Modular-Echo State Network Applied on Forecasting of Photovoltaic Power Generation

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Abstract. According to issues of the power system interconnection caused by uncertainty and intermittent of photo-voltaic (PV) power generation, a model based on modular-echo state network (M-ESN) is given to forecast power generation. Firstly, it is established forecast sub-models by modular neural networks (MNN) considering different seasons. Then, dividing each sub-model is based on similar days from history data of photovoltaic power generation with the average temperature as samples to train the model and generated power forecasting by the echo state network (ESN). Finally, integration output forecast numbers are gained. The results show that, compared with the ESN forecast model and BP forecast model, this prediction model has faster forecast speed, higher accuracy and better stability.

Introduction

Photo-voltaic (PV) power generation is one of the most promising new energy technologies after wind power generation [1]. PV power generation has the fluctuation, randomness and intermittence which are influenced by the uncertain factors such as solar irradiance, temperature and so on. Due to this, the perturbation of the output power of the PV system usually happens, which affects the safety, stability and economic operation of the power system [2-3]. It will help to adjust the scheduling plan and arrange the grid operation mode reasonably to forecast the output power of the PV power station.

In [4], BP neural network is used to build the prediction sub-model according to the season, and the daily generation power and weather are used as samples to train and forecast. The prediction accuracy is higher than that of the traditional BP, but there are still some shortcomings of learning algorithm to fall into the local minimal, slow convergence and so on. In [5], the traditional BP is improved by the combination of increasing momentum and variable learning efficiency, and the forecasting speed and prediction accuracy are improved effectively, but only for short-term PV power generation forecasting. In [6], based on the set forecasting model of multi-regression tree, the information is distributed along the path of each tree to the predicted capacity of the leaf node, and then the forecast of the power generation of the leaf nodes is averaged. The prediction accuracy is improved, but too much of the leaf node to increase the forecast time. In [7], ESN is used to predict the PV power generation. Only the network output weight is solved, the training process is simplified, the forecasting speed is improved, and the traditional BP convergence rate is slow and easy to fall into the local minimal problem. The accuracy and stability of the prediction results are improved, but the effect of the day type on the power generation is not taken into account.

Then, in response to above defects, a model based on Modular-Echo State Network (M-ESN) model is proposed to predict the PV power generation. Firstly, using the modular neural network to build four sub-modules by season. Then, the historical power generation data is divided into sunny, cloudy, cloudy and rainy, according to the main day type, and combined with the corresponding weather data as input samples. And the corresponding sub-modules are trained and forecasted by the echo state network. Finally, integrated output forecast results.
Photo-voltaic Power Generation Factors

The Main Influencing Factors of Photovoltaic Power Generation

The basic principle of PV power generation is the use of semiconductor photoelectric effect, the output power of PV system as

\[ P_s = \eta S I [1 - 0.005(t_0 + 25)] \]  (1)

Where \( P_s \) is the per unit area of the PV system output power (kW), \( \eta \) is PV power conversion efficiency, \( S \) is PV power supply area (m²), \( I \) is solar irradiance (kW•m⁻²), \( t_0 \) is ambient temperature (°C). For a particular PV power system can be \( \eta \) and \( S \) as a fixed value. By (1) known to affect the PV power system \( I \) and \( t_0 \) the main factors. The greater of the irradiation intensity, the greater the output power of the PV system [8-9]. And the level of temperature directly reflects the change in irradiation intensity, so most models use ambient temperature as the main influencing factor of PV power generation forecasting. In this paper, the ambient temperature is used as the influencing factor to forecast the PV power generation.

The Effect of Seasons on Photo-voltaic Power Generation

There are seasonal differences in ambient temperature, resulting in seasonal variations in PV power generation. Sunny sky shelter less, so the wind, cloud, relative humidity and other factors can be ignored. Here use sunny as a invariant, different seasons as a variable. Table 1 for the meteorological information and Fig.1 for a 30MW of PV power system in Fujian. It can be seen from Fig.1, in the same type of day, while different season, the PV power generation has the same curve trend, but the power generation there are differences. Therefore, the historical data on PV power generation is divided by season.

Table 1. The meteorological information.

