Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Environmental Sciences 11 (2011) 1308 – 1315

Procedia
Environmental Sciences

An ANN-based Approach for Forecasting the Power Output of Photovoltaic System

Ming Ding, Lei Wang, Rui Bi

Research Center for Photovoltaic System Engineering, Ministry of Education Hefei University of Technology Hefei, Anhui Province, China
mingding56@126.com, wang_lei_1987@126.com, biruizz@126.com

Abstract

With the increasing use of large-scale grid-connected photovoltaic system, accurate forecast approach for the power output of photovoltaic system has become an important issue. In order to forecast the power output of a photovoltaic system at 24-hour-ahead without any complex modeling and complicated calculation, an artificial neural network based approach is proposed in this paper. The improved back-propagation learning algorithm is adopted to overcome shortcomings of the standard back-propagation learning algorithm. Similar day selection algorithm based on forecast day information is proposed to improve forecast accuracy in different weather types. Forecasting results of a photovoltaic system show that the proposed approach has a great accuracy and efficiency for forecasting the power output of photovoltaic system.

Keywords: Photovoltaic system; 24-hour-ahead forecasting; Artificial neural network; Improved back-propagation learning algorithm; Similar day selection algorithm

1. Introduction

In recent years, photovoltaic (PV) technology has been rapidly developed due to the maintenance free, long lasting, and environment friendly nature of PV as well as government's support [1]. However, power output of PV system is a non-stationary random process because of the variability of solar irradiation and environmental factors. Any grid-connected PV system in the public power grid, is regarded as a non-controlled, non-scheduling unit, its power output fluctuations will affect the stability of power system [2]. As the use of large-scale grid-connected PV system is increasing, it's important to strengthen the prediction of PV system power output, which can help the dispatching department to make overall arrangements for conventional power and photovoltaic power coordination, scheduling adjustment, operation mode planning.

To forecast the power output of PV system, particularly the short term forecast (say 24-hour-ahead), applications can be grouped into two categories: one is the prediction model based on solar radiation intensity. Firstly obtain the predicted value of solar radiation based on solar radiation model, then use PV

Selection and/or peer-review under responsibility of the Intelligent Information Technology Application Research Association.
doi:10.1016/j.proenv.2011.12.196

output formula to calculate the power output of PV system [3]. Another method is to predict the power output of PV system directly [4]. Although the prediction model based on solar radiation intensity has been considered to be an effective method in the practical application, it takes a lot of meteorological and geographical data to solve complex differential equations [5]. Artificial neural network (ANN) has been viewed as a convenient way to forecast solar radiation intensity and power output of PV system, which can be trained to overcome the limitations of traditional methods to solve complex problems, and to solve difficult problems which are hard to model and analyze [6]. In this paper, an ANN-based approach for forecasting the power output of PV system at 24-hour-ahead is proposed. Instead of the prediction model based on solar radiation intensity, the proposed ANN-based approach uses feed-forward neural network (FNN) to predict the power output of PV system directly by reference to historical data of PV system. The improved back-propagation (BP) learning algorithm is adopted to overcome shortcomings of standard BP learning algorithm, such as slow convergence and easy to fall into local minimum. In order to improve forecast accuracy in different weather types, similar day selection algorithm based on forecast day information is proposed, and weather information is added as input of ANN. The validity of proposed ANN-based approach is verified by comparing the predicted value and actual value of PV system. It shows that the proposed ANN-based approach has a wide applicability.

2. Artificial Neural Network

2.1 Feed-forward Neural Network

Schematic diagram of a multilayer feed-forward neural network architecture is shown in Fig.1. The outputs of neurons in each layer are fed forward to their next level, until the entire output of network is obtained. It usually consists of an input layer, multiple hidden layers and an output layer. Through adaptable synaptic weights, each single neuron is connected to other neurons of a previous layer. Knowledge is usually stored as a set of connection weights [7].

Neural networks working process is divided into two steps: the first step is called learning (or training) process, connection weights are modified by learning, connection weights matrix changes adaptively with the external environment incentives essentially. The second step is called network operating process, connection weights are fixed at this time, and the corresponding output is obtained.

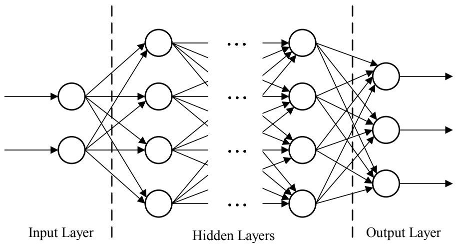

Figure 1 Schematic diagram of a multilayer feed-forward neural network architecture

2.2 Back-propagation Learning Algorithm

The learning step is an important subject of neural networks; supervised learning and unsupervised learning are two types of learning models [8]. The back-propagation (BP) algorithm is one of the most powerful supervised learning algorithms [9]. But it is discovered that BP algorithm has the following shortcomings: easily falling into local minimum by using gradient-descent algorithm to converge the error between actual output and expected output; slow convergence rate; training process prone to oscillations and so on.

