

Review

# Key Operational Issues on the Integration of Large-Scale Solar Power Generation—A Literature Review

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**Abstract:** Solar photovoltaic (PV) power generation has strong intermittency and volatility due to its high dependence on solar radiation and other meteorological factors. Therefore, the negative impact of grid-connected PV on power systems has become one of the constraints in the development of large scale PV systems. Accurate forecasting of solar power generation and flexible planning and operational measures are of great significance to ensure safe, stable, and economical operation of a system with high penetration of solar generation at transmission and distribution levels. In this paper, studies on the following aspects are reviewed: (1) this paper comprehensively expounds the research on forecasting techniques of PV power generation output. (2) In view of the new challenge brought by the integration of high proportion solar generation to the frequency stability of power grid, this paper analyzes the mechanisms of influence between them and introduces the current technical route of PV power generation participating in system frequency regulation. (3) This section reviews the feasible measures that facilitate the inter-regional and wide-area consumption of intermittent solar power generation. At the end of this paper, combined with the actual demand of the development of power grid and PV power generation, the problems that need further attention in the future are prospected.

**Keywords:** PV power generation; PV output forecasting; frequency regulation; electric vehicle charging and discharging station; balancing of whole network

## 1. Introduction

Energy plays a significant role in economic development and prosperity. Driven by environmental degradation, resource shortage, and fuel price fluctuations, governments of all countries have placed great importance on the development and consumption of renewable energy. Since the beginning of the 21st century, the global photovoltaic (PV) power generation capacity has been increasing rapidly, with an average annual growth rate of 50%. According to the statistics released by the International Renewable Energy Agency (IRENA) in 2019, the scale of PV plants in operation worldwide has reached 580 GW, and PV power generation accounts for nearly 3% of the total generating capacity, of which the newly installed capacity has reached 97.1 GW in 2019, and the increase in PV power generation accounts for 55.2% of the increase in renewable energy. In addition, China ranks first in the world in terms of installed capacity, with the cumulative installed capacity reaching 205.7 GW, followed by the USA (62.3 GW), Japan (61.8 GW), Germany (48.9 GW), and India (34.8 GW). IRENA predicts that PV power generation will account for 25% of total power generation by 2050, which is also the target of PV installation in 2050 proposed by the analysis report “the Future of PV” released by IRENA at the 2019 World Solar Congress held in Lima, Peru. PV power generation is expected to become one of the main resources of electric generation in the future.

Many large-scale PV grid-connected demonstration projects and plans have been launched around the world. Germany, one of the first countries in the world to use, advocate, and encourage PV power generation, began to promote and use PV power generation technology on a large scale as early as 1999; most famous is the “100,000 Roof Power Generation Plan” implemented by the German government [1]. In the late 1990s, the USA launched a similar “Million Roof PV” program, which was completed by the end of 2003. In addition, the USA Department of Energy formulated a five-year PV plan starting in 2000 and a 10-year PV development plan from 2020 to 2030. Japan has successively launched “Sunshine Plan”, “New Sunshine Plan”, and “Solar Power Popularization Action Plan”, etc. The Netherlands, Switzerland, Finland, Austria, the United Kingdom, Canada, and other developed countries have also launched similar PV power generation projects or plans [2]. India also announced that by the end of 2020, 500,000 solar rooftop power generation systems will be completed [3]. In December 2018, China’s first large-scale affordable grid connected PV project, “PV front-runner”, was officially connected to the grid in Golmud, Qinghai, with a total installed capacity of 500 MW. Work has begun on three solar energy storage projects in Clark County and Storey County, Nevada, which will build 555 MW PV plants and 800 MWh battery storage systems. The above policies make the proportion of PV access to the network increase rapidly.

With the increased proportion of grid-connected PV, how to improve the trust of operational and scheduling personnel on large-scale PV power generation forecasting results and effectively utilize PV power generation forecasting information, how to cope with the possibility of instability of power grid with the integration of large-scale PV generation, and how to further improve the consumption of large-scale PV power generation are the key issues nowadays for engineers and researchers of renewable power systems.

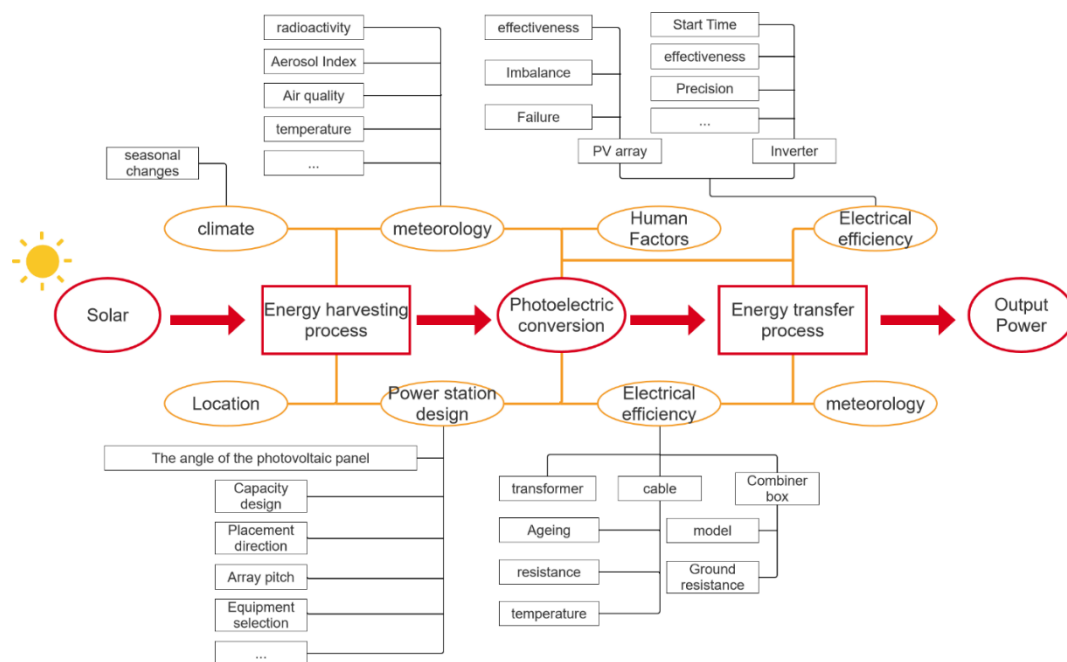
There are some previous reviews with also a wide range, but most of them only focused on a specific aspect of the key operational issues on the integration of large-scale solar power generation, such as advanced forecasting methods [4], or impacts of grid integration of PV and electric vehicle (EV) on energy economics [5]. Therefore, this paper presents a comprehensive review of the state-of-the-art techniques to integration of large-scale solar power generation, and the following aspects are discussed emphatically: (1) this paper comprehensively expounds the research on forecasting techniques of PV power generation output. Firstly, the state-of-the-art development forecasting techniques of PV power system are reviewed, and the main factors affecting the solar power output of the system are analyzed. Then, the prediction methods are sorted and classified according to the forecasting time frame, and the evaluation indexes of the prediction effect are summarized and commented on. Finally, according to the current status and development trend of the PV industry, the future research direction of PV power prediction is discussed. (2) In view of the new challenge brought by the integration of high proportion solar generation to the frequency stability of power grid, this paper analyzes the influence mechanism between them and introduces the current technical route of PV power generation participating in system frequency regulation. At the end of this section, combined with the actual demand of the development of power grid and PV power generation, the problems that need further attention in the future are prospected. (3) This section reviews the feasible measures that facilitates the inter-regional and wide-area consumption of intermittent solar power generation. For example, at the distribution level, the inter-regional consumption of solar power can be achieved through the coordinated scheduling of PV power generation and electric vehicle charging and battery-swapping infrastructure. Based on the research background of PV charging and swapping station for electric vehicles, this paper analyzes the basic principles of collaborative scheduling of PV power supplies and energy storage devices. Then, the dynamic programming theoretical model of collaborative scheduling is discussed and the effectiveness of cooperative scheduling strategy is evaluated. In view of the electric market mechanism, the trans-provincial transaction mechanism based on the balancing of whole network is established to break the barrier of the wide-area consumption of intermittent solar power. This paper not only has certain reference value to solve the problems caused

by grid-connected large-scale PV generation, but also promotes the application and development of large-scale PV generation system to a certain extent.

