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Taxonomy research of artificial intelligence for deterministic solar power forecasting

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ABSTRACT

With the world-wide deployment of solar energy for a sustainable and renewable future, the stochastic and volatile nature of solar power pose significant challenges to the reliable, economic and secure operation of electrical energy systems. It is therefore imperative to improve the prediction accuracy of solar power to prepare for the unknown conditions in the future. So far, artificial intelligence (AI) algorithms such as machine learning and deep learning have been widely-reported with competitive prediction performance because they can reveal the invariant structure and nonlinear features in solar data. However, these reports have not been fully reviewed. Accordingly, this paper provides a taxonomy research of the existing solar power forecasting models based on AI algorithms. Taxonomy is a process of systematically dividing solar energy prediction methods, optimizers and prediction frameworks into several categories based on their differences and similarities. We also present the challenges and potential future research directions in solar power forecasting based on AI algorithms. This review can help scientists and engineers to theoretically analyze the characteristics of various solar prediction models, thereby helping them to select the most suitable model in any application scenario.

1. Introduction

1.1. Motivation

In the face of severe energy crisis and fossil fuel pollution to the environment, the development of renewable energy has become a global consensus [1]. Due to its clean and green nature, solar energy is one of the most rapidly-deployed alternative energy sources in the world [2]. As a weather-dependent resource, solar power generation usually exhibits a certain degree of stochastics, volatility and variability [3], threatening the economic and stable operation of electrical power and energy systems. For example, the stochastics of solar energy directly aggravates the disturbance of an energy system, thereby increasing the reserve capacity and generation cost [4], because the real-time balance between power generation and consumption should be maintained. Moreover, power electronic equipment in solar power generation will reduce the rotational inertia of the power system, resulting in a decrease in the stability margin of the system [5]. It is therefore imperative to improve the prediction accuracy of solar power [6].

In fact, there are many factors that affect solar power generation, including solar radiation, cloud coverage, temperature, humidity, atmospheric pressure and wind speed, etc. [7]. Due to the chaotic nature of the Earth's weather system, these environmental factors may change dramatically at any time, making it a challenging task for reliable and accurate forecasting of solar power [8]. So far, many studies on solar power prediction have been conducted, which can be divided into physical modeling, statistical methods, regression methods and their hybrid methods [9]. Among them, artificial intelligence (AI) algorithm is basically the backbone of the existing solar power prediction structures. AI belongs to a branch of computer science and is an emerging technology that studies human logical thinking, reasoning, and group behavior through computer simulation [10]. The most commonly-used AI algorithms include machine learning (ML), expert system, fuzzy logic, and heuristic optimization [11]. The AI algorithms have at least the following three advantages [12]: (1) AI usually has powerful feature extraction and nonlinear mapping functions; (2) AI algorithm has good compatibility and can be flexibly embedded into various photovoltaic

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(PV) power prediction scenarios; (3) AI can achieve a certain degree of logical reasoning, which is helpful to realize a high level of intelligence for solar predictors. Hence, AI algorithms have been widely applied in solar radiation and PV power prediction with attractive performance [13].

Statistics show that there are more than 200 publications focusing on AI-based solar power forecasting, and several review articles have been reported from different angles. The existing solar power forecasting models were extensively reviewed from the perspective of competitive ensemble and cooperative ensemble [14]. Barbieri *et al.* compared solar power forecasting models based on cloud modeling and found that solar irradiance and battery temperature played a decisive role [15]. The latest developments in probabilistic solar power forecasting were investigated [16]. Sobri *et al.* divided the existing methods for solar power forecasting into three categories, namely time series statistical method, physical model method and multivariate method [17]. Wang *et al.* provided an overview of the existing wind and solar power prediction methods based on deep learning [18]. However, so far, despite the related reports flourish in recent years, the review of solar power forecasting from the perspective of AI has not yet been investigated. The review can help scientists and engineers analyze the characteristics of various solar prediction models and determine which AI can improve their prediction tools, thereby helping to maximize the potential of AI in solar energy prediction. The purpose of this paper is to fill this gap.

1.2. Literature review

Existing solar power prediction models can be divided into four types: physical models, statistical methods, regression methods and their hybrids.

1) Physical model: This type of research focuses on solar power prediction based on numerical weather prediction (NWP) and PV cell physical principles [19]. The input of the physical model consists of dynamic information such as NWP and environmental monitoring data, and static information such as the installation angle of the PV panel and the conversion efficiency of the PV cell [20]. Commonly-used physical models include ASHRAE and Hottel [21]. Although physical methods do not require any historical information, they rely on geographic information and detailed meteorological data of PV panels [22]. In addition, physical methods may have poor anti-interference capabilities and are not reliable for short-term solar power forecasting [23].

2) Statistical method: This type of research aims to establish a mapping relationship between historical time-series data and solar energy output [24]. Commonly-used statistical methods include autoregressive moving average [25], Kalman filter [26], Markov chain [27], spatiotemporal association [28] and grey theory. Generally, statistical methods have a simple modeling process, when compared with physical methods. A new statistical method based on Mycielski and Markov processes was developed to predict solar irradiance [29]. Probabilistic behavior of solar energy was analyzed in [30], and two novel stochastic PV power prediction models were proposed based on stochastic state space model and Kalman filter.

3) Regression method: This type of research takes solar radiation, the operating state of PV panels and environmental parameters as input variables, and attempts to establish the mathematical relationship between input and output through curve fitting and parameter optimization techniques [31]. Common regression methods include backward-propagation neural network (BPNN) [32], support vector machine (SVM) [33], extreme learning machine (ELM) [34], wavelet neural network [35] and deep learning [36]. A new prediction structure based on K-nearest neighbors has been developed for hourly solar radiation prediction [37]. William *et al.* proposed a short-term hybrid prediction model of solar irradiance based on SVM and genetic algorithm (GA) [38]. A new prediction framework was developed based on the deep belief network (DBN), and proved that its prediction performance was superior to a variety of shallow models [39].

4) Hybrid methods: The fourth category of research focuses on combining physical modeling, statistical method and regression into hybrid prediction structures [40]. Liu *et al.* first embedded PV geographic and meteorological data into a spatial mesh [28], and then proposed a solar power forecasting framework based on gate recurrent unit. A multivariate hybrid prediction model based on Bayesian average, feedforward neural network (FNN) and Elman neural network (ENN) was innovatively proposed [41]. The historical solar data of the University of Queensland was used to verify the feasibility of the prediction model.

1.3. Contribution

This paper provides a comprehensive review of the solar power forecasting publications based on AI algorithms to summarize the state-of-the-art progress and systematically evaluate the effectiveness and applicability of deterministic predictors. Compared with the existing research on similar topics, the novelties and contributions of this paper are mainly threefold:

1) Existing AI-based solar energy prediction methods, network optimizers and forecasting structures have been extensively reviewed for the first time from a perspective of taxonomy. Taxonomy provides a classification method to analyze the current solar power forecasting research based on their similarities and differences.
2) Comparative analyses of AI-based solar power prediction methods, network optimizers and forecasting structures are carried out. The obtained results can help scientists and engineers to choose the most suitable prediction method, optimizer and prediction structure in various application scenarios.
3) We explored the challenges faced by artificial intelligence in solar power forecasting and potential future research directions, thus guiding potential researchers to focus on key issues that have not yet been resolved.

In summary, this paper dissects the existing AI-based solar power prediction methods, network optimizers and forecasting structures from a taxonomy viewpoint, which provides useful guidance for the development of AI technologies in electrical power and energy systems.

2. Taxonomy of AI regression in solar power forecasting

AI is a comprehensive frontier discipline that combines computer science, cybernetics, information theory, and neuroscience to study human logical thinking, reasoning, and group behavior simulation [42]. AI algorithms usually have good knowledge representation and data fitting capabilities, making them popular in speech recognition, decision-making, and heuristic search [43]. To date, solar power prediction based on AI algorithms has been one of the research hotspots. Commonly-used AI algorithms include ML, deep learning and fuzzy logic. This section reviews the current research directions of solar power forecasting from the taxonomy perspective of AI methods. We now elaborate on the basic principles and application examples of the AI methods.

