Short-Term Solar Power Forecasting Using the Adaptive Network-Based Fuzzy Inference System

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Abstract—This paper proposes an adaptive network-based fuzzy inference system (ANFIS) based forecasting method for short-term solar power forecasting. An accurate forecasting method for power generation of the photovoltaic (PV) system is urgent needed under the relevant issues associated with the high penetration of solar power in the electricity system. To demonstrate the effectiveness of the proposed method, the method is tested on the practical information of solar power generation of a PV system installed on the St. John's University of Taiwan. Good agreements between the realistic values and forecasting values are obtained; the test results show the proposed forecasting method is accurate.

***Keywords-** solar power generation forecasting; photovoltaic system; adaptive network-based fuzzy inference system*

I. INTRODUCTION

Rising crude oil prices highlights the exploitation of renewable energy applications. The solar power is one of the most attractive renewable energy technologies because of its low pollution. However, high penetration of solar power in the electricity system provides many challenges to the power system's operator, mainly due to the uncertainty of solar radiation.

Since the power produced by the PV system is varied with the solar radiation and the ambient temperature, unexpected variations of the PV system power generation may increase operating costs for the electricity system because the increased operation and maintain costs associated with cycling existing generation [1]. In addition, solar power forecasting plays an important role in the allocation of balancing power. Besides, solar power forecasting is used for the day-ahead scheduling of conventional power plants and trading of electricity on the spot market [2].

Recently, several methods have been employed for the solar power forecasting. The solar power forecasting methods can be generally categorized into three groups, physical methods, statistical methods and artificial intelligence methods.

Physical systems use parameterizations based on a detailed physical description of the atmosphere, to reach the best prediction precision. Usually, solar radiation given by the weather service on a coarse grid is transformed to the onsite conditions at the location of the PV system. Physical methods have advantages in long-term solar power prediction. Several physical methods have been developed based on using weather data with sophisticated meteorological for solar radiation forecasting and solar power predictions [1].

Statistical methods aim at finding the relationship of the on-line measured power data. For a statistical model, the historical data of the PV system may be used. Statistical models are easy to model and cheaper to develop compared to other models. The statistical method has advantages in short-term solar power prediction. The disadvantage with this method is that the prediction error increases as the prediction time increases. The main methods of statistical methods are time series based methods [3]. Time series based methods include the auto regressive (AR), AR with exogenous input (ARX), auto regressive moving average (ARMA), and auto regressive integrated moving average (ARIMA).

Recently, with the development of artificial intelligence, various artificial intelligence methods for solar power prediction have been developed. The new developed methods include artificial neural network [4], fuzzy logic methods [5], weighted support vector machine [6], and grey model [7]. The artificial intelligence methods are self-designing ones that can be automatically adjusted in changing system.

To increase the accuracy of short-term solar power forecasting this paper takes the ANFIS based method to account for the nonlinearity and periodicity in the solar power generation time series. This paper deals with the power generation forecasting of PV system and is divided into five sections. After a brief introduction, Section II introduces the adaptive network-based fuzzy inference system. Section III describes the he ANSIF based solar power forecasting method. Numerical results are described in Section IV. The conclusions of the paper are summarized in Section V.

II. ADAPTIVE NETWORK-BASED FUZZY INFERENCE SYSTEM

Fuzzy logic is based on modeling human thinking and perception. Fuzzy systems make up the rule base and estimate sampled functions from linguistic input to linguistic output [8]. The neural networks are the powerful tool of artificial intelligence. The neural networks were widely applied in optimization, pattern recognition, forecasting. The main property of neural network is that it can learn from examples is the fact of preferring neural network in nonlinear or complex problems [9]. ANFIS was proposed via taking full advantage of both the processing fuzzy information of the fuzzy system and self-learning of the neural network.

Jang proposed the ANFIS model in 1993 [10]. ANFIS is based on a special fuzzy inference structure: the Takagi-Sugeno model and its output is a linear combination of all input variables [11]. In ANFIS model, the input series are converted to fuzzy inputs by using membership function for each input series. The membership function can be any shape but it depends on the data set [12].

ANFIS has been applied in several forecasting domains such as electricity price forecasting [11], weather forecasting [12], solar radiation data forecasting [13], daily stream flow forecasting [14], internet traffic time series forecasting [15] and demand forecasting [16]. In this paper, the membership function and fuzzy rule is obtained by historical solar power generation.

