Wind Power Forecast by Using Improved Radial Basis Function Neural Network

H. J. Lu, *Member, IEEE*, and G. W. Chang, *Fellow, IEEE*
Department of Electrical Engineering,
National Chung Cheng University
Chiayi, TAIWAN

***Abstract*—Forecasting wind speed or wind power generation is indispensable for the effective operation of a wind farm, and the optimal management of its revenue and risks. This paper proposes an improved radial basis function neural network structure for forecasting the wind power generation. Results are then compared with back propagation neural network (BPNN), BPNN with Levenberg-Marquardt (BPNN-LM), radial basis function neural network (RBFNN), and the actual measured wind power outputs. Test results show that the presented model can provide more accurate and stable time-horizons forecasting.**

***Index Terms*-- Wind power forecast, back propagation neural network, radial basis function neural network.**

I. INTRODUCTION

Wind power is one of the most rapidly growing renewable energy sources, and is regarded as an appealing alternative to conventional power generated from fossil fuel. This led to a collaborative effort to achieve 20% of U.S. electricity supplied from wind power by 2030 [1]. Although the integration of wind power brings many rewards, high penetration of wind power provides a number of challenges in power system operations and planning, mainly due to its uncertain and intermittent nature. In the electricity system the power supply must be equal to the power demand at all times. However, the variation of wind power output makes it difficult to maintain this balance. Short-term forecasting of wind speed is critical to the operation of wind turbines so that dynamic control can be accomplished to increase the energy conversion efficiency and reduce the risk of overloading [2]. With the greater penetration of wind power, the forecasting of wind speed and power generation plays a pivot role in improving energy market efficiency, reducing the amount of reserves while maintaining the system security, and maximizing revenue of wind generators by optimizing their daily and/or intraday bids in the electricity markets.

Short-term forecasts (ranging from 1 hour up to 72 hours) are useful in power system planning for unit commitment and dispatch, and for electricity trading in certain electricity markets where wind power and storage can be traded or hedged. Medium-term forecasts and predictions (ranging from 3 days to 7 days) are needed to plan maintenance of the wind farms, unit commitment and maintenance outages of thermal generators and to schedule grid maintenance and energy storage operations.

A number of time series forecasting methods have been successfully applied to the short-term prediction of wind speed and power generation. Autoregressive integrated moving average (ARIMA) is one of the most robust and widely used approach in wind forecasting [3] and linear approaches based on statistical regression [2]. The ARIMA family models can explicitly reveal the relationship between the inputs and outputs, but they are generally limited in linear forms. Artificial intelligence (AI) and machining learning (ML) approaches are also frequently adopted for wind forecasting. The AI and ML techniques have been adopted for the purpose of wind speed forecasting, such as neural networks (NN) of multi-layer perceptrons (MLP) [4], radial basis function neural network (RBFNN) [5], recurrent neural networks [6], support vector machine (SVM) [7], and fuzzy logic [8]. In general, the AI/ML models can better handle non-linear relationship and thus are more flexible, but they describe the relationship in implicit ways and sometimes are very computationally intensive.

In addition to the aforementioned single-model structures, two kind forecasting methodologies are emerging, namely combined forecasting or hybrid forecasting. The combined forecasting tackles the task in two steps, with the first step existence to make forecasts using multiple plausible models, and the second step existence to combine these forecasts into a single forecast time series using weighting algorithms. A new prediction tool using an adaptive combination of a variety of statistical models is applied. Reference [9] proposes the Bayesian model averaging approach to combine the forecasts from ANN and ARIMA models. It is found that the resultant forecast can always perform better or close to the best individual models. It is noted that the ensemble approaches can also be used to combine with the forecasts from different numerical weather prediction (NWP) models in literature. For instance, [10] combines a number of meteorological forecasts originating from three various global NWP models. Moreover, [10] proposes conditional weighted combination of wind power forecasts, and results show that the proposed

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combination method outperforms the least-squares combination method for almost all prediction.

On the other hand, hybrid forecasting methods take a different approach. It usually employs a linear model for the prediction of the linear component and a non-linear model for the non-linear component in time series. To make the study comprehensive, this paper adopts multiple forecastings, which is multiple input (i.e. ambient temperature and wind speed) to train wind power between the improved radial basis function neural network parameters. Furthermore, the study conducts the tests of a winter season type of wind time series data – the 24-hour ambient temperatures, wind speed time series, and wind power generation time series. Therefore, the paper proposes an enhanced forecasting model structure, improved radial basis function neural network, to forecast the wind power and results are compared with those obtained by back propagation neural network (BPNN), BPNN with Levenberg-Marquardt (BPNN-LM), and standard radial basis function neural network (RBFNN) forecasting models.

