Short-term Wind Power Forecasting Using a Double-stage Hierarchical Hybrid GA-ANN Approach

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***Abstract*—Power generation from wind generators is always associated with some intermittency due to wind speed and other weather parameters variation, and accurate short-term forecasts are essential for their efficient and effective operation. This can well support transmission and distribution system operators and schedulers to enhance the power network control and management in the smart grid context. This paper presents a double stage hierarchical genetic algorithm trained artificial neural network (double-stage hybrid GA-ANN) for short-term wind power forecast of a microgrid wind farm in Beijing, China. The approach has two hierarchical stages. The first GA-ANN stage employs numerical weather prediction (NWP) meteorological parameters to forecast wind speed at the wind farm exact site and turbine hub height. The second stage models the actual wind speed and power relationships. Then, the predicted next day's wind speed by the first stage is applied to the second stage to forecast next day's wind power. The presented approach has achieved considerable prediction accuracy improvements. The prediction performance of the proposed approach was also compared with another double-stage Back Propagation (BP) trained ANN prediction model and showed a better accuracy improvement.**

Keywords-artificial neural network; forecasting; genetic algorithm; numerical weather prediction; wind power

I. INTRODUCTION

Deployment of renewable energy resources primarily wind power generation has acquired magnificent considerations in eye-catching number of countries following the adoption of the Kyoto protocol environmental convention. Despite its significant environmental benefits, the continuous intermittency and chaotic fluctuations of wind speed and other weather variables make the output power of wind power generation systems completely stochastic and different from those of conventional energy sources. Due to this indeterminacy, it may get several challenges to connect large quantities of wind power into a power system network. However, this challenge is not surmountable. In order to enhance the economic competence and acceptability of the wind power and to allow a reduction in the penalty of an instantaneous spot market coming from over estimation or underrating of the generation, the exact forecasting of wind power as well as wind speed is necessary. Definitely, a reliable forecasting system can help distribution system operators and power traders to make a better decision on critical situation.

Recently, several techniques have been developed to forecast the wind power and speed. Existing techniques can be classified as statistical, physical and time series modeling techniques based on the forecasting models they used [1]. Currently, it is observed that researchers employ a combination of statistical model and physical methods besides each other to get an optimal approach that is applicable for longer horizons of prediction systems. In these techniques statistical model plays auxiliary role to data collected by physical methods.

Although two major classes of methods have been recognized for the wind power forecasting, (in [2] and [3], comprehensive reviews of these techniques are presented), as mentioned earlier, combination of statistical and physical techniques are more common than the others [4], [5]. Besides, numerous other spatial correlation methods are proposed for short term wind power prediction with the goal of attaining higher prediction accuracy [6]. However, through the passage of time, more advanced and intelligent methods have been proposed. For instance, Artificial Neural

Network (ANN) in [7], [8], [9], ANN with Gaussian process approximation and adaptive Bayesian learning in [10], combination of wavelet transform with ANN [11], fuzzy logic methods in [5], [12], Kalman filter in [13], support vector machine in [14], and adaptive neuro-fuzzy inference system (ANFIS) in [15] have been proposed for wind power prediction.

Considering the available research works in the area, new forecasting approaches and techniques of input-output data manipulations are still in demand in order to enhance prediction accuracy and decrease the uncertainty in wind power forecasting, while keeping practically acceptable computation time. This objective leads to the new double-stage hybrid approach proposed in this research paper to utilize both statistical (wind farm SCADA records) and physical (NWP meteorological variables) data sources for achieving an effective and more accurate short-term wind power forecaster in China.

In this research paper, a new effective short-term wind power forecasting approach based on combination of feedforward artificial neural network (ANN) and genetic algorithm (GA) is proposed. The proposed approach utilizes GA method to optimize the connection weights of the ANN to achieve a lower error. The proposed methodology has two hierarchical GA-ANN stages.

