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REVIEW

A Survey of the Researches on Grid-Connected Solar Power Generation Systems and Power Forecasting Methods Based on Ground-Based Cloud Atlas

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ABSTRACT

Photovoltaic power generating is one of the primary methods of utilizing solar energy resources, with large-scale photovoltaic grid-connected power generation being the most efficient way to fully utilize solar energy. In order to provide reference strategies for pertinent researchers as well as potential implementation, this paper tries to provide a survey investigation and technical analysis of machine learning-related approaches, statistical approaches and optimization techniques for solar power generation and forecasting. Deep learning-related methods, in particular, can theoretically handle arbitrary nonlinear transformations through proper model structural design, such as hidden layer topology optimization and objective function analysis to save information that can increase forecasting accuracy while filtering out irrelevant or less affected data for forecasting. The research's results indicate that RBFNN-AG performed the best when applying the predetermined number of days, with an NRMSE value of 4.65%. RBFNN-AG performs better than sophisticated models like DenseNet (5.69%), SLFN-ELM (5.95%), and ANN-k-means-linear regression correction (6.11%). Additionally, scenario application and PV system investment techniques are provided to evaluate the current condition of new energy development and market trends both domestically and internationally.

KEYWORDS

Photovoltaic power generating; deep learning; PV system

1 Introduction

Solar energy is a clean, green energy source. Photovoltaic (PV) power generation is one of the main methods for exploiting solar energy resources, with large-scale grid-connected photovoltaic power generation being the most effective method [1]. However, photovoltaic power generation is fundamentally unpredictable and unstable due to the influence of solar radiation intensity, temperature, humidity, cloud cover, and many other factors [2]. With the increasing proportion of PV power generation installed capacity in the power system, the decline in the quality of electricity and even the negative effect on grid safety caused by the fluctuation of PV power generation can not be ignored. It is an urgent task for photovoltaic power stations to improve the accuracy of ultra-short-term prediction as much as possible. At present, the research work on ultra-short-term PV power prediction at home and abroad can be divided into numerical forecast data-based prediction methods, cloud-based prediction methods, or hybrid prediction methods [3]. However, in cloudy weather, the prediction accuracy must be improved because numerical data cannot directly reflect the short-term variations in solar radiation caused by cloud growth and motion [4]. The numerical forecast data-based prediction method is typically straightforward to use, and the prediction results are robust. Cloud map-based prediction also includes both satellite-based cloud maps and ground-based cloud maps, which can be used to predict solar radiation in the ultra-short-term or even in real-time by determining the distribution and movement trends of sky clouds. Due to time and spatial resolution constraints, the forecast technique based on satellite cloud maps is more accurate for the overall prediction of large areas within a few hours, but the local prediction error may be significant [5]. In contrast, ground-based cloud map-based prediction techniques are more suited for predicting photovoltaic power over the next 0–4 h. In the ground-based cloud map prediction method, in order to improve the prediction accuracy of the model by taking into account the attenuation of cloud motion to solar radiation [6]. Because cloud growth and elimination make estimating cloud motion trend more challenging, this method of employing cloud map information as the direct input of the prediction model demands high accuracy of cloud recognition and motion trend prediction. Other researchers have developed other predictive submodels by investigating the various impacts of clouds on solar radiation in a variety of weather scenarios. In addition, the identification of the cloud map classification sample requires a significant time-consuming cost for experienced staff [7], greatly limiting the application of this method.

The outcomes of cloud mapping processing, i.e., cloud identification, cloud motion trend prediction, and cloud categorization accuracy, have a significant impact on the performance of the above ground-based cloud map-based prediction approach. The existing cloud recognition and cloud classification methods are mainly classified by professional pre-designed image features, and then by k-neighbor, support vector machine (SVM), decision tree, and other classification methods. Human-designed features, however, have a hard time accurately identifying the edge information of coiled and layered clouds, and it is more difficult to judge their motion changes. Further complicating the classification of clouds is the possibility of many clouds on a single foundation cloud map. Because the characteristics of the cloud are not visible and the cloud itself experiences expansion and melting, only the conventional image processing method, which uses artificially created features, can reliably predict cloud motion trends. The capacity of the model to generalize is strongly dependent on the structural design of the neural network because conventional neural network-based classification or modeling approaches use shallow (at least one hidden) network architectures. Deep learning makes full use of the computing power of the supercomputing platform to solve the above structural design problems, the traditional artificial feature extraction method to automatically "search" for characteristics on the computer, thus solving the traditional image processing methods in the feature extraction problem. Compared with traditional ground PV systems, floating PV systems can save a lot of land and water resources, and obtain higher power generation efficiency. Liu et al. [8] thoroughly studied the power generation efficiency of floating PV systems, and conducted a comprehensive analysis of the advantages and potential of floating photovoltaic systems in China. Compared with the strong land demand burden of solar panels installed on land, the floating PV technology of installing solar photovoltaic systems on oceans, lakes, reservoirs, and other water bodies has many advantages. Sahu et al. [9] gave a comprehensive overview of floating photovoltaic technology, status quo and various design options. Ranjbaran et al. [10] analyzed and updated different aspects of floating PV systems as power generation systems, introduced the comparison between ground-mounted and floating photovoltaic systems.

The remainder of this essay is structured as follows: Section 2 provides a scenario analysis of photovoltaic power (PV) systems, including distributed PV generating systems, standalone PV generation systems, and generation systems connected to the grid; Section 3 formulates methods for solar energy power generation and forecasting, including cloud cover pattern analysis for solar energy generation, cloud cover based on AVHRR scan geometry, and correlation analysis; Section 4 introduces ways linked to machine learning for solar energy forecasting, particularly those based on deep learning techniques; Section 5 analyzes statistical and hybrid approaches for solar energy forecasting. Section 6 develops an investment analysis and discussion of PV systems, and Section 7 brings this essay to a conclusion.

2 Scenario Analysis of Photovoltaic Power (PV) Systems

PV power systems are categorized based on their functional and operational requirements, component configurations, and how they are coupled to other power sources and electrical loads, distributed PV generation systems, standard-alone PV generation systems and grid-connected generation systems that are shown in Fig. 1. Distributed PV system can be divided into centralized large-scale grid-connected PV power plant and distributed PV system. The main feature of the centralized large-scale grid-connected PV system is that it can transmit the generated electricity directly to the grid, and the grid will be deployed to supply electricity to customers. Stand-along PV system is mainly composed of solar cell module, controller and battery. It can be divided into those with batteries, those without batteries, and hybrid PV systems. Grid-connected PV refers to systems that are directly connected to the public grid after the direct current produced by the solar module is converted into alternating current that satisfies the mains grid's requirements by a grid-connected inverter. Grid-connected PV power generation systems with storage systems and those without storage systems can be distinguished.

