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Short-Term and Very Short-Term Wind Power Forecasting Using a Hybrid ICA-NN Method

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Abstract: Utilization ofwind power as one of renewable resources of energy has been growing quickly all over the world in the last decades. Wind power generation is significantly vacillating due to the wind speed alteration. Therefore, assessment of the output power of this type of generators is always associated with some uncertainties. A precise wind power prediction can efficiently uphold transmission and distribution system operators to improve the power network control and management. This paper presents a new Imperialistic Competitive Algorithm- Neural Network (ICA-NN) method to enhance the short wind power forecasting exactness at a wind farm utilizing data from measured information of online supervisory control and data acquisition (SCADA) as well as Numerical Weather Prediction (NWP). Moreover, a very short-term wind power prediction is accomplished based on the past values of wind speed and wind generation and then a comprehensive comparative literature review on the proposed methods in cases of short-term and very short-term is presented. In the proposed method, first, a prediction model of the wind speed is built based on Multilayer Perception (MLP) artificial neural network considering environmental factors (*i.e.* Humidity, wind speed, temperature, geographical conditions and other factors). Then, Imperialist Competitive Algorithm is used to update the neural network weights. The proposed method has ability of dealing with data jumping and is suitable for any wind power and wind speed foreseeing.

Keywords: Imperialistic competitive algorithm- Neural network; supervisory control and data acquisition;numerical weather predictions; wind farm; wind power prediction.

I. INTRODUCTION

Kyoto Protocol with the aim of achieving the "stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" is an environmental covenant. By adopting this protocol, due to environmental behoof of renewable resources particularly wind power generation, utilization of these types of energy has acquired noticeable consideration in eye-catching number of countries, recently. In comparison with the environmental damages of traditional sources of energy, the ecological influences of wind power is proportionately negligible; in fact, wind power fuel usage is incomparable with fossil power planets as well as fuel emission. Furthermore, wind power enjoys infinitesimal progress expenses, in addition to an average cost of investigation. However, despite remarkable environmental benefits, the continuous and chaotic fluctuations of wind speed make the output power of wind farms completely stochastic and different from those of conventional units. However, instant electrical generation must be equal to the grid consumption to fulfill the network stability requirements and the spare capacity may be reduced in the power system. Due to this fickleness, it may bestow ample challenges to connect large quantities of wind power into a power system. However, this challenge is not insuperable. In order to increase the economic efficiency and acceptability of the wind power and to permit a diminishing in the punishment of an instantaneous spot market coming from extra estimation or underrating of the production, the exact prediction of wind power as well as wind velocity is required. Surely, a reliable prediction system can help distribution system operators and power marketers to make a better decision on critical situation.

Nowadays, several methods have been developed to predict the wind power and speed. Existing methods can be arranged as statistical, physical and time series modeling methodsbased on the used prediction models [1]. The physical methods are based on local meteorological service or NWP model data of the lower atmosphere (*i.e.* in relation with atmospheric pressure degree, at 2m or 10m heights above the ground) associated with topological data like obstacles, roughness and orography. The core idea of physical approaches is to estimate generation power of the wind turbine with outsourcing these obtained data up or down to exact height of the wind turbine hub and then, utilizing the manufacturer's power curve for the logarithmic power law or the specific wind turbine. Statistical forecasting techniques are only based on one or more models. These approaches found coordination between predict and historical numerical quantity of meteorological parameters and wind power measurements associated with the power quantities coming from historical data.

Moreover, statistical models enjoy freedom of using NWP models; whereas, physical models must utilize NWP models [2]-[5]. Recently, it is prevalent that authors use a combination of a progressive statistical model and physical methods besides each other to reach an optimal approach that is applicable for longer horizons of forecasting system. In these methods statistical model play supplemental role to data gathered by physical methods. In fact, models not utilizing numerical wind prediction suffer from lack of preciseness in time horizons more than 3 or 4 hours [6].

Although two main classes of techniques have been recognized for the wind prediction, (in [7] and [8],comprehensive reviews of these methodsareprepared), as aforementioned, combination of statistical and physical methods are more prevalent than the others [9], [10]. Furthermore, several other spatial correlation techniques are proposed for short term wind power forecasting with the goal of achieving higher prediction accuracy [11]. However, by the passage of time, more advanced methods have been proposed. To this end, Artificial Neural Network (ANN) in [12], [13], ANN with adaptive Bayesian learning and Gaussian process approximation in [14], combination of ANN with wavelet transform in [15], fuzzy logic methods in [10], [16], Kalman filter in [17], support vector machine in [18] and some hybrid methods in [6] have been proposed for wind power prediction.