3. Factors that Affect PV Power Output

For PV system with fixed orientation, the maximum DC power output can be described by the following empirical formula [10]:

$$P_s = \eta SI[1 - 0.005(t_0 + 25)]$$

Where, η is the conversion efficiency of solar cell array (%), S is the array area (m^2), I is the insolation ($kW \bullet m^{-2}$), t_0 is the outside air temperature ($^{\circ}C$).

As can be seen from the above formula， for the PV system, there are many factors that affect its power output, such as the conversion efficiency, the array area， the solar radiation intensity, the installation angle, pressure, temperature, etc. Since all of the time series of power output are from the same set of power generation system, an obvious feature of PV system is that the time series of power output have high correlation; it solves the impacts of installation location and use of time on conversion efficiency of PV system [11]. Conversion efficiency and array area have been implied in the historical data of power output, but the intensity of solar radiation and atmospheric temperature changes should be taken into account. The intensity of solar radiation varies greatly in different seasons, different weather types.

Power output comparison of different weather condition is shown in Fig.2 and Fig.3, and the weather can be seen in Table Ⅰ.It is clear that power output of a PV system varies widely in different weather types. There is a huge difference in power output between sunny day and rainy day, sunny day and snowy day. The power output curve of sunny day is smooth; the power output curve of rainy day or snowy day is fluctuant relatively. The power output of different seasons is not very different on condition that the weather type is all sunny, but the temperature will also affect the output.

Table 2 Weather Condition

Date	Weather Type	High Temperature	Average Temperature	Low Temperature
2010.10.01	Sunny	33	22	11
2010.10.23	Rainy	17	12	7
2010.10.27	Snowy	14	7	0
2010.04.18	Sunny	26	15	4
2010.07.07	Sunny	38	27	14
2010.09.20	Sunny	23	17	11
2010.11.25	Sunny	7	1	-6

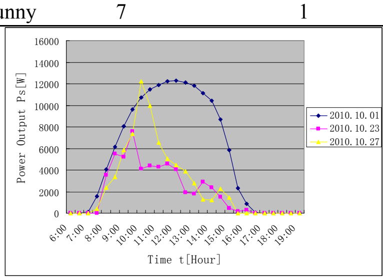

Figure 2 Power output comparison of different weather types

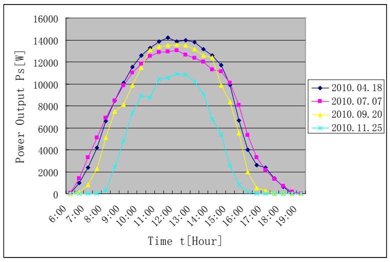

Figure 3 Power output comparison of different seasons

4. Algorithm

4.1 Improved Back-propagation Learning Algorithm

Search route of the standard back-propagation algorithm is shown in Fig.4. It can be seen that the standard BP learning algorithm uses a constant learning step length. In the early stages of network training, it will reduce error of the network output if appropriate learning step length is adopted. When the network is constantly in the training process, learning step length can not meet the requirements of smaller and smaller error of the network output, resulting in network oscillations during the training.

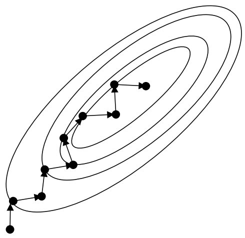

Figure 4 Search route of the standard back-propagation algorithm

Set E as the network output error, W as connection weights, n as the number of training iteration, η as the learning rate, i as the number of computing network output error in each training iteration. The flow chart of improved BP learning algorithm [12] is shown in Fig.5.

When $E(\mathrm{n})$ and $W(\mathrm{n})$ are determined, compute the network output error $E^{(1)}(\mathrm{n}+1)$:

If $E^{(1)}(\mathrm{n}+1) < E(n)$, increase the learning rate according to the formula $\eta = 1.1\eta$, and modify the corresponding weights to get $W^{(2)}(n+1)$ .Assuming that the new network output error $E^{(2)}(n+1) < E^{(1)}(n+1)$, repeat the above steps until the new network output error is not reduced.

If $E^{(1)}(\mathrm{n}+1) \geq E(n)$, decrease the learning rate according to the formula $\eta = 0.5\eta$, and modify the corresponding weights to get $W^{(2)}(n+1)$ .Assuming that the new network output error $E^{(2)}(n+1) > E^{(1)}(n+1)$, repeat the above steps until the new network output error is not increased.