<table>
<thead>
<tr>
<th>Date</th>
<th>Season</th>
<th>Day type</th>
<th>Highest temperature /°C</th>
<th>Lowest temperature /°C</th>
<th>Average temperature /°C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015.03.15</td>
<td>spring</td>
<td>sunny</td>
<td>26</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>2015.06.10</td>
<td>summer</td>
<td>sunny</td>
<td>28</td>
<td>20</td>
<td>25</td>
</tr>
<tr>
<td>2015.09.20</td>
<td>autumn</td>
<td>sunny</td>
<td>22</td>
<td>9</td>
<td>16</td>
</tr>
<tr>
<td>2015.12.26</td>
<td>winter</td>
<td>sunny</td>
<td>17</td>
<td>2</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 1. The PV power generation curve, in the same type of day, while different season.

The Effect of the Type of Day on the Photo-voltaic Power Generation

Different types of days, the irradiation intensity has significantly different, resulting in changes in ambient temperature, and PV power generation also changes. Here use the season as the invariant, the day type as a variable. Table 2 for the meteorological information and Fig. 2 for a 30MW of PV power
system in Fujian. The Fig. 2 shows that in the same season, while the daily type changes, the PV power generation changes significantly. It is necessary to divide the historical data of photovoltaic power generation data by day type.

<table>
<thead>
<tr>
<th>Date</th>
<th>Season</th>
<th>Day type</th>
<th>Highest temperature °C</th>
<th>Lowest temperature °C</th>
<th>Average temperature °C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015.06.15</td>
<td>summer</td>
<td>rainy</td>
<td>26</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>2015.06.27</td>
<td>summer</td>
<td>cloudy</td>
<td>28</td>
<td>20</td>
<td>25</td>
</tr>
<tr>
<td>2015.07.18</td>
<td>summer</td>
<td>overcast</td>
<td>22</td>
<td>9</td>
<td>16</td>
</tr>
<tr>
<td>2015.07.25</td>
<td>summer</td>
<td>sunny</td>
<td>17</td>
<td>2</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 2. The PV power generation curve, in the different type of day, while the same season.

**Design of Photo-voltaic Power Generation Forecasting Model**

**Modular Neural Network**

Modular Neural Networks (MNN) decompose complex neural networks into multiple simple sub-network modules, and each sub-network module processes a sub-task of the whole task, finally integrates the processing results of each module and to output[10-12]. MNN consists of three parts: task decomposition modular (TDM), training sub-network modular (TSNM) and integrated modular module (Integration modular, IM). Where TDM will be complex learning tasks into a number of relatively simple sub-tasks, and then each sub-task assigned to the corresponding sub-network module. TSNM receives the sub-tasks sent by TDM, then to learn and train to form a corresponding system environment. IM through a reasonable integration to integrate the trained sub-network modules and output the results. Fig.3 shows the structural diagram of MNN.

![Figure 3. The architecture of MNN.](image)

**Echo State Network**

Echo State Network (ESN) is a new recurrent neural network, proposed by Professor Jaeger [13] in 2001, consists of input layer, dynamic reservoir and output layer. ESN is a reservoir based neural network, which includes a fixed large reservoir with randomly and sparsely connected neurons. When the spectral radius of reservoir is less than 1, it has the echo state property, the stability of the network.
prediction is enhanced. ESN only through the training to determine the connection weights of hidden layer to the output layer, the other weights are maintained after the network initialization phase, so the training process is simplified, the training speed is improved and the global optimal [14-16]. The ESN structural diagram is shown in Fig.4.

![ESN Structural Diagram](image)

**Figure 4. The architecture of ESN.**

In Fig.4 the number of nodes in input layer, dynamic reservoir and output layer are $K$, $N$ and $L$. The training samples of the network are set $\{u(n), y(n), n=1,2,\ldots,r\}$, the input vector is $u(n)=[u_1(n), \ldots, u_k(n)]^T$, the internal state vector of the reservoir is $x(n)=[x_1(n), \ldots, x_s(n)]^T$, and the output vector is $y(n)=[y_1(n), \ldots, y_l(n)]^T$. Where $n$ refers to a moment, $T$ refers to transpose. The reservoir state update equation of ESN and output equation can be written as

$$x(n+1) = f(W_{in}u(n+1) + Wx(n) + W_{back}y(n))$$ (2)

$$y(n+1) = f_{out}(W_{out}(u(n+1).x(n+1).y(n)))$$ (3)