In this research, a new effective wind power forecasting method based on combination ofartificialneural network and imperialist competitive algorithm is proposed. The proposed method employs imperialistic competitive algorithm to optimize the weights of MLP artificial neural network. Forecasted meteorological parameters (*i.e.* temperature, wind speed, wind direction, humidity and pressure of the air) from a NWP model along with measured data from online supervisory control and data acquisition (SCADA) are utilized as the neural network inputs. An actual wind farm is used to validate the presented method. The forecasting is for the next 36 hours with an hour intervals. Simulation results show that the presented method can effectively enhance the exactness of the wind power forecasting.

This paper is organized as follows: Section II describes an overview of the wind power prediction. Section III introduces proposed model in which techniqueof employing SCADA system and NWP model is described. Descriptions of combination of ICA and ANN as prediction system and forming case-studies are provided in sections IV and V, respectively. The paper is concluded in section VI.

II. Literature Review of Short-Term and Very Short-Term Approaches

The very short-term wind power prediction techniques utilize statistical models such as ARX, ARMA and Kalman Filters; while, they are mostly based on time series approach. In this category, the input data is past values of the forecasted variable like wind generation and wind speed; whereas, explanatory variables like temperature, wind direction and humidity can be employed in order to enhance precision and applicability of the forecasting methods. This model has the capability of prediction for horizons between 3–6 hours according to this consideration that they merely use the past production data. In a hierarchical classification of very short-term wind power prediction approaches, two major groups are consisting: 1) those that use manufacturer’s power curve or empirical curves of wind turbines to map predicted wind speed to the generation output power, and 2)techniques in which wind generation power can be calculated directly without interfering the turbines’ characteristics and role of NWP model is intensively highlighted for the short-term wind power forecasting.

TABLE I. AN OVERVIEW OF PROPOSED METHOD IN CASES OF VERY SHORT-TERM AND SHORT-TERM WIND POWER FORECASTING

Very Short–Term models	Short–Term models
Markov-switching Autoregressive [20]	Adaptive Neural Fuzzy System [30]
Adaptive Fuzzy Logic Models [21]	Local Polynomial Regression [31]
Takagi-Sugeno [22]	Bayesian Clustering by Dynamics (BCD) [32]
Fuzzy Time Series [23]	Support Vector Machines [33]
Adaptive Linear Models [24]	Mixture of Experts [33]
Kalman Filter [25]	Locally Recurrent Neural Networks [3]
Discrete Hilbert Transform [26]	Autoregressive with Exogenous input (ARX) [34]
Abductive Networks (GMDH) [27]	Autoregressive with Exogenous Input and Multi-timescale Parameter (ARXM) [35]
Adaptive Neural Fuzzy Inference System [28]	Random Forests [36]
Grey Predictor [29]	Neural Networks [37]

III. Wind Power Prediction Model

A. Proposed wind power prediction method

In this paper, a short term wind power forecasting using ICA-NN is presented. The basic data source for wind power prediction is numerical weather prediction. In this study, the forecasting system uses the meteorological forecast of the NWP model obtained from the Summerside wind farm in Prince Edward, Canada. Each turbine of wind farm is modeled by an ICA-NN black box to develop a relationship between the forecasted meteorological parameters (*i.e.* temperature, wind speed, wind direction, humidity and pressure of the air from a numerical weather prediction model) and potential power output from the wind turbines. The performance of wind power forecasting deeply depends on the values of the NWP models. In fact, the focus of this study is on using the NWP data that noticeably plays a supplemental role to enhance exactness of the short term forecasting. The final prediction value is a summation of the forecasting results from the all ICA-NN black boxes. The forecasting scheme is depicted in Fig.1.

In the process of modeling, information provided from SCADA and historical data are used to train an ANN that effectively can estimate a transfer function between the specific patterns of input and output vectors. Then, ICA is applied to optimize the weights of ANN. This process continues until the error reaches to an appropriate value.