The paper is organized as follows: the various factors that affect the actual output of PV power station and the output characteristics of PV power are summarized in Section 2. Section 3 comprehensively expounds the research results of PV power generation forecasting technology based on different classification standards, summarizes the forecasting performance in different applications, and concludes the focus of PV generation forecasting technology in the future. Section 4 presents the technical route and different ways of PV power generation participating in system frequency regulation from the aspects of primary frequency regulation, frequency regulation by installing energy storage system, frequency regulation by demand side management technology, and frequency regulation by virtual synchronous generator technology. Promising research directions of PV power generation frequency regulation technology are given. Section 5 summarizes the study on improving the absorption of intermittent PV generation and reducing the PV generation curtailment locally and through wide-area balancing mechanisms. Section 6 summarizes and concludes the paper.

## 2. Factors Affecting the Generation and Efficiency of PV Generation Systems

PV power stations convert solar energy into electrical energy and feeds it into the power grid through three coupling processes, including solar energy collection, photoelectric conversion, and electrical energy transmission. There are many factors that affect the operation and efficiency of the PV plants [6], which are mainly divided into physical factors, external environmental factors, and human related factors [7], such as scheduling constraints and operation maintenance [8]. The detail is given in Figure 1.



**Figure 1.** Influencing factors of PV generation.

The physical factors involve: (1) generation efficiency, including the efficiency of PV modules, convergence boxes, cables, and other equipment, (2) electrical characteristics of the primary equipment in the power station, and (3) the type of PV modules.

External environmental factors refer to meteorology, climate, and geographical factors, and affect PV generation differently in different environments. The climatic conditions of a region are the comprehensive performance of general atmospheric status and weather process of a long time scale, which determines the grade of solar resources; specific meteorological conditions such as cloudy or less cloudy conditions mainly affect the short-term fluctuation frequency of PV power, therefore, the short-term fluctuation of

PV power is more frequent under cloudy weather. Taking the above factors into consideration, the total PV array conversion efficiency is about 10–15% when the irradiance of sunny day is greater than 400 W/m<sup>2</sup> [9].

In addition, human factors will also have a certain impact on the PV station's output power.

The above-mentioned factors determine that the PV generations systems have the following characteristics:

- (1) Strong diurnal and seasonal periodicity. As solar irradiance and ambient temperature are the principal environmental factors affecting the performance of PV modules, the PV power generation shows strong diurnal and seasonal periodicity.
- (2) Strong volatility and randomness, which is due to (1) the gradual decrease in PV power generation efficiency because of dust coverage and aging of PV module equipment; (2) the rapid change of PV output due to frequent bird passing and cloud cover; (3) the frequent abnormal climate change in recent years.

### 3. PV Power Forecasting Techniques

The predictability and controllability of conventional power generation are of great importance to maintain the system's supply–demand balance and stability under disturbance [10]. However, the output power of a PV system dynamically changes with time due to the variability of available solar resources [11]. Its curtailment, although some extent of control is obtained, damages the operating economy and runs counter to the vision of green power [12]. Accurate forecasting of the generation of a PV system can reduce the impact of the uncertainty in the generation of a PV system on the grid, maintain power quality, and increase the accommodation capability of the power grid with the PV's integration; therefore, it is always challenging but non-negligible for researchers and engineers at this moment and in the future.

#### 3.1. Classification of Forecasting Models and Forecasting Methods

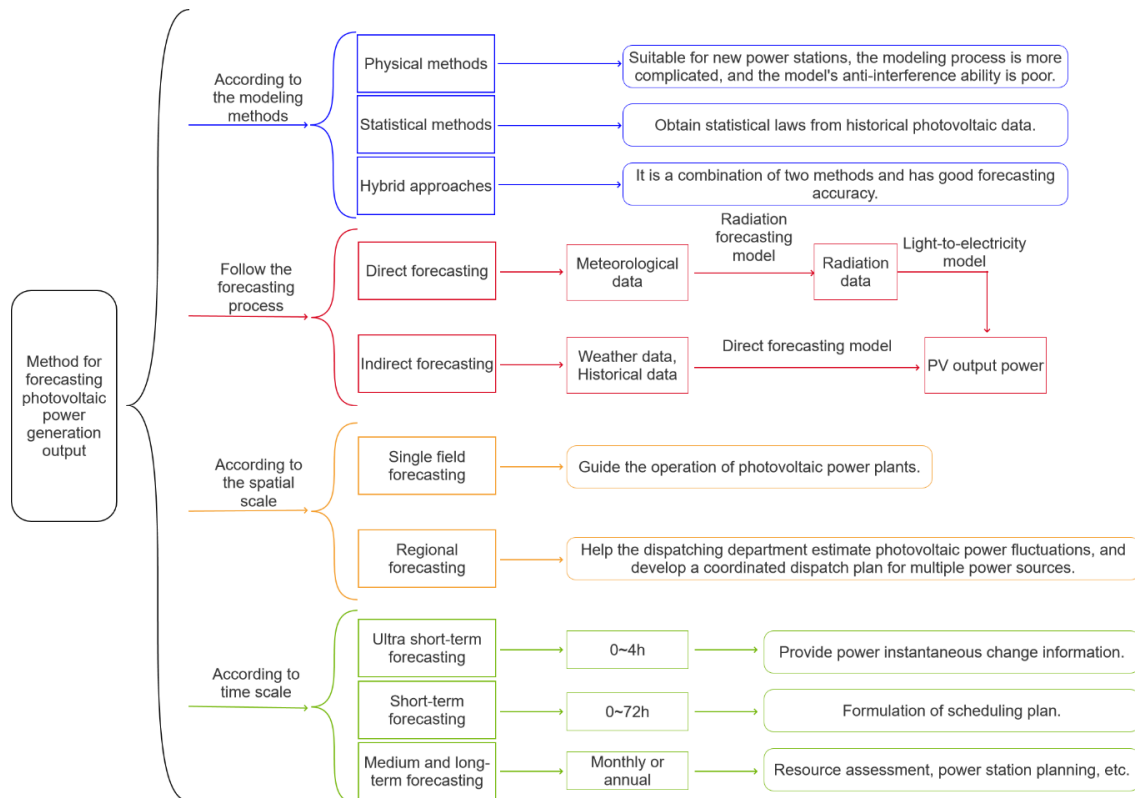
Different classification standards make the PV power generation forecasting methods classified in the following ways: (1) physical modeling method, data-driven method, and hybrid method according to different modeling methods; (2) direct forecasting and indirect forecasting according to different forecasting targets [13]; (3) single field forecasting and regional forecasting according to spatial scales [14]; (4) ultra-short term forecasting (0–4 h), short term forecasting (0–72 h) and mid-long term forecasting (1 month–1 year) according to different forecasting time scales. The forecasting of different time scales has its specific application. As given in Figure 2, the ultra-short-term forecasting result are used by dispatching management and for setting real-time electricity prices. Short-term horizons are adopted in optimizing the daily generation schedule of conventional power sources, adjusting maintenance schedules, load following, and day-ahead power markets. Medium and long-term horizon provides information for the planning of new PV plants and the evaluation of solar resources.