2.1. Machine learning

As the most important subset of AI, ML algorithms are designed to study the behavior in data and are often used to implement certain learning abilities and logical reasoning without using explicit instructions [44]. In the past few decades, ML algorithms have been proven to be useful in the fields of web search, autonomous driving, speech recognition and human genome recognition [45]. According to our survey, commonly-used ML algorithms in solar energy prediction include artificial neural networks (ANN), SVM, ELM, recurrent neural

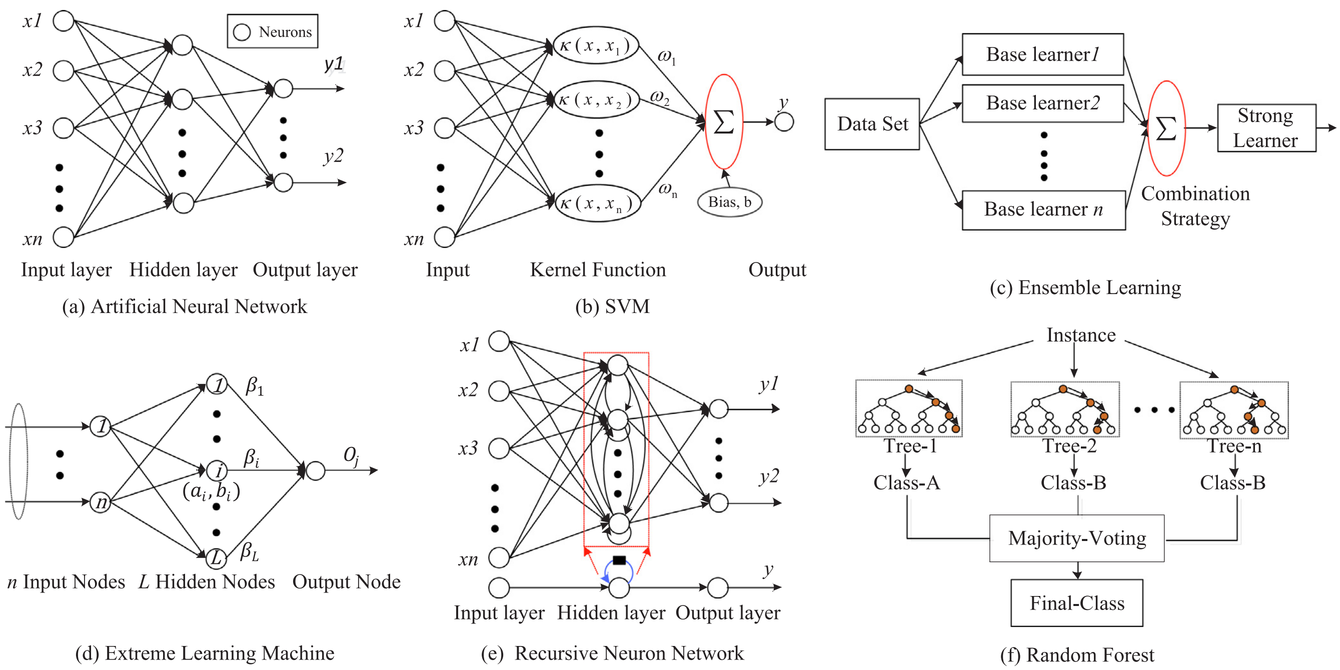

Fig. 1. The typical structures of machine learning algorithms.

network (RNN), ensemble learning [46] and random forest. The structures of typical ML algorithms are presented in Fig. 1.

2.1.1. *Artificial neural network*

ANN is a type of nonlinear models for information processing constructed by abstracting brain neurons. An ANN consists of a large number of nodes and their connections. Each node represents a specific output function termed an activation function. The connection between the nodes represents the weight of the signal flowing through, which gives ANN a memory [47]. The output of the ANN is determined by the weight, the activation function and the way ANN is connected [48]. Due to its strong nonlinear approximation capability, ANN is widely used in solar energy prediction.

Benali *et al.* proposed a hybrid method combining ANN and random forest to achieve real-time prediction of the three components in solar radiation including beam, diffuse and global [49]. Chigbogu *et al.* adopted ANN and auto regression for solar energy prediction [50]. Historical solar irradiance and monthly mean daily global solar irradiance are taken as the input and output of this prediction structure, respectively. The availability and effectiveness of this prediction structure were verified at Abuja. An ANN-based correction algorithm was proposed in [51] to improve the prediction accuracy of global horizontal irradiance. This algorithm has been proved to be very useful in energy management system with high penetration of solar energy. Ghimire *et al.* [52] developed an improved ANN model to enhance the predict ability of solar energy.

2.1.2. *Support vector machine*

SVM is a generalized classifier that classifies input data based on supervised learning [53]. The core principle of SVM is to find the support vector used to construct the optimal classification hyperplane in training set [54]. Generally, SVM adopts a hinge loss function to calculate empirical risk, thereby enhancing its sparsity and robustness. Up to date, studies with respect to SVM for solar energy forecasting have been frequently reported.

A new prediction model based on SVM was developed to forecast daily global solar radiation in India [55]. The prediction model adopted Waikato knowledge analysis environment software to determine the key input parameters. William considered random weather conditions and proposed a hybrid model based on GA and SVM for short-term prediction of PV power generation [56]. Experimental results show that, compared with traditional SVM, the prediction model has better root mean square error (RMSE) and mean absolute percentage error (MAPE). Jiang proposed a punitive kernel SVM method to realize the prediction of solar irradiance [57]. In addition, SVM can also be used in many other application scenarios, such as next day solar insolation prediction, performance evaluation of solar collector and efficiency estimation of solar air heater system [58].

2.1.3. *Extreme learning machine*

ELM is actually a new training algorithm for single-hidden-layer FNN. Compared with traditional FNN, ELM randomly generates its network parameters [59], including the connection weights between neurons and the thresholds in hidden layer. These weights and thresholds are not required to be trained during the training process. Compared with traditional training methods such as back-propagation algorithm, ELM has the advantages of fast learning speed and good generalization capability [60]. Accordingly, ELM is very popular in solar power prediction.

Deo *et al.* proposed a new point prediction model based on ELM [61]. Remote sensing satellite data and geological structure data were used as input parameters. The results obtained proved that the model was superior to the traditional random forest and multiple adaptive regression spline method. A new hybrid method combining grouping-GA and ELM was developed in [62] to predict global solar radiation. Group GA was used to perform feature selection, while ELM was used for nonlinear regression. The proposed hybrid method took into account multiple numerical weather mesoscale models. The proposed method was fully validated using data collected from PV plants in Toledo, Spain. A new prediction structure based on particle swarm optimization (PSO) and ELM was proposed to achieve real-time prediction of PV power [63]. PSO was adopted to optimize the weight parameters of ELM. The results obtained showed that the prediction structure was obviously superior to the traditional back propagation algorithm. A fast non-parametric regression model based on ELM was developed to achieve point prediction and quantile prediction of solar power generation [64]. Numerical results demonstrated that the proposed regression model can effectively generate accurate and reliable probabilistic prediction information.

2.1.4. Recursive neuron network

Basically, RNN is an ANN with a hierarchical tree structure. In RNN, neural nodes recursively input information in connection order [65]. In general, RNN delivers and processes data in a round-robin fashion with three main features [66]: (1) Durability. The current state of RNN will be affected by past decisions. Similarly, current RNN states will also affect subsequent decisions. (2) Memory. Similar to the human brain mechanism, RNN retains the memory of the input sequence and helps filter out useless information. (3) Gate mechanism and weight sharing mechanism. The two mechanisms are introduced into RNN to better learn the dependency of RNN output on RNN input. With these features, RNNs are well suited for processing time series data [67]. Typical RNN algorithms include ENN and long short-term memory network (LSTM).

Wang *et al.* proposed a hybrid prediction model based on LSTM and convolutional neural network (CNN) [68]. LSTM and CNN were used to extract the inherent temporal and spatial features in the input data, respectively. The forecasting results of the proposed model were compared with several single models, and eight performance evaluation indices were presented. Lin *et al.* proposed a new hybrid prediction model with a combination of K-mean clustering, gray correlation analysis and ENN [69]. K-mean clustering was used to classify the historical solar power dataset, and the gray correlation analysis was applied to determine the similarity between the historical data and the forecast day. Finally, ENN was adopted to learn the nonlinear relationship between multivariate meteorological factor and solar power. The variability of solar energy was fully investigated in [70], and a recursive arithmetic average integration model based on data-driven technique was developed for solar power forecasting. A prediction framework based on LSTM was mooted for short-term half-hour global solar radiation prediction [71]. In this framework, CNN was used to reliably extract the high-level features of the input data, and LSTM was integrated for time-series forecasting. The effectiveness of the proposed prediction framework was proved using solar power data from a photovoltaic power plant in Australia.

2.1.5. Random forest

As a supervised learning algorithm, random forest takes advantage of randomization strategies, alternative analysis and ensemble technique to generate accurate machine learning models [72]. The “forest” it builds is a combination of decision trees, which are trained using bagging methods. The main advantages of random forest include discovering data anomalies, identifying important features, discovering data patterns and providing insightful graphics [73]. Due to its simplicity and diversity, random forest is one of the commonly used algorithms for solar energy prediction.

A new hybrid model was proposed to predict ultra-short-term PV power generation [74]. This model is a combination of random forest and ant-lion optimizer. A data analysis pipeline was first mooted to preprocess electroluminescence module images [75], which are latter recognized by SVM, random forest and CNN, in order to predict the scores for each of the three solar power forecasting models. Ramendra *et al.* proposed a monthly solar radiation prediction model based on ant colony algorithm (ACA), random forest and multivariate empirical mode decomposition (EMD) [49]. The prediction model was tested in three locations in Queensland, Australia. Pan *et al.* developed a new solar power forecasting method based on cluster analysis, random forest and ensemble technique [76]. Random forest was implemented in this method to divide the weather conditions into different systems.