In the first stage, GA-ANN is implemented to predict wind speed at the exact height of the wind turbine hub at the point of wind farm installation. In this phase, forecasted meteorological variables (wind speed, wind direction, air pressure, air temperature and humidity) from NWP model as inputs and actual wind speed measurement recorded by the wind farm SCADA as output are utilized to train the ANN. In the second stage, GA-ANN is developed to map the wind turbine wind speed vs. wind power characteristics based on real operational conditions. Actual wind speed and power measurements recorded by the wind farm SCADA are used, respectively, as input and output to train the ANN in this stage. Then, the forecasted wind speed by the GA-ANN model in the first stage is applied to the developed (trained) GA-ANN model in the second stage in order to estimate the next day wind power output of the wind farm.

The forecasting results are presented for the next 24 hours with one hour time steps. The developed DSHGN (double-stage hybrid GA-NN) prediction approach is compared with a DSBPN (double-stage back propagation neural network) approach, to demonstrate its effectiveness regarding short-term wind power prediction accuracy and computational time.

The paper is organized as follows. Section II presents the proposed forecasting model. Descriptions of the GA-ANN framework as a prediction system and brief working principles of GA and ANN are provided in section III. Sections IV provides different criterions used to evaluate the prediction accuracy. The numerical findings and prediction results for the considered real case-study are provided in sections V. The paper conclusions are drawn in section VI.

II. Short-term Wind Power Forecasting Model

A. *Proposed Wind Power Forecasting Strategy*

In this research paper, a short-term (24-hour ahead) wind power forecasting using a double-stage GA-ANN is presented. The fundamental data sources are historical measurement records of the wind farm SCADA system database and meteorological variables of NWP model. The prediction system uses the meteorological predictions of the NWP model obtained at the vicinity of Goldwind microgrid system wind farm in Yizhuang, Beijing, China within 5km resolution, and actual measurement records of the wind farm SCADA system database. The proposed approach has two hierarchical GA-ANN stages. In the first stage, the wind turbine is modeled by a GA-ANN black box to develop a relationship between the predicted NWP meteorological variables (*i.e.* wind speed, wind direction, air pressure, air temperature and humidity) and the actual wind speed measurement recorded by the wind farm SCADA system. In the second stage, GA-ANN model is developed to map the wind turbine wind speed vs. wind power characteristics based on the real operational conditions. Then, the forecasted wind speed by the GA-ANN model in the first stage is applied to the developed (trained) GA-ANN model in the second stage in order to forecast the next day wind power output of the wind farm.

The double-stage forecasting scheme is depicted in Fig. 1.

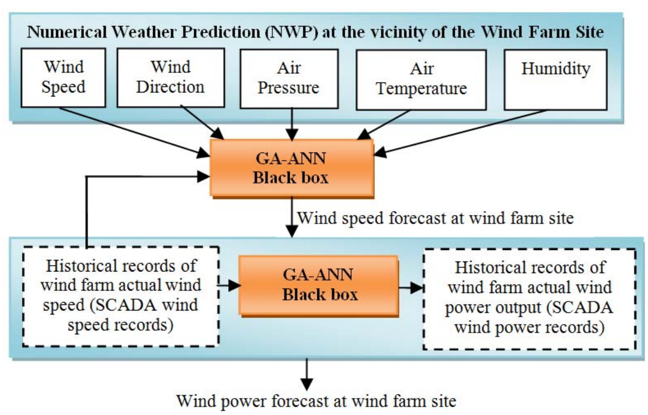

Figure 1. Double-stage forecasting model using GA-ANN

In the course of modeling, a one year information record provided from SCADA historical measurements and NWP/WRF model historical weather forecasts are used to train an ANN that successfully can estimate a transfer function between specific patterns of input and output quantities. Then, GA is applied to optimize the connection weights of ANN. This process continues until the prediction error reaches to a suitable value.