##### 3.1.1. Forecasting Techniques Based on Modeling Methods

###### Physical Modeling Forecasting Methods

Forecasting by a physical modeling method relies on the modeling of the conversion process from solar energy to electric energy. The improvement of forecasting accuracy depends on weather forecasting with higher temporal–spatial resolution, and more accurate photoelectric conversion models [15]. The advantage of the physical modeling method is that it does not require a large amount of historical data for the training of the forecasting model [16]. Therefore, it is a suitable method for newly built PV power station. The shortcoming is that it is difficult to simulate the impact of environmental conditions and operation time on the photoelectric conversion, such as dust cover, influence of rain and snow, and the deterioration of module's parameters. The model does not have enough robustness, unless all possible influencing factors are physically modeled. Meanwhile, due to

the requirement for some parameters and expensive equipment (such as solar simulator, thermal controlled test stage, environmental and reliability, etc.), the implementation of physical models is generally difficult, as these are not always available in many areas of the world.



**Figure 2.** Classification of forecasting methods for PV power output.

### Statistical Modeling Forecasting Methods

Data-driven forecasting methods refers to forecasting based on the processing of historical measured data of weather conditions, solar resources, or PV generations. It includes forecasting techniques based on statistical methods and forecasting by machine learning and artificial intelligence methods.

- Statistical or probabilistic method based on the statistical laws between the inputs and outputs of the forecasting model

The forecasting accuracy relies on the volume of historical data. The modelling does not need to consider the complex photoelectric conversion process; therefore, knowledge of multiple curricula is not necessary [17]. Common statistical methods include time series method [18], regression analysis method [19], grey theory [20], fuzzy theory [21], and spatial-temporal correlation method [22]. Attempts were tried in order to deal with the non-linearity in the forecasting process; for example, seasonal time series ensemble are treated specially for PV forecasting in [23].

- Advanced methods based on artificial intelligence and machine learning

These methods [24] include K nearest neighbor (KNN), support vector machine (SVM), artificial neural networks (ANNs), extreme learning machine (ELM), etc. These methods are data-driven methods and do not require information of the generation systems. In this way, it is similar to the statistical approaches. They are applied in conditions when historical and real-time measurements of the PV generation system are available, and basically are used for short-term applications [25]. For a detailed review please go to [26].

## Hybrid Forecasting Approaches

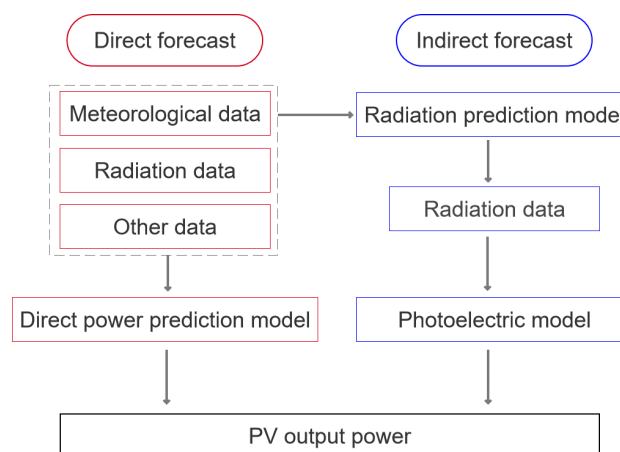
Hybrid approaches are performed with the physical method and one or several statistical approaches [27]. This type of technique usually presents a better forecasting accuracy as they benefit from the combination of two well-performing techniques [28].

### 3.1.2. Single Field Forecasting Method and Regional Forecasting Method

Single field forecasting refers to the forecasting of a single PV power station, which only provides power forecasting information of a single PV power station for power generation operators or the owner of the PV station, and it is mainly used for the optimized operation of PV plants and control of PV power generation, while regional forecasting refers to the forecasting of the total output of multiple PV plants in a certain region, which can provide PV output value within the region for grid operators, help the power dispatching department to estimate the PV power fluctuations, and formulate multiple power coordinated dispatch plans.

### 3.1.3. Direct Forecasting Method and Indirect Forecasting Method

The direct forecasting method directly performs power forecasting based on the historical data of PV generation, while the indirect forecasting method firstly predicts the solar irradiance received by the ground or PV panels, and then predicts the PV power. The flow chart of the two forecasting methods is shown in Figure 3.



**Figure 3.** Flow chart of direct and indirect forecasting methods.

Obviously, the direct forecasting method is difficult in modelling, and the change of mapping relation in different time scales and working conditions may cause model performance degradation or even failure. The indirect forecasting method may require the establishment of multiple forecasting models during the entire forecasting process, which is more complicated.

### 3.1.4. Ultra-Short-Term and Short-Term Forecasting Methods

Ultra-short-term and short-term forecasting are of great importance because their performances are closely related to the economic and safe operation of the power system.

#### Ultra-Short-Term Forecasting Methods

The methods of ultra-short-term forecasting of PV power include basic forecasting method, cloud images-based forecasting method and data-driven forecasting method. This part mainly introduces the first two kinds of methods.



- Basic forecasting method

The basic forecasting methods include a continuous forecasting method and clear sky forecasting method. The former assumes that the weather, radiation, and other conditions at the forecasting time are consistent with the current time, and the extrapolation method is used to forecast the PV output power. The latter is used under clear sky condition when the irradiance is taken advantage to the greatest extent by the photo-electric conversion devices, and the fluctuation of PV power is small. Therefore, it is often used as the basic calibration model. The main clear sky model include Bird and Hulstrom model, and Ineichen model. The above two basic forecasting models are suitable when historical data are partial missing or with poor quality. Because the fluctuation and randomness of irradiance cannot be considered, the forecasting accuracy of the models is low, and the forecasting effect is worse when the weather conditions change dramatically or the forecast time scale is long.

- Cloud images-based forecasting methods

Cloud moving and shading of buildings are the main reasons for the volatility and uncertainty of radiation intensity and PV output power. Therefore, the forecasting of PV generation based on cloud images is an important research direction. Commonly used cloud images are ground-based cloud images and meteorological satellite cloud images from sky imager and satellite. Image processing is needed to identify cloud clusters, predict cloud cluster movement, form cloud index maps, and predict cloud cluster occlusion through methods such as block matching technology and cross-correlation algorithms, etc. Table 1 compares the two forecasting methods based on satellite cloud images or ground-based cloud images.

Peng et al. proposed a model for short-term solar irradiance prediction through the proposed 3D cloud detecting and tracking (D&T) system based on multiple total sky imagers (TSIs). The resolution of the D&T system are pixel-level. The above model improved all irradiance forecasts by at least 26% in 1 to 15 min compared with the persistent model [29].

Fei et al. [29] improved the traditional Fourier phase correlation theory (FPCT) method, and proposed an image-phase-shift-invariance (IPSI) based cloud motion displacement vectors (CMDVs) calculation method. The accuracy and reliability under different circumstances is superior to the gray scale information-based methods, and it overcomes the shortcoming of the original FPCT method [30].

In addition, a single independent model can obtain considerable forecasting effects to some extent, but it also inevitably loses some important information of the data itself. Ensemble methods are presented to enhance their accuracy and to solve the weakness of individual methods [31]. The ensemble model has more advantages in data interpretation and fitting forecasting. At present, ensemble forecasting methods are mainly classified into two categories: competitive ensemble forecasting and cooperative ensemble forecasting. The competitive ensemble forecasting model uses multiple forecasting factors with different weights to build an integrated forecasting model. Ref. [32] proposed a model based on Hilbert Huang Transform (HHT), Improved Empirical Mode Decomposition (IEMD), feature selection, and Support Vector Regression (SVR). The forecasting performance is improved to some extent, but modal aliasing problem still exists. Cooperative ensemble forecasting method decomposes the historical PV data into multiple subsequences, and then use different forecasting methods to predict the subsequences, respectively, and finally, the PV power generation output forecasting is obtained by superposition of the predicted values of the subsequences [33].