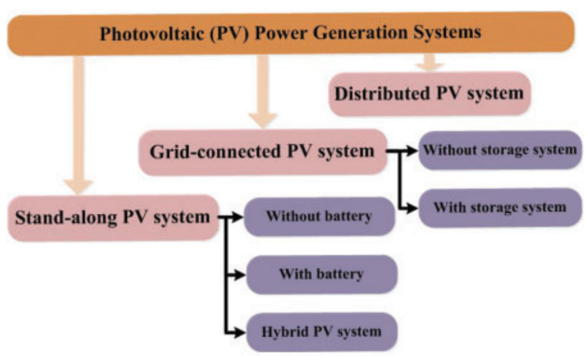

Figure 1: Photovoltaic power systems

Life cycle assessment (LCA) method was used in [11] to study the environmental impact of grid-connected generation of c-Si solar modules in China. According to the study, the energy return time (TEPBT) of the grid-connected PV power generation using crystalline silicon solar modules is 1.6–2.3 years, with greenhouse gas emissions ranging from 60.1 to 87.3 g-CO_2eq/kWh depending on different installation methods. Subhani et al. [12] studied the performance of a new Z-source inverter (ZSI)-based single-stage power conditioning system (PCS) analyzed for a standalone PV power generation system. Wang et al. [13] developed a new piecewise generalised state-space averaging (P-GSSA) model is derived and a multiple time scale modeling is achieved for the grid-connected converters in PV systems. Zhang et al. [14] analyzed the demand side of China's distributed photovoltaic (DPV) power generation by calculating the comparison of the levelized electricity cost (LCOE) with retail electricity prices and desulfurized thermal power benchmark electricity prices in 4 resource areas in 2018, 2020, and 2025. Mateo et al. [15] pointed out four obstacles to the large-scale integration of photovoltaics into the distribution network, and made recommendations to overcome these obstacles.

Remon et al. [16] analyzed the impact of large-scale PV power plants on the transmission grid under different penetration levels. Considering a power plant composed of multiple power converters using synchronous power controllers (SPC), the analysis results show that photovoltaic power plants using SPC can limit frequency deviation, improve oscillation damping, and reduce the stress of other units, thereby affecting the power system Have a beneficial impact. Ogbonnaya et al. [17] proposed a new type of thermodynamic efficiency index for selecting the best location for large-scale PV power generation as a resource reduction strategy. By choosing the best location for large-scale PV power generation (LSPPG), the same amount of land space, materials, and energy resources will achieve higher utilization efficiency. Gigoni et al. [18] extensively compared simple forecasting methods with more complex forecasting methods for 32 PV power plants of different scales and technologies throughout the year, and tried to assess the impact of weather conditions and weather forecasts on photovoltaic power generation forecasts. The direct prediction technology of photovoltaic power generation is comprehensively and systematically reviewed by Das et al. [19]. The impact of the dynamic behavior of PV power generation systems on the transmission system's short-term voltage stability was examined in [20], and the findings indicate that these measures are crucial in preventing voltage instability brought on by the sudden failure of photovoltaic systems due to faults. The study findings indicate that the installed hydropower capacity and the annual solar energy absorptivity play a significant role in the scale optimization of PV power stations. The complementary operation of hydropower and PV, as well as three new operation modes of the actual scenario, were explored in [21]. The methods to predict 1-day prior regional PV power was evluated in [22,23], and the results indicated that selecting the appropriate prediction method based on regional characteristics is critical. A nested model was created in [24] to estimate the PV energy delivered by analyzing the size of the PV power station integrated into the hydropower plant using cost-benefit analysis and accounting for changes in the downstream water level. This model incorporates both long-term and short-term operational decisions (VDWL). In [25], the direct prediction technology of PV power generation is thoroughly and methodically studied. The significance of input and output data correlation and model input data preparation are also covered. A medium- and long-term wind and photovoltaic power generation prediction method based on copula function and long- and short-term memory networks is proposed in [26], which can effectively extract the key meteorological factors of nonlinear effects and trends affecting power generation. Combined with the renewable energy management system, a multi-site PV power station prediction model based on a deep learning algorithm was proposed by [27]. A multivariable grey theory model based on the particle swarm optimization (PSO) algorithm is proposed in [28] for short-term photovoltaic power generation prediction. A mathematical calculation model of carbon emissions in the production, transportation, and waste treatment of PV power generation systems was proposed by [29,30] in order to study the carbon footprint of the supply chain of photovoltaic power generation and calculate the reduction of carbon emissions. Kawabe et al. [20] conducted research on the impact of the PV power generation system's dynamic behavior on the transmission system's short-term voltage stability. The findings demonstrate the significance of these procedures in minimizing voltage instability brought on by abrupt PV system failures.

A fault-tolerant strategy to maintain the current balance of the three-phase grid when an unequal power generation fault occurs in the healthy h-bridge was proposed in [31]. The effectiveness of the proposed fault tolerant control method is verified by the test results of a 430 V, 10 kW experimental prototype. Yu et al. [31] proposed a fault-tolerant strategy for maintaining the current balance of the three-phase grid when an unequal power generation fault occurs in the healthy h-bridge, and confirm the effectiveness of the proposed fault tolerant control method. Hancevic et al. [32] studied the possibility, benefits and challenges of the widespread application of distributed photovoltaic power generation in the Mexican residential sector to support eligible households to adopt distributed photovoltaic power generation (DPVG). Based on the positive results in terms of economic and environmental impact, it provided important support for the further design and implementation of the DPVG plan. A PV power generation system based on qzs-cmi energy storage was proposed in [33]. The system realized the distributed Maximum power point tracking (MPPT) of PV panels, balance the power between modules, and provide the required power for the grid. The real option model of renewable energy investment was established in [34]. This model empirically evaluates the investment value and optimal timing of solar PV power generation in China.

Studies have shown that the development of carbon market helps to promote the optimal investment time. A long-term multi-objective optimization model for integrated hydropower/PV power generation system was proposed in [35], which considers both the smoothness of power generation process and the annual power generation of the system. The results show that in nature, hydropower is an ideal compensation resource for PV power generation. A simulation model for the growth of photovoltaic power generation in China was created using the system dynamics method, and sensitivity analysis was performed [36]. The future development trend is forecasted by the simulation results of electricity generation, investment, and capacity in the years 2012–2032, and the efficacy and impact of incentive programs are assessed. Tafti et al. [37] proposed a constant power generation (CPG) algorithm for PV systems, suitable for single-stage and two-stage PV power plants, and can flexibly move the operating point to the right or left of the maximum power point. The experimental results of the 1-kVA PV system verify the effectiveness of the proposed algorithm under various operating conditions and prove the function of the proposed CPG algorithm.