2.1.6. Ensemble learning

Ensemble learning is basically an algorithm that combines several weakly supervised models into a strongly supervised model by adjusting sample weights to reduce output variance and deviation [77]. Ensemble learning pays more attention to improving its inherent learning ability from the perspective of sample diversity. Typical ensemble learning algorithms include bagging and boosting [78]. In the bagging algorithm, training samples are randomly selected from the original dataset, and a series of prediction results are obtained through multiple rounds of training. Finally, the rolling average method is applied to estimate the final prediction result. In the boosting method, the weights of the training samples are automatically adjusted at each iteration according to their errors, so that the boosting method focuses on the samples with larger errors, and ultimately improves the accuracy of the prediction model [79].

In solar power forecasting, ensemble learning is one of the most frequently-used algorithms due to its capability for reducing model misspecification and data noise uncertainties [80]. A solar irradiation prediction method combining signal decomposition, clustering approach and ensemble learning was proposed [81]. EMD was first used to decompose the original time series signal into multiple intrinsic mode functions and residual components. Subsequently, least square support vector regression (LSSVR) was applied to predict each component. In the end, multiple EMD/LSSVR prediction models were aggregated through ensemble learning to achieve the final prediction of solar radiation. A large number of case studies have shown that the proposed prediction method is very promising in solar irradiation prediction. Muhammad *et al.* proposed a robust prediction framework that combines random forest, extra tree and ensemble learning to forecast stochastic photovoltaic power output [82]. Numerical analysis showed that the proposed prediction framework had better generalization capability, prediction stability and less computational cost than traditional statistical methods. A new forecasting model based on continuous ranked probability score (CRPS) was proposed in [83]. This model first collected weather and environmental information from the NWP system. Then, an online non-parametric learning technique based on CRPS was proposed for PV power forecasting. An analog ensemble method was developed for day-ahead regional PV power forecasting with hourly resolution [84]. This method combines blending and clustering strategies to improve the prediction accuracy.

2.2. Deep learning

Deep learning is essentially a machine learning method that mimics the mechanism of the human brain to interpret data [85]. It uses multiple hidden layers to transform the initial low-level features into abstract high-level features to discover the distribution of input data [86]. Deep learning has three main advantages: (1) powerful unsupervised self-learning ability; (2) enhanced generalization ability; and (3) can be used to deal with the case of large training samples and complex initial features [87]. Many studies have shown that solar power prediction frameworks based on deep learning are relatively attractive. Typical deep learning algorithms include stacked automatic encoders (SAE), DBN, CNN, and generative adversarial networks (GAN). The structure and features of these deep learning algorithms are plotted graphically in Fig. 2.

2.2.1. Stacked auto-encoder

As a deep neural network, SAE consists of multiple autoencoders (AE) [88]. An AE includes an input layer, a hidden layer and a reconstruction layer. The nonlinear transformation from the input layer to the hidden layer is the encoder, and the transformation from the hidden layer to the reconstruction layer is the decoder. With the help of encoders and decoders, AE can reconstruct the input data within an acceptable error range [89]. Generally, SAE is considered to be an effective feature extractor.

Up to date, there have been several studies on SAE-based solar power prediction models. Gensler *et al.* developed a new solar power prediction model based on SAE [90]. LSTM was adopted as the basic structure with inter-layer connections. The availability of the proposed forecasting model was numerically verified on the data collected from

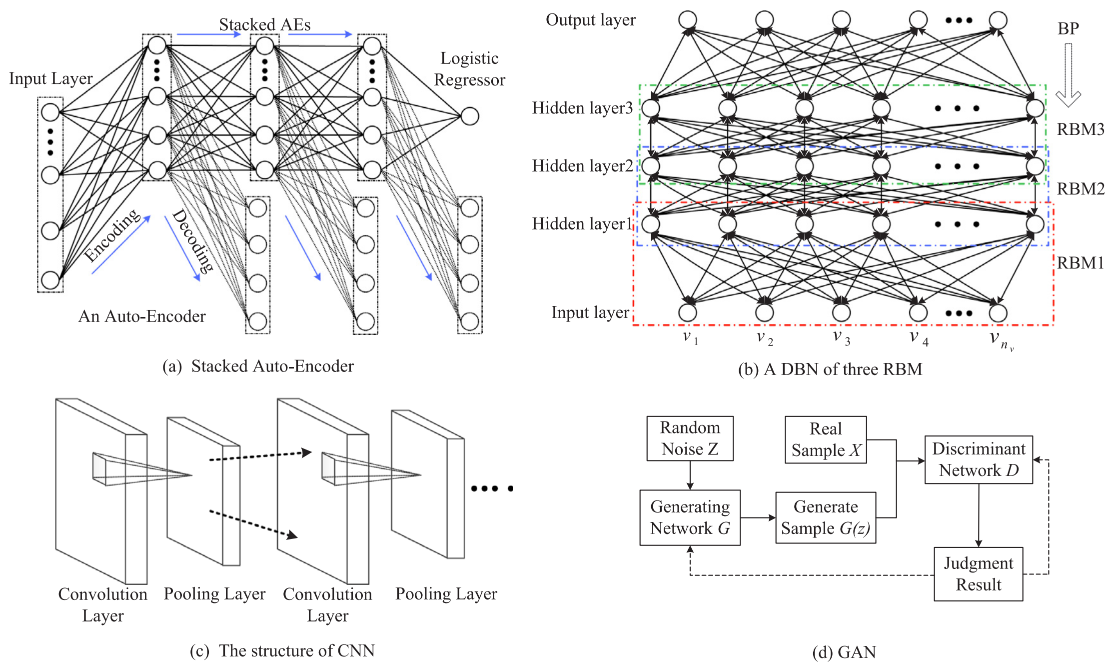

Fig. 2. The typical structures of deep learning algorithms.

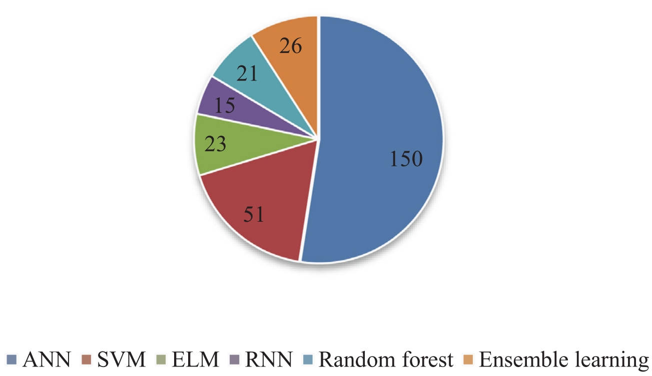

Fig. 3. Number of publications for solar power prediction based on ML.

21 solar power plants. Daniel *et al.* proposed a new prediction structure based on SAE to evaluate the long-term dependency between solar power data [91]. The obtained results showed that this structure can significantly improve the forecasting performance on chaotic time series data.

2.2.2. Deep belief network

As a typical generative model, DBN allows the entire neural network to generate training samples with maximum probability [92]. Basically, DBN is an unsupervised learning with restricted Boltzmann machine (RBM) being its cornerstone. RBM is a stochastic neural network that contains visible and hidden layers [93]. By minimizing the predefined energy function, it can effectively learn the probability distribution of the input data. In RBM, there is no connection between neurons in the same layer, but there is a full connection between neurons in the adjacent layers. These connections are bidirectional and symmetrical. The training process of DBN consists of a pre-learning process and a fine-tuning process [94]. Due to its attractive feature extraction capabilities, DBN has become one of the commonly-used algorithms for solar energy prediction.

Xu *et al.* proposed a hybrid DBN-AR model for time-series forecasting [95]. DBN was used to approximate the nonlinear properties of state-dependent autoregressive. Case studies showed that the proposed model was suitable for solar power prediction. Chang *et al.* developed a solar power prediction model based on gray theory and DBN [96]. DBN was integrated in the forecasting model to perform high-level abstraction of historical solar power data. The results showed that the forecasting model was superior to other benchmark models in prediction accuracy.

2.2.3. Convolutional neural network

CNN is a typical deep learning algorithm with convolution and pooling operators. CNN mimics the visual perception mechanism of living beings and can perform supervised learning and unsupervised learning. The parameter sharing mechanism in convolutional kernel and the sparseness of inter-layer connections enable CNN to achieve representation learning with less computational complexity [97]. In addition, CNN can perform shift-invariant classification on input information according to its hierarchical structure [98]. In recent years, research on solar power prediction based on CNN has been booming.

