Forecasting Power Output of Photovoltaic Systems Based on Weather Classification and Support Vector Machines

Jie Shi, Wei-Jen Lee, *Fellow, IEEE*, Yongqian Liu, Yongping Yang, and Peng Wang

***Abstract*—Due to the growing demand on renewable energy, photovoltaic (PV) generation systems have increased considerably in recent years. However, the power output of PV systems is affected by different weather conditions. Accurate forecasting of PV power output is important for system reliability and promoting large-scale PV deployment. This paper proposes algorithms to forecast power output of PV systems based upon weather classification and support vector machines (SVM). In the process, the weather conditions are divided into four types which are clear sky, cloudy day, foggy day, and rainy day. In this paper, a one-day-ahead PV power output forecasting model for a single station is derived based on the weather forecasting data, actual historical power output data, and the principle of SVM. After applying it into a PV station in China (the capability is 20 kW), results show the proposed forecasting model for grid-connected PV systems is effective and promising.**

***Index Terms*—Forecasting, photovoltaic cell radiation effects, photovoltaic systems, support vector machine (SVM), weather classification.**

I. Introduction

SINCE IT is inexhaustible, clean, and safe, solar energy is one of the most desirable green energies among many of the renewable energy resources. The solar energy resources are abundant in China. According to statistical record, the Tibet and southeast of the Qing-Zang altiplano are situated in the highest irradiation zone of solar energy where the annual hours of sunlight are more than 3200 h and the annual irradiation amount is approximately 6600–8500 MJ/m^2[1]. The annual hours of better irradiation zone are about 3000 h–3200 h, and the annual irradiation amount is about 5800–6600 MJ/m^2. The available zone for PV installation is about 2200 h–3000 h, and the annual irradiation amount is about 5000–5800 MJ/m^2[1]. Therefore, the solar energy in the vast area of China has a significant development potential. Recently, photovoltaic (PV) technology has been improved significantly, and its application crosses different aspects of our lives. In the past 30 years, the cost of per kWh output from PV has dropped to about 1 RMB/kWh (US$0.15/kWh) with the potential to go down even further. In China, the domestic PV power market is undergoing a profound change with the shift from an independent power generation system in the remote area to a large-scale grid-connected generation system. Since the early 1990s, the Chinese PV generation market has steadily developed with an annual growth rate of about 20%. As shown in Fig. 1, there is a significant increment between 2009 and 2010E (2010 Estimation) [18]. The newly total installed PV in China grew 140% to nearly 900 megawatts in 2010 [19].

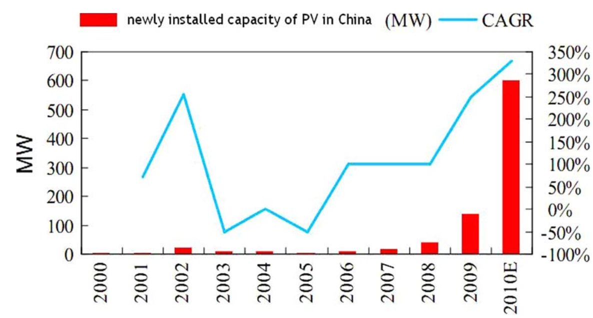

Fig. 1. Annual installation capacity of PV in China (2000–2010E, CAGR: Capacity Annual Growth Rate).

The new installed capacity in 2009 in China was 160 MW, which was about three times of the installed capacity in 2008. The total installed capacity was 486 MW in 2009 [2]. It can clearly be seen that the integrated PV system will grow rapidly due to its simple structure, short installation period, and preferential government policy. Similar to wind power, PV systems are sensitive to random and uncontrollable climate changes. Accurate forecasting of PV power output can reduce the impact of PV output uncertainty on the grid, improve system reliability, maintain power quality, and increase the penetration level of PV systems. Much research has been devoted in this area, and estimation algorithms on solar radiation have improved precision. However, the PV power output forecasting technology at present is still on a theoretical exploration stage. Several

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technologies, such as satellite cloud, numerical weather predictions (NWP), have been adopted in PV output forecasting. The errors of short-term PV power output forecasting are in the range of $10 \sim 20\%$. However, in the morning, evening, or under rainy weather conditions, the forecasting precision is lower, and sometimes the relative mean square error (RMSE) can be higher than 50%.