B. Online SCADA System

SCADA system as the nerve center and inseparable element of the wind farm plays a vital role for the prediction system. Usage of an online SCADA gives the operator freedom to oversee wind farm by supervising all of the wind turbines. This opportunity is provided for operator to set proper actions in critical situations by a 10 minutes record of the wind park turbines. Moreover, this supervision system provides a comprehensiverecord of the output powers as well as availability of turbines, which acts as a foundation for the short term wind power forecasting. However, occasionally no sufficient data is available online by SCADA to access accurate operational information of the wind farm. This data may contain at least the number of turbineswhich are in operation cycle and the total available power or can be detailed in speed and related power of each wind turbine.

C. Numerical wind prediction model

Nowadays, wind data has a non-negligible impact on wind power prediction. There are several approaches to obtain the wind data: observations, data mining and numerical weather simulations. The most straightforward and reliable way to obtain wind data is through on-site observations. However, they are not usuallyavailable.

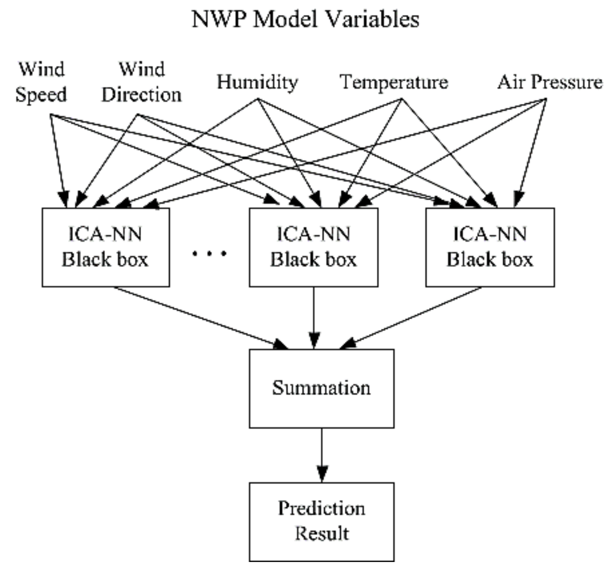

Figure 1. Prediction model using ANN and ICA.

Data mining is flexible, but itsability to downscale the weather data is limited. The NWP models use physical conservation of energy equations and this allows a more realistic downscaling of the data. In fact, high-resolution NWP of wind plays the key role for power forecasting.

In recent years, regarding availability of enhanced computational systems, many wind power estimation researches are directedutilizing NWP models wind data. This researchers use severalNWP models like WRF, COSMO, MM5, and RAMS[30]-[33]. Also, various methods of extrapolation such as logarithmic law and wind shear power law have proposed by authors to provide appropriate wind information at theheight of wind turbine hub (*i.e.* approximately 50 m) using meteorological data that are gathered at 10 m above of the ground (According to World Meteorological Organization (WMO) approval)[19]. Needless to say, usage of extrapolation laws may create considerable deviation in the accurate assessment of wind power prediction[38].

IV. Proposed Framework for MLP-ICA

A. Multi-layer perceptron neural networks

Neural network is a powerful data modeling tool that is able to capture and represent the complex input/output relationships. The most common neural network model is multilayer perceptron. Moreover, this is the most prevalent form of the ANNs employed for predication objectives. It is generally made up of different layers of input, hidden and output nodes, interconnected through some weighted connections [39]. An illustrative representation of an MLP is shown in Fig. 2.

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

WhereX_j is the j^{th} input to the node, Y_i is the output of the node, W_{ij} is the connection weight between the input node and output node, b_i is the bias of the node, and f_i is

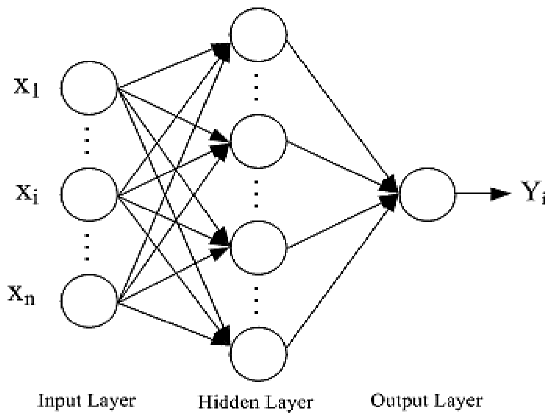

Figure 2. Multi-layer perceptron Neural Network.