Dong *et al.* first proposed a new prediction framework based on CNN [99], and then adopted chaotic GA to optimize the network structure. The efficiency and prediction accuracy of the proposed framework have been fully studied. A new hybrid prediction model based on CNN and LSTM was proposed in [6], and the solar data measured at DKASC and Alice Springs PV plants was used to evaluate its prediction performance. The simulation results showed that CNN helped to improve the prediction accuracy of solar energy. Zang *et al.* developed a hybrid approach based on variational mode decomposition (VMD) and CNN to achieve short-term forecasting of solar power [100]. VMD decomposed historical solar power sequences into different frequency components. CNN was responsible for extracting the intrinsic correlation in solar data. Case studies showed that the proposed hybrid method had better prediction performance than other benchmark algorithms.

2.2.4. Generative adversarial network

GAN with a generative model and a discriminant model has attracted a lot of attention in recent years. The generative model maps noise variables to a multi-layer perceptron network so that the generated data is as close as possible to the distribution of training samples [101]. The discriminative model aims to determine whether the input data comes from the training sample or from the generative model. It is

Table 1
Taxonomy research of typical prediction models based on machine learning.

Article	Year	Methods	Input parameters	Output	Prediction results
[47]	2019	ANN + Random forest	Historical solar power	Solar irradiation	Normalized RMSE = 19.65%
[50]	2019	Autoregressive model + ANN	Historical data	Solar power	R^2 = 0.96 and correlation coefficient = 0.98
[51]	2019	ANN-based correction algorithm	Global solar irradiation	Solar irradiation	GPI based on seven statistical indicators and forecast score are 1.066 and 0.348
[55]	2017	SVM, ANN and empirical model	Latitude, longitude, bright sunshine hours, relative humidity, temperature	Solar irradiation	The ANN-ST model with both sunshine hour and temperature as input parameters has the best results
[56]	2019	GA + SVM	Historical weather data	Solar power	Better than conventional SVM
[61]	2019	ELM	Satellite-based data and geo-temporal variables	Solar irradiation	Relative RMSE = 3.715–7.191%
[64]	2018	ELM	Historical dataset	Solar power	53% better than climatology model
[67]	2019	LSTM	Wind speed, temperature, relative humidity, global horizontal radiation, diffuse horizontal radiation	Solar power	PMAE = 10.0%, RMSE = 2.0%, MAPE = 9.000%
[69]	2018	K-means clustering + Elman NN	Multivariate meteorological data and historical solar power	Solar power	RMSE = 4.3210 kW, MAPE = 2.84%, R2 = 0.9953
[79]	2018	Ensemble learning	Solar radiation dataset	Solar irradiation	MAPE = 2.83%, 88.24% better than the benchmarking algorithms
[84]	2019	Ensemble learning + clustering	Historical meteorological data	Solar power	The normalized RMSE has been reduced by 13.80%

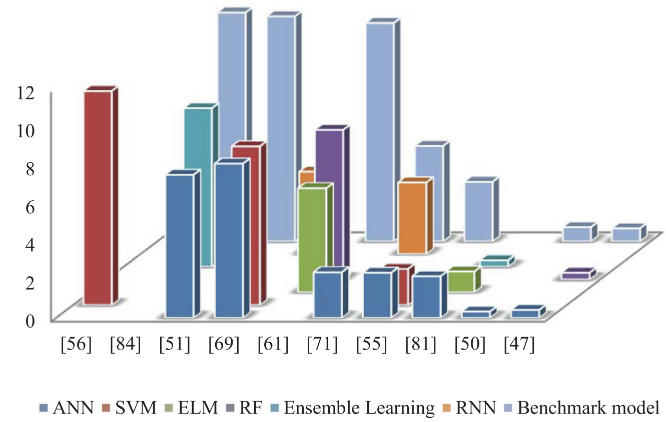

Fig. 4. RMSE of the prediction models based on ML.

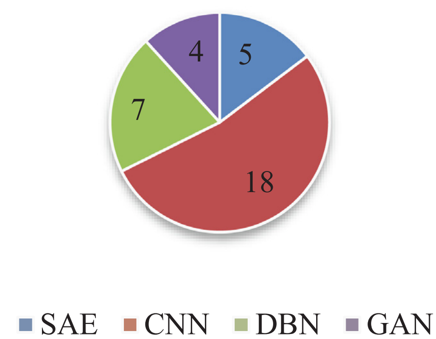

Fig. 5. Number of publications for solar power prediction based on deep learning.

worth noting that the generation model and discriminant model should be alternatively trained to guarantee GAN convergence [102]. The main advantage of GAN is that it can explain the underlying structure of the input dataset even without any labels [103]. This advantage can be used for automatic feature extraction when processing solar sequences.

Hu *et al.* proposed a modified GAN model to capture the temporal-spatial correlations between wind farm and photovoltaic power plant [104]. Wang *et al.* developed a weather classification model based on GAN and CNN to improve the prediction accuracy of solar power [105]. GAN was introduced to enlarge the training dataset for each weather type, while CNN was used to implement nonlinear regression. Chen *et al.* proposed a new data-driven scheme with two interconnected deep neural networks for scene generation based on GAN [106]. This scheme was effective to extract the spatial-temporal characteristics in integrated energy system with renewable energy.

2.3. Fuzzy logic

As an intelligent method, fuzzy logic can simulate the human brain to deal with the uncertainty in nature. It employs qualitative knowledge and experience with unclear boundaries, and adopts membership function and fuzzy set to achieve regular reasoning [107]. Fuzzy logic is good at making fuzzy judgment based on inaccurate non-numeric information, and can solve the problem with regular fuzzy information [108]. In solar power forecasting, fuzzy logic has been applied in two ways [17]:

(1) Fuzzy logic is used as a data preprocessing technique. In this way, the raw solar PV data is usually converted into a fuzzy time series [109]. Membership functions can be optimized by heuristic algorithms. Li *et al.* proposed a time series prediction method based on fuzzy logic, multi-objective imperialist competitive algorithm

Table 2
Comparison of typical deep learning algorithms.

Algorithms	Advantages	Disadvantages	Applicable scenarios
CNN	Capable for processing image data;Strong capability for feature extraction.	Low computation efficiency;The features should be better predetermined.	The solar energy data includes image or can be converted into images.
DBN	Unsupervised feature extraction capability;High computation efficiency.	Disable to process multi-dimensional solar energy data.	The features of solar energy data are not identifiable.
SAE	Unsupervised feature extraction capability;Easy to be implemented.	Optimization of the network is difficult.	Solar energy data needs dimensionality reduction.
GAN	Capable for generating new data with the same distribution as the input data;	Unable to effectively describe the features of the input data;Low computation efficiency;	Solar energy data has a lot of missing data.

(MOICA) and ELM [110]. Fuzzy logic was integrated to establish the nonlinear relationship between time series input and output. MOICA was used to optimize the parameters in the membership function of fuzzy logic. Jiang *et al.* proposed a hybrid method based on fuzzy time series and multi-objective differential evolution (DE) algorithm to achieve accurate prediction of time series signal [111]. Sivaneasan *et al.* mooted a solar power prediction method combining ANN and fuzzy logic [112]. In this method, fuzzy logic was adopted to estimate the correlation between cloud cover, temperature, wind speed, wind direction and solar irradiance.

(2) Fuzzy logic is used for weather and environment classification. Many machine learning methods can then be integrated for forecasting of solar PV power under each fuzzy classification. He *et al.* proposed a new probabilistic density estimation model for solar power prediction [113]. Fuzzy logic was implemented to extract the fuzzy information granularity in time series signal. A solar irradiation prediction model based on ANN and fuzzy algorithm was proposed to improve the prediction accuracy of solar irradiation under different weather conditions [114]. In this model, fuzzy logic was applied for classification of sky and temperature. Baser *et al.* [115] developed a fuzzy regression method with SVM to estimate annual and daily average global solar radiation. An empirical study was conducted on a dataset collected in Turkey. A hybrid method was proposed in [116] for medium-term prediction of dynamic irradiance based on neural-fuzzy estimator. The input includes meteorological parameters and spatial-temporal distribution features. Thair *et al.* adopted fuzzy logic to evaluate the main factors of solar radiation attenuation, and proposed two solar radiation assessment models [117]. Erdem *et al.* predicted day-ahead meteorological condition based on ANN and adaptive fuzzy network [118]. The prediction results of 50 cities in Turkey showed that the proposed prediction method was of great significance for the design of heating, ventilation and air-conditioning system.

2.4. Taxonomy research of the AI prediction methods

In this subsection, a series of taxonomy research of AI methods for solar energy prediction is carried out. The taxonomy research is the link between our review work and solar power prediction filed. We counted the number of publications for solar power prediction based on ML algorithms. The results are presented in Fig. 3. As shown, traditional ANN and SVM have been frequently-used for solar power prediction. This can be explained by the fact that ANN and SVM have a long history and there are many variants. In addition, a total of 23 related-reports on ELM-based solar power forecasting have been found. There are 15, 21 and 26 publications on RNN, random forest and ensemble learning-based solar power prediction models, respectively. Although ELM, RNN, random forest and ensemble learning attract less attention than ANN and SVM, they each have their own specific prediction scenario. Specifically, ELM only needs to train weights in the output layer, so it is suitable for situations where computing resources are limited. Due to the inherent recursive chain, RNN is suitable for processing solar power/irradiance time series data. Random forest is appliable for forecasting when the training set can be divided into several typical subsets. Ensemble learning can be applied to effectively eliminate the model misspecification and data noise uncertainty in solar power forecasting, so it is suitable for situations that require higher prediction accuracy.

