Solar Irradiance Forecasting Using Intelligent Technology

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Abstract—*Because solar power is susceptible to clouds and substances in the air, the solar photovoltaic cannot produce stable power output. Solar irradiance is a measurement of the power output of photovoltaic module. Therefore, this paper uses some different combination inputs of the neural network to develop the solar irradiance forecasting with 24 hours ahead. Their forecasting performances are evaluated and some comparison results in Taichung solar farm are given.*

Keywords—Neural network, Solar Irradiance, Solar Power Systems.

I. INTRODUCTION

To solve the problems of limited fossil fuels and their impact on the environment, renewable resources play an important role. Solar energy is a very important renewable energy. Based on evaluated condition of solar power, solar photovoltaic becomes the most potential renewable energy in Taiwan. Solar irradiance is a measurement of the power output of photovoltaic module. However, because solar irradiance is influenced by substances in the air, the solar photovoltaic cannot produce stable power output. The power output of photovoltaic module is influenced immediately when the module is sheltered from the clouds. Besides, the material of solar cell, air temperature, module's position and orientation also affect the power output of the photovoltaic module. Therefore, it is an important issue to forecast solar irradiance accurately. Forecasting accuracy is not only influenced by the change of weather but also surroundings and the effectiveness of method and data. Developing an excellent solar power systems not only can wield the change of solar power but also help power company to allocate power. The accuracy of solar irradiance forecasting is the basis of solar power forecasting [1-6]. There are many intelligent approaches to forecast solar irradiance, such as neural networks [7-13].

The paper uses neural network technology to develop the solar power forecasting with 1-24 hours ahead. Some different features for solar forecasting are proposed and their forecasting performances are evaluated. Moreover, comparison results in Taichung solar farm in Taiwan [14] are given.

II. METHODS OF SOLAR IRRADIANCE FORECASTING

The backpropagation (BP) neural network is used in this paper, and the main structure of which is input layer, hidden layer, and output layer. Input layer transfer received external information into the network, and which is used to represent the input variable. Hidden layer process the input data, which is used to represent the relationship between input variables. Input data are transferred to the output layer after being converted by nonlinear transform function. Output layer receives and outputs the information from upper layer, and is used to represent the output variable of network. The layers connect to each other to deliver information, and this connection is called "weight". The weight value is acquired from the iterative learning calculation of the neuro. Using supervised learning method is to reduce the discrepancy between output and expected value, and to minimize the performance index of the network. The training method in this paper is Levenberg-Marquardt algorithm, which is a modified gradient descent method and possesses the ability of fast training.

Based on the assumption that there is no cloud and shelter, solar irradiance can be calculated as follows [15].

A. The air mass is defined as follows.

$$\mathrm{AM} = \frac{1}{\cos\zeta} \tag{1}$$

where ζ is zenith angle.

B. The intensity of the direct component of sunlight in units of kW/m^2 on the assumption that the location height above sea level is zero is defined as follows.

$$I_D = 1.353 \cdot 0.7^{AM^{0.678}} \tag{2}$$

where the value 1.353 is solar constant, the value 0.7 means that solar irradiance irradiates to the earth's surface through atmosphere is 0.7 times of itself, and the value 0.678 is empiric value.

C. The global solar irradiance is defined as follows.

$$I_G = 1.1 \cdot I_D \tag{3}$$

where the diffuse radiation is about 10% of the direct component of sunlight.

Root Mean Square Error (RMSE) can show the difference between the forecasting values and observed values, judge the quality of the neural network, and judge the level of convergence in the process. RMSE is closely related to the number of training data. The larger the RMSE, the greater the difference of the forecasting values and observed values may be. The closer the difference between RMSE and 0, the closer the difference between the forecasting values and observed values may be. RMSE is defined as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(Y_j - \hat{Y}_j\right)^2} \tag{4}$$

where Y_j is forecasting values , $\hat{Y}_j$ is observed values.