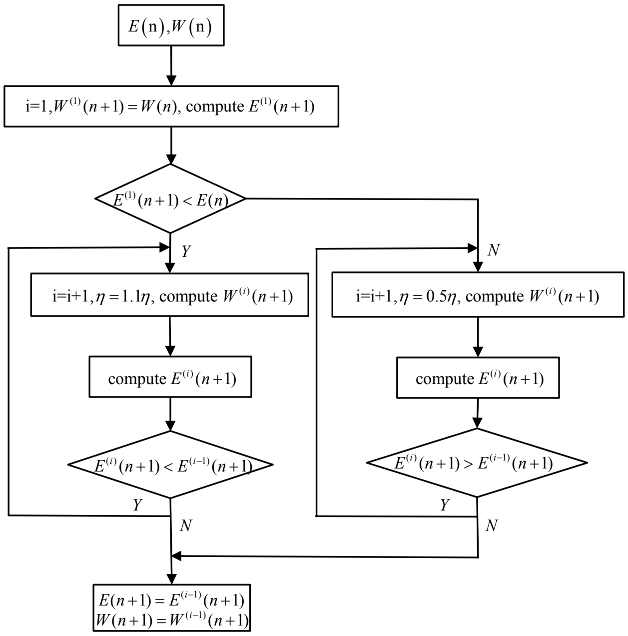

Figure 5 The flow chart of improved BP learning algorithm

4.2 Similar Day Selection Algorithm

Similar day selection algorithm is proposed to find the closest historical record which has the similar weather condition with the forecast day, and normalized information of this record is set as input of the network. Selecting appropriate training set according to forecast day information has the following benefits: 1) Making the training process carried out based on forecast day information. 2) Improving the forecast accuracy. 3) Having ability of forecasting the power output of PV system in non-sunny days. Although this will sacrifice some time, it is acceptable due to 24-hour-ahead forecast being discussed in this paper.

Similar day selection algorithm can be summarized as follows:

1) Calculate Euclidean distance of temperature between forecast day and i days before forecast day.

$$d_i = \left[\sum_{j=1}^{3} (Y_j - X_{ij})^2 \right]^{\frac{1}{2}}, i = 1, 2, ..., n$$

Where, Y_1, Y_2, Y_3 are high temperature, low temperature and average temperature of forecast day, X_{i1}, X_{i2}, X_{i3} are high temperature, low temperature and average temperature of i days before forecast day.

2) If the weather type of i days before forecast day is different from forecast day, set d_i to maximum.

3) Find the minimum value in $D = \{d_1, d_2, ..., d_n\}$ and set it as the similar day of forecast day.

5. Feed-forward Neural Network Design

5.1 Data Source

The historical power data was obtained from a PV system located in Ashland, Oregon (Latitude: 42.19; Longitude: 122.70; Altitude: 595 m) of United States of America [13]. The Ashland station is part of Ashland's Solar Pioneer project, and it has 5 kW array and 15 kW array. We choose the 15 kW array to study.

Ashland's historical weather data and forecasted weather data was from a public weather forecast website [14].

5.2 Input Layer

As power output of the PV system is zero in 19:01-05:59, study period is from 06:00 to 19:00 with the interval of half-hour, a total of 27 points per day. Input data $x_1 - x_{33}$ are shown in Table Ⅱ.

Table 2 Input Data

$x_1 - x_{27}$	27 points of power output in similar day from 06:00 to 19:00 with the interval of half-hour
$x_{28} - x_{30}$	High, low, average temperature value in similar day
$x_{31} - x_{33}$	Forecasted high, low, average temperature value in forecast day

5.3 Hidden Layers

Simply, it has only one hidden layer in the feed-forward neural network. A trial-and-error method [15] has been used to determine the appropriate number of hidden neurons in this paper.

5.4 Output Layer

Since the objective of this paper is to forecast PV power output at 24-hour-ahead with the interval of half-hour, a total of 27 points of power output from 06:00 to 19:00 in forecast day are taken as the output.

5.5 Assessment Method

There are many ways to assess the prediction model; the most common one is the Mean Absolute Percentage Error (MAPE) which is adopted in this paper.

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|P^i{}_f - P^i{}_a\right|}{P^i{}_a}\%$$

Where, N is the total number of data, $P^i{}_f$ is the forecasted value, $P^i{}_a$ is the actual value, i is the index of data. In order to avoid $\left|P^i{}_f - P^i{}_a\right| / P^i{}_a$ approaching to infinity, $P^i{}_a$ will be discarded if it's close to zero.

6. Forecast Results and Discussion

In order to validate the accuracy of prediction model of PV power output, the PV power output of a sunny day and a rainy day were forecasted using historical power data and weather data, the curves of actual value and forecasted value are shown in Fig.6 and Fig.7. Prediction for the sunny day is shown in Fig.6, the MAPE is 10.06%, and prediction for the rainy day is shown in Fig.7, the MAPE is 18.89%. The prediction for the sunny day is more accurate, because the PV power output in sunny day is relatively stable, the fluctuation is small. Although there is some distant between the forecasted and the actual power output, it still has a high reference value.