Several representative publications were selected for taxonomic research. The input parameters, output, method, prediction performance and characteristics of the selected prediction model are shown in Table 1. The performance comparison of existing ML-based solar energy prediction models is presented in Fig. 4. RMSE is used as an error. It can be seen that all the prediction methods proposed in these studies claim that their RMSE is superior to their respective benchmark methods. In addition, it is clear that ML methods have different RMSE indices. This is because: (1) Solar power plants are located in different sites with different climates; (2) These methods have different prediction scenarios.

Similarly, we also counted the total number of publications in solar power prediction based on deep learning. The results obtained are presented in Fig. 5. As shown, DBN and CNN are very popular in solar power prediction, with 7 and 18 related reports respectively. Although SAE is a typical deep learning algorithm, only 7 articles have been found. In addition, there are few reports of GAN-based solar power forecasting. This is mainly because the history of GAN is very short, which is a deep learning structure proposed in 2016. Table 2 shows the advantages, disadvantages and application scenarios of these four typical deep learning algorithms. Fig. 5 also shows that deep learning is gaining more and more attention in solar power prediction, which is a research hotspot in recent years.

A taxonomy research has been conducted on several typical studies based on deep learning. The data source, method, benchmark models and superiority of these proposed solar power prediction models are given in Table 3. As shown, deep learning methods always have promising feature extraction capabilities, making these prediction models highly accurate, robust and stable in solar energy forecasting. In addition, Fig. 6 graphically shows the statistical performance of the existing solar power prediction models based on deep learning. Obviously, different deep learning methods have different RMSEs. It is worth noting that the prediction performance of various deep learning algorithms cannot be simply compared because they have their own prediction scenarios. All existing studies claim that the proposed deep learning-based prediction model has better prediction performance than the benchmark algorithms.

Fuzzy logic is also one of the commonly-used AI algorithms in solar power generation prediction, and there have been more than 40 related reports. Two reasons account for this: (1) fuzzy logic has a wide range of application scenarios, such as regression, preprocessing and classification; (2) fuzzy logic can be combined with various neural networks and optimization algorithms. The taxonomic study on fuzzy logic can be found in Table 4. However, fuzzy logic can only fully describe the linear regression functions due to its fuzzy membership. Apparently, fuzzy logic is not recommended when nonlinear regression is involved in soar power prediction. At this time, fuzzy logic can be used to classify the input data, so that the neural network adopted can more easily extract

Table 3
Taxonomy research of deep learning based forecasting models.

Article	Data sources	Methods	Benchmarking model	Prediction performance	Superiority
[90]	Germany	DBN, AE, and LSTM	Physical model, multilayer perceptions	RMSE = 0.0714	DBN has feature extraction capability, which can improve solar power forecast accuracy
[96]	Taiwan	DBN + gray theory	ARIMA, BPNN, RBF, SVM	RMSPE = 6.029%	DBN is capable for learning the feature representations of the data
[98]	America	CNN + GA/PSO	ANN, RBF and GBRT	20.34% MAE better than GBRT	GA/PSO can be applied to optimize the parameters of the prediction framework based on deep learning
[6]	DKASC, Australia	CNN, LSTM	DBN, SAE	13.83%-54.92% RMSE better than the benchmarking algorithms	High prediction stability and robustness
[105]	NOAA, America	GAN + CNN	SVM, multilayer perceptron	Better classification performance than traditional machine learning models	GAN can generate new samples that have the same intrinsic features of the original data
[106]	NREL, America	GAN	Gaussican copula method	It captures solar energy production patterns in both temporal and spatial dimensions	Do not require any particular statistical distribution assumptions

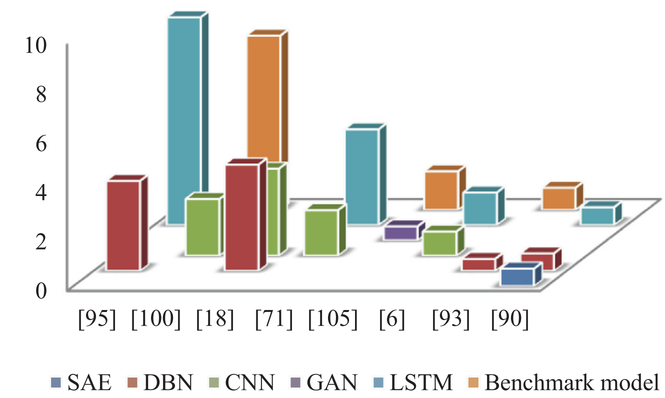

Fig. 6. RMSE of the prediction models based on deep learning.

the hidden features in each fuzzy classification, thereby improving the accuracy of solar PV power prediction.

3. Taxonomy of AI optimizer in solar power prediction

ML and deep learning can have different structures, in which the number of layers, the number of neurons in each layer and the parameter training method can be different. Different structures correspond to different solar power forecasting accuracies. Thus, choosing the appropriate AI optimizer to well-tune the prediction structure and parameters is one of the main research directions of solar energy prediction. To date, the AI optimizer consists of PSO, GA, DE, etc. In this section, we will review these AI optimizers in solar energy prediction model.

3.1. Particle swarm optimization

PSO is a heuristic optimization method for AI evolution computing. It originated from the study of bird predation behavior, proposed by Eberhart and Kennedy in 1995 [119]. PSO aims to find the optimal solution through cooperation and information sharing among individuals in the group. In PSO, a bird is designed as a particle without mass. Particles have only two properties: velocity and position, where velocity represents the velocity of the particle and position represents the direction of movement [120]. Each particle searches for the best solution in the search space. The solution found by any particle in each iteration is called an individual extremum, which will then be shared with other particles. The optimal individual extremum in the whole group is taken as the global optimal solution of the particle group. All particles in this group adjust their speed and position according to their respective extremums and the current global optimal solution shared by the entire particle swarm. The main advantage of PSO is that it is easy to implement and does not require adjustment of many parameters [121]. Consequently, PSO has been widely-used in solar power forecasting to optimize the structure and parameters of neural network.

Zhen *et al.* proposed a hybrid method to estimate the cloud image motion speed based on pattern classification and PSO, and thus to achieve solar power prediction [122]. Real solar power data collected by Yunnan Electric Power Research Institute was used to demonstrate the feasibility of the proposed method. Wen *et al.* developed an ensemble method based on ship's random motion model for optimal interval prediction of solar power on board [123]. PSO was adopted to optimize the connection weights of the proposed ensemble method and thus to reduce prediction error. Zheng *et al.* proposed a time series solar power forecasting approach combining LSTM and PSO. PSO was used to optimize the parameters of LSTM, thereby improving the prediction accuracy [124]. Sensitivity analysis was performed to determine the final prediction structure. Moulay *et al.* combined PSO and fuzzy neural

Table 4
Taxonomy research of the fuzzy logic based forecasting algorithms.

Article	Usefulness	Methods	Performance
[109]	Pre-processing	Multi-objective optimization + ELM + fuzzy	Prediction results are in good accordance with the observation
[112]	Pre-processing	Fuzzy + ANN	16.7% better than ANN
[113]	Fuzzy classification	Fuzzy, SVM + quantile regression	1.87% PINAW better than quantile regression
[115]	Fuzzy classification	Fuzzy regression and SVM	RMSE = 1.571, MAE = 0.531
[116]	Fuzzy classification	Neuro-fuzzy estimator, ARMA	NRMSE = -9.11%, NMBE = 3.96%.

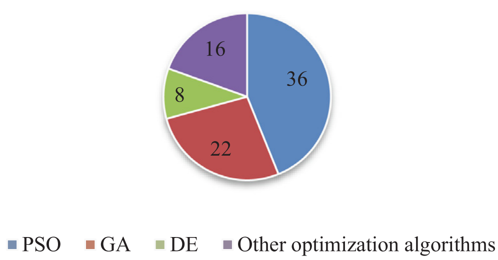

Fig. 7. Number of publications for solar power prediction based on AI optimizers.

network to extract the features in solar power generation, and proposed a photovoltaic power prediction model with compactness and interpretability [125]. Here, PSO was used to optimize the structure of the neural fuzzy model to achieve maximum power point control. A hybrid model combining wavelet transform, SVM and PSO was proposed in [126] for short-term forecasting of photovoltaic power generation in microgrid. PSO was applied to optimize the parameters in SVM. A three-phase hybrid SVR model was proposed in [127]. This model adopted PSO to screen the variables of the moderate resolution imaging spectro-radiometer. RMSE, MAPE and Wilmot index were applied to evaluate the prediction accuracy.