Generally speaking, there are two frequently used approaches for PV output forecasting: one is based on the sunshine intensity method (indirect methods), and the other one is based on the system output (direct methods). Researchers have been doing research of forecasting sunshine intensity for a long time and have obtained many achievements, which have been widely applied in agricultural production, construction, PV power generation, and other fields. In recent years, with the development of synchronous meteorological satellites and NWP technology, new methods are able to apply satellite cloud graphs or NWP technology into meteorological analysis models and take random factors such as clouds as the model input [3]–[6]. However, if a big deviation exists in the transformation algorithm, it would degrade the accuracy on the prediction of solar radiation intensity. [7] established four kinds of ARMA methods with different time intervals to verify which ARMA model can reflect the correlation of the existing data and the accuracy of short term solar radiation forecasting. Time series forecasting methods are suitable for linear system, while for nonlinear systems, it is difficult to find a proper parameter estimation method. There are many factors affecting sunshine intensity, which is typically a nonlinear problem. [8] built the sunshine intensity neural networks model by using measurement data along with the radiation mean value, air temperature mean value, and date as input values to predict one-day-ahead hourly sunshine intensity. The forecasting results show that the overcast forecasting error was larger than the sunny weather forecasting error. [9] selected back-propagation artificial neural network (ANN), and [10] applied a support vector machine (SVM) method to build a forecasting model that produced a forecasting error between 10% and 20%.

At present, the main challenge of PV output forecast system is the relative poor prediction accuracy in the short forecasting time scale. To overcome these deficiencies, this paper presents a novel PV forecasting model using historical data and weather report information in the forecasting process.

In this paper, after analyzing PV system power output characteristics and the influential factors on forecasting accuracy, a SVM model based on the weather classification is established. The PV system output forecasting characteristics are demonstrated in Section II, followed by SVM principle in Section III. The modeling process and forecasting results are presented in Section IV.

II. Photovoltaic System Power Output Characteristics

Attributing to many meteorological factors, PV power output is unsteady and difficult to control. The power output from the instrument fluctuates along with the intensity of solar radiation, which has random affections based on the season and the geographical location. In addition, the radiation has a closed relationship with weather, solar hour angle, observation date, time and clouds [11]. Because of meteorological uncertainties, the PV output power also has strong cyclical characteristics including the daytime cycle and yearly cycle. The PV output power generation is usually available from 8:00 am to 5:00 pm. It will cause fluctuation to the grid when integrating unsteady and periodic PV power into the grid.

In addition, the temperature of the PV affects the conversion efficiency. PV systems have negative efficiency coefficients. Higher temperature will reduce the conversion efficiency. The temperature inside PV systems is normally higher than the environment temperature. To simplify the prediction process, we make the assumption that two temperatures are the same. If the temperature at P time moment is T_p, then conversation efficiency of the PV system can be expressed as follows:

$$\eta = \eta_0 \left[1 - \gamma(T_p - T_\gamma)\right] \tag{1}$$

where T_γ is the reference temperature (298 K); η_0 is the conversion efficiency under the reference temperature; γ is the temperature coefficient of solar batteries where the value is normally between 0.003 $^\circ\mathrm{C}^{-1}$ and 0.005 $^\circ\mathrm{C}^{-1}$[14]. The power generation from PV is proportional to the solar radiation, and the power output at t moment is shown as follows:

$$P = I \times A \times \eta \tag{2}$$

where A is the PV area, m^2; η is the rating conversion efficiency; I is radiation intensity of the PV inclined plane, ($\mathrm{kW/m}^2$).

If there are n pieces of PVs working at t moment, the total power output is nP.