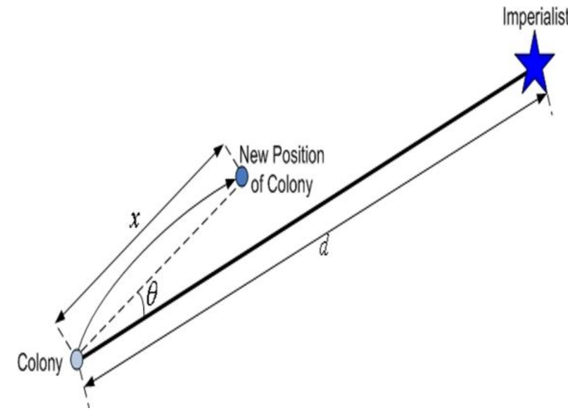

Figure 3. Movement of colonies toward their relevant imperialist.

the node transferfunction.

The mean squared error (MSE) of the network is defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(T_i - Y_i)^2 \quad (2)$$

Where T_i is the target at i^{th} pattern, Y_i is the prediction of the network's output at i^{th} pattern and N is the number of training set samples.

B. Imperialist Competitive Algorithm (ICA)

The Imperialist Competitive Algorithm is a new evolutionary algorithm in the evolutionary computation field based on the imperialistic competition [40]. This algorithm starts with an initial solution of $N_{country}$ that are categorized to two different forms of imperialists and colonies depending on the solution costs that are showed with (N_{col}) and (N_{imp}), respectively. Combination of imperialist and colonies are called empires in this algorithm terminology. At next stage, colonies have proportionally distributed between empires basedon every imperialist's power [41]. The normalized cost of each imperialist is defined as:

$$C_n = c_n - \max_i \{c_i\} \quad (3)$$

Where c_n is the cost related to the n^{th} imperialist and C_n is its normalized cost. Each imperialists power is calculated as following relationship, assuming imperialist costs are in assessable.

$$P_n = \left| \frac{c_n}{\sum_{i=1}^{N_{imp}} c_i} \right| \quad (4)$$

At Assimilation procedure, each empire's colonies begin to move toward their destination (pertinent imperialist), immediately following the initial empires development. Fig. 3 indicates this movement toward its pertinent imperialist by x units; where, x is a stochastic parameter that enjoys a constant distribution.

$$x \;\alpha\; U(0, \beta \times d) \quad (5)$$

Where β is defended as a slightly more than one integer; also, d is the straight space between the imperialist and colony. The total cost by each empire is defined by fallowing relationship that is related to the power of imperialist as well as its colonies.

$$\begin{aligned} T.C._n &= Cost(imperialis_n) \\ &+ \xi mean\{Cost(colonies\ of\ impire_n)\} \end{aligned} \quad (6)$$

At aforementioned relationship, $T.C._n$ is defined as the absolute cost related to the n^{th} empire, ξ is considered to be slightly less but a positive integer. In fact, increasing or decreasing value can change colonies impact in the entire power of empire.

In the social-political competition process, imperialists are attending to reach a higher position than before by increasingtheir gluttony to seize more colonies. Therefore, the forcefulimperialist's power will be progressed at the competition process whereas week imperialists will experience lower rank in the power. It is high time that empire to be collapsed when it loses all of its possessions. This process will continue until, finally, the richest imperialist will abide and all the countries will be seized by that imperialist to act as colonies of that imperialist.

C. Proposed method for ANN weight optimization

As aforementioned, MLP neural network is a feed forward Back Propagation (BP) based algorithm. BP performs a gradient descent within the solution's vector space towards a global minimum along the steepest vector of the error surface. Although, BP algorithms are fast but they are trapped in local minimums. To overcome BP method adversities, ICA isemployed as a global optimum search algorithm. Moreover, ICA is highly independent on structuring of ANN;whereas, gradient based methods deeply suffer from dependence on the network structure.

In this study, ANN connection weights are formed as variables of the ICA and the mean square error is used as a cost function in ICA. The proposed method aim is to reach a minimum value for this cost function. Fig. 4 shows an outline of the forecasting system.

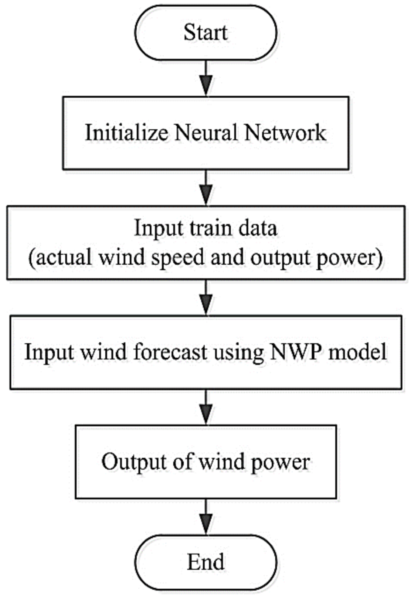

Figure 4. ICA-NN forecasting algorithm.