3.2. Genetic algorithm

GA simulates Darwin's theory of biological evolution and genetics. It was first proposed by Professor Holland at the University of Michigan in the 1960s and 1970s [128]. GA continuously updates its chromosomes through operations such as selection, crossover, and mutation to obtain the optimal solution to the optimization problem [129]. The selection operation is used to select individuals with better fitness from the group and to eliminate individuals with poor fitness. Cross refers to the operation of replacing and recombining part of the genes of two parent individuals to generate a new child individual. Through crossover, the search ability of GA is greatly improved. The mutation operation is to randomly change some gene values in an individual. According to the principle of survival of the fittest, GA evolves from generation to generation. The main features of GA are: (1) There is no need to be restricted in terms of derivatives and function continuity; (2) It has hidden parallelism and better global optimization ability [130]. In addition, GA basically belongs to a kind of probability optimization method that can adaptively adjust the search direction.

William *et al.* proposed a GA-based SVM model to achieve short-term prediction for a residential-scale photovoltaic system [56]. SVM was used to classify historical weather data, and these classifiers were optimized by GA. RMSE and MAPE were adopted to evaluate the prediction accuracy. A cloud image prediction method based on GA was developed to improve the prediction accuracy of solar power [131]. In this method, GA optimized the cloud deformation process according to historical digital cloud information. A hybrid model with adaptive learning ability was proposed in [132] to predict solar intensity. GA was used to optimize the weights of the back-propagation network to learn the nonlinear relationships in the samples. A hybrid solar power prediction method combining GA, PSO and adaptive neural fuzzy inference system was mooted by Semero *et al.* [133]. GA determines the input parameters of the Gaussian regression model. The feasibility of the hybrid model was verified on the PV power generation system of Beijing Jinfeng Microgrid. The study in [134] proposed a new adaptive selection strategy to choose the most suitable prediction subset, thereby improving the short-term forecasting accuracy of distributed photovoltaic power generation. GA was implemented to select the features hidden in photovoltaic power generation, and SVM was used to evaluate the fitness of the prediction model. Tsai *et al.* proposed a hybrid Taguchi GA to adjust the network structure and parameters of FNN [135]. A Taguchi method was inserted between the crossover and mutation operations of GA. Simulation results showed that the hybrid method had strong robustness and fast convergence speed. Mohammad *et al.* proposed a method for solar power prediction based on high-order Markov chain [136]. It integrated a GA optimized Gaussian mixture method (GMM) to predict the probability distribution of PV power generation.

3.3. Differential evolution

DE is a population-based global heuristic optimization algorithm based on modern intelligence theory [137]. It adopts group intelligence to guide individuals' best search directions in terms of cooperation and competition among individuals in the group. The main steps of DE include [138]: (1) Start with a randomly-generated population; (2) Generate a new individual by adding the vector difference between any two individuals in the population and the third individual; (3) The old individual will be replaced by the new individual in the next generation if the fitness of the new individual is better than the fitness of the old one, otherwise the old individual will still be saved. The individuals in the population gradually approach the optimal solution as the evolution of DE continues. So far, due to its simple structure, fast convergence speed and strong robustness, DE has also been widely used in solar PV power prediction to improve prediction accuracy [139].

Liu *et al.* first adopted principal component analysis and K-mean clustering to extract the hourly features of photovoltaic power generation, thereby reducing the data noise [140]. Then, DE algorithm was used to optimize the parameters of the prediction structure based on random forest, so as to reduce the prediction error. Jiang *et al.* collected monthly average global solar radiation from four sites in United States, and proposed a prediction model based on the radial basis function neural network (RBFNN) and DE [141]. DE was integrated to determine the optimal network structure of RBFNN. Zhang *et al.* proposed a weighted temporal prediction model combining nu-SVR and epsilon-SVR, and adopted DE to determine the weight of each sub-prediction model [142]. The simulation results showed that the weight of nu-SVR was higher than that of epsilon-SVR in solar power dataset with a half-hour interval. Alrashidi *et al.* proposed a prediction framework for solar power based on SVM, cuckoo search and DE [143]. DE was also adopted to optimize SVM parameters. The prediction framework was validated on a 6.4 kW rooftop solar photovoltaic power station at Virginia Tech. Shantanu *et al.* employed DE to solve the unit commitment problem with solar power generation, and proposed a solution based on fuzzy logic [144].

Table 5
Taxonomy research of the AI optimizers in solar power prediction.

Article	Optimizer	Forecasting model	Features	Performances
[123]	PSO	BPNN, RBFNN, ELM, and Elman network	Ensemble strategy is employed to reduce the forecasting error; Various environmental variables along with ship moving and rolling impacts are taken into account.	The difference between prediction intervals and experimental observations is small with the absolute error of 14.96%
[124]	PSO	LSTM	Different LSTM structures are illustrated to determine the final prediction model	RMSE = 15.49
[56]	GA	SVM	A local weather station was installed along with the PV system at Deakin University	98.7648% MAPE better than traditional SVM
[132]	Binary GA	SVM	Binary GA enhances the quality and efficiency of the predictor	58.4% better than original predictor
[140]	DE, Grey Wolf Optimization	Principal component analysis, K-means, random forest	Optimizer quickly selects the random forest parameters	0.18 higher MAE than the benchmarking algorithm
[147]	FA	Random forests	FA is utilized to find the best number of trees and leaves per tree in the forest	RMSE = 18.98%, MAPE = 6.38%, mean bias error = 2.86%
[151]	ACO	Empirical mode decomposition, random forest	The proposed model can be considered as a pertinent decision-support framework	Relative percentage error = 4.45%, RMSE = 3.79%
[152]	Multiobjective bat algorithm	ANN	Statistical method and data mining approach are used to determine the input variables	MAPE = 4.7530

3.4. Other optimization algorithms

At present, other AI optimization algorithms, such as firefly algorithm (FA), ACA and multi-objective optimization methods, are also adopted for solar power prediction to optimize the prediction structure and network parameters [145]. FA was inspired by the flashing behavior of fireflies and was proposed by Yang Xinshe of Cambridge University [146]. In FA, each firefly moves randomly to other fireflies, and the probability of random movement is proportional to the brightness of the fireflies, that is, fitness. Ibrahim *et al.* proposed a solar radiation prediction method combining random forest and FA [147]. FA was employed to find the optimal number of trees in the forest and leaves for each tree. The simulation results showed that the RMSE, MAPE and average deviation error of the proposed model are 18.98%, 6.38% and 2.86%, respectively, which are better than the performance of ANN-based prediction structure. A hybrid SVM-FFA method was developed to improve the accuracy of solar radiation prediction [148]. Three meteorological parameters and time series data were taken as the inputs of the prediction model. Numerical results showed that the developed prediction model had better prediction accuracy than ANN and genetic programming.

ACA belongs to a kind of probabilistic optimization algorithm, usually used to find the best path. It was proposed by Marco Dorigo in 1992 [149]. The basic idea of ACA is to represent the feasible solution of the problem to be optimized by the walking path of ants. All paths in the ant colony constitute the entire solution space of the problem. Ants on shorter paths release more pheromones. As time passes, pheromones gradually concentrate on shorter paths, and the number of ants choosing shorter paths will increase [150]. Consequently, ants will focus on the best path of all. At this moment, the corresponding solution is the optimal solution to the problem. Ramendra *et al.* proposed a hybrid forecasting model based on EMD, ACA, and random forest to predict monthly solar radiation [151]. ACA was used to determine the best features of the intrinsic mode function. The prediction model was tested at three sites in Queensland, Australia. Khosravi *et al.* proposed a new horizontal solar radiation prediction model [152]. This model is a hybrid of adaptive neural fuzzy inference system, PSO and ACA. Its input variables include average temperature, maximum/minimum temperature of the day, relative humidity, air pressure, wind speed, latitude and longitude.

In addition, many studies formulate solar radiation and PV power prediction into multi-objective optimization problems that can be properly addressed by multi-objective optimization algorithms. Heng *et al.* mooted a multi-objective prediction model to simultaneously improve the prediction accuracy and stability [153]. A new multi-objective bat algorithm was developed to optimize the weight coefficients of each sub-prediction model. Statistical and data-mining methods were adopted to determine the input variables of the prediction model. Hassan *et al.* proposed a hybrid prediction structure based on Kalman filter and type 2 fuzzy logic system, so as to realize real-time prediction of solar power generation [154]. Multi-objective PSO was used to optimize the parameters of the prediction structure to minimize the RMSE and the maximum absolute error at the same time. A new interval prediction model based on ANN and lower and upper bound estimation (LUBE) was constructed [155]. This prediction model took the prediction reliability and interval sharpness as two optimization goals to create an optimal prediction interval. Multi-objective PSO was applied to solve the optimization problem. Solar power data from real plants in America was adopted to verify the validity of the proposed interval prediction model.