Where the connection weight matrix $W_{in}$, $W_{x}$, $W_{back}$ and $W_{out}$ are input weights, internal connection weights, feedback connection weights and output weights, they are the input layer to the reservoir, the internal neurons of the reservoir, the output layer to the reservoir and the reservoir to the output layer. Their connection weights dimension are $N \times K$, $N \times N$, $N \times L$, $L \times (K+N+L)$, $f(\cdot)$ and $f_{out}(\cdot)$ are the Activation function for the reservoir nodes and output nodes.

**Design of Modular Echo State Network Model**

In this paper, firstly input the historical data into the MNN and the data is decomposed by TDM. Then the decomposed data are sent to the corresponding TSNM for training, the TSNM is composed of ESN. Finally the trained data is output by IM. Fig.5 shows the structure of the M-ESN.

![M-ESN Architecture](image)

**Figure 5. The architecture of M-ESN.**

**The Learning of Modular Neural Network.** Let the learning sample of the network is $\{(U,Y)\}$, $U$ is the input vector, $Y$ is the expected output, and the actual output of the network is $Y'$. Where $U_i=(u_{i1},u_{i2},\ldots,u_{ik})$, $i=1,2,\ldots,N$, $N$ is the total number of samples. $Y_k=(y_{k1},y_{k2},\ldots,y_{kn})$, $k=1,2,\ldots,M$, $M$ is the total number of expect outputs. In the training phase, after input vector $U$, TDM in accordance with a certain algorithm from the original sample space decomposition of the sample subspace $U$ and
the expected output $Y$. Then send $(U_i, Y_i)$ to the corresponding TSNM, and trigger TSNM training. Finally, TDM control IM for output, that is, the output of the TSNM participating in the learning is integrated by IM, then output the result. In the testing phase, after the test sample input is judged by TDM, the subspace TSNM of the sample subordinate is analyzed and the corresponding TSNM is worked. The result of TSNM is sent to IM, then IM assigns an integrated weight for the output of each TSNM under the control of TNNM. Finally, integrate output results $Y^*$. 

**The Learning of Echo State Network.** The training sub-network module (TSNM) in the modular neural network (MNN) is composed of echo state network (ESN), and the training process of the ESN is divided into sampling phase and output weight calculation phase.

Sampling phase, first set the basic parameters of the network, initialize the network weight matrix $W_{in}$, $W$, $W_{out}$ and remain fixed, set the initial state of the network $x(n) = 0$. Input vector $u(n)$ through $W_{in}$ input to the internal of the reservoir, the output vector $y(n)$ through $W_{out}$ reaction to the reservoir. The system completes the calculation and collection of the internal state of the reservoir according to the equation (2). The equation (3) is the calculation of the output result, before this must be determined $W_{out}$ by training.

Output weight calculation phase, the output weight is calculated by the reservoir internal state matrix $B$ obtained by sampling phase and matrix $Y$ obtained by the corresponding sample output vector $y(n)$ conversion. Where $B$ is the matrix of the ESN at the sampling phase when the reservoir is in steady state with a size of $m \times N (m < N)$, and the size of $Y$ is $m \times 1$. Finally, the pseudo-inverse algorithm is used to calculate the output weight, the equation is written as

$$W_{out} = \text{prinv}(B) \times Y$$ (4)

**Results and Analysis**

Due to the large difference of magnitude and dimensions in the input data of the power generation forecasting model of the PV power system, cause the prediction results are biased. It is necessary to normalize the historical data before training, the equation is written as

$$P^* = \frac{P - P_{\text{min}}}{P_{\text{max}} - P_{\text{min}}}$$ (5)

Where $P^*$ is the normalized power generation data, $P$ is the historical data of the power generation, $P_{\text{min}}$ and $P_{\text{max}}$ are the minimum and maximum values of $P$, respectively.

