Uncertain Siting Choices. *IEEE Trans. Sustain. Energy* **2021**, *12*, 1984–1995. [CrossRef]
48. Parastegari, M.; Hooshmand, R.A.; Khodabakhshian, A.; Zare, A.H. Joint Operation of Wind Farm, Photovoltaic, Pump-Storage and Energy Storage Devices in Energy and Reserve Markets. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 275–284. [CrossRef]
49. Li, Y.; Zou, Y.; Tan, Y.; Cao, Y.; Liu, X.; Shahidehpour, M.; Tian, S.; Bu, F. Optimal Stochastic Operation of Integrated Low-Carbon Electric Power, Natural Gas, and Heat Delivery System. *IEEE Trans. Sustain. Energy* **2018**, *9*, 273–283. [CrossRef]
50. Qiao, X.; Zou, Y.; Li, Y.; Chen, Y.; Liu, F.; Jiang, L.; Cao, Y. Impact of Uncertainty and Correlation on Operation of Micro-Integrated Energy System. *Int. J. Electr. Power Energy Syst.* **2019**, *112*, 262–271. [CrossRef]
51. Tang, S.; Jiang, M.; Abbassi, R.; Jerbi, H.; Latifi, M. A Cost-Oriented Resource Scheduling of a Solar-Powered Microgrid by Using the Hybrid Crow and Pattern Search Algorithm. *J. Clean. Prod.* **2021**, *313*, 127853. [CrossRef]
52. Panwar, M.; Suryanarayanan, S.; Hovsapian, R. A Multi-Criteria Decision Analysis-Based Approach for Dispatch of Electric Microgrids. *Int. J. Electr. Power Energy Syst.* **2017**, *88*, 99–107. [CrossRef]
53. Wang, Q.; Zhang, X.; Yi, C.; Li, Z.; Xu, D. A Novel Shared Energy Storage Planning Method Considering the Correlation of Renewable Uncertainties on the Supply Side. *IEEE Trans. Sustain. Energy* **2022**, *13*, 2051–2063. [CrossRef]
54. van der Meer, D.; Wang, G.C.; Munkhammar, J. An Alternative Optimal Strategy for Stochastic Model Predictive Control of a Residential Battery Energy Management System with Solar Photovoltaic. *Appl. Energy* **2021**, *283*, 116289. [CrossRef]
55. Kaffash, M.; Bruninx, K.; Deconinck, G. Data-Driven Forecasting of Local PV Generation for Stochastic PV-Battery System Management. *Int. J. Energy Res.* **2021**, *45*, 15962–15979. [CrossRef]
56. Toubeau, J.F.; Nguyen, T.H.; Khaloie, H.; Wang, Y.; Vallee, F. Forecast-Driven Stochastic Scheduling of a Virtual Power Plant in Energy and Reserve Markets. *IEEE Syst. J.* **2022**, *16*, 5212–5223. [CrossRef]
57. Tang, C.; Wang, Y.; Xu, J.; Sun, Y.; Zhang, B. Efficient Scenario Generation of Multiple Renewable Power Plants Considering Spatial and Temporal Correlations. *Appl. Energy* **2018**, *221*, 348–357. [CrossRef]
58. Camal, S.; Teng, F.; Michiorri, A.; Kariniotakis, G.; Badesa, L. Scenario Generation of Aggregated Wind, Photovoltaics and Small Hydro Production for Power Systems Applications. *Appl. Energy* **2019**, *242*, 1396–1406. [CrossRef]
59. Zhang, H.; Lu, Z.; Hu, W.; Wang, Y.; Dong, L.; Zhang, J. Coordinated Optimal Operation of Hydro–Wind–Solar Integrated Systems. *Appl. Energy* **2019**, *242*, 883–896. [CrossRef]
60. Densing, M.; Wan, Y. Low-Dimensional Scenario Generation Method of Solar and Wind Availability for Representative Days in Energy Modeling. *Appl. Energy* **2022**, *306*, 118075. [CrossRef]
61. Zhou, N.; Xu, X.; Yan, Z.; Shahidehpour, M. Spatio-Temporal Probabilistic Forecasting of Photovoltaic Power Based on Monotone Broad Learning System and Copula Theory. *IEEE Trans. Sustain. Energy* **2022**, *13*, 1874–1885. [CrossRef]