II. Modeling Wind Power Generation

A. Power Output of Wind Turbines

The energy conversion that takes place at the turbine level is characterized by (1).

$$E_K = \frac{1}{2}\rho_{air} A v^3 \quad (1)$$

where ρ_{air} is the density of the air. A is the area swept by the turbine's rotor blades. Therefore, the power in the wind passing through an area A with speed is v.

$$P = \frac{1}{2}\rho_{air} A v^3 C_P \quad (2)$$

where CP is the power coefficient [11].

B. Power Curve

As indicated in (1), the available energy in the wind varies with the cube of the wind speed. Thus, a ten percent increase in wind speed will result in a thirty percent increase in available energy. The power curve of a wind turbine follows this relationship between cut in wind speed (the speed at which the wind turbine starts to operate, V_1), the rated capacity (V_2) and the cut out (V_3) see also Fig. 1.

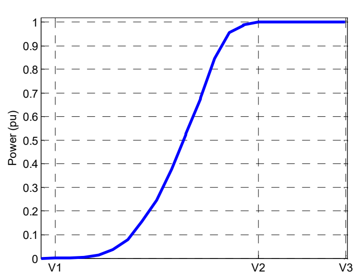


Fig. 1. Power Curve

C. Capacity Factor

The ratio P_A/C_{IC} is called the capacity factor (CF), and can be calculated for individual units or for the total production of several units. The capacity factor depends on the wind resources at the location and the type of wind turbine, where C_{IC} is the total installed capacity and P_A is the mean power production of all units can be calculated as

$$P_A = \int_0^{C_{IC}} S f_P(S) dS \quad (3)$$

and where f_P(S) is the total wind power from several wind power units during a specific period. The utilization time in hours per year is defined as 8760 P_A/C_{IC}. The yearly energy production, W can be calculated as

$$W = P_A \times 8760 = C_{IC} \times 8760 \times CF \quad (4)$$

III. Proposed Method

A. Overview of Improved Radial Basis Function Neural Network

The radial basis function neural network (RBFNN), due to the advantages addressed in the introduction, is very suitable for non-linear time series prediction, such as in wind power forecasting. RBFNN is a forward network. As shown in Fig. 2, the structure of RBFNN is composed of the input, the hidden and the output layer. The function of the input layer is to transmit signals. The parameters of the activation function, which is a Gaussian Function, are regulated by the hidden layer, where the nonlinear optimization strategy is used. Linear weights are adjusted by the output layer, and in general the linear optimization strategy is adopted.

The Gaussian function defined as below is the usual choice for an RBFNN, as given in (5).

$$Z_j(x) = R(\|x - c_j\|) = exp(-\frac{V_j^2 (x - c_j)^2}{\sigma_j^2}),\ j = 1, 2, ..., M \quad (5)$$

where x represents the input vector including x_1 through x_N, Z_j is the output of each neuron in the hidden layer, c_j is the center of the j^{th} neuron, σ_j is the standard deviation [17] to indicate the variation of the input data relative to the center c_j, and V_j is the Gaussian of input variables weighting values of j^{th}. ||.|| denotes the Euclidean distance. Then, the output of the network is

$$y_j = \sum_{j=1}^{M} w_j Z_j(x) \quad (6)$$

where w_j is the weight between the j^{th} hidden neuron and the output neuron.

The learning process in neural network could be viewed as a search for free parameters by minimizing or maximizing a predefined criterion function, like mean squared error (MSE). These parameters are the hidden neuron centers (i.e. the means of Gaussian function), the hidden neuron widths (i.e. the variances of Gaussian function), and the weights which is from hidden layer to output layer.

Because the purpose of supervised learning is to reduce the network of output unit of output target value and the inference output value of the gap, therefore the error function expressed by the quality of learning as follows (11), where t_j

is the training samples in the output layer of the j^{th} output target value, y_j is the training sample in the output layer of the j^{th} output inference value. In order to achieve the minimum error function, GSDM can be used to adjust the weighted value of the network link parameters of the Gaussian parameters.

$$e(n)=\frac{1}{2}(t_j-y_j)^2 \tag{7}$$

The hidden layer and the output layer connection weights, output unit of the threshold correction and hidden layer of Gaussian parameter such as (8), (9), (10), and (11) where η is the learning rate. Stop the training to limit the number of learning cycle.

$$w_j(n+1)=w_j(n)+\eta e(n)R(\|x-c_j(n)\|) \tag{8}$$

$$c_j(n+1)=c_j(n)+\eta\frac{w_j(n)e(n)}{\sigma_j^2(n)}R(\|x(n)-c_j(n)\|)(x(n)-c_j(n)) \tag{9}$$

$$\sigma_j(n+1)=\sigma_j(n)+\eta\frac{w_j(n)e(n)}{\sigma_j^2(n)}R(\|x(n)-c_j(n)\|)\|x(n)-c_j(n)\|^2 \tag{10}$$

$$V_j(n+1)=V_j(n)+\eta\frac{w_j(n)e(n)}{\sigma_j^2(n)}R(\|x(N)-c_j(n)\|)(x(n)-c_j(n)) \tag{11}$$