III. Support Vector Machine

SVM is a general learning method developed from Statistical Learning Theory with better performance than many other routine methods. Statistical Learning Theory is based on a set of rigid theory foundation that provides a united frame in order to solve the problem of limited sample learning. The basic idea of SVM applied to regression prediction is described as follows [16][17]:

For a given observations sample set: $P(x, y)$, (x_1, y_1), $(x_2, y_2), \ldots, (x_n, y_x) \in R^n \times R$. It is assumed that the regression function is: $F = \{f | f(x) = \omega^T \cdot x + b, w \in R^n\}$. We can introduce the structure risk function

$$R_{\mathrm{reg}} = \frac{1}{2}\|\omega\|^2 + C \cdot R_{\mathrm{emp}}[f] \tag{3}$$

where $\|\omega\|^2$ is the describing function; $f(\cdot)$ is the complexity term; C is a constant which determines the tradeoff between the empirical risk and the model complexity.

To construct the optimal hyperplane in the case where the data is linearly inseparable, the main idea of nonlinear support vector regression is to map the input vector x into high-dimensional feature space by using a nonlinear mapping process and then perform linear regression in the feature space. In this higher space, there is a greater possibility that the data can be linearly separated. Then, the problem can be described as

$$\min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}\xi_i \tag{4}$$

subject to

$$y_i\left(\omega \cdot \phi(x_i) + b\right) \geq 1 - \xi_i, \quad \xi \geq 0, i = 1, \ldots, C > 0.$$

The inner products $\phi(x_i)$ in the high-dimensional space can be replaced by some special kernel functions $K(x_i, x_j)$.All the necessary computations can be performed directly in input space by calculation kernels. The popular kernels are shown as follows:

radial basis function (RBF) kernel

$$K(x, x_i) = \exp\left(-\gamma\|x - x_i\|^2\right) \tag{5}$$

polynomial kernel

$$K(x, x_i) = (1 + x \cdot x_i)^d \tag{6}$$

where d is the degree of polynomial kernel, γ is a constant determining the width of RBF kernel.

Different learning machines with arbitrary types of decision surfaces can be constructed by using various kind of kernel functions $K(x_i, x_j)$.

In actual application, the kernel function has the influence on realized effect. It is important to select a proper kernel function to optimize the kernel function solution. As is mentioned above, polynomial kernel function, RBF kernel function, and sigmoid function are three commonly selected methods for the kernel function [12], [21].

IV. Photovoltaic Power Output Forecasting Model Based on Weather Classification

Since there are various factors affecting the PV output power, it is difficult to figure out the tendency with a single model. Based on the unsteady, periodic characteristics and the nonlinear relationship between power outputs and affecting factors, we present SVM model for forecasting PV power output. In this paper, the PV system power output is classified into four types according to weather condition, which is cloudy, foggy, sunny, and rainy. The same type data can be applied to the SVM model for training. Based on the weather report of the next day, the weather type and condition are selected, after which the related SVM forecasting model is chosen to forecasting the one-day-ahead power output.

A. Data

For the research objective in this paper, the radiation angle and location of PV are fixed. Therefore, this information is blended in the historical power output data, with higher self-correlation than the indirect forecasting method. In this paper, the PV power system in south China is applied as the sample system. The test time period is from 2010-01-13 to 2010-10-29. The data interval is 15 min, which is the requirement of grid in China. The daily radiation time is from 6:00 A.M. to 8:00 P.M. Fig. 2 shows the generation power in 6 days. All the days are sunny in this time period, so the solar radiation is mainly the same. From this figure, we can see that there is a high correlation between power outputs every day.

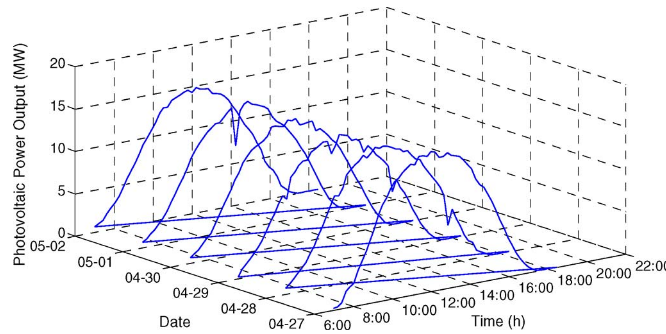

Fig. 2. Daily photovoltaic system power output generation in 6 days.