Based on some different combination inputs of the neural network, this paper proposes six methods to develop the solar irradiance forecasting with 24 hours ahead. The method 1 is to use the historical solar irradiance values in the daytime. The method 2 is to use the historical solar irradiance values in the daytime and the temperature. The method 3 is to use the historical solar irradiance values in the daytime and the solar altitude. The method 4 is to use the historical solar irradiance values in the daytime, the temperature and the solar altitude. The method 5 is to use the difference value of historical solar irradiance values and the solar altitude. The method 6 is to use the historical solar irradiance values and the future solar irradiance value that is calculated on the assumption that there is no cloud and shelter [15]. The training data in Taichung solar farm in Taiwan [14] were in the period from March 2014 to September 2015. In the methods 1-6, the values of solar irradiance next hour is the only output. The data of the network training only apply the daytime data. Defining the day or night is depending on the calculated values of solar altitude [15]. If the solar altitude is larger than zero, it is in the daytime. Conversely, it is at night.

In the method 1, the architecture of back propagation neural network was made from 3 inputs, 7 hidden layer neurons and 1 output. The transition function of hidden layer neurons is on-linear hyperbolic tangent function. 3 inputs are the observed value of solar irradiance at the time *t*, the time *t*-1, the time *t*-2.

In the method 2, the architecture of back propagation neural network was made from 4 inputs, 9 hidden layer neurons and 1 output. The transition function of hidden layer neurons is on-linear hyperbolic tangent function. 4 inputs are the observed value of solar irradiance at the time *t*, the time *t*-1, the time *t*-2 and the temperature.

In the method 3, the architecture of back propagation neural network was made from 4 inputs, 11 hidden layer neurons and 1 output. The transition function of hidden layer neurons is on-linear hyperbolic tangent function. 4 inputs are the solar altitude, the calculated value of solar irradiance, the observed value of solar irradiance at the time *t*, and the time *t*-1.

In the method 4, the architecture of back propagation neural network was made from 5 inputs, 10 hidden layer neurons and 1 output. The transition function of hidden layer neurons is on-linear hyperbolic tangent function. 5 inputs are the solar altitude, the temperature, the calculated value of solar irradiance, the observed value of solar irradiance at the time *t*, and the time *t*-1.

In the method 5, the architecture of back propagation neural network was made from 3 inputs, 8 hidden layer neurons and 1 output. The transition function of hidden layer neurons is on-linear hyperbolic tangent function. 3 inputs are the solar altitude, the difference value of calculated value and observed value of solar irradiance, and the difference values of solar irradiance at the time *t*, and the time *t*-1.

In the method 6, the architecture of back propagation neural network was made from 4 inputs, 7 hidden layer neurons and 1 output. The transition function of hidden layer neurons is on-linear hyperbolic tangent function. 4 inputs are the calculated value of solar irradiance next hour, the observed value of solar irradiance at the time *t*, the time *t*-1 and the time *t*-2.

In order to judge the quality of the forecasting, the RMSEs of the methods 1-6 are calculated by equation (4). The RMSEs of the methods 1-6 are shown in Figs.1-5. The results of RMSE comparison for the solar irradiance forecasting with 1, 3, 6, 12 and 24 hours ahead are shown in Figs.1-5, respectively.

According to comparison for the values of RMSE, neural networks combined with future solar irradiance have the lowest value of RMSE.