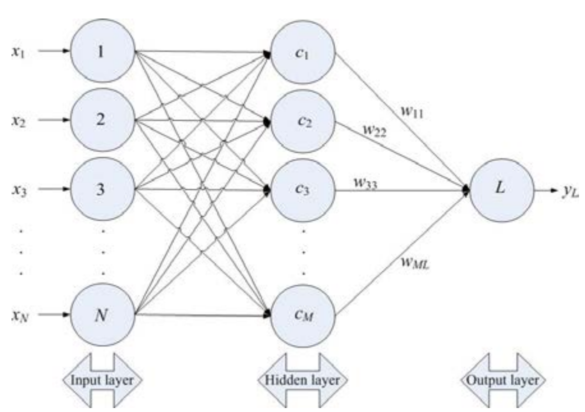


Fig. 2. Improved Radial Basis Function Neural Network Structure.

For convenience of initial calculation, the standard deviation of each neuron in the hidden layer is given by (12), where M is a selected big number and d_{max} is the maximum distance appearing among central points.

$$\sigma=d_{\max}/\sqrt{M} \tag{12}$$

B. Solution Procedure for Wind Power Training and Forecasting

Listed below are major steps of the proposed solution procedure for wind power output forecast.

1. Take the number of learning cycles, the learning rates, the numbers of neurons of the input, hidden, and output layers, and the convergence threshold values.

2. Input consecutive one day (i.e. 24 hours) at 10-minute resolution of actual measured ambient temperature, wind speed, and wind power data sets for training.

3. Enter a training example of the input vectors and the target output vectors, moreover, calculate the hidden layer of the output vectors for (5) and the target output vectors of inference for (6).

4. Iterate the neural network four parameters, c_j, σ_j, w_j, and V_j, according to (8), (9), (10), and (11), respectively, and update those values saved in the built look-up table at step 3 of the trained parameters set.

5. Update the step **4.** parameter of the Gaussian basis function values (i.e. the weights, w_j and V_j; the center, c_j, and the standard deviation, σ_j) and save in the built look-up table.

6. Stop the training to limit the number of learning cycle for repeat the step **3.** to the step **5.**

7. Give the parameters of the network architecture (input layer, hidden layer and output layer of the number of neurons).

8. Input a different set of actual measured ambient temperature and wind speed time series data samples for initial input vector to be forecast to (5).

9. Calculate associated forecasted by (6) according to the saved look-up table.

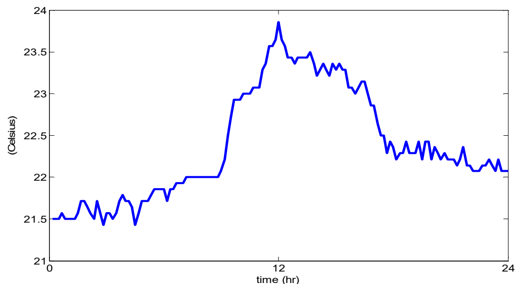
10. Return to step **8.** for maximum number of power output samples of forecasting, if the present number of power output time series sample is not the last sample. Otherwise, stop.

IV. Test Results

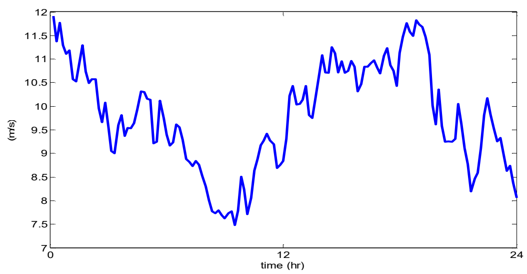
In this study, the ambient temperature, wind speed, and wind power data sets extracted by the Taiwan Power Company (TPC), the ambient temperature, wind speed, and wind power for the winter season (December) of training and forecasting, respectively. The actual ambient temperature, wind speed and wind power measured sets will build in two modes: training (or learning) and forecasting (or examining) processes. To compare the proposed method with back propagation neural network (BPNN), BPNN with Levenberg-Marquardt (BPNN-LM), and standard radial basis function neural network (RBFNN), this paper employs BPNN, BPNN-LM, and RBFNN to forecast the same section of the wind power, respectively.

Figs. 3(a) and 3(b) display the actual measured data set of wind speed and wind power time horizons corresponding to the wind farm which is operated 72 hours for training the two compared methods to forecast the on-shore wind power. In order to compare the ARIMA, BPNN, and RBFNN between the measured and forecasting wind power time horizons data, the distribution curves are also shown in Figs. 3(c), 3(d), 3(e), and 3(f). Table 1 displays the ARIMA, BPNN, RBFNN, and proposed method were expressed by the forecasting error of the mean absolute percentage error (MAPE) and root mean squared error (RMSE) of the four days after training data of the wind power time horizons for the forecasting processes comparison table.

