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Day-ahead Hourly Photovoltaic Generation Forecasting using Extreme Learning Machine

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***Abstract*—The photovoltaic (PV) generation systems as environmentally friendly renewable energy sources are increasing. However, the power generation of solar has high uncertainty and intermittency and brings significant challenges to power system operators. The accurate forecasting of photovoltaic (PV) power production is good for both the grid and individual smart homes. In this paper, we propose a novel weather-based photovoltaic generation forecasting approach using extreme learning machine (ELM) for 1-day ahead hourly forecasting of PV power output. In the proposed approach, the weather conditions are divided into three types which are sunny day, cloudy day, and rainy day and training the PV power output forecasting models separately for those three weather types. In this paper, we take the PV output history data from the PV experiment system located in Shanghai for case study. The forecasting results show that the proposed model outperform the BP neural networks model in all three weather types.**

Keywords—BP Neural Networks; Day-ahead; Photovoltaic; Forecasting; Extreme Learning Machine

I. INTRODUCTION

In order to supply the increasing demand for electricity, one key goal for the grid is to substantially increase the penetration of environmentally-friendly renewable energy sources, such as wind and solar [1]. The installed capacity of solar photovoltaic (PV) generation has increased rapidly in recent years. In the United States, 3313 MW of solar PV was installed in 2012, an increase of 76% compared to the previous year, taking the cumulative solar PV installed capacity to 7.2 GW [2]. The power generation of solar is weather dependent, which has high uncertainty and intermittency and brings significant challenges to power system operators. The accurate forecasting of PV power production is good for both the grid and individual smart homes. The grid can use the forecasting data to schedule generators in advance. The smart homes can use the forecasting data to plan their consumption patterns to save electricity costs.

The PV generation forecasting approaches can be classified into three categories, that is Numerical Weather Prediction (NWP)-based forecasting approach, data-driven statistical approach and hybrid approach [2]. NWP-based forecasting approach was discussed in [3], which uses the first principles for predicting solar irradiance and PV generation. Data-driven statistical approach includes auto regression (AR)-based models [4] and computational intelligence tools such as artificial neural networks (ANNs) [5]. The third approach is a hybrid one, which combines the NWP-based and data-driven models [6]. Based on different time horizons, PV generation forecasting methodologies can also be classified into short term forecasting (from minutes-ahead up to days ahead), long term forecasting (weeks ahead up to months ahead).

Hammer, A. et al. proposed a PV output forecasting method which uses information about cloud movement in the local area for very short-term horizons from satellite images in the forecasting process [7]. This can improve the forecasting accuracy in some degree. However, in order to operationalize such forecasting method, the satellite images must be available in almost real-time, which is costly.

Jie Shi et al. proposed a one-day-ahead PV power output forecasting model for a single station, which is based on the weather forecasting data, actual historical power output data, and the principle of SVM [8]. A radial basis function neural network (RBFNN) model is utilized to predict the output characteristic of a commercial PV module in [5]. But, both SVM and RBFNN models have high-computational complexity and require large training data for the network.

A two-staged PV output forecasting method was proposed in [9], which predict the meteorological conditions such as solar radiation, air mass, temperature and wind spped firstly, and then predict the PV output through the parameterized models with the meteorological conditions forecasted in the first stage. For this forecasting method, a detailed characterization of all the influencing parameters that interact with the conversion of solar radiation into AC electricity need to be carried out, which increase complexity of the forecasting system.

The extreme learning machine (ELM) algorithm was proposed by Huang G-B et al for single-hidden layer feed forward neural networks (SLFN) [10, 11]. The learning speed of ELM can be thousands of times faster than traditional feed forward network learning algorithms like back-propagation algorithm while obtaining better generalization performance [10]. Over the past few years, ELM has been applied in many fields [12, 13]. ELM was

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used for the reconstruction and prediction of wind speed series in [14], which can obtain good results in terms of accuracy, within an extreme fast computation time.

The forecasting framework presented in this paper addresses the short-term horizon. The prediction accuracy in the short forecasting time scale is relative low at present. To overcome these drawbacks, we propose a day-ahead hourly photovoltaic generation forecasting method using ELM. In this proposed model both historical data and weather report information are used in the forecasting process. For arbitrary one day, each hour has a SLFN to forecast the PV output for that hour. We also build up three sets of SLFNs based on the weather condition: sunny day, rainy day, and cloudy day. The historical PV power output data were classified into three groups based on the above-mentioned three kinds of weather conditions. The three groups of historical data were used to train the three sets of SLFNs using the ELM, accordingly. Then, one can choose the corresponding set of SLFNs based on the weather forecasting data to forecast the PV power output. The number of hidden nodes for SLFN was optimized according to the evaluation indices. The proposed forecasting method shows better evaluation indices and faster than BP neural networks based forecasting method.