**Table 1.** A comparison between satellite images based and sky images based forecasting models [34].

Forecasting Methods	Spatial Resolution	Temporal Resolution	Temporal Scale	Update Frequency	Space Range	Application Time
Satellite Images [35]	2.5/km <sup>2</sup>	30.0/min	6/h	Low	Big	Early
Ground-based Images	1.0/km <sup>2</sup>	0.5/min	0–0.5/h	High	Small	Late

## Short-Term Forecasting Methods

The main algorithms used for short term irradiance and PV power forecasting are as follows:

- ANN

ANN has the characteristics of distributed parallel processing, nonlinear mapping, and strong robustness. It has self-learning, self-organization, and self-adaptation capabilities, and is suitable for solving some random nonlinear problems. At present, based on the neural network algorithm, many researchers adapt to the actual forecasting problems by establishing the combination model, optimizing the structure of input neurons, and improving the internal algorithm of the network [36]. In addition, some scholars use back propagation neural networks (BPNN) [37], feedback neural networks, and self-organizing neural networks [38], etc., to predict the output of PV power generation.

A high-precision neural network forecasting model requires high-precision input data [39]. When the samples are complex and scattered, the neural network may not be able to effectively learn the rules between input and output, resulting in low forecasting accuracy. At the same time, the algorithm has the defects of over learning and easy to fall into the local optimal solution.

- Classification regression algorithm

Based on the periodicity and regularity of PV power, the classification regression algorithm firstly establishes the characteristic index system, divides the data samples, obtains the similar daily samples, then establishes the forecasting model according to the characteristics of the samples, and uses the sample training model with high similarity with the predicted target period to carry out the forecasting. Support vector machines (SVR/SVM) [40] and decision trees (Classification and Regression Tree, CART) [41] are typical representatives of classification and regression algorithms. The establishment of a classification feature index system is the key to this kind of method, and there is still a lack of in-depth research in this aspect. Literature [42] uses the SVM method based on the weather classification model to forecast the short-term PV generation, and finds that SVM performs well in small sample scale; while the data sample is large enough, the forecasting accuracy is difficult to satisfy the requirements.

- Time series algorithm

The time series algorithm can be used for both short-term and ultra-short-term PV power forecasting, and it is applicable to the case of low requirement for forecasting accuracy and insignificant weather change [43]. Literature [44] studies the short-term (1 h) statistical time series forecasting method, and proposes a multivariable forecasting model combining different meteorological variables, which achieves good forecasting effect with the help of Long Short-Term Memory (LSTM) unit.

- Random forest (RF) Algorithm

RF is a statistical learning theory, which firstly draws multiple samples through re-sampling method, then builds a decision tree, and finally combines multiple decision trees to predict the result. It has a strong tolerance for outliers and noise, and is not prone to overfitting problems [45]. Literature [46] selects factors of the forecasting model based on RF sequencing of feature factors and eliminates factors that have less influence on PV generation, thus simplifying the model and improving the accuracy of forecasting.

- Probability forecasting algorithm

The probability forecasting method can give the value of all possible PV power generation and the probability of its occurrence at the next moment. It has a significant advantage in the forecasting accuracy and provides an important reference for the operation risk assessment and risk decision-making of the power system containing PV plants [47]. Literature [48] applies the probabilistic method combining the bootstrap method and the quantile regression method to the hybrid intelligent model for output power prediction, which effectively quantifies the uncertainty of PV power.



- Combination forecasting algorithm

This kind of algorithm can integrate the advantages of various forecasting methods and improve the forecasting accuracy to a certain extent, which is one of the research hotspots [26]. In [49], the hybrid method of clear sky model or ANN has been verified in actual PV plant. Literature [39] combines satellite imagery with ANN, using a minimum number of input variables to forecast PV output. As a result, the normalized root mean square error under all sky conditions is less than 26%, achieving high forecasting accuracy.

### 3.2. Metrics Assessment of PV Power Forecasting Techniques

Appropriate error indicators are of great significance to evaluate the rationality and reliability of the prediction results. For different prediction methods, the accuracy index of prediction can be used to judge the advantages and disadvantages of prediction methods. Generally, the accuracy of solar forecasting is quantified by solar irradiance in terms of  $W/m^2$ , while the error of output of PV station is quantified by kW.

The unified and effective prediction accuracy evaluation index is conducive to the comparison of different research results. The commonly used forecasting and evaluation indexes are presented in Table 2.

**Table 2.** Metrics assessment of solar PV power forecasting techniques.

Statistical Indicators	Computational Formula	Implication and Application
Mean Square Error (MSE) [50]	$MSE = \frac{1}{N} \sum_i^N (W_{fore} - W_{meas})^2$ where $W_{fore}$ , $W_{meas}$ refer to the forecasted PV power at each time point, the measured PV power at each time point, respectively. $N$ is the number of data sample for the time scale.	MSE is the expected value of the squared difference between the predicted values and the measured values, which evaluates the variation degree of data. The smaller MSE value is, the better accuracy the prediction model has in describing experimental data.
Root Mean Square Error (RMSE) [51]	$RMSE = \sqrt{\frac{1}{N} \sum_i^N (W_{fore} - W_{meas})^2}$	RMSE is the arithmetic square root of MSE. RMSE measures the deviation between the forecasted values and the measured values.
Mean Absolute Error (MAE) [52]	$MAE = \frac{1}{N} \sum_i^N  W_{fore} - W_{meas} $	MAE is the average distance between the forecasted values and the measured values, which is suitable for reflecting the actual situation of the forecasted value errors.
Mean Absolute Percentage Error (MAPE) [53]	$MAPE = \frac{1}{N} \sum_i^N \frac{ W_{fore} - W_{meas} }{W_{meas}} \times 100\%$	MAPE is used to assess uniform prediction errors.
cvMAE, cvMBE [54]	$cvMAE = \frac{MAE}{W_{mean}}, cvMBE = \frac{MBE}{W_{mean}}$ Where $W_{mean}$ indicates the mean of measured PV power.	cvMAE and cvMBE are proposed to evaluate market models that penalize the hourly or daily energy error.
Mean Bias Error (MBE) [54]	$MBE = \frac{1}{N} \sum_i^N (W_{fore} - W_{meas})$	MBE is appropriate to evaluate the forecast bias.
Correlation Coefficient [43]	$r = \frac{cov(W_{fore} - W_{meas})^2}{var(W_{fore})}$	The metric studies the degree of linear correlation between actual values and forecasted values
Standard Deviation Error (SDE) [47]	$SDE = \sqrt{\frac{1}{N} \sum_{i=1}^N (W_{fore} - W_{meas} - MBE)^2}$	SDE measures the dispersion of the error.
Pearson's correlation coefficient [43]	$(\rho) = \frac{cov(\hat{\rho}, \rho)}{\sigma(\hat{\rho})\sigma(\rho)}$ where $\rho$ and $\hat{\rho}$ define the actual and forecasted solar output, respectively.	The metric measures the correlation between two parameters or two groups of data, the greater the value is, the better the forecasting effect is.
Maximum absolute error (MaxAE) [47]	$MaxAE = \max( W_{fore} - W_{meas} )$	MaxAE indicates the biggest forecasting error and affects the economic operation of power grid.
Mean Absolute Scaled Error (MASE) [55]	$MASE = \frac{MAE}{(\frac{1}{N-1}) \sum_{i=1}^N  W_{meas,i} - W_{meas,i-1} }$	The small values of MASE indicate good forecasting effect.
Brier Score (BS) [56]	$BS = \frac{1}{N} \sum_{i=1}^N (p_n - o_n)^2$ where $p_n$ and $o_n$ represent the predicted probability of the occurrence and observation of category, respectively; $N$ is known as the total number of the $(p_n, o_n)$ pairs.	BS is developed for probabilistic analysis, which is applicable to measures the distinction between the distribution of predicted probability and actual occurrences. Generally, the smaller the BS value, the better the performance of the forecasting model.