By observing the results obtained in Fig. 3 and Table 1, it shows that the proposed method leads to better solution than others. The proposed method is effective in forecasting wind power output.



(a)



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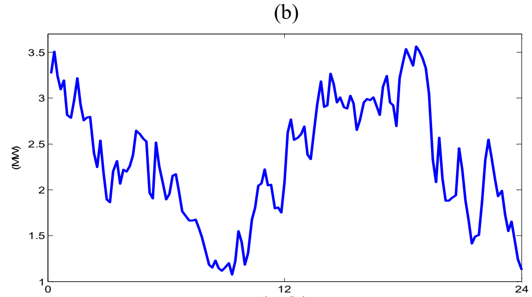
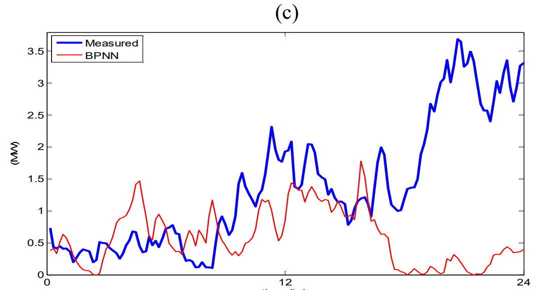


(c)



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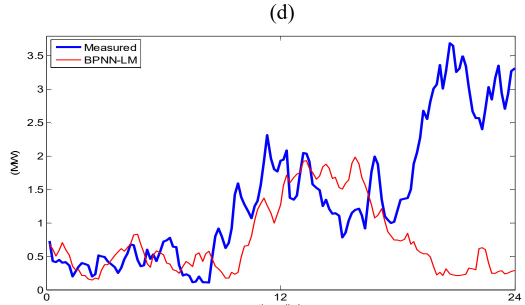

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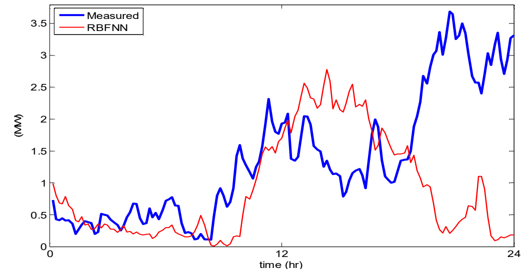

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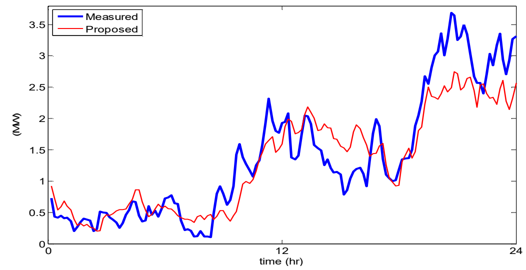

(g)

Fig. 3. Data in the training, measured, and forecasting processes: (a) ambient temperature consecutive one day for training, (b) wind speed consecutive three days for training, (c) wind power consecutive three days for training, (d) next day after training data of the wind power measured and the BPNN forecasting distribution curve, (e) the measured and the BPNN-LM wind power time horizon forecasting, (f) the measured and forecasting by RBFNN, (g) the measured and the wind power time horizon forecasting by proposed method.

Table 1. Errors of Methods under Comparisons for Fig. 3

	MAPE(%)	RMSE(%)
BPNN	17.478	21.373
BPNN-LM	11.104	14.927
RBFNN	9.177	11.762
Proposed	7.981	8.991

MAPE = {sum [(abs (predictive)-abs (measured))/abs (measured)]}/144

RMSE = $\{[\text{sum}\ [(\text{predictive} - \text{measured})/\text{measured}]^2]/144\}^{1/2}$

VI. Conclusions

As wind energy becomes the world's fastest growing source of clean and renewable energy, the predictability of wind power generation is essential for the integration of wind energy into the power system. With the rapid growth of wind energy, accurate and reliable methods and techniques for short-term wind speed forecasting are urgently needed. This paper has proposed to use an improved radial basis function neural network model to ameliorate wind power output time horizons forecasting. The proposed method from the training ambient temperature, wind speed, and wind power time series to forecast the future of wind power output time horizons and compared the results of the back propagation neural network (BPNN), BPNN with Levenberg-Marquardt (BPNN-LM), and standard radial basis function neural network (RBFNN). Results confirm that the proposed method can learn the center, radius of the Gaussian units and other parameters of the relative size; moreover, the convergence speed and accuracy of the proposed method are superior to the traditional radial basis function neural network and other methods under comparison.

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