In this paper, the historical power generation data and weather data are taken as the research object, which provided by a 30MW PV power station in Fujian, and the data is screened and trained according to the season and day types. Select summer (5 ~ 7 months) for training data, use the data of the hourly power generation data 7:00 ~ 19:00 and the average temperature of the day before the forecast day and the forecast day as the input data set to forecast the next day 7:00 ~ 19:00 hourly power generation.

To the day before the forecast day and the forecast day, the day type is the same and the different, respectively, for example, comparison analysis the forecast result of the M-ESN and BP, ESN forecast model. Table 4 shows the error results of the comparison between the optimal forecasted value in the 100 forecast results and the actual value of the forecast results of the three prediction models in the case of the same day type and different. Fig.6 (a) and (b) shows the forecasted model of PV power generation in the three forecasting models with the same and different day types, respectively.
Table 4. Error results of forecasting models.

<table>
<thead>
<tr>
<th>Time</th>
<th>The same day type</th>
<th>The different day type</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual value</td>
<td>Forecast value</td>
</tr>
<tr>
<td></td>
<td>M-ESN</td>
<td>ESN</td>
</tr>
<tr>
<td>7:00</td>
<td>0.1299</td>
<td>0.1355</td>
</tr>
<tr>
<td>8:00</td>
<td>0.2776</td>
<td>0.2686</td>
</tr>
<tr>
<td>9:00</td>
<td>0.5145</td>
<td>0.5277</td>
</tr>
<tr>
<td>10:00</td>
<td>0.7061</td>
<td>0.7119</td>
</tr>
<tr>
<td>11:00</td>
<td>0.8365</td>
<td>0.8272</td>
</tr>
<tr>
<td>12:00</td>
<td>0.8932</td>
<td>0.8897</td>
</tr>
<tr>
<td>13:00</td>
<td>0.8972</td>
<td>0.9013</td>
</tr>
<tr>
<td>14:00</td>
<td>0.8204</td>
<td>0.8270</td>
</tr>
<tr>
<td>15:00</td>
<td>0.6724</td>
<td>0.7367</td>
</tr>
<tr>
<td>16:00</td>
<td>0.4700</td>
<td>0.5497</td>
</tr>
<tr>
<td>17:00</td>
<td>0.2324</td>
<td>0.3128</td>
</tr>
<tr>
<td>18:00</td>
<td>0.0886</td>
<td>0.1410</td>
</tr>
<tr>
<td>19:00</td>
<td>0.0308</td>
<td>0.0299</td>
</tr>
</tbody>
</table>

RMSE: - 0.0394 0.0395 0.0529 - 0.1141 0.1498 0.4053
MAE: - 0.0258 0.0328 0.0417 - 0.1079 0.1356 0.3628

(a) PV power generation forecast curve in the same day type

(b) PV power generation forecast curve in the different day type

Figure 6. PV power generation forecast curve of forecasting models.

It can be seen from Table 4 and Fig.6 that the three forecasting models have better forecast result when the forecast day is the same as the day before the forecast day, but the forecast result has a larger error when the day type is different. Mainly due to different types of days than the same type of day, the weather changes more intense, caused by strong random. Fig.6(b) obviously shows that the M-ESN forecasting model has the smallest root mean square error (RMSE) and mean absolute error (MAE) compared with ESN and BP when the forecast day is different from the day before the forecast day. Where the RMSE of M-ESN is 0.0357 and 0.2912 lower than that of ESN and BP, respectively, and the MAE of M-ESN is about 0.3 times of BP. The results show that, under the same day type and the different day type conditions the M-ESN forecasting model has higher forecast accuracy than the ESN and BP, and the feasibility and effectiveness of using the M-ESN forecasting model to forecast the PV power generation are verified.
**Conclusion**

In this paper, through analyzing the influencing factors of PV power generation, and combined with the historical power generation data and meteorological data given by PV power stations, to propose a forecasting model of PV power generation based on M-ESN. The model builds four forecasting sub-models according to the season, and each sub-model divides the data according to the day type. The divided data and the average temperature of the previous day and the forecast day are taken as the input variables. And then ESN is used as the sub-module for sample training. Finally, using the IM to integrate the data, and then output forecasted value. The forecast results show that the model has higher accuracy and better stability, which provides an effective method for the grid dispatching department to adjust the scheduling plan and reasonable arrangements for grid operation mode.

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**References**