3 Solar Energy Power Generation and Forecasting Techniques

The pattern analysis of cloud cover for solar energy generation, cloud cover based on AVHRR scan geometry and correlation analysis of the inputs for solar forecasting are provided in this Section. Solar energy power generation and forecasting based on the processing steps and time horizon is shown in Fig. 2. Short-term forecasts are useful in integrated renewable energy management systems, including economical load scheduling and power system operation, and typically span from one hour to one day. The scheduling of electronic systems made up of high-end transformers and various forms of electromechanical equipment requires a medium-term projection with a time horizon of one week to one month. Long-term forecasts have a time horizon between one month and one year, and this decision is suitable for long-term generation, transport, distribution, and solar rationing that takes into account seasonal trends. Due to the large time span of long-term forecasting, there are too many factors to be considered, resulting in a decrease in the accuracy of forecasting. An alternative is to use short-term forecast extension to make long-term and medium-term forecasts, although it also reduces forecast accuracy [19]. Clouds are variously shaped mixtures of tiny water droplets, supercooled water droplets, ice crystals, and snow crystals that are formed by condensation of water vapor in the atmosphere. The macroscopic characteristics and quantity of clouds, especially the corresponding distribution and evolution in the sky, can show the relevant movement, stability, and water vapor of the atmosphere over time [38]. This is also one of the most important signs for the evolution of the future weather. The cluster-classify method must be used for the pattern analysis of clouds in order to precisely detect and record clouds under various types of weather. The worldwide cloud categorization technique, which strictly separates clouds into 29 categories, 10 genera, and 3 families according to their visual features, structure characteristics, and cloud base height, is currently used in the observation of meteorological stations. Approximately, the cloud cover can be categorized as three types of clouds: cumulus, stratus and cirrus. The outlined three types of clouds produce ten basic types of clouds if the corresponding height and words for rainfall are all considered together [39].

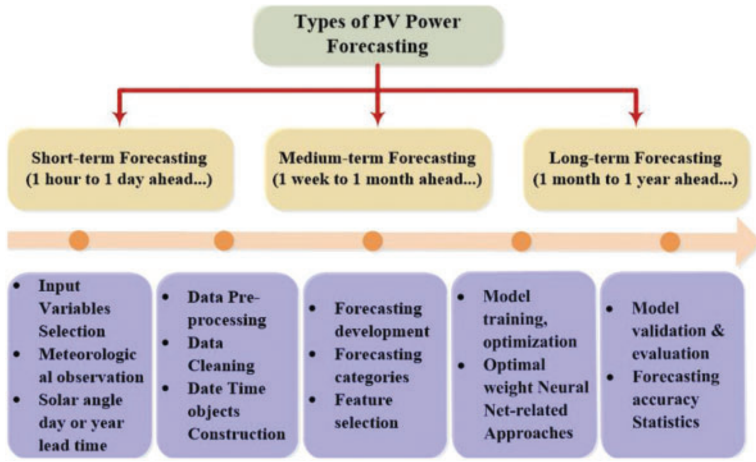

Figure 2: Types of PV power forecasting

3.1 Patterns Analysis of Cloud Cover for Solar Energy Generation

In the actual program, a lot of trustworthy expertise with forecasting weather changes over the following 12 h is employed. Villous cumulus clouds, for instance, may signal favorable weather even though they are widely spread, whereas expanding or fresh growth may signal an unexpected rain. Although the troposphere is where the majority of clouds on Earth originate, they can occasionally be seen in the stratosphere and mesosphere. The outlined three main layers of the atmosphere are often referred to as the "homogeneous layer", in which the composition ratio of all atmospheric substances is roughly uniform and does not change much due to location, time and altitude [40]. The "homogeneous layer" is often contrasted with the heterogeneous layer, which consists of the warming layer and the exosphere and belongs to the transitional zone of outer space. The supervised cloud classification methods usually consist of Maximum Likelihood Estimation (MLE) [3] and Support Vector Machines (SVM) [41]. In recent years, many neural networks have been widely used for cloud classification, such as Probabilistic Neural Network (PNN) [42] and Self Organizing Feature Maps (SOM) Network [43]. Ameur et al. [44] used C-means clustering method for cloud pattern analysis, and the results related to texture features that were obtained from four directions of Meteosat satellite images, i.e., 0, 45, 90 and 135, and made use of k-means clustering for image segmentation. Li et al. [45] improved the traditional single classification method by intergating the Genetic Algorithm (GA) fuzzy C-means clustering and fuzzy subtraction clustering. Welch et al. [46] used BP neural network to divide AVHRR-LAC data images into 10 categories. The model architecture of used neural network is 20-55-55-10, where 20 represents the dimension of the input feature space, and the overall accuracy of Bootstrap classification was 87.6%. For accurate ground-based meteorological cloud classification, Zhang et al. [47] proposed CloudNet, a new CNN model. Liu et al. [48] presented the novel joint fusion convolutional neural network (JFCNN) to integrate multimodal information for ground-based cloud classification.

For ground-based cloud recognition, a novel technique known as the multi-evidence and multi-modal fusion network (MMFN) has been put out. MMFN might learn extended cloud information by fusing heterogeneous data into a cohesive framework. The MMFN is evaluated on a multimodal ground-based cloud database (MGCD) and achieves a classification accuracy of 88.63%. Ye et al. [49] proposed "DeepCloud" as a novel cloud image feature extraction approach by resorting to deep convolutional visual features. Kurihana et al. [50] presented a framework for cloud characterization that makes use of modern unsupervised deep learning technologies. The study showed that the proposed method extracted physically relevant information from radiance data and produced meaningful cloud classes. Compared with the window clustering algorithm currently used by FY-2C, and figured out that SOM method had better classification accuracy [51]. The cluster results show that the SOM method cannot only greatly improve the classification results at the pixel level, but also accurately classify cloud clusters into cumulonimbus, cirrus, and altostratus clouds. The existing cloud pattern analysis methods can detect clouds by using data from infrared channels and distinguish altostratus clouds by using the brightness temperature gradient of water vapor channels. High-accuracy cloud cover forecasting is critical to the analysis and evolution of climate predictions in many regions [52]. Oktas is a classical performance indicator used to measure the cloud amount based on the cloud cover with a discrete scale, which consists of an eighth of the sky domes based on the pre-divided eight boxes. Particularly, 0 oktas and 9 oktas depict, respectively, a cloudless sky and a sky with some weather events. The experimental results demonstrate that the cloud cover distribution patterns in spring and summer have obvious seasonal characteristics and that there are also significantly different distributions of meteorological features [53–55]. These patterns are related to the 22-year satellite-derived cloud cover record in the Pacific Northwest (PNW).