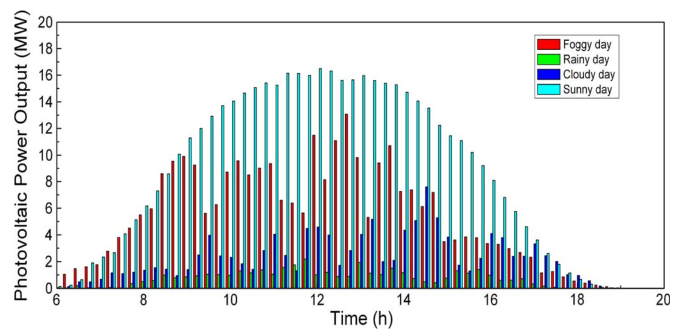

Fig. 3. Photovoltaic system power output under different weather conditions.

The solar radiation plays a significant role in PV power output forecasting, and the quantity of cloud layers affects the radiation to a certain extent. Fig. 3 shows the power output data in PV system in different days under four weather types. From Figs. 2 and 3, it is obvious that the power output varies greatly under different weather conditions, while matching weather conditions have a similar trend. This observation indicates the forecasting model should be based on weather classifications.

B. Data Preprocessing

The model input data is the historical PV power output from 0 to rated power. SVM is a nonlinear model that maps the nonlinear model input to a higher space to make it linear. Data with wider range will generate imprecise data fitting and cause the regression to reduce precision. If the data is preprocessed into a smaller range before it is inputted into the model, the precision can be increased. One of the well-known solutions is normalization, by which the data can be restricted within the range between 0 and 1 to minimize the regression error, improve precision, and maintain correlation among data set. The process formula is shown as follows [13]:

$$P_n = \frac{p_n - p_{\min}}{p_{\max} - p_{\min}} \tag{7}$$

where, P_n is the original input data; $P_{\min}$ and $P_{\max}$ are the minimum and maximum input data.

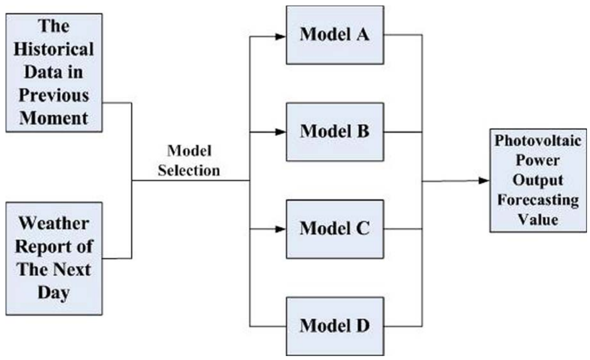

Fig. 4. Flow chart of photovoltaic power output forecasting.

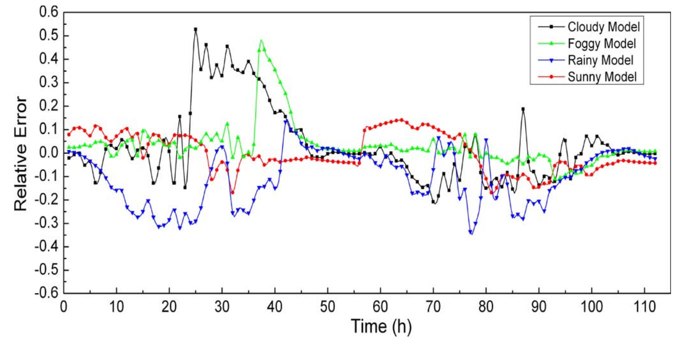

Fig. 5. Relative errors of four forecasting models using testing data.

C. Support Vector Machine Model

The SVM is an effective nonlinear artificial intelligence model. In comparison with ANN, SVM has better calculating speed and good convergence results and will not be trapped into local minimum values. Although there are many factors that affect the result, there is a strong correlation between inputs that belong to the same weather condition as the output power data. In this paper, based on the advantages and the characteristics of SVM of PV systems, the short-term PV power output model is established through the following steps.

a) The historical model data samples are classified into four groups based on the historical weather condition: sunny day, foggy day, rainy day, and cloudy day;
b) In each group, according to the preprocessing normalization method, the data samples which include training data and testing data are created;
c) Global variables in SVM are defined as P1 and C. P1 is the width of the kernel function and C is a coefficient. Both variables are given an idiographic data range; in general, the range of P1 is (1, 10) while the range of C is (1, 10) according to model setting experience;
d) The RBF function, which is frequently used to establish the model, is selected to be the kernel function in this paper where the insensitive coefficient ε is defined as 0.005;
e) After antinormalization of the forecasting data, four SVM PV power forecasting models are set up to deal with different weather conditions.