62. Li, Z.L.; Li, P.; Yuan, Z.P.; Xia, J.; Tian, D. Optimized Utilization of Distributed Renewable Energies for Island Microgrid Clusters Considering Solar-Wind Correlation. *Electr. Power Syst. Res.* **2022**, *206*, 107822. [CrossRef]
63. Yan, B.; Wang, B.; Zhu, L.; Liu, H.; Liu, Y.; Ji, X.; Liu, D. A Novel, Stable, and Economic Power Sharing Scheme for an Autonomous Microgrid in the Energy Internet. *Energies* **2015**, *8*, 12741–12764. [CrossRef]
64. Vagropoulos, S.I.; Kardakos, E.G.; Simoglou, C.K.; Bakirtzis, A.G.; Catalão, J.P.S. ANN-Based Scenario Generation Methodology for Stochastic Variables of Electric Power Systems. *Electr. Power Syst. Res.* **2016**, *134*, 9–18. [CrossRef]
65. Zeynali, S.; Rostami, N.; Ahmadian, A.; Elkamel, A. Two-Stage Stochastic Home Energy Management Strategy Considering Electric Vehicle and Battery Energy Storage System: An ANN-Based Scenario Generation Methodology. *Sustain. Energy Technol. Assess.* **2020**, *39*, 100722. [CrossRef]
66. Nuno, E.; Koivisto, M.; Cutululis, N.A.; Sorensen, P. On the Simulation of Aggregated Solar PV Forecast Errors. *IEEE Trans. Sustain. Energy* **2018**, *9*, 1889–1898. [CrossRef]
67. Luo, F.; Ranzi, G.; Wang, S.; Dong, Z.Y. Hierarchical Energy Management System for Home Microgrids. *IEEE Trans. Smart Grid* **2018**, *10*, 5536–5546. [CrossRef]
68. Quan, H.; Srinivasan, D.; Khambadkone, A.M.; Khosravi, A. A Computational Framework for Uncertainty Integration in Stochastic Unit Commitment with Intermittent Renewable Energy Sources. *Appl. Energy* **2015**, *152*, 71–82. [CrossRef]
69. Quan, H.; Srinivasan, D.; Khosravi, A. Integration of Renewable Generation Uncertainties into Stochastic Unit Commitment Considering Reserve and Risk: A Comparative Study. *Energy* **2016**, *103*, 735–745. [CrossRef]
70. Woodruff, D.L.; Deride, J.; Staid, A.; Watson, J.P.; Slevogt, G.; Silva-Monroy, C. Constructing Probabilistic Scenarios for Wide-Area Solar Power Generation. *Sol. Energy* **2018**, *160*, 153–167. [CrossRef]
71. Xing, F.; Li, X.; Fan, H.; Zhao, K.; Li, S.; Li, C. Static Equivalent of Distribution Network with Distributed PV Considering Correlation between Fluctuation of PV and Load. *Front. Energy Res.* **2023**, *10*, 1119174. [CrossRef]
72. Kim, H.; Lee, D. Probabilistic Solar Power Forecasting Based on Bivariate Conditional Solar Irradiation Distributions. *IEEE Trans. Sustain. Energy* **2021**, *12*, 2031–2041. [CrossRef]

73. Park, H. A Stochastic Planning Model for Battery Energy Storage Systems Coupled with Utility-Scale Solar Photovoltaics. *Energies* **2021**, *14*, 1244. [CrossRef]
74. Gazafroudi, A.S.; Prieto-Castrillo, F.; Pinto, T.; Prieto, J.; Corchado, J.M.; Bajo, J. Energy Flexibility Management Based on Predictive Dispatch Model of Domestic Energy Management System. *Energies* **2017**, *10*, 1397. [CrossRef]
75. Grantham, A.P.; Pudney, P.J.; Boland, J.W. Generating Synthetic Sequences of Global Horizontal Irradiation. *Sol. Energy* **2018**, *162*, 500–509. [CrossRef]
76. Li, H.; Ren, Z.; Xu, Y.; Wenyuan, L.; Hu, B. A Multi-Data Driven Hybrid Learning Method for Weekly Photovoltaic Power Scenario Forecast. *IEEE Trans. Sustain. Energy* **2022**, *13*, 91–100. [CrossRef]