The most recent research on PV power are reported in Table 3.

**Table 3.** Recent papers on PV power forecasting.

Author (Year)	Forecast Horizon	Direct Forecasting/Indirect Forecasting	Forecasting Model	Forecast Error
Zhu et al. (2015) [57]	1 d ahead	Direct forecasting	Hybrid model: ANN-wavelet decomposition (WD)	RMSE = 7.193%–19.663%
Li et al., (2016) [58]	24-h ahead	Direct forecasting	Multivariate Adaptive Regression Splines (MARS)	Testing data: RMSE = 119.0 MAD = 89.8 MAPE = 69.2%
Sanjari et al. (2017) [59]	15-min ahead	Direct forecasting	Higher-order Markov Chain	Average value of MAE is 2.18%
Mahmou et al. (2017) [60]	1 h ahead	Direct forecasting	Deep LSTM network	RMSE = 82.15
Hossain et al. (2017) [61]	Day ahead; 1-h ahead	Direct forecasting	ELM algorithm	Day ahead: RMSE = 13.83–21.84%(training) RMSE = 17.89–35.39%(testing) 1-h ahead: RMSE = 55.32–89.55%(training) RMSE = 54.96–90.1%(testing)
Al-Dahidi (2018) [62]	24 h ahead	Direct forecasting	ELM-ANN	MAE = 1.08%
Liu et al. (2018) [63]	1 h ahead	Indirect forecasting	SVM and ANN	MRE = 11.61%
Han et al. (2019) [64]	Few hours interval	Direct forecasting	ELM	MAE = 2.13%
Lee et al. (2019) [65]	1 h ahead	Direct forecasting	RNN-LSTM DNN	MAE = 0.23%
Yao et al. (2019) [66]	1 h ahead	Direct forecasting	ESN	MAPE = −0.00195%
Wang et al. 2020 [67]	10 min ahead	Indirect forecasting	BPNN-SVM-ARIMA	Blocky clouds: MAPE = 22.66%; RMSE = 92.72; MBE = −1.26% Thin clouds: MAPE = 20.44%; RMSE = 132.15; MBE = −1.06% Thick clouds: MAPE = 18.82%; RMSE = 120.78; MBE = −0.98%
Mei et al. (2020) [68]	1 d ahead	Direct forecasting	LSTM-QRA	MAE = 34.89

#### 4. Frequency Regulation of System with Large-Scale PV Power Generation

A PV power station working under the maximum power point tracking (MPPT) strategy often does not have the ability to respond to frequency regulation orders. The drastic fluctuation of PV array output caused by weather change will be mitigated by adjusting the output of conventional generators, which directly affects the economic operation of conventional generators. Frequency instability caused by insufficient frequency regulation capacity under the integration of large-scale PVs will be inevitable if no further measures are taken.

The primary frequency regulation is differential regulation, which can only adapt to mitigate the load variation with small amplitude for a short period of time. For large-scale grid connected PV power generation, it is necessary to deal with the system frequency fluctuation caused by PV power fluctuation through the secondary frequency regulation by conventional units in the power system. If the secondary regulation fails to meet the needs caused by PV power fluctuation, the greater the PV active power change rate, the greater the system frequency deviation, which further deepens the degree of system frequency deviation. With the increasing penetration of PV generation, the system's inertia is further reduced, and the frequency stability of the system is seriously threatened. Therefore, it is necessary to study the frequency regulation mechanism and potentials of the power system with the integration of large-scale PV generations.

#### 4.1. The Primary Frequency Regulation

By controlling the actual working voltage of the PV array to be slightly higher than the voltage at strategy of maximum power tracking point, PV system does not operate under maximum generation status, and the PV system is able to respond to system's frequency regulation commands at any time [69]. Ref. [70] proposes a control strategy based on power–frequency function to smooth the frequency deviation of a high permeability PV power generation system. In [71], aiming at the limitation of frequency regulation of droop control strategy with fixed coefficient, different methods are adopted to adjust droop control parameters in two-stage PV grid connected system under over-frequency and low-frequency modes, so as to give full play to the frequency regulation ability of PV. Reference [72] studies the primary frequency regulation control strategy based on the frequency drop of PV power frequency static characteristics, which eliminates the energy storage system and reduces the cost in the PV power generation system.

The above-mentioned literature studies the primary frequency regulation characteristics of PV systems from a similar perspective of conventional units. Since a PV system uses different generation technology from that of conventional units, in order to maximize the frequency support capability of the PV generation system, the impact of other constraints such as reserve capacity and conventional primary frequency regulation on the PV system's frequency regulation capability should also be considered. For this reason, reference [73] analyzes the operational characteristics of PV under two different regulation modes, meaning PV's participating in frequency regulation alone and PV's participating in frequency regulation together with conventional units.

The volatility and uncontrollability of PV output increases the difficulty and complexity of PV systems participating in system frequency regulation. How to realize the optimal dynamic matching between the control parameters of PV power-frequency characteristics and the reserve capacity, so that the PV system can effectively participate in the system frequency regulation and reasonably share the frequency regulation pressure of conventional generators, remains to be further studied. In addition, when the PV system is considered in the frequency regulation, the withdrawal of the PV power station from the primary frequency regulation due to weather condition may cause frequency instability due to the lack of enough rotary reserve, and this issue needs to be studied.

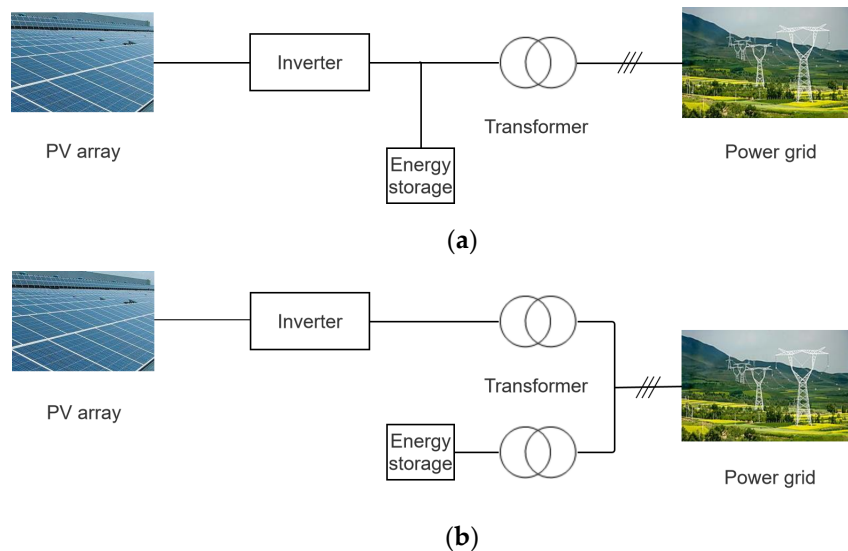
#### 4.2. Additional Energy Storage System Participates in System Frequency Regulation

Energy storage system (ESS) has the advantages of fast response speed, two-way regulation, and high regulation accuracy, which can effectively suppress the random fluctuation of the power output of renewable generation systems [74], and is suitable for providing frequency regulation service. The comparison of frequency regulation characteristics between energy storage unit and conventional unit is shown in Table 4.