The four models are named as A, B, C, D in the following flow chart of PV output power forecasting as shown in Fig. 4. After forecasting the next day weather, one of the four models is selected. Using the data sample obtained from the selected model, the one-day-ahead output value can be obtained.

D. Forecasting Accuracy Evaluation

The historical data of PV output power, which has a 15-min interval and varies according to various weather conditions, is utilized in this paper to forecast the one-day-ahead mean power output. Mean relative error (MRE) and root mean square error (RMSE) as shown below will be used to evaluate the forecasting accuracy

$$\mathrm{MRE} = \frac{1}{N}\sum_{t=1}^{N}\frac{W_{\text{forecasting}} - W_{\text{true}}}{W_{\text{total}}} \times 100\% \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(W_{\text{forecasting}} - W_{\text{true}})^2}{N}} \tag{9}$$

where, $W_{\text{forecasting}}$ is the forecasting result at each time point; W_{true} is the historical data at each time point; W_{total} is the PV installation capacity. For the case in this paper, the value is 20 MW; t is the time variable; N is the data sample scale, which stands for the time scale in this paper.

E. Forecasting Result and Discussion

As mentioned above, the forecasting models are defined and trained, respectively, to obtain the best forecasting result. For each model, the input data set include 15-min-interval historical PV output power from the nearest day with the same day type, the maximum temperature, the minimum temperature, and the average temperature of the next day from a local weather report. The model output is the PV output power forecasting results of the next day with a 15-min interval. The data period is from 2010-01-13 to 2010-10-29. After model training and testing, the forecasting results of the four models are shown in Fig. 5. Based upon the 24-h-ahead weather report, we know the next day's weather condition in advance. The historical output data from the nearest day with the same weather condition as the forecasting day are utilized in the model input. In addition, the parameters and settings of the related model type are applied to obtain the forecasting results.

From Table I, it can be seen that the four models, particularly the Sunny Model, perform well in PV power output forecasting. The average forecasting precision for one-day ahead is 2.10 MW in RMSE and 8.64% in MRE, which are fewer than the previous study [15]. In addition, the results satisfy the industrial requirements, which the short-term PV forecasting RMSE should be less than 20% [20]. However, for each individual model, the forecasting errors fluctuate, which are shown in the relative errors in Fig. 5.

Given the testing data, after selecting the model type based on the weather report of the next day, the forecasting output

TABLE I
SUMMARY OF FORECASTING RESULTS ERRORS OF RMSE AND MRE

Model Classification	RMSE (MW)	MRE (%)
Cloudy model (Model A)	1.824	12.42
Foggy model (Model B)	2.52	8.16
Rainy model (Model C)	2.48	9.12
Sunny model (Model D)	1.57	4.85
Average Value	2.10	8.64