3.2 Cloud Cover Based on AVHRR Scan Geometry

The feedback system for weather analysis benefits from the cluster analysis of the cloud cover, particularly its important climatic traits and probable cloud dispersal patterns. Clouds have a direct impact on the earth-atmosphere system's radiation balance, heat balance, temperature, and humidity distribution as an internal characteristic of the climate system. The connection between clouds and climate can become quite intricate by taking part in a number of positive and negative feedback mechanisms. Cloud cover is one of the significant meteorological factors which can reflect the feedback mechanism to a large extent. However, few studies on cloud cover change were focused on while most data was collected from ground observation due to the lack of data. Cloud cover is typically treated as cloudiness, which is used to measure the cloud amount and obscured by a portion of the sky from a particular location. The cloud cover is always correlated to the sunshine duration, and the sunshine is most abundant when the amount of clouds is the least. The unsupervised cloud classification methods can be divided into three types of methods: the threshold method, the histogram method, and clustering method. Earth-satellite geometry, as one of the important modern geodesy approaches, is usually treated as a measurement technique based on the observation of man-made Earth-satellite to construct the measurement method. The ground position, water, space position, as well as the shape, size and gravity field of the Earth is the main components of the outlined methods.

3.3 Correlation Analysis of the Inputs for Solar Forecasting

With the application of ground observation data, researchers are gradually learning some climate characteristics of the cloud and the feedback effect of cloud, radiation and precipitation. However, station observation has its own insurmountable defects, such as cloud overlap error, weather dependence and restrictions on the observation area. Satellite data, with its wide coverage, large volume, high repetition frequency, strong objective truth, reliable source of information, and many other advantages, has become a good supplement of ground observation data.

$$\operatorname{cov}\left(X_i, X_j\right) = \frac{\sum_{k=1,\ldots,m}\left(x_{ki} - \overline{x}_{\cdot i}\right)\left(x_{kj} - \overline{x}_{\cdot j}\right)}{m-1} \tag{1}$$

where $X = [X_1, X_2, \cdots, X_n]^T$, $\left\{x_{k\cdot} = [x_{k1}, x_{k2}, \cdots, x_{kn}]^T \middle| 1 \le k \le m\right\}$, X_i and X_j represent two variables of different correlation, and m is the length of the given cloud data. The correlation coefficient is used to reflect the degree of correlation between different variables. The correlation coefficient is calculated by the product difference method, which reflects the degree of correlation between different cloud variables and their corresponding mean values. The $m-1$ represents the sample mean of the random variable, because the mathematical expectation of the variable is not obtained.

PV generation capacity is generally influenced by a variety of factors, such as: (1) The height angle of the sun and geographic latitude; Generally, the higher the height angle of the sun, the lower the solar radiation intensity; however, in low latitude regions, the higher the height angle of the sun, the higher the radiation intensity (2) The impact of altitude and atmospheric transparency: When the sky is clear, the atmosphere is more transparent and the sun's radiation is stronger. The atmosphere is more transparent at higher altitudes since the air is thinner there, hence the higher the height, the more transparent the atmosphere will be. (3) The number of hours of sunlight, the longer the sunlight duration, the more total solar radiation is obtained on the ground. (4) The inverter efficiency, high-power inverters must have high efficiency even while delivering electricity to low loads. The effectiveness of the inverter in PV generating systems has a big impact on increasing solar power generation capacity and reducing power generation expenses. For PV generating systems, the inverter should have low power loss and great efficiency. As a result, the grid-connected inverter should have a maximum power point tracking control feature that can be engaged whenever there is sufficient solar radiation in order to increase output efficiency. In addition, total PV generation is linked to wind speed, wind direction, surface temperature, relative humidity, total cloud cover, zenith and azimuth [56] as listed in Table 1. Correlation analysis of the inputs for PV forecasting and feature importance (from highest to lowest) related to Table 1 is shown in Figs. 3 and 4, respectively.

Table 1: Feature importance

shortwave_radiation_backwards_sfc	0.38
shortwave_radiation_backwards_sfc	0.38
mean_sea_level_pressure_MSL	0.12
wind_speed_80_m_above_gnd	0.07
wind_speed_10_m_above_gnd	0.02
snowfall_amount_sfc	0.02
wind_direction_80_m_above_gnd	0.01
wind_direction_10_m_above_gnd	0.01
wind_direction_900_mb	−0.00
total_precipitation_sfc	−0.00
wind_gust_10_m_above_gnd	−0.03
high_cloud_cover_high_cld_lay	−0.04
medium_cloud_cover_mid_cld_lay	−0.04
low_cloud_cover_low_cld_lay	−0.04
otal_cloud_cover_sfc	−0.08
temperature_2_m_above_gnd	−0.09
relative_humidity_2_m_above_gnd	−0.11
wind_speed_900_mb	−0.13
Zenith	−0.15
Azimuth	−0.43
angle_of_incidence	−0.44

Figs. 3–4 are generated based on the methods provided in the [56]. Based on the outlined discussion, the following conclusions have been reached: Shortwave radiation rearward and Generated Power KW have a 0.56 correlation. Relative Humidity and Zenith are correlated (+0.51), Relative Humidity and Low Cloud Cover are also correlated (+0.49), Angle of Incidence and Zenith are negative associated with Generated Power (−0.65). Shortwave radiation backwards and Zenith have a negative correlation of (−0.55), and which and Relative humidity have a negative correlation of (−0.72), and Relative humidity and Temperature have a negative correlation of (−0.77).