77. Yang, J.; Zhang, S.; Xiang, Y.; Liu, J.; Liu, J.; Han, X.; Teng, F. LSTM Auto-Encoder Based Representative Scenario Generation Method for Hybrid Hydro-PV Power System. *IET Gener. Transm. Distrib.* **2020**, *14*, 5816–5822. [CrossRef]
78. Chen, Y.; Wang, Y.; Kirschen, D.; Zhang, B. Model-Free Renewable Scenario Generation Using Generative Adversarial Networks. *IEEE Trans. Power Syst.* **2018**, *33*, 3265–3275. [CrossRef]
79. Huang, N.; Wang, W.; Guowei, C. Optimal Configuration Planning of Multi-Energy Microgird Based on Deep Joint Generation of Source-Load-Temperature Scenarios. *CSEE J. Power Energy Syst.* **2019**, *9*, 1090–1102. [CrossRef]
80. Wei, H.; Hongxuan, Z.; Yu, D.; Yiting, W.; Ling, D.; Ming, X. Short-Term Optimal Operation of Hydro-Wind-Solar Hybrid System with Improved Generative Adversarial Networks. *Appl. Energy* **2019**, *250*, 389–403. [CrossRef]
81. Zhou, S.; Hu, Z.; Zhong, Z.; He, D.; Jiang, M. An Integrated Energy System Operating Scenarios Generator Based on Generative Adversarial Network. *Sustainability* **2019**, *11*, 6699. [CrossRef]
82. Huang, N.; Wang, W.; Cai, G.; Qi, J.; Jiang, Y. Economic Analysis of Household Photovoltaic and Reused-Battery Energy Storage Systems Based on Solar-Load Deep Scenario Generation under Multi-Tariff Policies of China. *J. Energy Storage* **2021**, *33*, 102081. [CrossRef]
83. Jiang, C.; Mao, Y.; Chai, Y.; Yu, M. Day-Ahead Renewable Scenario Forecasts Based on Generative Adversarial Networks. *Int. J. Energy Res.* **2021**, *45*, 7572–7587. [CrossRef]
84. Qiao, J.; Pu, T.; Wang, X. Renewable Scenario Generation Using Controllable Generative Adversarial Networks with Transparent Latent Space. *CSEE J. Power Energy Syst.* **2021**, *7*, 66–77. [CrossRef]
85. Yang, X.; He, H.; Li, J.; Zhang, Y. Toward Optimal Risk-Averse Configuration for HESS with CGANs-Based PV Scenario Generation. *IEEE Trans. Syst. Man. Cybern. Syst.* **2021**, *51*, 1779–1793. [CrossRef]
86. Dumas, J.; Wehenkel, A.; Lanaspeze, D.; Cornélusse, B.; Sutera, A. A Deep Generative Model for Probabilistic Energy Forecasting in Power Systems: Normalizing Flows. *Appl. Energy* **2022**, *305*, 117871. [CrossRef]
87. Bagheri, F.; Dagdougui, H.; Gendreau, M. Stochastic Optimization and Scenario Generation for Peak Load Shaving in Smart District Microgrid: Sizing and Operation. *Energy Build.* **2022**, *275*, 112426. [CrossRef]
88. Dong, W.; Chen, X.; Yang, Q. Data-Driven Scenario Generation of Renewable Energy Production Based on Controllable Generative Adversarial Networks with Interpretability. *Appl. Energy* **2022**, *308*, 118387. [CrossRef]
89. Yuan, R.; Wang, B.; Sun, Y.; Song, X.; Watada, J. Conditional Style-Based Generative Adversarial Networks for Renewable Scenario Generation. *IEEE Trans. Power Syst.* **2023**, *38*, 1281–1296. [CrossRef]
90. Xu, J.; Ji, Z.; Liu, X.; Bao, Y.; Zhang, S.; Wang, W.; Pang, Z. Two-Stage Scheduling of Integrated Energy Systems Based on a Two-Step DCGAN-Based Scenario Prediction Approach. *Front. Energy Res.* **2023**, *10*, 1012367. [CrossRef]
91. He, G.; Liu, K.; Wang, S.; Lei, Y.; Li, J. CWM-CGAN Method for Renewable Energy Scenario Generation Based on Weather Label Multi-Factor Definition. *Processes* **2022**, *10*, 470. [CrossRef]