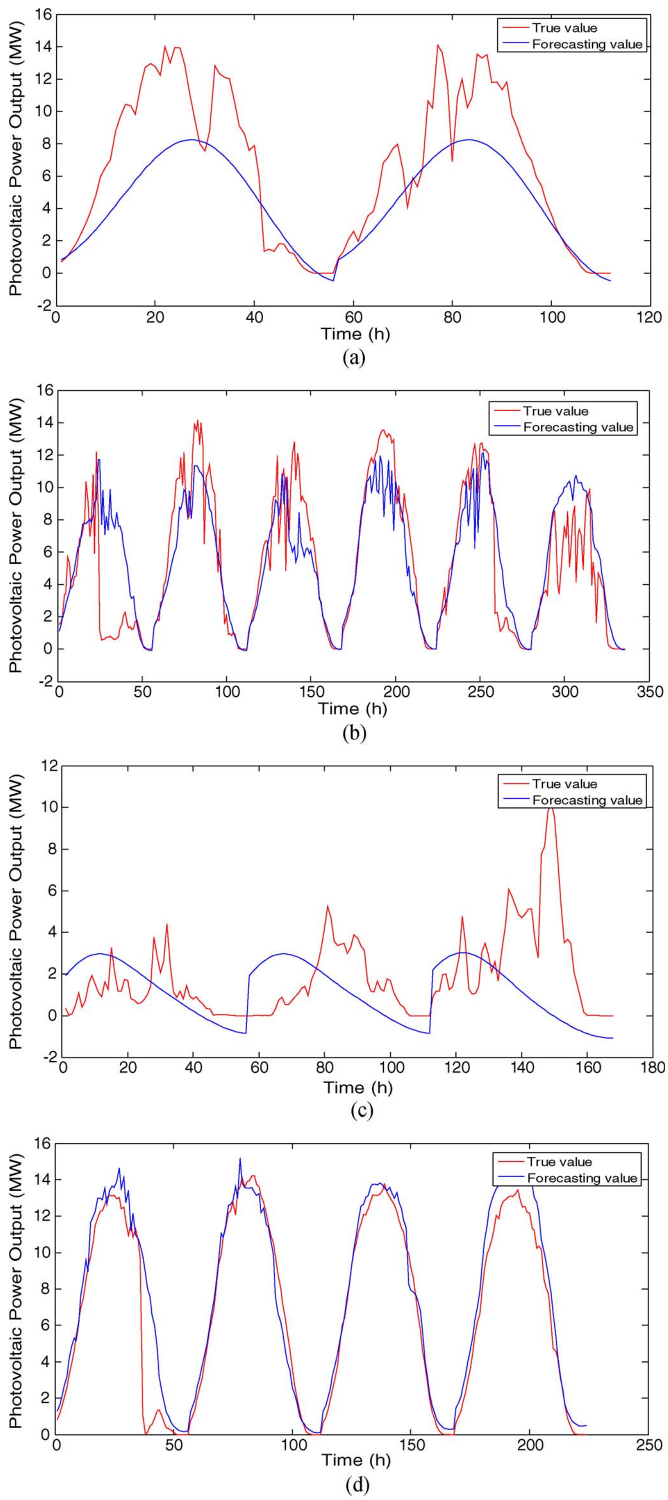

Fig. 6. Results of SVM models for photovoltaic power forecasting: (a) cloudy day, (b) foggy day, (c) rainy day, and (d) sunny day.

data can be obtained after the training process. The relative error between measurement data and forecasting data at the same time moment (the same length of data sample) is shown in Fig. 5. Among the four models, the errors range from 50% to −39%. Generally speaking, the Sunny Model performs the best with a mean value of 4.85%, following which are the Foggy Model, the Rainy Model, and the Cloudy Model with the mean value of 8.16%, 9.12%, and 12.42%, respectively. The following graphs demonstrate the forecasting results and measurement data for the whole year according to different weather conditions.

From Fig. 6, we can see that the Foggy Model and the Sunny Model outperform other models. For (a) and (c), there are significant differences between the historical and forecasting values. Since the weather report utilized in this paper comes from the same source, the differences are mainly attributed to the weather variation patterns and their change rate. In this case study, the PV system is located in south China where the sunny and foggy days are present during most of the year. SVM is a nonlinear model which needs large amount of data for fitting and regression. The parameters of the model also play a pivotal role in forecasting precision. According to the above models, research should be carried out to further study methods such as enlarging data sample size, enhancing the algorithm, and optimizing model parameters.

V. CONCLUSION

This paper presented a novel model for one-day-ahead PV power output forecasting based on the principle of SVM and the characteristic of weather classification.

a) Based upon correlation analysis, the time series of PV power output data in the test period are classified into four groups based on the local weather report.
b) Four SVM models are set up according to algorithm principle and data samples characteristics including maximum, minimum, and mean temperature of different weather classification. After the case study, the forecasting errors of the proposed model are 2.10 MW (RMSE) and 8.64% (MRE), for the sample PV installation. The approach shows promising results for the application of SVM model in PV power output forecasting.

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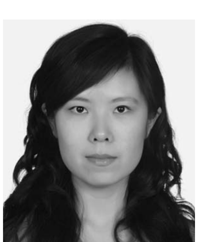

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