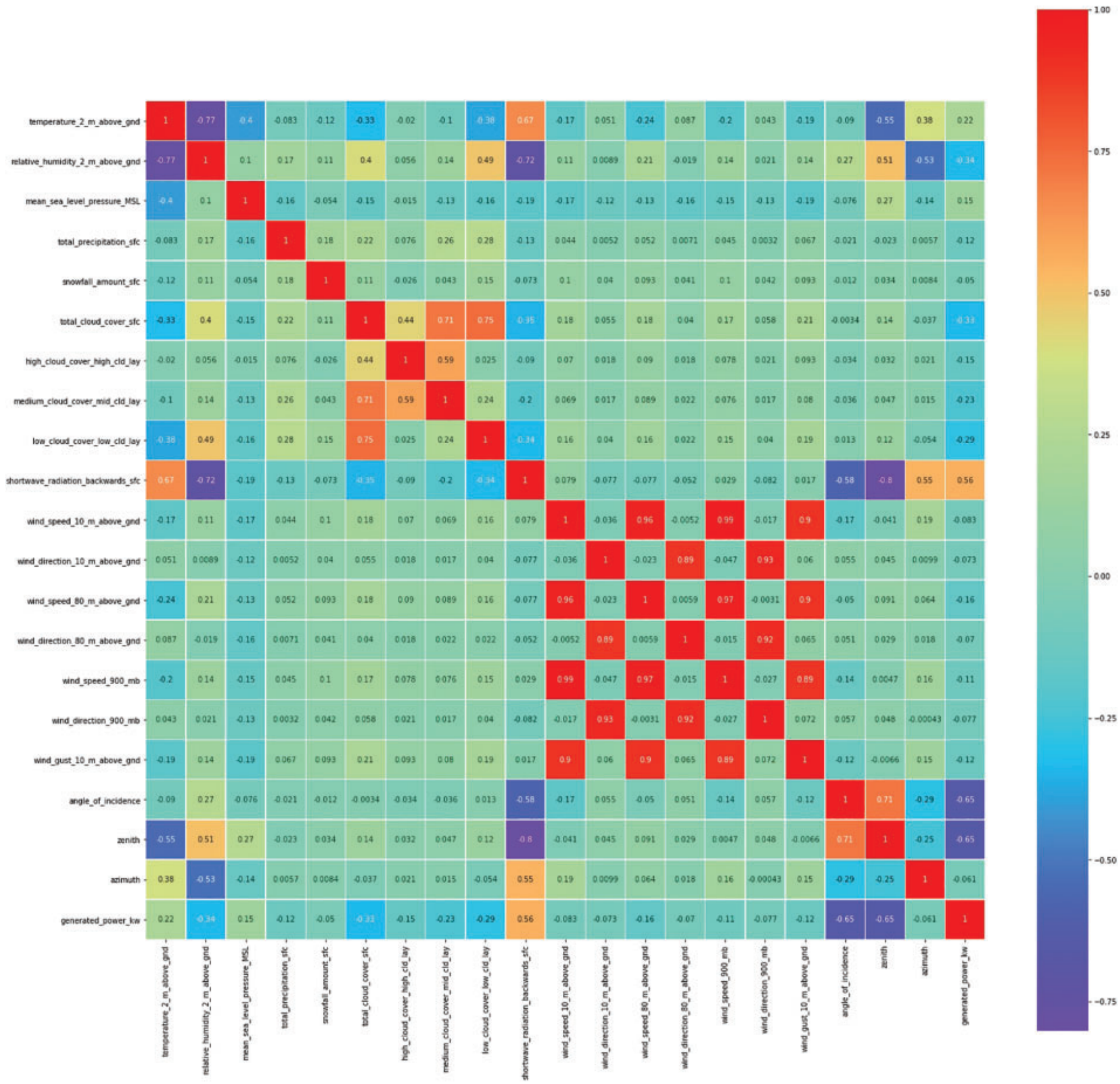

Figure 3: Correlation analysis of the inputs for PV forecasting

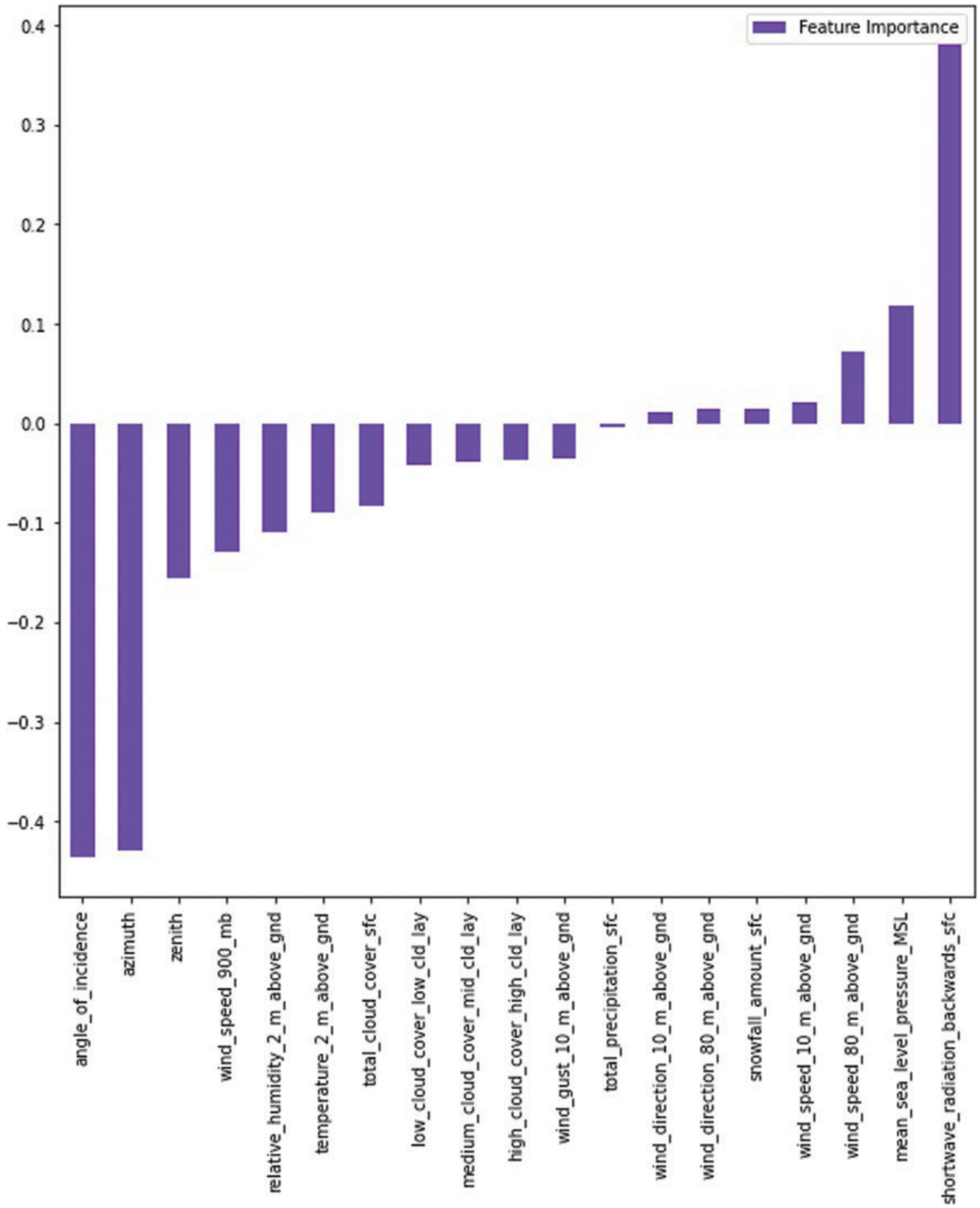

Figure 4: Feature importance (from highest to lowest)

4 Machine Learning-Related Approaches for Solar Energy Forecasting

Solar energy forecasting and classification techniques based on historical data are shown in Fig. 5. In order to predict the PV output more accurately, the inertia weighting strategy and Cauchy mutation operator were introduced [57] to improve the moth flame optimization algorithm predicted by the PV power generation SVM.

