An Advanced Statistical Method for Wind Power Forecasting

George Sideratos and Nikos D. Hatziargyriou, *Senior Member, IEEE*

***Abstract*—This paper presents an advanced statistical method for wind power forecasting based on artificial intelligence techniques. The method requires as input past power measurements and meteorological forecasts of wind speed and direction interpolated at the site of the wind farm. A self-organized map is trained to classify the forecasted local wind speed provided by the meteorological services. A unique feature of the method is that following a preliminary wind power prediction, it provides an estimation of the quality of the meteorological forecasts that is subsequently used to improve predictions. The proposed method is suitable for operational planning of power systems with increased wind power penetration, i.e., forecasting horizon of 48 h ahead and for wind farm operators trading in electricity markets. Application of the forecasting method on the power production of an actual wind farm shows the validity of the method.**

***Index Terms*—Fuzzy sets, radial base function networks, self-organized map, wind power forecasting.**

I. Introduction

HIGH penetration of wind power in the electricity system provides a number of challenges to the grid operator, mainly due to the intermittency of wind. Since the power produced by a wind farm depends critically on the volatility of wind, unexpected variations of a wind farm output may increase operating costs for the electricity system by increased requirements of primary reserves, as well as place potential risks to the reliability of electricity supply [1]. A priority of a grid operator is to predict changes of the wind power production, mainly using persistence-type methods, in order to schedule the spinning reserve capacity and to manage the grid operations [2]–[6]. However, such methods cannot guarantee accurate prediction of wind production variations; therefore, wind power forecasting tools become very important. Next to transmission system operators (TSOs), such tools are required by various end-users as energy traders and energy service providers (ESPs), independent power producers (IPPs), etc. and to provide inputs for different functions like economic scheduling, energy trading, security assessment, etc.

Many researches focus on providing a forecasting tool in order to predict wind power production with good accuracy. Depending on their input, these tools are classified as physical or statistical approaches or a combination of both. The physical models use physical considerations, as meteorological (numerical weather predictions) and topological (orography, roughness, obstacles) information, and technical characteristics of the wind turbines (hub height, power curve, thrust coefficient). Their purpose is to find the best possible estimate of the local wind speed and then use model output statistics (MOS) to reduce the remaining error. Statistical models use explanatory variables and online measurements, usually employing recursive techniques, like recursive least squares or artificial neural networks. Furthermore, physical models must and statistical models may use numerical weather prediction (NWP) models [7]–[11]. Models not using NWP might have acceptable accuracy for the first 3–4 h but generally produce very inaccurate results for longer prediction horizons. Often, the optimal model is a combination of both, using physical considerations to capture the airflow in the region of the wind turbines and using advanced statistical modeling to supplement the information given by the physical models.

The most known wind power forecasting tools are listed next. In the Technical University of Denmark, a wind power prediction tool is developed that is based on adaptive recursive least square estimation with exponential forgetting, in order to predict from half to 36 h ahead [12], [13]. The Zephyr tool is the combination of the wind power prediction tool and the predictor tool that is a physical model [14]. A similar model is the Sipreolico tool that is developed by the University of Carlos III of Madrid [15]. This tool consists of nine adaptive nonparametric statistical models that are recursively estimated with either the recursive least squares algorithm or a Kalman filter. The EWIND model developed by TrueWind, Inc. applies a once-and-for-all parameterization for the local effect using the output of the ForeWind NWP model, and it uses either a multiple screening linear regression model or a Bayesian neural network to find out the systematic errors [16]. The Institute of "Solare Energieversorgungstechnik" has developed the advanced wind power prediction tool (AWPT) [17]. This tool uses weather forecasts coming from Lokalmodell (LM) of the Deutsche Wetterdienst (DWD) and predicts the wind power with artificial neural networks. Finally, Ecole de Mines de Paris (ARMINES) and Rutherford Appleton Laboratory (RAL) have developed models for short-term prediction based on statistical time-series approach and models for long-term prediction using fuzzy-neural networks [5], [18], [19]. An excellent overview of wind power forecasting methods is provided in [11].