The typical structure of ANFIS is shown as Figure 1. ANFIS contain layers: the fuzzy layer, the product layer, the normalized layer, the defuzzification layer, and the output layer. Every node at the same layer has similar function. The framework of ANFIS can be expressed as following:

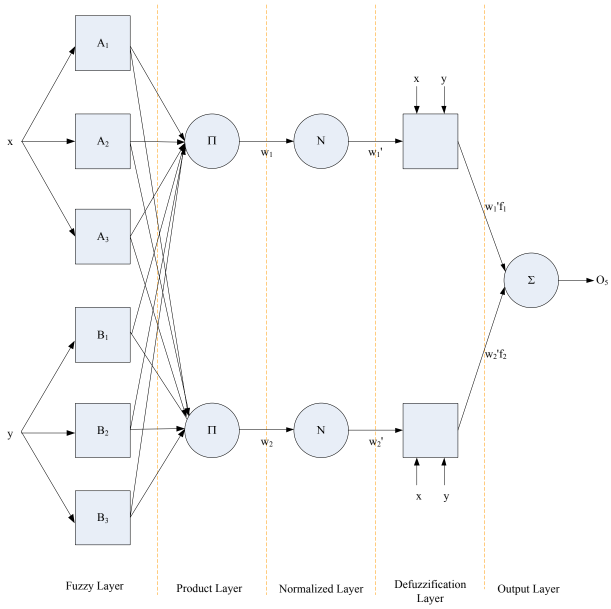

Figure 1. The typical structure of ANFIS.

The first layer is the fuzzy layer. The fuzzy layer contains of adaptive nodes that generate the membership grades of linguistic labels. Any appropriate parameterized membership function can be used such as the generalized bell function. A_1, A_2, A_3, B_1, B_2, B_3 are the linguistic labels used in the fuzzy set for dividing the membership functions. The relationship between the output and input functions of this layer can be expressed as below:

$$O_{1,i} = \mu_{Ai}(x), \qquad i = 1,2,3 \tag{1}$$

where $O_{1,i}$ is output function, and μ_{Ai} is the membership function of the fuzzy set A.

The second layer is the product layer. The product layer consists of rule nodes designated as Π which signifies the firing strength of each rule. The output of the product layer is the product of the input signal, which is defined as follows:

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y), \qquad i = 1,2,3 \tag{2}$$

where $O_{2,i}$ is output of the product layer, μ_{Ai} is the membership function of the fuzzy set A, and μ_{Bi} is the membership function of the fuzzy set B.

The third layer is the normalized layer. In this layer the fixed nodes are labeled as N. The output of the normalized layer is to normalize the weight function or the sum of all the rules firing strength as following:

$$O_{3,i} = w_i' = \frac{w_i}{w_1 + w_2 + w_3}, \qquad i = 1,2,3 \tag{3}$$

where $O_{3,i}$ is output of the normalized layer, w_i is output of the product layer.

The fourth layer is the defuzzification layer. The nodes in the defuzzification layer are also adaptive nodes besides the nodes in the fuzzy layer. Those adaptive nodes calculate the rule outputs based on consequent parameters. The adaptive nodes of this layer calculate the rule outputs based on consequent parameters by following equation:

$$O_{4,i} = w_i' f_i = w_i'(p_i x + q_i y + r_i), \qquad i = 1,2,3 \tag{4}$$

where $O_{4,i}$ is output of the defuzzification layer and p_i, q_i, r_i are consequent parameters of the node.

The fifth layer is the output layer. This layer is the final layer. The output layer gives the output by the summation of all incoming signals. The fixed node in this layer is labeled as Σ calculates the overall output from the sum of the node input signals. The output of the output layer can be expressed as below:

$$O_{5,i} = \sum_{i=1}^{3} w_i' f_i, \qquad i = 1,2,3 \tag{5}$$

where $O_{5,i}$ is the output of the fifth layer which is the academic marks, w_i' is output of the defuzzification layer.

The training scheme of the ANFIS is a two-pass process over a number of epochs. The node outputs of first layer to the fourth layer are calculated through each epoch. At the fifth layer, the consequent parameters are calculated using a least-squares regression method [13]. During each epoch, the output of the ANFIS is calculated and after calculation of the error, the ratio of error is back propagated over every layers and those values are adapted based on error descent gradient method [14].