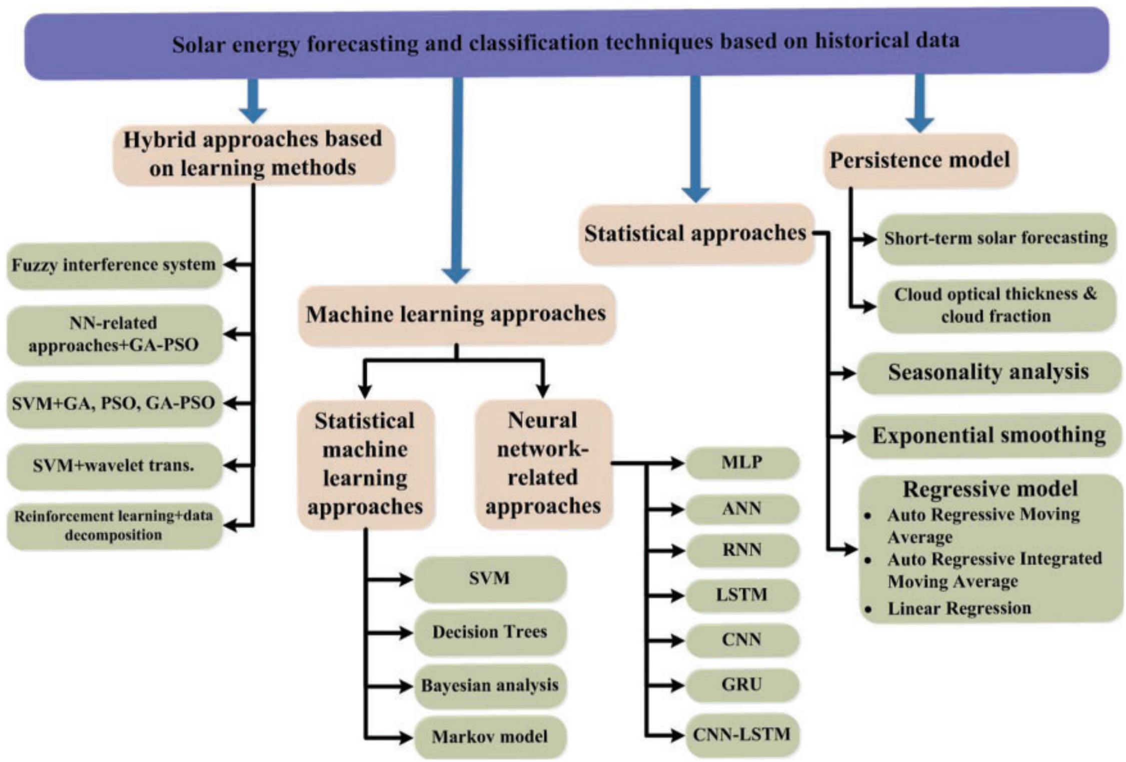

Figure 5: Solar energy forecasting and classification technique

To predict these disturbances, Monteiro et al. [58] analyzed seven training algorithms used in artificial neural networks to generate active power estimates, and then compared their best statistical results with SVM and Kalman filtering (KF) techniques. It is concluded that artificial neural networks (ANN) are more suitable for this kind of problem than SVM and KF.

4.1 Neural Network-Related Approaches

For power generation forecasting of photovoltaic panels, da Silva et al. [59] used ANN with seven training algorithms, which outperformed SVM. Leva et al. [60] proposed ANN for PV plant energy forecasting to analyze the input dataset sensitivity.

Chen et al. [61] presented a prediction model for PV power generation based on the back propagation (BP) neural network optimized by the mind evolutionary algorithm (MEA), which used the MEA to optimize the weights and thresholds within the BP neural network to overcome the drawbacks of traditional learning algorithms, the proposed MEA-BP prediction model, which can more accurately predict the PV output. Zhong et al. [62] used Pearson's correlation coefficient to analyze meteorological factors, and selected irradiance and battery temperature as important influencing variables. The power generation of PV power plants is predicted using general regression

(GR) and BP neural networks on the basis of this. The BP neural network forecasts the approach has superior prediction results than the GR method in PV power generation, according to comparison and analysis of the two models' outputs. In order to reduce the negative impacts of PV energy on electric power and energy systems, Wang et al. [63] proposed a novel hybrid method for deterministic PV power forecasting based on wavelet transform (WT) and deep convolutional neural network (DCNN). The original signal is decomposed into several frequency series using WT, and DCNN is used to extract the nonlinear features and invariant structures present in each frequency. It is critical to accurately predict PV power in order to reduce the negative impact of PV plants on power systems. As a result, Li et al. [64] developed a hybrid deep learning approach based on convolutional neural network (CNN) and long-short term memory recurrent neural network (LSTM) for PV output power forecasting. Zang et al. [65] developed a hybrid method for short-term PV power forecasting based on a deep CNN to mitigate the impact of solar radiation uncertainty on grid-connected PV systems. Korkmaz [66] proposed a new CNN model, SolarNet, for short-term photovoltaic output power forecasting under different weather conditions and seasons. Compared with other deep learning methods, SolarNet has higher accuracy and stability in short-term PV power forecasting. Wang et al. [63] proposed a CNN, an LSTM network, and a hybrid model based on a CNN and an LSTM network model to predict and compare photovoltaic power generation. The results show that the prediction effect of the mixed model is the best, followed by CNN, and the LSTM has the worst prediction effect. A medium and long-term wind and photovoltaic power generation prediction method based on copula function and LSTM network is proposed [26], which can effectively extract the key meteorological factors of nonlinear effects and trends affecting power generation. A new PV power prediction model is proposed, and the BP ANN method is used to predict the PV power generation in the next 24 h. Experiments show that compared with the traditional model, the model can improve accuracy [67]. Recent research on PV power forecasting is listed in Table 2.

Table 2: Recent researches on PV power forecasting

References	Forecast horizon	Forecast error	Forecasting model
[60]	24 h	RMSE 12.5%–36.9%	ANN
[63]	15–120 min	RMSE, CRPS	WT-DCNN-QR
[64]	15–180 min	RMSE	Pers., BP/RBF, CNN-LSTM
[65]	1 h	RMSE, MAE, MASE	VMD-CNN, CNN
[67]	24 h	MAPE 7.65%	ANN
[68]	7.5/15/30/60 min	MAE, RMSE, MAPE	LSTM
[69]	6/12/24 h	MAE, RMSE	LSTM, RNN, GRNN, ELM
[70]	6 days	RMSE	LSTM, RNN, GRNN, ELM
[71]	15 min	MAPER2	LSTM