3.5. Taxonomy research of the AI network optimizer

Here, a taxonomic research of AI optimizers in solar power prediction model is conducted. We counted the number of research articles on several commonly-used optimization algorithms, as shown in Fig. 7.

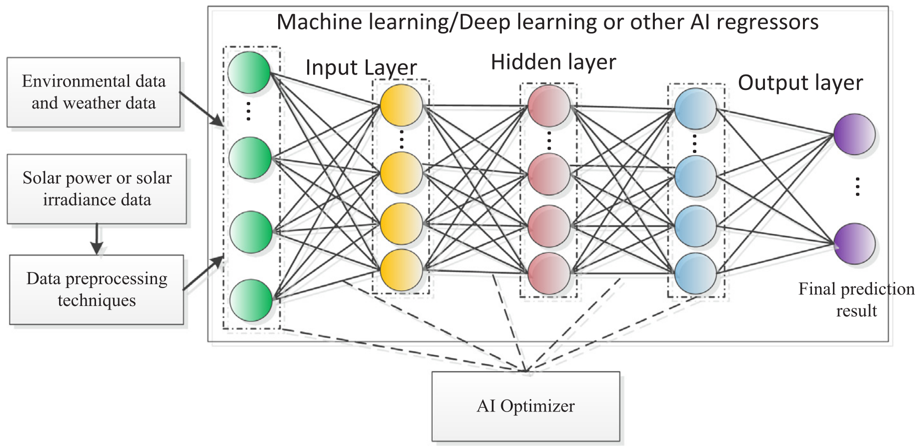

Fig. 8. First type of solar power/irradiance forecasting structure.

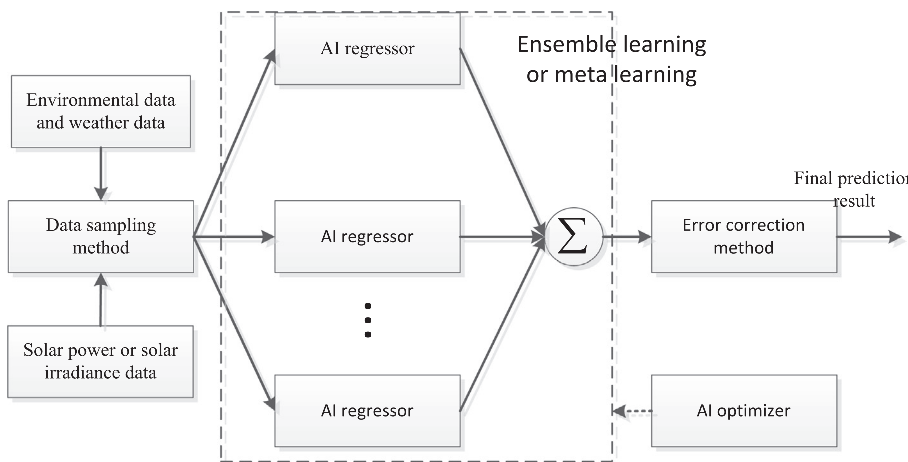

Fig. 9. Second type of solar power/irradiance forecasting structure.

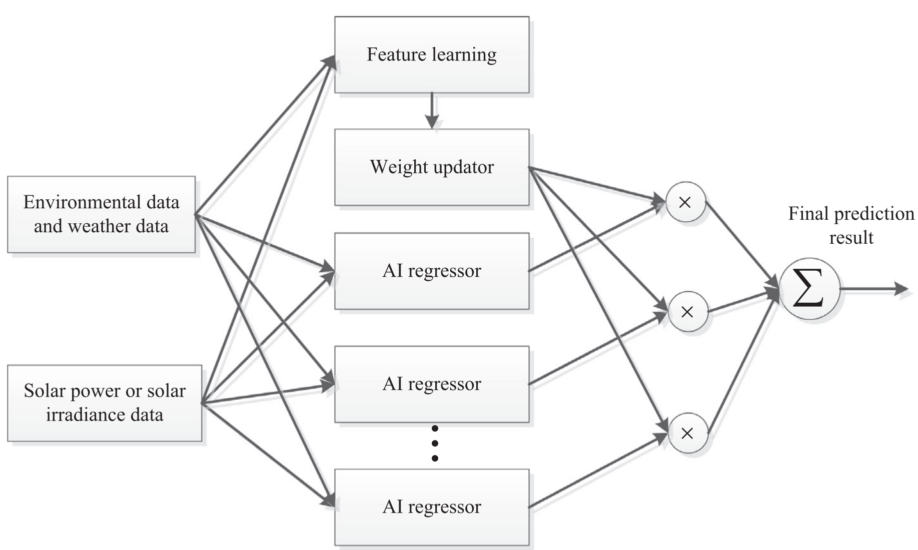

Fig. 10. Third type of solar power/irradiance forecasting structure.

It can be seen that the most popular optimization algorithm in solar power prediction is PSO, with a total of 36 related-reports. Followed by GA and DE, there are 22 and 8-related articles respectively. In addition, FA, ACA, biogeography optimization [156], glowworm swarm optimization [157], and cuckoo search algorithm [158] have also been applied in solar power prediction structures, thereby improving the prediction accuracy. All the above algorithms are actually heuristic optimizers. They do not require assumptions such as the differentiability of the objective function, continuous independent variables, and the feasible region being a convex structure. These optimization algorithms are relatively simple and easy to implement. Consequently, AI optimizers in solar power prediction often adopt the above heuristic

Table 6
The features, advantages and disadvantages of the three typical prediction structures.

	Features	Advantages	Disadvantages
First prediction structure	Simple structure;Only having a regressor;	High computing efficiency; High compatibility;Having wide application scenarios.	Limited prediction accuracy; A lack of theoretical analysis of prediction error.
Second prediction structure	Having an ensemble learning or meta learning structure;Data sampling method is generally used.	Providing quantitative analysis of model misspecification and data noise uncertainties; High prediction accuracy; Providing statistical analysis of the prediction errors.	Low computing efficiency;Limited application scenario.
Third prediction structure	Having a feature selector and a weight updater;	Taking advantage of human experience and prior knowledge; Flexibility; Adaptivity; High prediction accuracy.	Low computing efficiency;Narrow application scenario.

methods. Table 5 lists the taxonomy research of AI optimizers in solar power prediction. It can be seen that the AI optimizer is usually used to adjust the parameters of the neural network instead of the prediction structure. This can be explained from two aspects: (1) These two types of optimization have the same purpose, i.e., minimizing the forecasting error, but optimizing the prediction structure is more complicated than parameter adjustment; (2) The parameter adjustment problem is continuous, and it is easier to find the optimal solution. Moreover, it is clear that the application area of AI optimizers is very wide. In other words, AI optimizers can basically be combined with all AI regressors for solar power prediction.

Multi-objective optimization also plays an important role in solar power prediction. In order to improve prediction accuracy and ensure prediction stability, solar power forecasting can be modeled as a multi-objective optimization problem. There are two solutions: (1) Directly adopt multi-objective optimization methods to simultaneously optimize multiple objectives to form a Pareto frontier, and then use decision-making methods to select a solution in the Pareto set as the optimal solution [146]. The advantage of this method is that it allows researcher to fully understand the feasible space of the optimal solution, but the disadvantage is that it is generally time-consuming. (2) Convert multi-objective optimization problem into a single-objective optimization problem, which can be solved by a single-objective optimization method. Table 5 lists the typical solar energy prediction research based on multi-objective optimization.

4. Taxonomy of forecasting structure

This Section mainly reviews the three main deterministic solar power prediction structures based on AI algorithms, and also analyzes their respective advantages and disadvantages.

4.1. Deterministic solar power forecasting structure

In general, there are three types of deterministic forecasting structures commonly used in solar power prediction and solar radiation prediction [159], as shown in Figs. 8–10, respectively. In the first typical structure, preprocessing techniques are usually used to decompose the historical time series data of solar radiation and PV power into multiple sub-signals. Each sub-signal exhibits a smooth outline, which is easier to be predicted [160]. Preprocessing techniques include wavelet decomposition (WT), EMD, Fourier transform and seasonal adjustment methods [161]. These sub-signals, together with environmental data and weather data, are taken as the inputs of an AI regressor. Then deterministic predictions of solar power and solar radiation can be achieved. In addition, an AI optimizer can also be integrated into this prediction structure to adjust AI regression parameters.