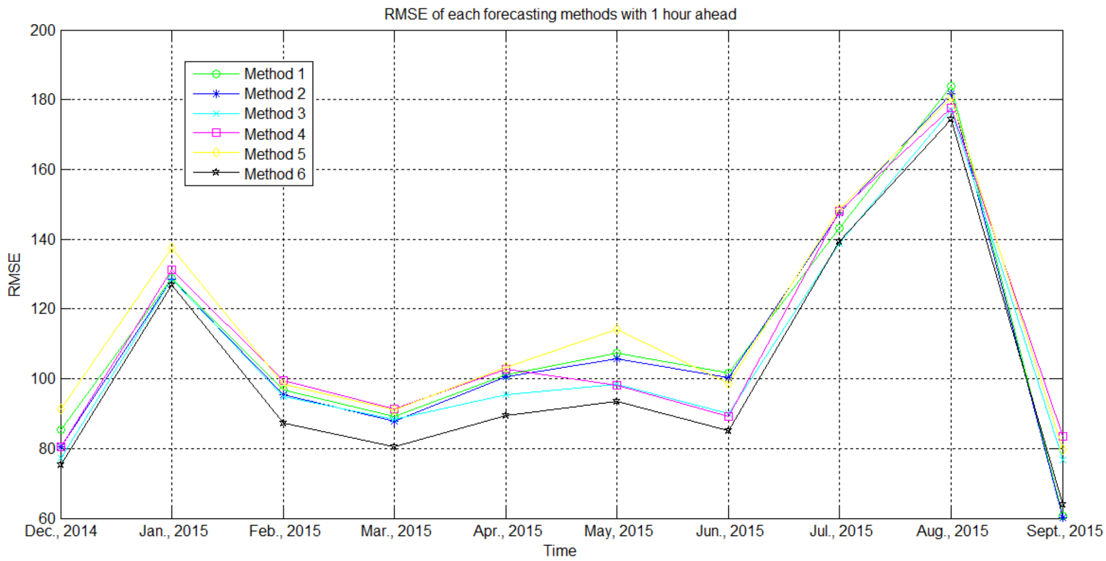

FIG.1. RMSE of each forecasting methods with 1 hour ahead.

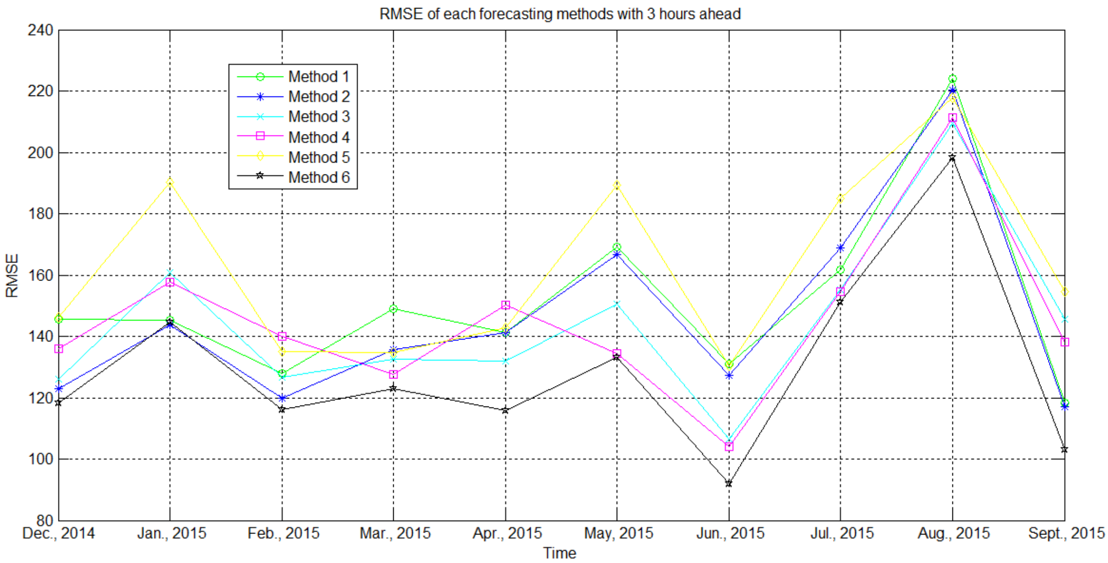

FIG.2. RMSE of each forecasting methods with 3 hours ahead.

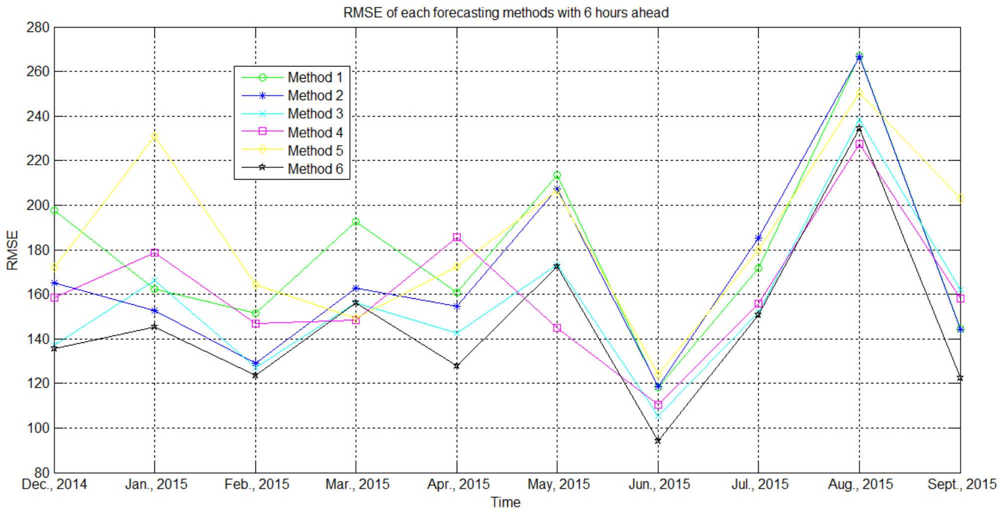

FIG.3. RMSE of each forecasting methods with 6 hours ahead.