**Table 4.** Comparison of frequency regulation characteristics between battery energy storage system and conventional unit.

Frequency Regulation Equipment	Frequency Regulation Characteristics
Thermal power unit	The adjustment speed is slow, the accuracy is low, and the adjustment output is limited. Frequent frequency adjustment of the unit will reduce the utilization rate of thermal power units, accelerate equipment wear, increase maintenance costs, and increase coal consumption [75].
hydropower unit	The adjustment speed is fast, the adjustment range is large, the frequency adjustment effect is better than the thermal power unit, there is the problem of unit wear, and the adjustment is limited by region and season [76].
energy storage unit	The response is fast and accurate, the capacity is adjustable, and it does not directly produce pollutants [77]. The frequency adjustment effect is 1.7 times that of hydropower units, 2.5 times that of gas-fired units, and more than 20 times that of coal-fired units [78].

PV stations equipped with energy storage devices can use the ESS to rapidly release or absorb electric power [79], so as to smooth the PV output power curve and reduce the impact of the fluctuation of active power on system frequency and ultimately assist traditional units to improve the overall frequency regulation capability of the grid [80]. At present, ESS' integration can be divided into two ways: Direct Current (DC) side access and Alternating Current (AC) side access. At the AC side, the integration is divided into low-voltage side access and high-voltage side access, as shown in Figure 4.



**Figure 4.** Schematic of PV-energy storage system: (a) PV energy storage system configured on the AC low-voltage side; (b) PV energy storage system configured on the AC high voltage side.

The configuration of additional EES in PV station for frequency regulation increases the operating cost of PV power station and reduces the economy of system operation. Therefore, it is necessary to comprehensively evaluate the reliability, safety, and economy of system operation to seek the optimal capacity configuration scheme. Reference [81] proposes the battery energy storage system (BESS) and PV parallel model to mitigate the negative impact of PV access on the distribution network in terms of load change rate, frequency, and voltage fluctuation, but the configuration cost is not considered. Reference [82] determines the goal of PV fluctuation mitigation by analyzing the ramping characteristics of PV power generation, and establishes an energy storage optimization model aiming at the optimal economic performance of the system in combination with the power generation capacity and load demand of the system. Most of the existing optimal configuration models for ESS adopt mathematical modeling. With the continuous improvement of the power market, the uncertainty factors of demand response in different scenarios increase the difficulty of mathematical modeling. Therefore, it is necessary to further study the impact of demand response on the optimal configuration of energy storage systems under the environment of power market.

#### 4.3. Demand Side Management (DSM) Technology Participates in System Frequency Regulation

The production, transmission, distribution, and consumption of electric energy are carried out simultaneously, and the system frequency is not only affected by the fluctuation of large-scale PV output, but also affected by the fluctuation of load. Therefore, in addition to installing the ESS on the generation side to smooth the PV output fluctuation, it is also feasible to pay attention to demand side management (DSM). DSM dynamically balances the system by adjusting the load demand in the power system, which also contributes to system frequency stability.

Since DSM are in distribution level, study of DSM's participating in frequency regulation mainly focuses on the distribution level. Reference [83] discusses the feasibility to use demand response (DR) to follow the variation of PV generation in low-voltage distribution network, and proposes

a centralized model predictive control algorithm, which is used to calculate the optimal hourly DR. The precise control of the output provides a primary frequency adjustment function for the power grid, effectively suppressing the frequency fluctuation of the power grid. Reference [84] added a DR control loop to the microgrid in the conventional load frequency control model to balance the power between generation and consumption and stabilized the frequency by using a certain proportion of the available response load auxiliary control.

#### 4.4. Virtual Synchronous Generator Technology

Virtual synchronous generator (VSG) technology enables PV systems to have an external characteristic similar to conventional units by controlling interface inverter and realizes active frequency regulation control. It is becoming one of the effective schemes to improve the stability of the system with the integration of large-scale PV grid-connected [85]. In [86], with the help of solar-storage virtual synchronous generator technology, the integrated renewable generation system is basically equivalent to the synchronous generator physically and mathematically. Reference [87] studies the proportional control of DC link capacitor voltage and grid frequency variation to realize system frequency regulation. Reference [88] introduces adaptive virtual inertial control into a PV array, which makes the PV array have the ability to provide virtual inertial response similar to conventional units, and successfully realizes a reasonable power sharing among PV arrays.

### 5. Research on Promoting PV Power Consumption

In 2018, wind power curtailment in China reached 27.7 billion kWh, while PV power curtailment rate reached 5.49 billion kWh. In Xinjiang and Gansu, which are rich in renewable energy resources, the wind curtailment reached 23% and 19%, respectively, and the solar curtailment was 16% and 10%, respectively [89].

Consumption of large amounts of PV generation is not only a matter of planning, but also a problem of coordination between source, grid, and demand. At present, in China, there is an imbalance between the development of generation systems and the development of power consumption, and the latter determines the consumption space, which leads to the problem of how to share the benefits between renewable generation system and traditional thermal, hydro, and nuclear generation system.

Therefore, how to consume PV in an effective way is of great research significance for improving the accommodation capacity of the power system for PV generation, and is also the hotspot in PV system related research in recent years. Based on the existing research, this paper will review the PV consumption measures through operational strategy and cross-region consumption by market mechanism.

#### 5.1. Operation Strategy

##### 5.1.1. The Strategy of Incorporating Renewable Energy into the Day-Ahead Generation Scheduling

Along with the increase in wind power and PV power generation integrated into power system, challenges are brought to the active power scheduling of the grid.

The traditional method of the optimal scheduling of renewable energy is to minimize the generation cost with consideration of the forecasted renewable generation under specific scenarios. The priority is given to the renewable generation units due to the lowest generation cost. The adjustable conventional fossil fuel power plants take the responsibility of load following and frequency restoration that could be needed in real time operation.

The main problem is how to minimize the deviation of forecasted base case and real-time, for the deviation will cause the increase in operational cost [90] and sometimes cause reliability issues [91]. Study [92] shows that the predictability of renewable generation and the reliability of the system is increasing when the renewable generation is balancing across a wider area, and the correlation of wind generation and solar generation is considered. Reference [93] proved by their study that the variation



of wind and PV generation present complementary characteristics. This correlation is modeled by Copula theory in [94] in the proposed stochastic coordinated scheduling model.

### 5.1.2. The Strategy of Incorporating Renewable Energy Generation into Reserve

The inclusion of intermittent renewable energy into the reserve capacity has a promoting effect on the consumption of renewable generation, but the difficulty of renewable generation's forecasting and strong volatility restrict its reliability as a reserve. Therefore, with a higher integration proportion of PV and wind generation, how to balance the power supply and renewable energy consumption, and scientifically arrange the reserve capacity, have become a problem worth studying.

In recent years, some researchers have carried out relevant studies on reserve optimization of power systems with a high proportion of renewable energy. Considering the uncertainty of the system load forecasting and wind power forecasting, a general model for calculating reserve demand of power system was proposed in [95]. Optimal spinning reserve capacity of power grid considering the relevance of renewable energy sources was studied by Nataf Transform in [96]. Through the cost–benefit analysis, an optimal spinning reserve capacity allocation model is proposed. In [97], an expression of the system's reliability is derived and considered as part of the objective function by taking the generator failure rate, load, and wind energy forecasting errors into account to quantify the reserve capacity system required. The above literature has conducted in-depth studies on the backup optimization of power system with high proportion renewable energy from different aspects. However, the renewable generation is, in general, not considered as reserve capacities.