The research based on the first type of prediction structure is very extensive. Dong *et al.* developed a new solar irradiation prediction model combining self-organizing map (SOM), SVM, and PSO [162]. The SOM divided the training samples into multiple separate areas based on the input features. Then, the samples of each area were fitted by SVM whose parameters are optimized by PSO. Hourly solar irradiance data from Colorado and Singapore was used to validate the prediction model. Feng *et al.* proposed a short-term solar irradiation prediction method based on unsupervised clustering [163]. This method contains three parts: unsupervised clustering of solar irradiation, SVM and unsupervised clustering-based prediction. The prediction results showed that the prediction performance of this method was improved by about 20% compared with multiple traditional models. Capizzi *et al.* conducted a research on solar radiation prediction based on meteorological data, and proposed a hybrid method combining WT and RNN [164]. WT decomposed the original time series data into multiple sub-signals with different frequencies, and RNN was used to extract the correlation features between solar irradiation and wind speed, humidity and temperature. A hybrid approach with combination of ENN and WT was mooted in [165] for hourly solar irradiation forecasting. ENN was used to extract the time-series features in each wavelet sub-signal. Simulation results showed that the hybrid method had better prediction performance than other alternative methods.

The second typical prediction structure of PV power generation is based on a general model of ensemble learning and *meta*-learning [166], as shown in Fig. 9. This type of prediction structure usually adopts data sampling methods to achieve uniform sampling of the input data. Data sampling methods include bootstrap, reservoir sampling and Monte Carlo *et al.* [167]. An AI regressor is then constructed for each batch of the sampled data to achieve its point prediction. Subsequently, the prediction results of all AI regressors are integrated through ensemble learning or *meta*-learning to reduce the model misspecification uncertainty and data noise uncertainty. Error correction methods and AI optimizers can also be integrated into the prediction structure. The error correction method is used to theoretically analyze the correlation between the prediction error and the input data [168], thereby improving the prediction accuracy.

Zhang *et al.* proposed a new analog ensemble method to predict regional PV power [84]. A clustering method, earth declination angle change limit algorithm and historical day change limit algorithm were adopted to forecast PV power at a single site. Experimental results showed that compared with the three benchmark models, the normalized RMSE of the prediction model could be reduced by 13.80–61.21%. The authors in [169] conducted a study on ensemble method using seasonal time series data as input parameters, and proposed a new prediction structure with 142 sub-models based on NWP. These 142 sub-models include SARIMA, exponential smoothing, multilayer perception, seasonal-trend decomposition, TBATS, and theta method. Case studies showed that the proposed ensemble structure can improve the overall accuracy of solar radiation prediction. Wang *et al.* proposed a high-accurate prediction model based on WT, echo state network (ESN) and ensemble learning [170]. Ensemble technique was used to reduce the forecasting deviation of individual AI regressors based on ESN. A research on solar irradiation prediction based on multi-stage intelligent approach was carried out in [171]. Least absolute shrinkage and selection operator and FA were combined to form an effective prediction method. Global irradiation data from four sites in India was used to prove the effectiveness of the proposed prediction method.

In the third type of prediction structure, the AI regressor is used to achieve a point forecasting of solar power. Feature learning is generally

Table 7
Taxonomy research of the AI based prediction structures.

Article	Structure Type	Applied methods	Input	Performances	Characteristics
[162]	First typical prediction structure	SOM, SVR, PSO	Solar power time series data	Better than ARIMA	SOM is used to partition the whole input space into several disjointed regions.
[163]	First typical prediction structure	Unsupervised clustering	Daily solar irradiance time series data	Approximately 20% better than the prediction model without unsupervised clustering	The daily time series data is clustered by an optimization method.
[84]	Second typical prediction structure	Clustering, blending strategies	Meteorological and astronomical data	Normalized RMSE has been reduced by 13.80% to 61.21%	Different numerical weather prediction models are used to validate the proposed method.
[171]	Second typical prediction structure	Ensemble learning, multistage intelligent approach	Solar irradiation	MAPE indices are reduced by 7.148%, 13.101%, 7.756% and 1.782% in four PV sites.	A feature selection method is performed in the input space. A weight determination method is provided by glowworm swarm optimization.
[173]	Third typical prediction structure	Copula-based Bayesian approach	Solar irradiation, temperature	Pinball loss is reduced by 4.19%	Parametric and empirical copulas of solar power are developed to update the prior distribution to the posterior forecast distribution.
[174]	Third typical prediction structure	Hourly-similarity based method	1-year data with six solar features	Normalized MAE = 10.94%, RMSE = 7.74%	Diurnal patterns, statistical distinctions between different hours, and hourly similarities in solar data are used to improve the forecasting accuracy.

applied to extract the hidden features in input data [172]. These features are then used to train the weight updater. Subsequently, combining the AI regressor and weight updater is the final prediction result. Panamtash *et al.* proposed a Bayesian method for probabilistic solar power prediction [173]. This method first adopts multiple point predictors to obtain a prior probability distribution. The distribution is then corrected by extracting the joint distribution characteristics between solar energy and ambient temperature. Feng *et al.* conducted a research on solar irradiation prediction based on hourly similarity, and then proposed a multi-model machine learning blending method [174]. Data collected by National Renewable Energy Laboratory in America was used to demonstrate the superiority of the proposed prediction method. The study in [175] theoretically analyzed the key weather factors in the solar power generation, and proposed a prediction method combining ML and deviation analysis. Numerical results demonstrated that key weather features can greatly improve the prediction performance.

4.2. Taxonomy research of solar power forecasting structures

Each typical structure for solar power prediction has its own advantages and disadvantages. The advantage of the first typical structure in Fig. 8 is its simple structure and high computational efficiency because it has only one regressor. In addition, the first prediction structure can be easily applied to a wide range of application scenarios such as point prediction, multi-step prediction, and day-ahead prediction. Its shortcomings mainly include limited prediction accuracy and lack of theoretical analysis of prediction errors. The advantages of the second typical prediction structure include the ability to quantify model misspecification and data noise uncertainty, and higher prediction accuracy. The second prediction structure can also provide statistical analysis of prediction errors. However, due to the use of multiple regressors, data sampling methods and AI optimizers, the computational efficiency of the second prediction structure is relatively low. Thus, this forecasting structure is not suitable for multi-step forecasting and day-ahead forecasting, because its structure is much more complex. The third typical prediction structure has a feature-learning part, which can take advantage of human experience and prior knowledge to extract features in the training set. The weight updater can automatically adjust the weight of each AI regressor, so it is more flexible than the second prediction structure. The disadvantages of the third typical prediction structure also include low computational efficiency and narrow application scenarios. Table 6 shows the characteristics, advantages and disadvantages of three typical prediction structures.

The solar power prediction structure in the existing literature basically belongs to one of the three typical structures in Figs. 8–10. We made a statistic on the number of the research reports of the three typical prediction structures. The results show that the first, second and third typical forecast structures account for 47%, 34% and 12% of the total number of reports, respectively. The remaining 7% are reports based on other prediction structures. It can be seen that the current research of the first and the second prediction structures is sufficient. The third prediction structure has not yet received enough attention. A taxonomy research is performed on multiple typical studies. The methods adopted in these prediction structures, input parameters, prediction performance, and their respective characteristics are shown in Table 7.

5. Challenges and future research directions

Although there have been many research reports on solar power forecasting, there are still some key issues that have not yet been effectively resolved.

1) Solar power prediction is very complex. It is not only related to the real-time operating conditions of PV cells, but also related to

weather and environment factors. Therefore, how to combine the physical model of the battery, weather and environmental factors into an effective prediction model is one of the key scientific problems to be solved in the future.

2) At present, almost all reports generally formulate the problem of solar energy prediction as a black box model. The mathematical relationship between the input factors and PV power output is not fully revealed. In addition, it is unclear which input parameter is the main factor affecting the prediction accuracy. In summary, how to explain the solar power prediction model is one of the main research directions in the future.
3) There are many sub-problems in PV power prediction, such as point prediction, multi-step prediction, day-ahead prediction and probability prediction. In the existing literature, these predictor sub-problems are not economically and independently solved. In short, how to conduct collaborative training on multiple prediction tasks is a major problem that the academic community needs to solve urgently.
4) To date, the probabilistic prediction of solar energy has not attracted enough attention. In electrical power and energy systems, probabilistic predictions can provide a range of solar energy changes, thereby quantifying the uncertainty involved. This helps the power system to prepare for future unknown operating conditions. Thus, probabilistic prediction of solar power is a hot research topic in the future.
5) The movement and thickness of clouds have a great influence on the prediction accuracy of solar power generation. This is because the movement and thickness of clouds have a large randomness. In the future, research on this topic will need to be strengthened.

6. Conclusions

An extensive and systematic review of artificial intelligence-based solar power prediction is for the first time conducted from the viewpoint of Taxonomy. A lot of statistical analysis on current research interests and research hotspots for solar power prediction is carried out. Taxonomy provides an order classification of artificial intelligence method, optimizer and prediction structure according to their natural characteristics and relationships. Several challenges and future research directions in solar power prediction based on artificial intelligence are also given. Our theoretical analysis show that each AI method, optimizer and prediction structure has its own advantages and disadvantages. These analyses and numerical presentations can help solar energy practitioners such as scientist and engineer to determine which artificial intelligence algorithms and prediction structures can improve their specific prediction tools, thereby helping to investigate the potential of artificial intelligence in solar power forecasting.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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