III. PROPOSED CONFIGURATION FOR GA-ANN

A. *Genetic Algorithm (GA)*

Most practical optimal design engineering problems are described by mixed continuous-discrete variables, and discontinuous and con-convex design domains. If traditional and standard nonlinear optimization techniques are implemented for this sort of engineering problem they will be inefficient, computationally expensive, and, in most cases, find a relative optimal solution that is closest to the starting point.

Genetic algorithms (GAs) are more suitable for solving such engineering problems, and in most cases they are able to find the global optimal solution with a high degree of probability. GAs were first presented systematically by Holland [16]. The GA basic ideas of analysis and design based on the concepts of biological evolution can be found in the work of Rechenberg [17].

GAs were inspired by Darwin's theory of *survival of the fittest*. They are based on the principles of natural selection and genetics. The natural genetics fundamental elements—*reproduction, crossover*, and *mutation*—are used in the genetic search process.

B. *Artificial Neural Networks (ANN)*

Neural network is a robust data modeling tool that is able to capture and represent the complex input/output relationships. ANN is a data processing paradigm that is inspired by the way biological nervous systems, like the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of processing elements (neurons) made up of different layers of input, hidden and output nodes highly interconnected through some weighted connections and all working in unison to solve specific problems [18], [19].

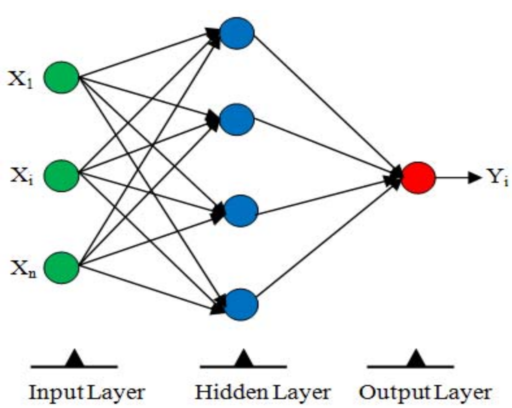

Figure 2. Multi-layer feedforward neural network

ANNs, like human, learn by example. An ANN is configured for a specific application, such as data classification or pattern recognition, via a learning process. Learning in biological systems includes fine-tunings to the synaptic connections that exist between the neurons. This is true of ANNs as well. And for the validation process ANN follows the human brain that provides evidence of the existence of massive neural networks that can succeed at those perceptual, cognitive, and control tasks in which humans are successful.

A descriptive representation of a multi-layered neural network is shown in Fig. 2.

where X_j is the j^{th} input to the i^{th} node (neuron) and Y_i is the output of the i^{th} node.

The mathematical equation which shows the relationship between the inputs X_i to the neural network and the output Y_i of the network is given by (1) as:

$$Y_i = f_i\left(\sum_{j=1}^{n} w_{ij}.X_j + b_i\right) \tag{1}$$

where w_{ij} is the connection weight between the input neuron and output neuron, b_i is the bias of the neuron, and f_i is known as activation function that determines the characteristics of the neural network.

C. *Proposed Approach for ANN Weight Optimization*

In this paper, the two-stage hierarchical ANN networks utilize GA technique to optimally tune the connection weight parameters between neurons. The GA method has the advantages of implementation simplicity and being less computationally expensive for a specified size of network topology. The neural network topology considered in this research paper is a multi-layered feedforward (MLFF) type.

Basically, MLFF neural network is a Back Propagation (BP) algorithm based network whose connection weight parameters are tuned with a BP algorithm based on some collection of input-output data. This allows the ANN network to learn. BP carries out a gradient descent within the solution's vector space towards a global minimum value along the steepest vector of the error surface. Though BP learning algorithms are fast, they are trapped in local minimums and unable to attain global minimums.