92. Liao, W.; Bak-Jensen, B.; Pillai, J.R.; Yang, Z.; Wang, Y.; Liu, K. Scenario Generations for Renewable Energy Sources and Loads Based on Implicit Maximum Likelihood Estimations. *J. Mod. Power Syst. Clean. Energy* **2022**, *10*, 1563–1575. [CrossRef]
93. Salehi Borujeni, M.; Akbari Foroud, A.; Dideban, A. Accurate Modeling of Uncertainties Based on Their Dynamics Analysis in Microgrid Planning. *Sol. Energy* **2017**, *155*, 419–433. [CrossRef]
94. Tanaka, I.; Yuge, H.; Ohmori, H. Formulation and Evaluation of Long-Term Allocation Problem for Renewable Distributed Generations. *IET Renew. Power Gener.* **2017**, *11*, 1584–1596. [CrossRef]
95. Apostolopoulou, D.; De Grève, Z.; McCulloch, M. Robust Optimization for Hydroelectric System Operation Under Uncertainty. *IEEE Trans. Power Syst.* **2018**, *33*, 3337–3348. [CrossRef]
96. Medina-Santana, A.A.; Cárdenas-Barrón, L.E. Optimal Design of Hybrid Renewable Energy Systems Considering Weather Forecasting Using Recurrent Neural Networks. *Energies* **2022**, *15*, 9045. [CrossRef]
97. Velasquez, M.A.; Quijano, N.; Cadena, A.I.; Shahidehpour, M. Distributed Stochastic Economic Dispatch via Model Predictive Control and Data-Driven Scenario Generation. *Int. J. Electr. Power Energy Syst.* **2021**, *129*, 106796. [CrossRef]
98. Chowdhury, M.G.; Goossens, D.; Goverde, H.; Catthoor, F. Experimentally Validated CFD Simulations Predicting Wind Effects on Photovoltaic Modules Mounted on Inclined Surfaces. *Sustain. Energy Technol. Assess.* **2018**, *30*, 201–208. [CrossRef]
99. Goverde, H.; Goossens, D.; Govaerts, J.; Dubey, V.; Catthoor, F.; Baert, K.; Poortmans, J.; Driesen, J. Spatial and Temporal Analysis of Wind Effects on PV Module Temperature and Performance. *Sustain. Energy Technol. Assess.* **2015**, *11*, 36–41. [CrossRef]
100. Tomczak, J.M. *Deep Generative Modeling*; Springer International Publishing: Berlin/Heidelberg, Germany, 2022.
101. Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; Bengio, Y. Generative Adversarial Nets. In Proceedings of the 27th International Conference on Neural Information Processing Systems, Montreal, QC, Canada, 8–13 December 2014; Volume 2, pp. 2672–2680.

102. Goverde, H.; Goossens, D.; Govaerts, J.; Catthoor, F.; Baert, K.; Poortmans, J.; Driesen, J. Spatial and Temporal Analysis of Wind Effects on PV Modules: Consequences for Electrical Power Evaluation. *Sol. Energy* **2017**, *147*, 292–299. [CrossRef]
103. Eid, M.A.E.; Elbaset, A.A.; Ibrahim, H.A.; Abdelwahab, S.A.M. Modelling, Simulation of MPPT Using Perturb and Observe and Incremental Conductance Techniques For Stand-Alone PV Systems. In Proceedings of the 2019 21st International Middle East Power Systems Conference (MEPCON), Cairo, Egypt, 17–19 December 2019; pp. 429–434.
104. Anagnostos, D.; Schmidt, T.; Cavadias, S.; Soudris, D.; Poortmans, J.; Catthoor, F. A Method for Detailed, Short-Term Energy Yield Forecasting of Photovoltaic Installations. *Renew. Energy* **2019**, *130*, 122–129. [CrossRef]
105. Watari, D.; Taniguchi, I.; Goverde, H.; Manganiello, P.; Shirazi, E.; Catthoor, F.; Onoye, T. Multi-Time Scale Energy Management Framework for Smart PV Systems Mixing Fast and Slow Dynamics. *Appl. Energy* **2021**, *289*, 116671. [CrossRef]