III. ANSIF Based Solar Forecasting Method

The architecture of the ANSIF based solar power forecasting method is shown in Fig. 2. The ANSIF model was developed for 10 min. ahead solar power forecasting. The architecture of ANSIF used in this study contains five layers. The first layer (fuzzy layer) has 4 inputs: x for the solar power output of 20 minutes ago, y for the solar power output of 10 minutes ago, z for the current solar power output, and u for the current solar radiation value. The output layer has one output for the 10 minutes ahead solar power forecasting. The number of fuzzy rules is 81. The membership functions of the ANSIF model are the generalized bell functions.

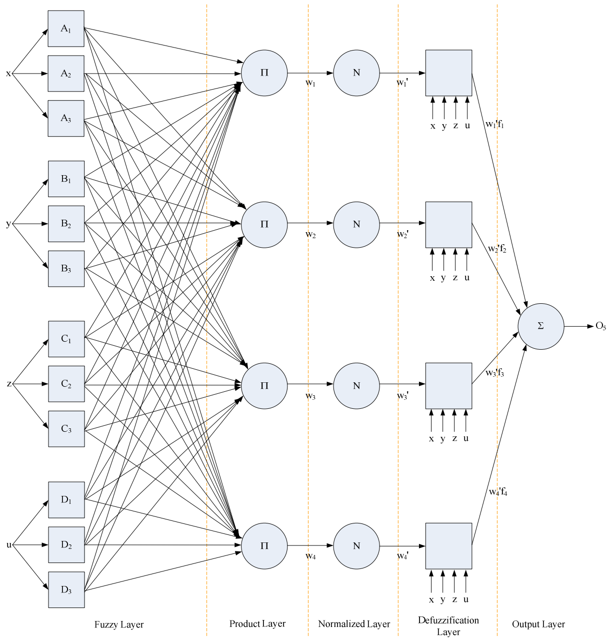

Figure 2. The architecture of the ANSIF based solar power forecasting method.

IV. NUMERICAL RESULTS

In order to verify the proposed forecasting method, the method was used for solar power forecasting in Taiwan. Solar power forecasting was computed using the historical solar power and solar radiation data for every 10 minutes for a 9kW PV system installed in St. John's University of Taiwan. The solar power time series data for this PV system were recorded. In order to ensure a clear comparison, no exogenous variables are considered. Because of seasonal atmospheric weather characteristics, the solar power and solar radiation data are divided into 4 categories: spring, summer, autumn and winter. The four season day test data results are shown below.

From the winter day data, the following days were selected: January 21-25, 2015, corresponding to a typical winter day. The historical data set with 720 patterns were divided into a training data set for the ANFIS, of 576 patterns, collected from January 21-24, and a test data set of 144 patterns, collected from January 25. Numerical result of the ANFIS-based method for typical winter day is shown in Fig. 3.

From the spring day data, the following days were selected: March 21-25, 2015, corresponding to a typical winter day. The historical data set with 720 patterns were divided into a training data set for the ANFIS, of 576 patterns, collected from March 21-24, and a test data set of 144 patterns, collected from March 25. The numerical results of the ANFIS-based method for typical spring day are shown in Fig. 4.

From the summer day data, the following days were selected: August 21-25, 2014, corresponding to a typical winter day. The historical data set with 720 patterns were divided into a training data set for the ANFIS, of 576 patterns, collected from August 21-24, and a test data set of 144 patterns, collected from August 25. The numerical results of the ANFIS-based method for typical summer day are shown in Fig. 5.

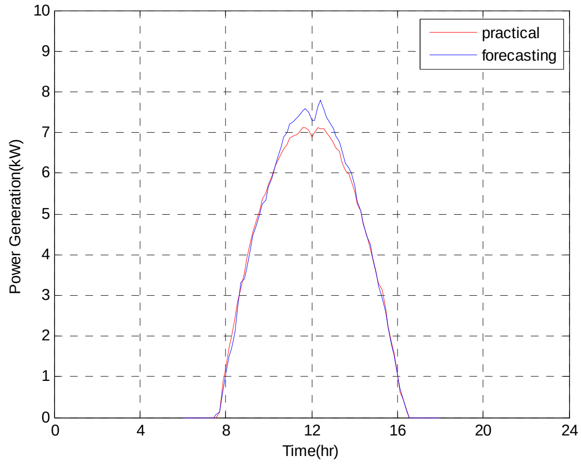

Figure 3. Numerical result of the ANFIS-based method for typical winter day.