In the actual scheduling operation of a power grid, there are two common methods for renewable energy to be included into reserve: (1) the probability distribution of the renewable generation is obtained by statistical analysis of the historical output of renewable energy, and then the output of renewable energy is included into the reserve following a certain reliability requirement on its generation. This method does not consider the real-time prediction of the renewable generation, but only uses the statistical law obtained from historical data, and a fixed value of generation is considered into the reserve. The method tends to be conservative. (2) the probability distribution of the forecasting error is obtained through the statistical analysis of the forecasting error of renewable generation, then the confidence interval of the predicted value is obtained, and the renewable generation is considered in the reserve according to the lower boundary of the confidence interval. This method does not consider the impact of load forecasting bias. Therefore, although the impact of renewable energy forecasting bias is considered, the total risk of load loss is not controllable [98]. Based on the above analysis, literature [99] analyzed the influence of reserve on power grid scheduling and operation from the aspects of power grid security and renewable energy consumption. Based on the error analysis of load and renewable energy forecasting, a method of considering renewable energy into reserve with regard to the risk of load loss was proposed. Aiming at maximizing the consumption of renewable energy, a flexible standby mechanism was put forward, which considered both the safety of power grid and the consumption of renewable energy.

### 5.1.3. The Strategy of Renewable Energy Participating in Grid Depth Peak Regulation

The integration of large-scale renewable energy has brought great pressure on the peak shaving of thermal power units in specific periods of time, for it reduces the output space of thermal power units. The conventional way of peak shaving by thermal power units cannot mitigate the generation fluctuation due to the increase in the installed capacity of wind power and solar power, and the reduction in renewable energy generation due to the lack of peak regulation capacity from thermal power units will lead to a waste of resources. The shortage of peak regulation resources not only restrains the capacity of clean energy consumption, but also adversely affects the economy of power grid operation and flexibility of peak load regulation. Therefore, the impact of deep peak regulation operation of the power grid system under the integration of large-scale renewable energy need to be excavated to quantify the direct correlation between renewable energy consumption and units' peak regulation operation



indicators. With an understanding of this correlation, the optimal operation strategy of power grid units can be further studied and analyzed.

Reference [100], aimed at a regional power grid in East China, proposed an optimal strategy for the configuration of peak-regulating power supply according to the characteristics of regional power supply structure, configuration strategy of peak-regulating power, DC links and inter-regional peak-regulating capacity.

Energy storage system provides a certain degree of flexibility related to peak regulation. The application of a hybrid storage system by a new type of liquid compressed air energy storage and electrochemical storage installed in a wind farm is studied in [101]. By optimal operation of the integrated energy storage system and wind farm, the operational economy of the wind farm can be effectively improved; therefore, the accommodation of wind power into the system is improved. In [102], the coordinated operation of hydropower and renewable energy in a provincial power grid is explored to alleviate fluctuation and aid peak regulating. Furthermore, the distribution of forecasted error of wind and solar power is analyzed with kernel density estimation. Then, based on the principles of using hydropower to compensate for fluctuating wind and solar power, a day-ahead peak regulating model with an objective of minimizing peak-valley difference is built, which introduces chance constraints for forecast errors and coordinates hydropower operation with wind and solar power.

#### 5.1.4. The Consumption Improvement through the Coordination of Renewable Energy and Load

Developing renewable energy and vigorously promoting electric vehicles (EV) have become important ways to ensure energy security, energy conservation and emission reduction in the world. In the future, the charging demand of large-scale EVs will bring a large amount of load growth to the distribution network, which will cause the negative impact on the distribution network, such as the intensification of peak and valley load difference and line overload [103]. Adopting the quick charging station of EV with PV power generation, the complementary characteristics of EV charging load and PV output can be utilized to absorb as much PV power as possible to reduce consumption pressure. As a new type of energy storage device, the coordinated scheduling of EV and PV has become a research hotspot for scholars all over the world. At present, the research on joint scheduling of EV and renewable energy mainly focuses on the premise of large-scale grid connection of distributed clean energy such as wind generation and PV generation, making full use of the controllability of EV's battery, and regulating the charging of EV by means of demand side management such as price policy stimulation, so as to improve the spatial and temporal distribution of load, increase the utilization rate of clean energy and ensure the stability of power grid to operate effectively.

Reference [104] analyzes the charging stations equipped with energy storage equipment and PV power generation devices, classifies charging users according to their sensitivity to charging prices, and proposes different satisfaction functions for each category. Then, it is solved according to the non-cooperative Stackelberg game. Reference [105] also analyzes the charging station equipped with PV power generation and energy storage equipment. Under the background of implementing time-of-use tariffs in power grid, aiming at minimizing the sum of power purchase cost, PV power generation energy cost and charge-discharge loss cost of energy storage device, the corresponding energy management strategy is proposed and solved based on linear programming. In [106], a stochastic model of conditional value at Risk (CVaR) is established based on the market risk brought by the randomness of EV charging load and electricity trading price. Under the random environment, the benefits and risks of renewable energy participating in market transactions can be effectively controlled.

Taking PV power as the main body, the PV-equipped charging station is constructed and the intelligent energy scheduling of the charging station is carried out, so that the generation curve of clean energy and the EV's charging curve can be effectively matched; therefore, the operation of distributed clean energy can be effectively combined with operation of the EV's charging station. In this way, the energy transmission loss as well as the operation and maintenance costs can be reduced, and the effective consumption of PV power generation is promoted. Meantime, from the perspective of

the power grid, the coordination of PV's generation and EV's charging behavior can reduce the volatility on both the power generation and electricity consumption side, and relieve the pressure of peak regulation and frequency regulation.

### 5.2. Cross-Regional Consumption of Renewable Generation

Cross-regional consumption becomes a feasible solution to accommodate the increasing amount of volatile renewable generations due to the following reasons: (1) with the rapid development of renewable energy and the insufficiency of local consumption, the inter provincial, transnational, and even transcontinental power grid interconnection need to be implemented to improve the flexibility of the power system by taking advantage of the spatial-temporal complementary characteristics of power sources and loads in different regions and countries; (2) Under the background of global energy Internet, the interconnection of transnational power grids has opened up new possibility to contribute to mitigate the imbalance of regional economic development, such scenarios are mainly reflected in the cross-border interconnection of China's Xinjiang and Central Asia power grids: Xinjiang wind power has the characteristics of large installed capacity, being far away from the load center and suffering high rate of power curtailment, which hinders the efficient utilization and further development of clean energy; however, the slow growth of power generation in Central Asian countries cannot meet the needs of rapid social and economic development, and the supply gap of power demand will continue to grow in the future. Therefore, reasonable and feasible interconnection framework from the planning level should be studied to reduce the curtailment of wind and solar generation and find room for the accommodation of newly installed renewable energy units in the future.

With the upsurge of global energy Internet, the cross-regional absorption of renewable energy has aroused the research enthusiasm of many scholars. Taking the development of interconnection among Gulf countries (Kuwait, Saudi Arabia, Bahrain, Qatar, and Oman) as an example, literature [107] introduces the establishment of GCC interconnection bureau, cost-sharing and financing and other problems that must be solved during the initial construction of power grid interconnection. By analyzing the correlation between the maturity value of key transmission technologies and the development status of power grids, literature [108] illustrates that regional power grid interconnection will be the inevitable trend of power grids in the future. Literature [109] takes the inter-regional interconnection of power grids in Arab countries as an example, proving that inter-regional consumption of power grids can significantly improve economic benefits and environmental costs. Literature [110] proposes a statistical method to evaluate the voltage distribution changes of the whole system before and after large-scale power network interconnection, which can effectively estimate the dynamic stability and economy after power network interconnection.

Aiming at gaining the maximum profit, literature [111] uses stochastic production simulation method to establish the probabilistic model of the outgoing of wind-coal-fired combined generation. Literature [112] establishes a cross-regional consumption model of renewable energy based on the sequential production simulation method.