The paper is organized as follows, in section II, the ELM are introduced. Section III proposes PV generation forecasting model. Section IV presents the simulation and results. Section V concludes this paper.

II. Extreme Learning Machine

Huang G-B et al. proposed a simple learning algorithm for SLFN called ELM whose learning speed can be thousands of times faster than traditional feed forward network learning algorithms like back-propagation algorithm while obtaining better generalization performance [10]. Over the past few years, ELM has been applied in many fields [12-14]. The ELM algorithm is a novel method to train the feed forward neural networks, with the structure shown in Fig. 1. For ELM training, the network weights were randomly set, and then obtain the inverse of the hidden-layer output matrix. The advantages of ELM are its simplicity, fast, and outstanding performance when compared to other learning methods [14].

For N arbitrary distinct samples $(\mathbf{X}_i, \mathbf{t}_i)$, where $\mathbf{x}_i = [x_{i1}, x_{i2}, ..., x_{in}]^T \in \mathbf{R}^n$ and $\mathbf{t}_i = [t_{i1}, t_{i2}, ..., t_{im}]^T \in \mathbf{R}^m$ are the input and ideal output, respectively. As shown in Fig. 1, for a standard SLFN with L hidden neurons and activation function $g(x)$ are mathematically modeled as (1) [10].

$$\mathbf{o}_i = \sum_{j=1}^{L} \boldsymbol{\beta}_j g(\mathbf{w}_j \cdot \mathbf{x}_i + \mathrm{b}_j), \quad i = 1, 2, ..., N \tag{1}$$

Where $\mathbf{w}_j = [w_{j1}, w_{j2}, ..., w_{jn}]^T$ is the weight vector connecting the jth hidden node and the input nodes, $\boldsymbol{\beta}_j = [\beta_{j1}, \beta_{j2}, ..., \beta_{jm}]^T$ is the weight vector connecting the jth

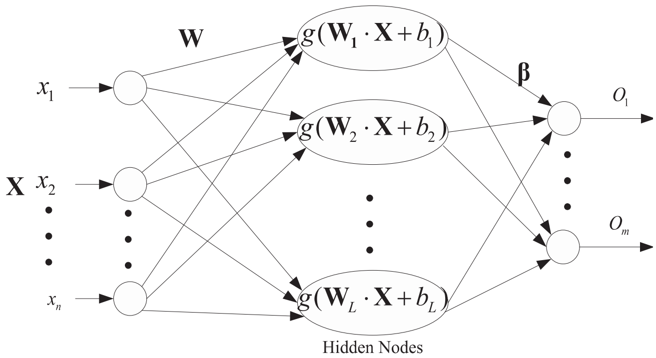

Fig. 1 Structure of an ELM network.

hidden node and the output nodes, $\mathbf{w}_j \cdot \mathbf{x}_i$ is the inner product of $\mathbf{w}_j$ and $\mathbf{x}_i$, and b_j is the threshold of the jth hidden node. For the standard SLFN with L hidden nodes with activation function $g(x)$ can approximate those N samples with zero error [11]. Thus, there exist $\boldsymbol{\beta}_j$, $\mathbf{W}_j$ and b_j such that satisfy (2).

$$\sum_{i=1}^{N} \left\| \sum_{j=1}^{L} \boldsymbol{\beta}_j g(\mathbf{w}_j \cdot \mathbf{x}_i + \mathrm{b}_j) - \mathbf{t}_i \right\| = \sum_{i=1}^{N} \left\| \mathbf{o}_i - \mathbf{t}_i \right\| = 0 \tag{2}$$

Equation (2) can be rewritten compactly as (3):

$$\mathbf{H}\boldsymbol{\beta} = \mathbf{T} \tag{3}$$

Where, $\boldsymbol{\beta} = [\boldsymbol{\beta}_1^T; \boldsymbol{\beta}_2^T; ...; \boldsymbol{\beta}_L^T]_{L \times m}$, $\mathbf{T} = [\mathbf{t}_1^T; \mathbf{t}_2^T; ...; \mathbf{t}_N^T]_{N \times m}$ and the hidden layer output matrix $\mathbf{H}$ is defined as (4).