To accurately predict the power output of PV systems in the short term, an LSTM-based deep learning approach was proposed by Harrou et al. [71]. The application of the latest 10 neural networks and intelligent algorithms in short-term PV prediction is comprehensively compared and analyzed [70]. The simulation results in MATLAB show that season affects the accuracy of all methods, and the proposed hybrid method has the best overall performance. A BESSs scale and control strategy for market scheduling of PV power plants one hour ago and one day ago was presented in [72]. The Levenberg-Marquardt back propagation learning algorithm is used to train the feed forward neural network, and the prediction model is established to predict solar irradiance and load energy consumption. Niu et al. [73] proposed based on random forest (RF), improved grey ideal approximation (IGIVA), complementary integrated empirical mode decomposition (CEEMD), particle swarm optimization algorithm based on dynamic inertia factor (DIFPSO) and back propagation neural network (BPNN) hybrid forecasting model for PV power generation, RF-CEEMD-DIFPSO-BPNN. Through empirical analysis, the effectiveness of the model in the prediction of photovoltaic power generation is verified. Zhou et al. [68] proposed a hybrid integrated deep learning framework to predict short-term PV power generation in a time series manner. Use two LSTM neural networks for temperature and power output prediction, and add an attention mechanism to adaptively focus on the more important input features in the prediction. Al-Dahidi et al. [74] utilized Extreme Learning Machines (ELMs) to provide accurate 24 h-ahead solar PV power production predictions. Wang et al. [75] presented a short-term PV power prediction model based on the online sequential extreme learning machine with a forgetting mechanism (FOS-ELM) to reduce the negative impact of the use of PV power.

In order to better demonstrate the quality of the different models, a comparison in Table 3 of model results from recent literature was made. The peak power normalized RMSE was used to evaluate the prediction quality of the models (NRMSE). The model prediction results of all the models in the literature were analyzed and it was found that RBFNN-AG showed the best performance using the number of setup days. The performance of RBFNN-AG outperformed many other complex models such as DenseNet, SLFN-ELM, and ANN-k-means-linear regressive correction.

Table 3: Comparison of PV prediction accuracy

References	Model	Testing set (days)	NRMSE (%)
[76]	RBFNN-AGO	730	4.65
[77]	DenseNet	765	5.69
[78]	SLFN-ELM	730	5.95
[79]	ANN-k-means-linear regressive correction	730	6.11
[78]	BPNN	730	6.30
[80]	SOM-LVQ-SVR-fuzzy inference	730	7.00
[79]	ANN-k-means	730	7.05
[77]	ResNet	365	7.16
[77]	MLP	365	7.43
[77]	CNN	365	7.67
[81]	SDD-LSTM	730	7.74
[80]	SVR	730	8.05
[77]	ETS	365	8.15
[77]	SVR	365	8.37
[77]	Theta	365	9.01
[82]	NWP-LS	365	9.30
[77]	RFR	365	9.70
[77]	Physical	365	9.82
[83]	Ensemble SARIMA(X)	730	10.25
[81]	BPNN	730	10.47
[82]	NWP-LS	365	11.00

(Continued)

Table 3 (continued)

References	Model	Testing set (days)	NRMSE (%)
[81]	SVR	730	11.17
[83]	ANN	730	11.26
[82]	KNN-weighted average	630	15.30

4.2 Statistical Machine Learning-Related Approaches

In order to predict the PV output more accurately, the inertia weighting strategy and Cauchy mutation operator was introduced [57] to improve the moth flame optimization algorithm predicted by the PV power generation SVM.

Statistical and artificial intelligence-based time series forecasting techniques for PV power output were introduced and compared by Sharadga et al. [84], who also employed hourly solar power projections to assess the efficacy of various models. Monteiro et al. [58] examined seven training algorithms used in ANN to produce active power estimations and compared the best statistical outcomes with SVM and Kalman filtering (KF) methods to forecast these disruptions. The conclusion is that artificial neural networks, as opposed to SVM and KF, are better suited for this type of challenge. Lamsal et al. [85] used method of using a discrete Kalman filter (DKF) to lessen the bias error existing in the projected data was recommended as a way to predict the actual power of wind and PV systems.

Hossain et al. [69] proposed an algorithm for short-term PV power prediction using an LSTM neural network and comprehensive weather forecast. The k-means algorithm is used to classify historical irradiance data into a dynamic type of sky group that changes hourly in the same season, and the statistical characteristics of historical weather data are embedded, which greatly improves the prediction accuracy. Ekström et al. [86] proposed the statistical method based on Monte Carlo simulation to analyze the PV power generation scenarios containing new power generation sites that lack data measurement. Ding et al. [87] designed a new discrete grey model with time-varying parameters to deal with various PPG time series with nonlinearity, periodicity, and volatility widely existing in long-term PPG sequences. The study results show that the model has high prediction accuracy, small empirical results volatility, and generalization. Statistical, random and hybrid machine learning algorithms based on different numerical weather prediction (NWP) input data were developed in [88], and NWP data from IFS and WRF models was treated as input for solar energy forecasting.

5 Statistical Approaches and Hybrid Approaches for Energy Forecasting

Through empirical analysis, the effectiveness of the model in the prediction of photovoltaic power generation is verified. Zhou et al. [68] proposed a hybrid integrated deep learning framework to predict short-term PV power generation in a time series manner. Yi et al. [89] combined the Data envelopment analysis (DEA) and Tobit regression analysis methods to analyze the factors affecting efficiency and improve the efficiency of PV power generation. For the short-term forecasting of PV power, Bracale et al. [90] suggested a new probabilistic approach based on a competitive ensemble of several base predictors. A probabilistic forecasting method for single household electricity, photovoltaic power generation and net demand using the Gaussian process was studied in [91]. The discriminant ability of relevant scoring rules for the performance evaluation of the spatio-temporal trajectory of PV power generation was studied in [92]. The advantages of considering spatio-temporal correlation over probability prediction and point prediction have been studied. Dong et al. [93] proposed two novel stochastic forecasting models for solar PV, namely, using uncertain basis functions to predict solar radiation and PV power and using stochastic state-space models to characterize the behavior of solar radiation and PV power output. Wang et al. [94] proposed a two-tier model to coordinate the operation of cascade hydropower and adjacent wind and PV facilities.