Foreign countries generally combine renewable energy with other types of power supply to achieve the effect of energy saving and emission reduction through power trading in a larger region and market. The current situation of China's resources and economic development also requires renewable energy to be consumed across different regions and provinces in order to realize the optimization of resource allocation. In the process of electricity marketization in China, it is also necessary to innovate and establish a trans-regional and trans-provincial market consumption mechanism that adapts to the characteristics of renewable energy generation, encourage end users to purchase green electricity generated by renewable energy through marketization, gradually break down the barriers of trans-regional and trans-provincial market, and promote the consumption of renewable energy in a wider range. Zhou et al. [113] studied the trans-provincial consumption and compensation mechanism of clean energy based on generation right transaction, and presented the operation characteristics of the market by constructing the intelligent agent simulation model. Aiming at the problem of

“wind and PV power curtailment” in Northwest China, Zheng et al. [114] established a cross-provincial generation right trading revenue model based on the minimum coal consumption and pollutant emission. Li et al. [115] analyzed the allowable installed capacity of wind generation of the Northeast regional power grid of China and the external economic influence of wind power trans-provincial consumption, then proposed a model to realize middle-long term wind power transaction through trans-provincial generation right transaction. In order to promote the development of clean energy and its optimal allocation, Gao et al. [116] proposed a new trading mechanism of transferring provincial base-charge electricity through cross-regional generation right trading.

In conclusion, to facilitate the development of renewable energy, policy makers, researchers, and engineers should take measures from the side of power supply, power grid, end users, and market simultaneously. Comprehensive implementing policies are needed.

## 6. Conclusions and Future Research Topics

Due to climate change and global warming in recent years, grid-connected solar power generation has become a research hotspot. This paper mainly focuses on how to improve the trust of operation personnel in large-scale solar power generation forecasting and effectively use solar power forecasting information, how to deal with the stability of power grids with the integration of large-scale solar generation, and how to further improve the consumption of large-scale solar power generation.

### 6.1. Conclusions

In light of detailed overview presented in this paper, the main contents are summarized as follows:

- It summarizes the various influencing factors of solar power generation and summarizes the power characteristics of solar power generation; based on different classification standards, it comprehensively expounds the research results of solar power generation prediction technology.
- From the aspects of primary frequency regulation, additional energy storage systems participating in system frequency regulation, demand-side management technology participating in system frequency regulation, and virtual synchronous generator technology, the technical route of current solar power generation participating in system frequency adjustment is introduced, combined with the current grid and solar power generation.
- Critical issues to facilitate the accommodation of large amount of intermittent solar power generation are introduced, including the inclusion of renewable energy into the day-ahead dispatch plan, the inclusion of renewable energy into the system's reserve capacity, the deep peak regulation strategy of the grid, the mining of source-load coordination, and the cross-regional absorption of renewable energy.

### 6.2. Future Research Topics

By comprehensively reviewing the state-of-the-art technologies of large-scale solar power integration, the research prospect and future development direction of these subjects are further discussed.

#### 6.2.1. Future Research Topics of PV Generation Forecasting Technology

- Monitoring the data quality from the measurement and transmission stage, selecting more reliable transmission protocols, and utilizing the data pretreatment technology to eliminate abnormal data and reconstruct the missing data set in order to improve the credibility of the input data.
- Conducting the evaluation and analysis of various models. Defining and identifying extreme weather conditions, and therefore determining the accurate prediction models for those weather conditions.
- Excavating new evaluation indicators, and building a more practical evaluation index system, to improve the prediction performance.
- Establishing forecasting model with updating capabilities.

### 6.2.2. Future Research Tasks of PV Generation Participate in System Frequency Regulation

- In view of the current power grid development pattern and the requirements of renewable energy consumption, the rapid PV frequency response under the complex and large power grid structure such as ultra-high voltage (UHV) AC–DC hybrid connection is further studied in the coordinated operation strategy of conventional units, DC system frequency regulation, and demand-side load management in the system.
- Considering the constraints of PV operation conditions, performance of various types of ESS, frequency regulation requirements of the system, and optimal operation efficiency under different weather conditions, the operation modes of different types of energy storage assisted PV frequency regulation under disturbance scenarios such as system failure and load switching require further study. Then, it is necessary to propose the optimal energy storage selection scheme and system parameter configuration principle, and improve the coordination mechanism and control strategy of energy storage assisted renewable power system.
- Comprehensively considering the factors such as frequency regulation demand, VSG grid-connected stability, fault suppression, multi-machine parallel operation, and operation economy, the influence of system control parameters on the performance of VSG needs to be further clarified, and the coordinated optimization control strategy among VSGs and between VSG and conventional units needs to be put forward.
- A data service platform that supports PV participating in frequency regulation and stable operation of power grid is needed by making full use of advanced information technologies including big data, cloud computing, edge computing, etc.

### 6.2.3. To Facilitate the Development of Renewable Energy, the Specific Measures Are as Follows

- On the power supply side: emphasizing the construction of flexible capacity, increasing the proportion of flexible power supply such as pumped storage and gas turbine, promoting the transformation of peak regulation capacity of thermal power units, and improving the peak regulation depth of thermal units.
- On the power grid side: speeding up the construction of trans regional and trans provincial transmissions, expanding the scope of renewable energy allocation, and giving full play to the allocation and balance capacity of larger power grids.
- On the users' side: utilizing the market method to guide the users to participate in peak-frequency regulation and respond to the change of renewable energy output actively.
- On the market side: improving the compensation mechanism for peak shifting of thermal power, speeding up the construction of a unified national power market, and building a price mechanism and renewable energy quota system that are conducive to break inter-provincial barriers and promoting the consumption of clean energy across regions and provinces.

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### Nomenclature

#### Acronyms

PV	photovoltaic
IRENA	International Renewable Energy Agency
EV	electric vehicle
KNN	K Nearest Neighbor
SVM	Support Vector Machine

*Acronyms*

ANN	Artificial Neural Network
ELM	Extreme Learning Machine
D&T	Detecting and Tracking
TSIs	Total sky imagers
FPCT	Fourier Phase Correlation Theory
CMDVs	Cloud Motion Displacement Vectors
HHT	Hilbert Huang Transform
IEMD	Improved Empirical Mode Decomposition
SVR	Support Vector Regression
BPNN	Back Propagation Neural Network
CART	Classification and Regression Tree
LSTM	Long Short-Term Memory
RF	Random Forest
MSE	Mean Square Error
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MBE	Mean Bias Error
SDE	Standard Deviation Error
MaxAE	Maximum Absolute Error
MASE	Mean Absolute Scaled Error
BS	Brier Score
WD	Wavelet Decomposition
MARS	Multivariate Adaptive Regression Splines
MR-ESN	echo state network
ARIMA	Autoregressive Integrated Moving Average
QRA	Quantile Regression Averaging
MPPT	Maximum Power Point Tracking
ESS	Energy Storage System
DC	Direct Current
AC	Alternating Current
BESS	Battery Energy Storage System
DSM	Demand Side Management
DR	demand response
VSG	Virtual Synchronous Generator
UHV	ultra-high voltage
CVaR	conditional value at Risk
GCC	Gulf Cooperation Council

*Parameters and Variables*

$W_{\text{fore}}$	the forecasted PV power at each time point
$W_{\text{meas}}$	the measured PV power at each time point
$N$	the number of data sample for the time scale.
$W_{\text{mean}}$	the mean of measured PV power
$r$	Correlation Coefficient
$\rho$	the actual solar output
$\hat{\rho}$	the forecasted solar output
$p_n$	the predicted probability of the occurrence
$o_n$	the predicted probability of the observation
$M$	the total number of the $(p_n, o_n)$ pairs

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