$$\mathbf{H} = \begin{bmatrix} g(\mathbf{w}_1 \cdot \mathbf{x}_1 + \mathrm{b}_1) & \cdots & g(\mathbf{w}_L \cdot \mathbf{x}_1 + \mathrm{b}_L) \\ \vdots & \cdots & \vdots \\ g(\mathbf{w}_1 \cdot \mathbf{x}_N + \mathrm{b}_1) & \cdots & g(\mathbf{w}_L \cdot \mathbf{x}_N + \mathrm{b}_L) \end{bmatrix}_{N*L} \tag{4}$$

The input weights $\mathbf{w}_j$ and biases b_j are randomly assigned, then we can calculate the output weight vector $\boldsymbol{\beta}$ as (5) shows, to fulfill the ELM training.

$$\boldsymbol{\beta} = \mathbf{H}^\dagger \mathbf{T} \tag{5}$$

Where $\mathbf{H}^\dagger$ stands for the Moore-Penrose inverse of matrix $\mathbf{H}$ [11].

In this paper, the number of hidden nodes L must be optimized, in order to obtain accurate forecasting for the PV output.

III. Photovoltaic Generation Forecasting Model

In this section, the characteristics of PV power output were analyzed firstly, according to the characteristics of PV power outputs, we proposed the weather classification based forecasting model.

A. Characteristics of PV Power Output

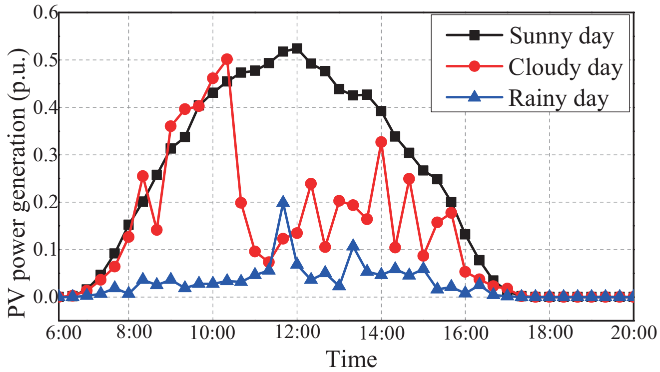

Fig. 2 PV power output curves (in p.u.) for three classic weather types.

The PV power output is dependent on many meteorological factors, such as intensity of solar radiation, temperature, geographical location, and hourly solar angle [15]. In this paper, we take the PV output history data from the PV experiment system located in Shanghai for case study. The test time period is from 2012-09-01 to 2013-03-31. In Shanghai, the solar irradiance is available during about 6:00 am to 19:00 pm in summer season. Thus the PV output curves is sampled only during that time interval.

Fig. 2 shows the PV power output curves (in p.u.) for three classic weather types: sunny day, cloudy day and rainy day. The PV generation system has higher powr output on a sunny day, because the intensity of solar irradiance is stable and high. While on the rainy day or cloudy day, the PV power output is very low and unstable. Thus, the PV power generation is weather dependent. In order to forecast the PV power output accurately, we need to set up individual forecasting model for each weather type.

B. *Weather Classification based Forecasting Model*

As shown in Fig. 2, the PV power output curves are weather dependent and time dependent. Thus, we forecast the PV power output for each hour and each weather type independently. For each hour we use a SLFN for PV output power forecasting. ELM algorithm was used for the training of SLFN and the PV power output history data and weather history data are as training samples.

The schematic diagram of PV power output forecasting was shown in Fig. 3. In this proposed forecasting approach both historical data and weather report information are used in the forecasting process. For arbitrary one day, each hour has a SLFN to forecast the PV output for that hour. There are three sets of SLFNs used for PV power output forecasting on sunny day, rainy day, and cloudy day, separately. The historical PV power output data were classified into three groups based on the above-mentioned three kinds of weather condition. Then, the historical data were used to train the three sets of SLFNs by ELM algorithm, accordingly. Based on the weather forecasting data, one can choose the corresponding set of SLFNs to forecast the PV power output.

IV. Simulation and Results

In this paper, the PV power output is classified into three types according to the weather condition: sunny day, cloudy day, rainy day. The same type data are applied to the SLFN model and ELM algorithm is used for training the SLFN. Based on the weather report of the next day, the related SLFN forecasting model is chosen to forecast the day ahead PV power output.