The proposed method is evaluated a three layered Perceptron neural network for training including an input, a hidden and an output layers. The number of input nodes set to be 81(among the 81 input nodes, the first 24 inputs represent the next 24h wind speed prediction. Nodes 25 to 72 represent the previous 48h wind speed. Nodes 73 to 78 represent the previous 48h temperature, air pressure and humidity average values. Nodes 79 to 81 represent the next 24h temperature, airpressure and humidity average prediction values), hidden nodes are 47, and one node in the output layer. The number of imperialists and the colonies considered being 10 and 90, respectively; parameter β is set to 2. Finally, this trained network applied on the meteorological forecast data provided by the NWP model. Maximum number of iterations is considered to be 300 decades.

V. Case Study and Results

In order to evaluate performance of the proposed wind power forecasting scheme, the prediction model was built for the Summerside wind farm in Prince Edward, Canada. This windfarm has a generating capacity of 12MW and consists of 4windturbines (3MW each). Following figures present the system performance in the period of 18st to 19st March 2011.

The wind power time series of this wind farm are recordedfrom the 1st January 2010 to the 31st February 2011 [42]. The forecasting information is given for the next 36 hours forevery hour intervals in case of short-term and for every 20 minutes intervals in case of very

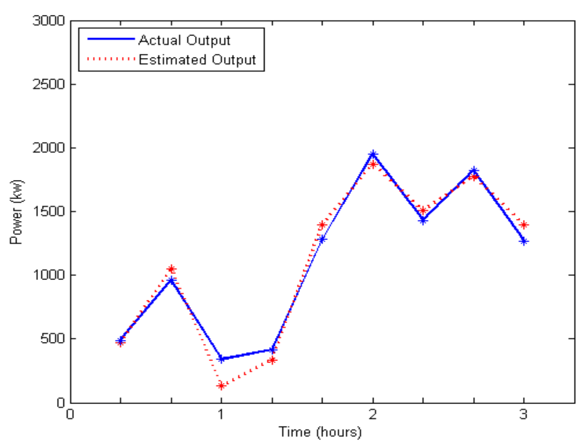

Figure 5. wind power Prediction for 3 hour ahead

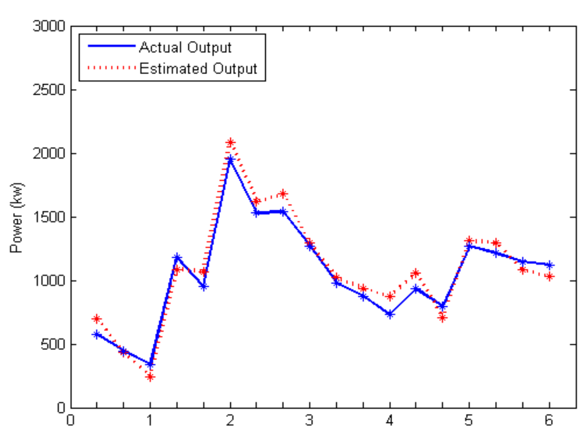

Figure 6. wind power Prediction for 6 hour ahead

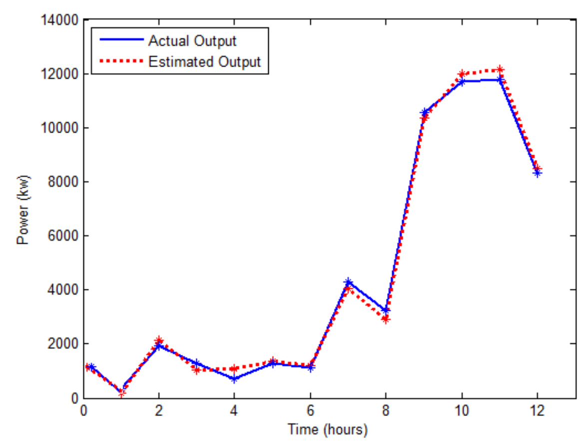