To overcome the BP algorithm difficulties, GA is employed as a global optimum search algorithm. Furthermore, GA is highly independent on structuring of ANN; whereas, gradient descent based techniques deeply suffer from dependence on the ANN network structure. In this study, ANN weight parameters are formed as variables of the GA and the mean squared error is utilized as a cost function in GA. The objective of proposed approach is to reach a minimum value for this cost function.

IV. WIND POWER FORECASTING ACCURACY EVALUATION

In order to evaluate the accuracy of the DSHGN (double-stage hybrid GA-NN) wind power prediction approach, the mean absolute percentage error (MAPE), the sum squared error (SSE), the root mean squared error (RMSE), and the standard deviation of error (SDE) criterions are used. These performance criterions are computed as a function of the actual wind power that occurred, and defined as follows.

The MAPE criterion is defined as:

$$MAPE = \frac{100}{N}\sum_{h=1}^{N}\left|\frac{P_h^a - P_h^f}{\overline{P}_h^a}\right| \tag{2}$$

$$\overline{P}_h^a = \frac{1}{N}\sum_{h=1}^{N} P_h^a \tag{3}$$

where P_h^a and P_h^f are respectively the actual and forecasted wind power at hour *h*, $\overline{P}_h^a$ is the average actual wind power of the prediction horizon and *N* is the prediction horizon.

The SSE criterion is defined as:

$$SSE = \sum_{h=1}^{N}\left(P_h^a - P_h^f\right)^2 \tag{4}$$

The RMSE criterion is defined by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{h=1}^{N}\left(P_h^a - P_h^f\right)^2} \tag{5}$$

The SDE criterion is defined by:

$$SDE = \sqrt{\frac{1}{N}\sum_{h=1}^{N}\left(e_h - \overline{e}\right)^2} \tag{6}$$

$$e_h = P_h^a - P_h^f \tag{7}$$

$$\overline{e} = \frac{1}{N}\sum_{h=1}^{N} e_h \tag{8}$$

where e_h is the prediction error at hour *h* and $\overline{e}$ is the average error of the prediction horizon.

V. Case Study and Numerical Results

The DSHGN approach has been applied for short-term wind power forecasting in a microgrid wind farm in Beijing, China. This wind farm has a single wind turbine unit with a generation capacity of 2500kW. NWP meteorological forecasts and historical SCADA records of wind speed and power data are the main data inputs for training.

Time series of NWP weather forecast, actual SCADA measurement of wind speed and actual SCADA measurement of wind power for the wind farm are recorded from the 1st May 2014 to the 31st April 2015. The forecasting information is given for four days corresponding to the four seasons of a year (July 21, 2015, October 15, 2015, January 4, 2016 and April 13, 2016). Thus, days with specifically good wind power characteristics are purposely not selected. This results in an irregular accuracy allocation throughout the year that shows the reality.

Numerical results with the DSHGN approach are shown in Figs. 3 to 4, respectively for the winter and spring days, and summer and fall days. Each figure shows the SCADA actual wind power record with the forecasted wind power by the proposed approach.