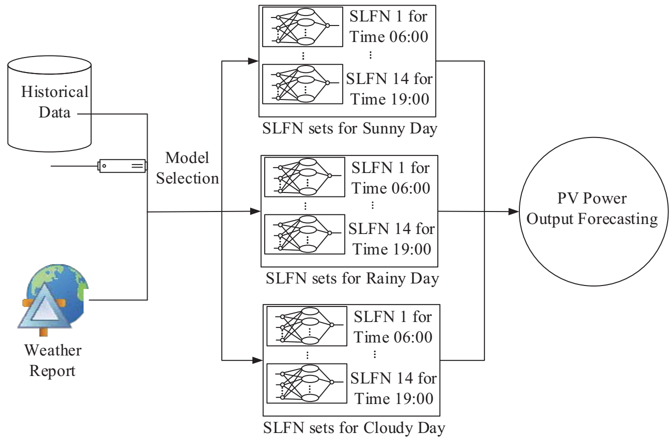

Fig. 3 Schematic diagram of PV power output forecasting.

The experiments are implemented in MATLAB R2010b and the computing platform for execution of the program is on a windows-7-based PC. For comparison purpose, the methods of BP neural networks based forecasting method is also tested by the same databases.

A. *Test Data and Data Preprocessing*

In this paper, the data for case study is taken from the PV experiment system located in Shanghai. The real PV power generation data is sampled every 20 min. The hourly PV power output data is then obtained by averaging the data collected within 1 h. In Shanghai, the solar irradiance is available during about 6:00 am to 19:00 pm in summer season. Thus the PV output curves is sampled only during that time interval. The test time period is from 2012-09-01 to 2013-03-31.

As shown in Fig. 3, each hour has a SLFN to forecast the PV output for that hour. The input data for each SLFN is the forecasting day's weather forecasting information, such as the highest, lowest and average temperature, the history PV output data, such as the PV power output of the same hour on the latest similar 5 days, the PV power output of the former and the later 1 hour on the latest similar 1 day. In order to increase the precision for PV power output forecasting, the input data for the forecasting model is normalized between 0 and 1 before it is inputted into the model. The input data are normalized through the formula shown in (6) [8].

$$P_{normal} = (P_n - P_{\min}) / (P_{\max} - P_{\min}) \tag{6}$$

Where, P_{normal} is the normalized input data, $P_n, P_{\max}, P_{\min}$ are the original, maximum and minimum input data, respectively.

TABLE I MAPE AND NRMSE COMPARISON OF THE PROPOSED MODEL WITH DIFFERENT HIDDEN NODES NUMBERS IN SUNNY DAY

L	5	10	15	20	25	30	35
MAPE	3.64	3.07	2.70	3.32	3.44	4.14	4.63
NRMSE	5.64	4.77	4.21	5.34	5.40	6.58	7.47

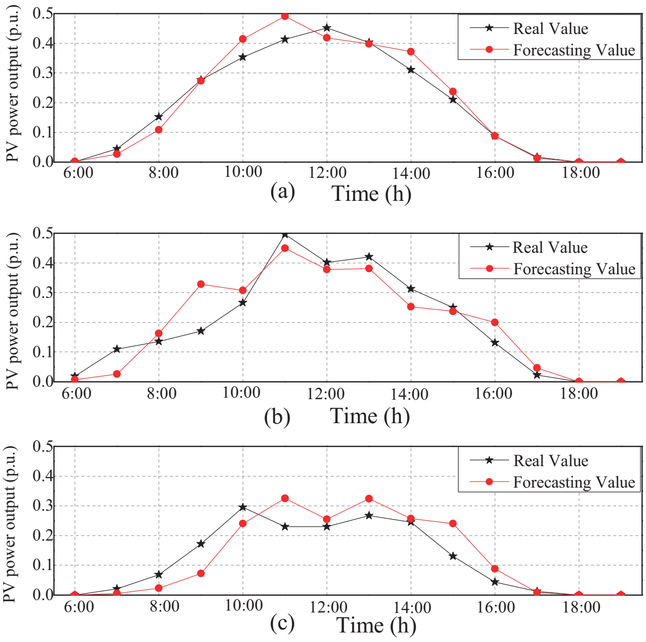

Fig. 4 PV power output forecasting results of the proposed model: (a) sunny day, (b) cloudy day, (c) rainy day.

B. Evaluation Indices

In order to verify the performance of the proposed approach, the mean absolute percentage error (MAPE) and normalized root mean square error (NRMSE) are computed as shown in (7) and (8) [16].

$$MAPE(\%) = 1/N \times \sum_{i=1}^{N} (\left| P_i^a - P_i^f \right| / P_N) \times 100 \qquad (7)$$

$$NRMSE(\%) = \sqrt{1/N \times \sum_{i=1}^{N} ((P_i^a - P_i^f)/P_N)^2} \times 100 \qquad (8)$$

Where, P_N is the nameplate capacity of the PV system, P_i^a is the actual power output of the PV system in the ith hour, while P_i^f is the forecasting value of the PV power output in the ith hour.