Figure 7. wind power Prediction for 12 hour ahead

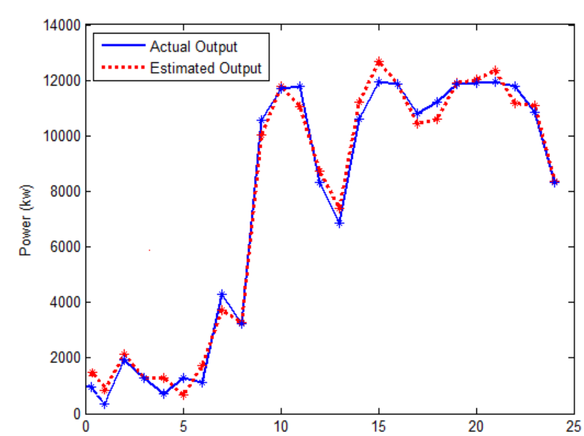

Figure 8. wind power Prediction for 24 hour ahead

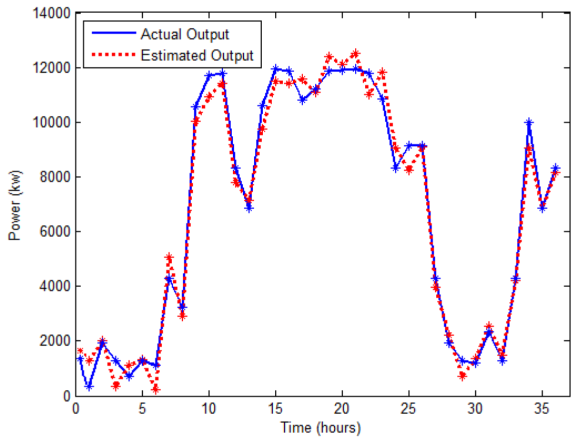

Figure 9. wind power Prediction for 36 hour ahead

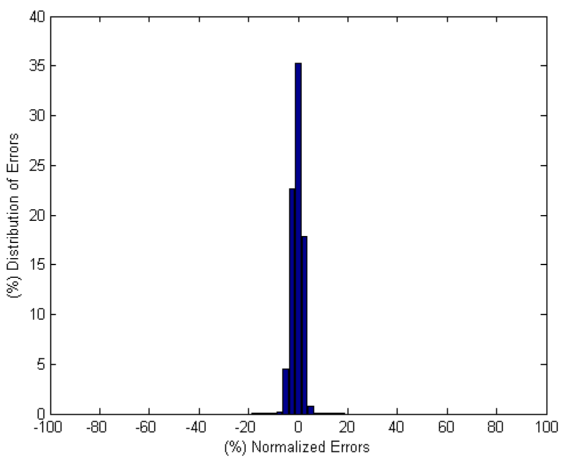

Figure 10. Distributions of normalized errors for the 3h ahead prediction

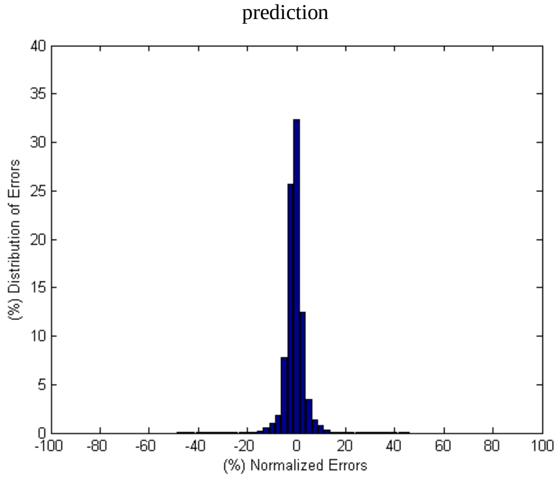

Figure 11. Distributions of normalized errors for the 6h ahead prediction

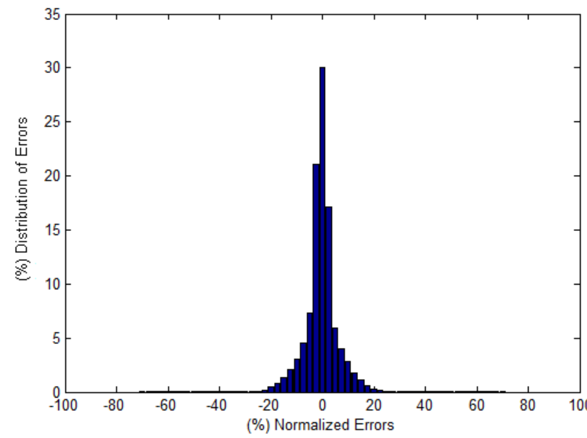

Figure 12. Distributions of normalized errors for the 12h ahead prediction

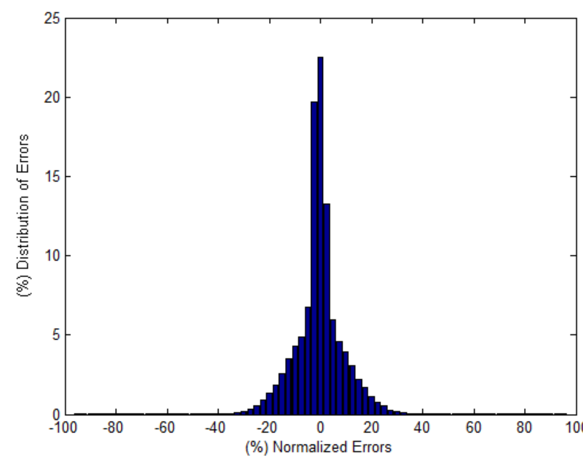

Figure 13. Distributions of normalized errors for the 24h ahead prediction

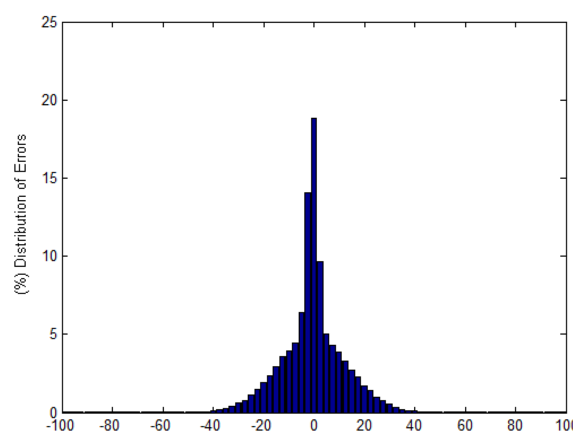

Figure 14. Distributions of normalized errors for the 36h ahead prediction

short-term. Figs. 5-9 show indicative results from the performance of the model 3h (00a.m- 3.00a.m), 6h (00a.m- 6.00a.m), 12h (00a.m- 12.00a.m), 24h (00a.m- 00a.m next day), and 36h (00a.m- 12p.m next day) ahead from a specific day.

Distribution of normalized errors for five different look-ahead times are shown in Figs. 10-14. It is clear that error distribution, depending on the prediction horizon, issignificantly different. Obviously, the uncertainty for these various horizons must be different. As it is shown, the larger percentage of errors is concentrated between -15% and 15% in short-term look-ahead times. In longer term horizons, zero error is obtained between 15% and 25%, and the distribution of the maximum errors is less than 1%. Prediction values of error obtained by method

TABLE II.
WIND POWER FORECASTING RMSE OF EACH CASE

CASE	RMSE
3h	3.7%
6h	5.2%
12h	7.1%
24h	11.8%
36h	17.2%