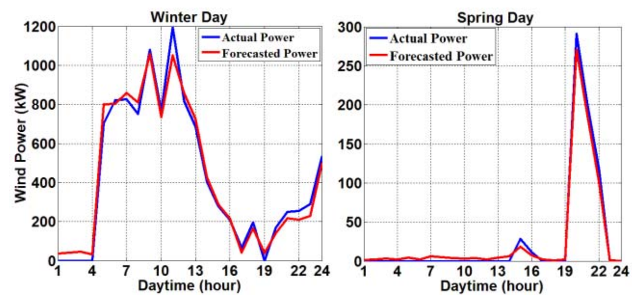

Figure 3. Actual vs. forecasted wind power for winter and spring days

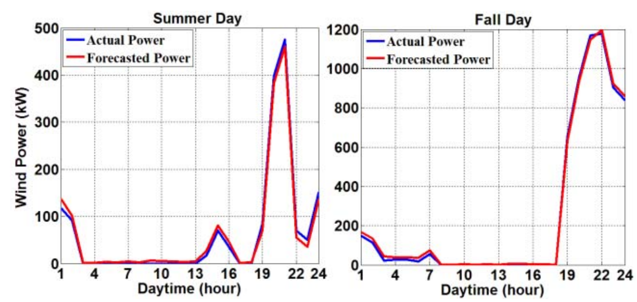

Figure 4. Actual vs. forecasted wind power for summer and fall days

Table I gives the values of the criterions used to evaluate the accuracy of the DSHGN approach in predicting wind power. Table II presents a comparison between the DSHGN prediction approach and the DSBPN (double-stage back propagation neural network) approach, with respect to the MAPE criterion.

The proposed forecasting approach gives better forecasting accuracy: the MAPE has 10.893% average value. The proposed approach's average MAPE improvement with respect to the DSBPN approach is 2.74%.

TABLE I. Daily Forecasting Error Statistical Analysis

Day Type	MAPE	$\sqrt{SSE}$	RMSE	SDE
Winter	8.8829	211.8925	43.2524	43.1861
Spring	18.449	36.4995	7.4504	7.3428
Summer	11.85	47.9634	9.7905	9.7647
Fall	4.3908	67.1676	13.7105	12.1157

TABLE II. COMPARISON OF MAPE RESULTS

	Winter	Spring	Summer	Fall	Average
DSBPN	9.4074	18.52	12.33	4.5055	11.191
DSHGN	8.8829	18.449	11.85	4.3908	10.893

The absolute values of prediction errors with respect to the maximum capacity of the wind farm (i.e., normalized by the maximum wind farm capacity), considering all the approaches, are shown in Figs. 5 to 6, respectively for the winter and spring days, and summer and fall days. The DSHGN approach provides smaller errors compared with the DSBPN approach.

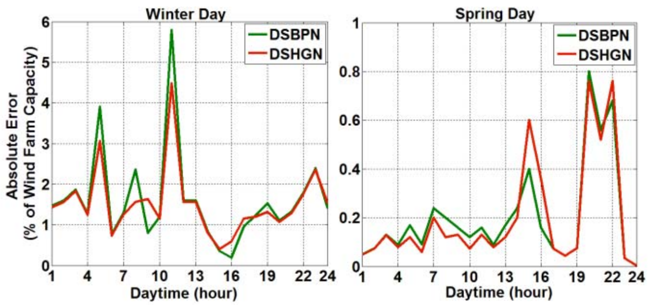

Figure 5. Normalized absolute forecast errors for winter and spring days

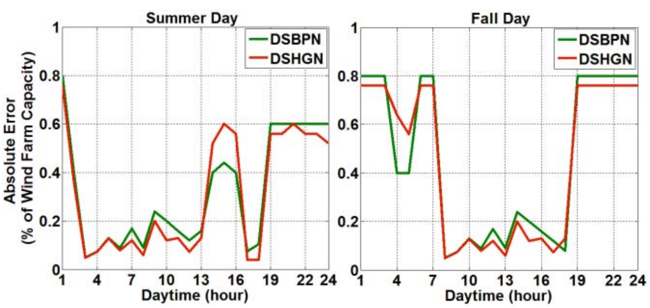

Figure 6. Normalized absolute forecast errors for summer and fall days

In addition, the average computation time is around 9 seconds, using MATLAB on a PC with Intel core i5-5200 CPU, 2.20 GHz processor and 4 GB RAM.

VI. CONCLUSION

In this study, a new hierarchical hybrid approach is proposed for short-term wind power forecasting based on the combination of GA and ANN. The approach has two hierarchical stages. The proposed strategy for the wind power prediction is both novel and effective. The MAPE has 10.893% average value, outperforming the DSBPN prediction method while the average computational time is lower than 9 seconds. Thus, the obtained numerical results validate the effectiveness of the proposed strategy for short-term wind power forecasting.

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