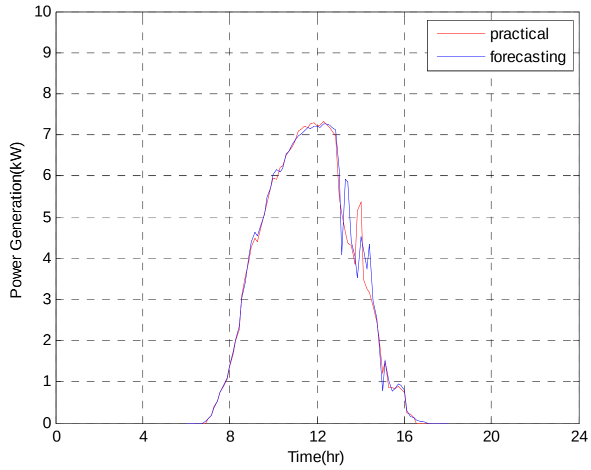

Figure 4. Numerical result of the ANFIS-based method for typical spring day.

From the autumn day data, the following days were selected: October 14-18, 2014, corresponding to a typical winter day. The historical data set with 720 patterns were divided into a training data set for the ANFIS, of 576 patterns, collected from October 14-17, and a test data set of 144 patterns, collected from October 18. The numerical results of the ANFIS-based method for typical summer day are shown in Fig. 6.

Comparing the four season data, a general conclusion that may be drawn from the obtained results is that proposed forecasting methods can forecast the solar power accurately.

V. CONCLUSIONS

This paper proposes an ANFIS based forecasting method using for 10 min. ahead solar power forecasting. The performance of the proposed method to short-term solar power forecasting is effective. An evaluation of the forecast methods is performed, using the practical information of solar power generation of a PV system. The results demonstrate the effectiveness of the proposed forecasting method and this method provided improved accuracy in the solar power forecasting.

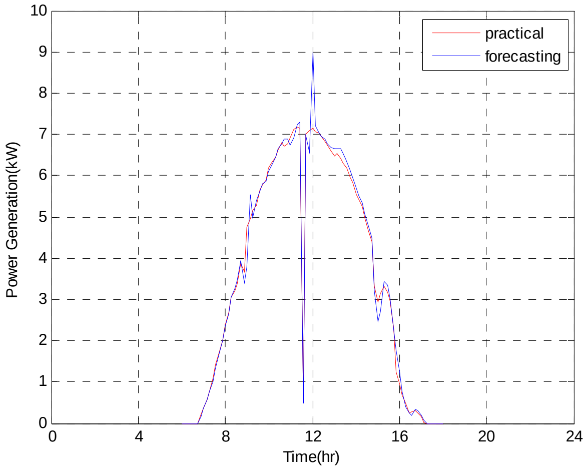

Figure 5. Numerical result of the ANFIS-based method for typical summer day.

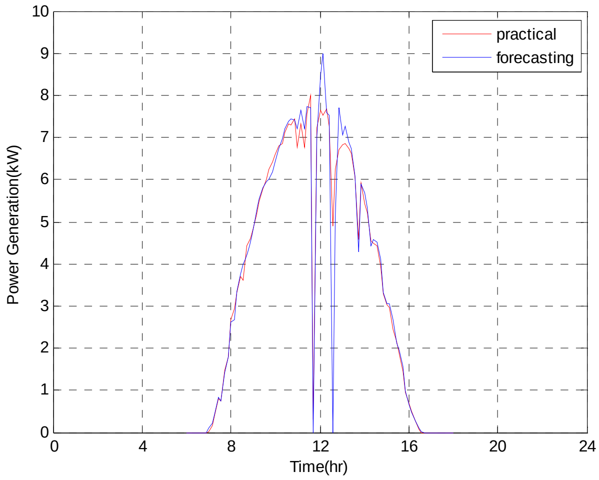

Figure 6. Numerical result of the ANFIS-based method for typical winter day.

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