proposed in [6] are 14% and 17% for 12h and 24h ahead from a specific day, respectively. While, this error values for the presented paper are 7.1% and 11.8% that are severely lower than [6]. Also, error value for 36h ahead forecasting by method presented in this paper is 17.2% that is approximately equal to similar parameter of [6] and slightly higher than [43].

The root mean square error related to each case is depicted in Table II. Interestingly, RMSE of each case is less than 20%.It is noteworthy that, considering numerous researches accomplished in this field, majority of these contributions have been focused on specific time periods or case studies; While, results are not fairly comparable.

Results indicate that proposed method enjoys significantly effective performance for less than 24h ahead forecasting; whereas, with the increasing prediction time prepared approach enjoys almost equal performance in comparison with other models.

VI. CONCLUSION

In this paper, a new hybrid short term wind power prediction model is proposed based on combination of Neural Network and Imperialistic Competitive Algorithm for next 36 hours in cases of short-term and very short-term prediction methods. The proposed system is applied to an actual wind farm with a total installed power of a few tenths of MW using meteorological predict data provided by the NWP model. Imperialistic Competitive Algorithm employed to optimize training process of Neural Network. Historical wind data and electric power information exported from the SCADA system are considered as the input variables of training. The obtained result shows effectiveness of the proposed method and this method is capable to enhance accuracy of the wind power forecasting.

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