The MAPE is a commonly used evaluating index for the precision of trend forecasting. The NRMSE measures the average magnitude of the percentage errors. For PV power output forecasting, a suddenly large error is particularly undesirable than a bunch of small errors. Thus NRMSE is a good evaluation indice, because it gives a relatively higher weight to larger errors.

C. Hidden Nodes Number Evaluation

As shown in section II, the number of hidden nodes L is a free parameter of the ELM training. In order to obtain high forecasting precision, the parameter of L must be estimated.

TABLE II NUMERICAL RESULTS OF MAPE NRMSE AND RUNNING TIME OF ELM AND BP NEURAL NETWORKS

Method / Index	ELM			BP Neural Networks		
	Sunny Day	Cloudy Day	Rainy Day	Sunny Day	Cloudy Day	Rainy Day
MAPE	2.78	4.78	3.03	3.82	6.53	5.04
NRMSE	4.24	7.66	5.15	4.47	8.12	6.14
Time (ms)	0.66	0.66	0.64	124.2	121.2	125.0

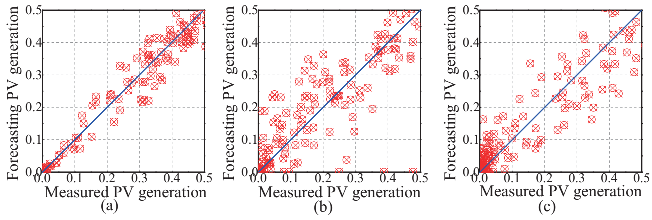

Fig. 5 PV power output forecasting values of the proposed model versus the measured values: (a) sunny day, (b) cloudy day, (c) rainy day.

In this paper, a sigmoidal function was chosen as the activation function $g(x)$ in (2). It has been proved that if the activation function $g(x)$ is infinitely differentiable, the required number of hidden nodes $L \le N$ [11].

TABLE I shows the MAPE and NRMSE comparison of the proposed model with different hidden nodes numbers for PV power output forecasting in sunny days. As observed from TABLE I, the generalization performance of ELM tends to become worse when too few or too many nodes are randomly generated. When the number of hidden nodes L is 15, both the values of MAPE and NRMSE are lower than the others. Thus, the number of hidden nodes L for SLFN was chosen to be 15 in this paper.

D. Forecasting Results Comparation with BP Neural Networks

In order to verify the performance of the proposed method, the evaluation indices of MAPE, NRMSE and running time of ELM and BP neural networks are presented in TABLE II. The number of hidden nodes for BP neural networks is also chosen to be 15.

From TABLE II, it can be seen that the proposed model have better forecasting performance than BP neural networks in all three weather types. Furthermore, the trainning time of the proposed model is only about 1/186 of the BP neural networks' training time. For both forecasting model, they have better forecasting performance in sunny day than rainy day and cloudy day. Because the PV power output is very low and unstable on the rainy day or cloudy day.

Fig. 4 shows the PV power output forecasting results of the proposed model in different weather types. From this figure, it can be seen that the proposed model perform well in PV power output forecasting, especially in sunny day. The average forecasting precision for sunny days' one-day ahead is 2.78% in MAPE and 4.24% in NRMSE. Following which are the rainy day and the cloudy day with the MAPE of 3.03% and 4.78%, respectively.

For clearly comparison the forecasting performance of the proposed model in different weather types, the PV power output forecasting values versus the measured values are illustrated in Fig. 5. The forecasting point is more accurate if it is closer to the diagonal line in the figure. The more points are on the diagonal or in a narrow band around it, the better the performance of the corresponding forecast model. From this figure, we find that the sunny day model outperform the cloudy day model and rainy day model. The differences are mainly attributed that the weather are more unstable in cloud day and rainy day.

V. Conclusion

A novel weather-based PV generation forecasting approach using ELM for 1-day ahead hourly forecasting of PV power output is proposed in this paper. The time series of PV power output data in the test period are classified into three groups based on the weather types: sunny day, cloudy day, and rainy day. Two evaluation indices, the MAPE and NRMSE, were used to verify the forecasting errors of the proposed approach. Numerical results show that the proposed approach outperform the BP neural networks forecasting model in all three weather types. Furthermore, the training time of the proposed model is only about 1/186 of the BP neural networks' training time.

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