Through the effective analysis of influencing factors of PV power output, combined with the improved BP learning algorithm and similar day selection algorithm, an ANN-based approach for forecasting the power output of photovoltaic system is proposed. The benefit of the proposed approach is that it does not require complex modeling and complicated calculation, forecast under different weather types can be carried out using only historical power data and weather data. The test results proved validity and accuracy of the proposed approach; the proposed approach can be used to forecast the power output of photovoltaic system precisely.

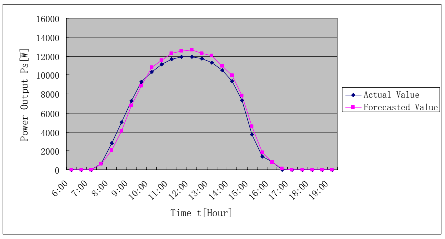

Figure 6 Comparison between actual value and forecasted value

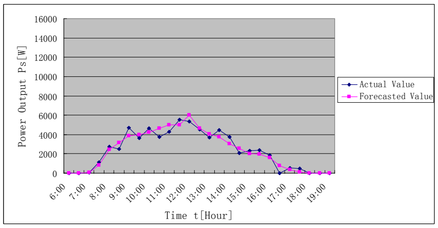

Figure 7 Comparison between actual value and forecasted value

7. Acknowledgment

This work was supported by the National High Technology Research and Development of China under Grant 2007AA05Z240, National Natural Science Foundation of China under Grant 50837001, and the Fund of Hefei University of Technology under Grant 2010HGXJ0061.

References

[1] Md.H. Rahman and S. Yamashiro, “Novel distributed power generating system of PV-ECaSS using solar energy estimation,” IEEE Trans. on Energy Conversion, vol. 22, pp. 358-367, June 2007.

[2] A. Woyte, V. Van Thong, R. Belmans, and J. Nijs, “Voltage fluctuations on distribution level introduced by photovoltaic systems,” IEEE Trans. on Energy Conversion, vol. 21, pp. 202-209, March 2006.

[3] E. Lorenz, J. Hurka, D. Heinemann, and H.G. Beyer, “Irradiance forecasting for the power prediction of grid-connected photovoltaic systems,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 2, pp. 2-10, 2009.

[4] Cai. Tao, Duan. Shanxu, and Chen. Changsong, “Forecasting power output for grid-connected photovoltaic power system without using solar radiation measurement,” 2nd International Symposium on Power Electronics for Distributed Generation Systems, PEDG 2010, pp. 773-777, 2010.

[5] A. Yona, T. Senjyu, A.Y. Saber, T. Funabashi, H. Sekine, and Kim. Chul-Hwan, “Application of neural network to one-day-ahead 24 hours generating power forecasting for photovoltaic system,” 2007 International Conference on Intelligent Systems Applications to Power Systems, ISAP, 2007.

[6] Adnan So¨zen, Erol Arcaklıog˘lu, Mehmet O¨zalp, and Naci C¸ ag˘lar, “Forecasting based on neural network approach of solar potential in Turkey,” Renewable Energy, vol. 30, pp. 1075-1090, June 2005.

[7] Soteris A. Kalogirou, “Applications of artificial neural-networks for energy systems,” Applied Energy, vol. 67, pp. 17-35, September 2000.

[8] Adnan So¨zen, Erol Arcaklıog˘lu, Mehmet O¨zalp, and E. Galip Kanit, “Use of artificial neural networks for mapping of solar potential in Turkey,” Applied Energy, vol. 77, pp. 273-286, March 2004.

[9] Rumelhart DE, Hinton GE, and Williams RJ, “Learning internal representations by error propagation,” Parallel distributed processing: explorations in the microstructure of cognition, vol. 1. Cambridge (MA): MIT Press, 1986 (chapter 8).

[10] A. Yona, T. Senjyu, and T. Funabashi, “Application of recurrent neural network to short-term-ahead generating power forecasting for photovoltaic system,” 2007 IEEE Power Engineering Society General Meeting, PES, 2007.

[11] Chen. Changsong, Duan. Shanxu and Yin. Jinjun, “Design of photovoltaic array power forecasting model based on neutral network,” Transactions of China Electrotechnical Society, vol. 24, pp. 153-158, September 2009.

[12] Yuan. changan, Data mining theory and application of SPSS Clementine, 1st ed., BEIJING: Publishing House of Electronics Industry, 2009, pp. 247-251.

[13] http://solardat.uoregon.edu/index.html.

[14] http://www.wunderground.com.

[15] Bahman Kermanshahi, “Recurrent neural network for forecasting next 10 years loads of nine Japanese utilities,” Neurocomputing, vol. 23, pp. 125-133, December 1998.