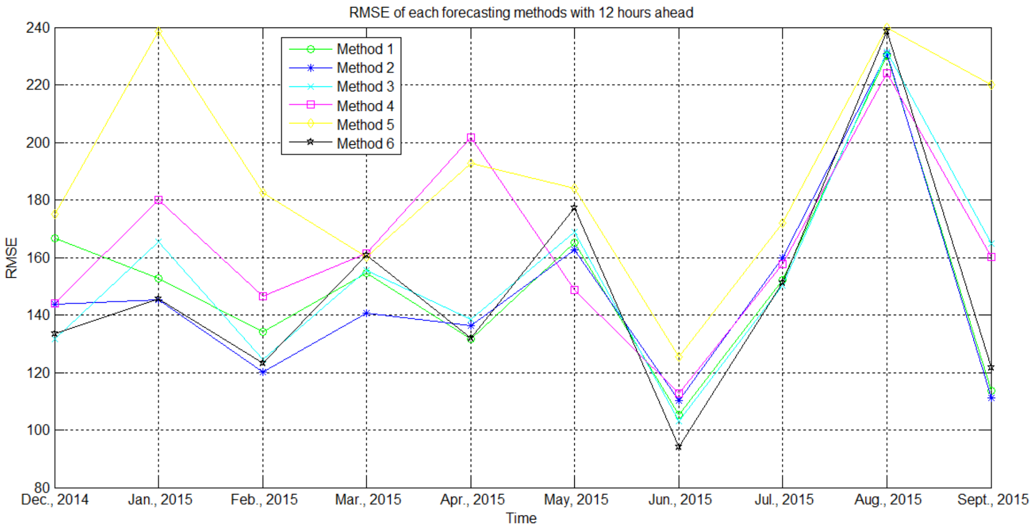

FIG.4. RMSE of each forecasting methods with 12 hours ahead.

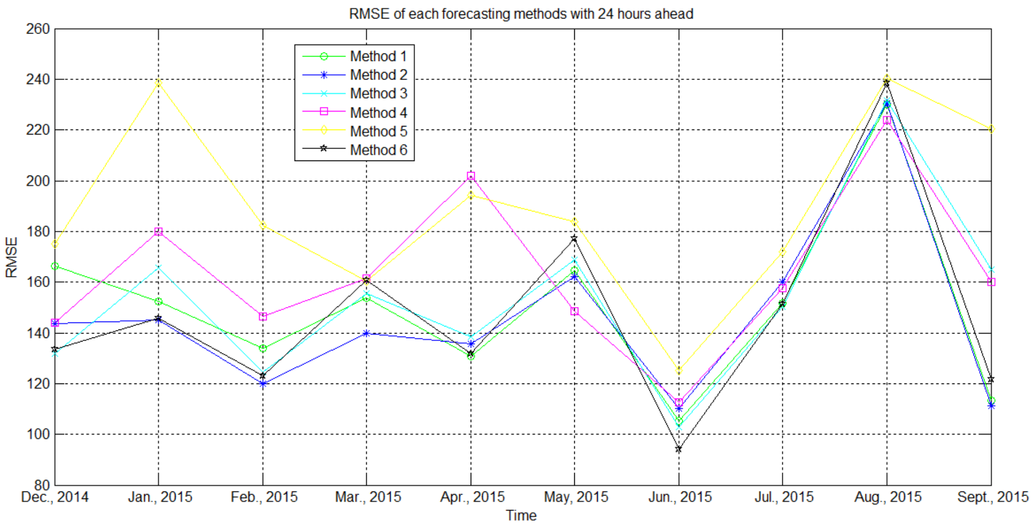

FIG.5. RMSE of each forecasting methods with 24 hours ahead.

III. CONCLUSION

This paper has proposed some different features for solar irradiance forecasting and presented some comparison results of solar irradiance forecasting in Taichung solar farm. According to the RMSE comparison figures, the method depend on historical and future solar irradiance values is better than other methods in forecasting with 1-24 hours ahead. Moreover, the results are likely to be affected by the historical data in the forecasting with short-time ahead.

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