In order to solve the pressure problem that the hybrid power generation of dispatchable hydropower and non-dispatchable PV power energy may bring to the integrated management of water resources, Ming et al. [95] proposed an adaptive operating rule program for large-scale hydro-PV hybrid power plants. Shepero et al. [96] summarized the research results on spatio-temporal PV power generation and electric vehicle charging load modeling at home and abroad. The two main goals of PV potential research are to increase the precision of the ramp rate model for PV power generation and to calculate the overall clear sky index at the city size. An efficient home energy management system (HEMS) concept for self-dispatching the assets of residential end users was put out by Javadi et al. [97]. The self-dispatching problem is represented using a random mixed integer linear programming (MILP) framework, which enables the best possible determination of the state of household appliances throughout the day and quickly converges to the global optimal solution. Liu et al. [98] proposed a short-term PV power prediction model using an improved chicken flock optimization algorithm. The input of the model is determined by the correlation coefficient method, and the weight and the threshold of the extreme learning machine are optimized by the improved chicken flock optimization algorithm. The average absolute percentage error and root mean square error (RMSE) of the improved model are 5.54% and 3.08%, respectively. Yang et al. [99] proposed an equivalent modeling method based on the Canopy-FCM clustering algorithm to accurately analyze the dynamic characteristics of a grid-connected photovoltaic power station. Gan et al. [100] proposed a photovoltaic thermal (PVT) system that combined with a phase change material (PCM) as a thermal storage medium for managing the photovoltaic temperature. Jiang et al. [101] introduced the power sharing problem between different energy storage components and two optimization objectives for the energy loss of the energy storage system and the state of charge of the energy storage system. To cope with abrupt variations in load demand requiring energy storage with high power density capabilities, Aktas et al. [102] presented a hybrid energy storage system (HESS) comprising of a high energy and power density storage battery bank and an ultra-capacitor unit, respectively. Chen et al. [103] proposed a smoothing method for fuzzy complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) based on the optimal base power of a variable-speed pumped storage station (VSPSS). When compared to the fixed base power smoothing method, this method effectively suppresses PV power fluctuations. The proton exchange membrane fuel cell system (PEMFCS) in combination with PV and battery is now seen as a promising alternative to power generation. A dual mode distributed economic control for a fuel cell-photovoltaic-battery hybrid power generation system (HPGS) was proposed by Yang et al. [99]. In order to solve the problem that the maximum power of PV will cause the overvoltage of the grid, Prasetyono et al. [104] proposed a modified MPPT algorithm using incremental conductance for constant power generation of PV systems. Nguyen et al. [105] introduced a new MPPT algorithm for photovoltaic power generation systems. Compared with the existing popular MPPT algorithm (P&O), its performance is superior.

6 PV System Investment Analysis and Discussion

The amount of solar energy produced by the system needs to be better understood because it is a crucial component of the power producing system. The best possible distribution of solar and other energy sources can balance supply and demand. Improved solar forecasting will increase the flexibility and adaptability of PV systems to changing environmental conditions while reducing disruption and total investment costs. These predictions are becoming more accurate thanks to research. Solar forecasting essentially gives PV systems a mechanism to foresee and balance energy production and consumption. Reliable solar predictions can best optimize the way they plan controlled units when a PV system has numerous generating resources available.

Integrated energy systems (IESs) are considered a trending solution to the energy crisis and environmental issues. Wang et al. [106] established an IES operation optimization model that included photovoltaic, combined heat and power generation systems (CHP) and battery energy storage to achieve the goal of optimal component scheduling. In addition, the improved differential evolution algorithm (IDEA) was used to validate the effectiveness of the model. Tian et al. [107] provided a method based on real options to analyze the investment value of PV power generation under the linkage of the carbon market. From the perspective of power generation companies, evaluate PV power generation under uncertain conditions of investment costs, electricity prices, carbon prices, and subsidy payments. Briese et al. [108] developed a solar PV power generation system ecological network analysis based on the CdTe PV module material, energy and water life cycle inventory. The technical and economic performance of two HESs composed of BAPV and batteries for residential and commercial housing was studied in [109]. The results show that the use of BAPV in commercial building HES can reduce customer electricity costs.

Krauter [110] proposed a simple and effective method for matching PV power generation with the grid load curve of PV-based energy systems. During periods of high demand, peak power generation is accomplished by the following operations: azimuth and tilt angle adjustment, usage of angle-selected optical surfaces, photovoltaic module thermal control, and smart site selection, showing how PV power plants should adapt to load requirements. The selection of a case study was presented [111] to evaluate the possibility of solar energy combining heat and power generation. The results of case study show that it is beneficial in economy and environment to invest in small and large solar-biomass hybrid power plants for cogeneration under the climate conditions of northern Europe. The potential of renewable energy technologies was investigated [112], especially PV power generation and its economic and environmental impacts on Bangladesh. The future dynamic PV power generation potential was evaluated [113] based on the resources suitable for photovoltaic systems. Priyadarshi et al. [114] proposed a three-phase voltage source inverter current control method based on fuzzy space vector pulse width modulation (FSVPWM), which uses a MPPT algorithm based on hybrid fuzzy particle swarm optimization to achieve high tracking efficiency and the optimal maximum power point under unfavorable operating conditions. In particular, the suggested hybrid system accurately obeys MPPT with excellent performance regardless of solar irradiation and wind velocity. The market participation based on different firming control strategies of an IPV power plant was proposed by Saez-de Ibarra et al. [115], to optimize the economic exploitation based on the storage system management, taking PV generation predictions into account. A method for determining the PV potential of rooftops in cities or regions was decribed in [116]. The method estimates the total area that can be used for rooftop PV installation and the solar radiation throughout the event year. In order to determine the best on-grid price for solar PV power generation in 30 Chinese provinces, Zhang et al. [117] coupled the least square Monte Carlo method with the backward dynamic programming algorithm. Hosenuzzaman et al. [118,119] conducted an examination of the PV cell technology, energy conversion efficiency, economic analysis, energy policy, environmental impact, diverse applications, prospects, and advancement.

Although there is a high trend of government and policy makers to deploy PV technology in Iran, there are still some obstacles to the potential of the sector due to insufficient industry growth, financing issues, lack of governance rules and lack of a sustainable development roadmap. Addressing these problems requires long-term and sustained policies to obtain technological and industrial development in order to achieve large-scale advances in the sector in the coming decades [120,121].

7 Conclusions

This paper offers a thorough, up-to-date assessment of machine learning, statistical, and optimization strategies for solar power generation and forecasting. Investment in PV systems and solar forecasting are discussed in particular. This study formulates and addresses solar energy power generation and forecasts. The literature comparison of deep learning-related approaches then delves further into the benefits and drawbacks of various related methods as well as the improvement plan. The PV system investment analysis and discussion are offered in the final section. This study's suggested approach will aid relevant academics and engineers in their understanding of and application of solar energy power generation and forecasting in architectural design and analysis. In order to lower generation system costs and integrate renewable energy, the most recent research on PV generation forecasts is crucial. Energy merchants and power plant managers can use it to obtain more precise projections. The collection of meteorological data from the atmosphere is made possible by the use of remote sensing technology. It is possible to forecast the power of photovoltaic generating using this statistics. In the forecasting of renewable sources, accuracy is crucial. When compared to single error forecasts, the usage of group error forecasts can provide more reliability. The processes taken to process meteorological data and the precision of the forecasts are directly tied to the proper model. It is anticipated that more appropriate data pre-processing techniques and neural network models will emerge in the future, improving forecast precision and supporting solar power generation as a source of renewable energy.

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