In this paper, a new statistical approach for wind power forecasting is presented using artificial intelligence and fuzzy logic techniques. The proposed method provides a preliminary forecasting of wind power based on numerical weather predictions

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The authors are with the National Technical University of Athens, Athens 15773, Greece (e-mail: joesider@power.ece.ntua.gr; nh@power.ece.ntua.gr).

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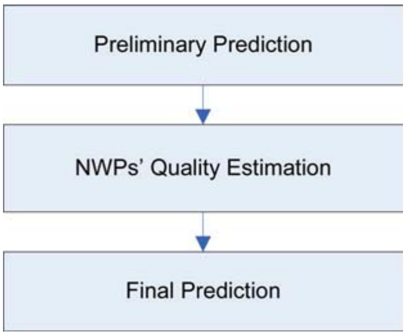

Fig. 1. Outline of the proposed method.

(NWPs) using radial base function (RBf) network, but subsequently, it estimates the quality of the forecasts provided by the NWPs using fuzzy rules. Thus, it is able to improve its performance by a further application of RBfs. Since NWPs are often inaccurate, the main contribution of the method is that it makes the best use of the NWPs available based on fuzzy logic rules. Results obtained from the application of the proposed method on wind power forecasting of an actual wind farm show the applicability of the method and the improvement of the obtained results over other wind power forecasting methods currently applied.

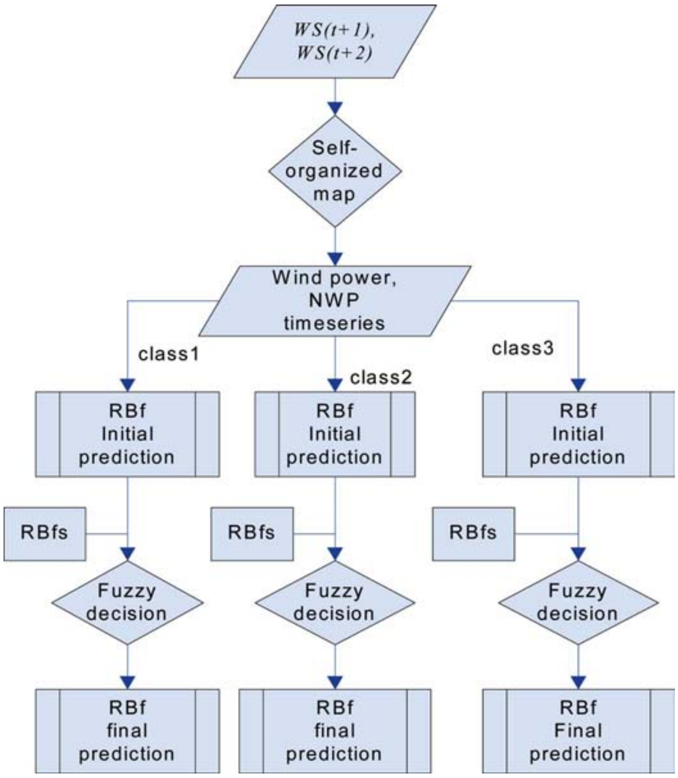

Fig. 2. Structure of the wind prediction model.

II. Description of the Wind Power Prediction Method

The proposed model is based on neural networks that use as inputs time-series of wind power and NWPs, in order to estimate the future wind power production. These time series come at different frequencies, i.e., the supervisory control and data acquisition (SCADA) system provides the values of wind power every minute, i.e., practically online, while meteorological services send NWPs a few times per day covering a 48- or 72-h horizon. NWPs provide the most important information for a forecasting model, especially in long-term horizons. They contain information usually about the wind speed, wind direction, and temperature and are provided at 2- or 10-m heights above the ground or at several levels related to levels of atmospheric pressure. They can also be provided as a grid of four points surrounding the wind farm, and their accuracy is dependent on the spatial resolution of the meteorological model. Models with high resolution perform better but need longer time to provide their results. Usually, these models update their forecasts every 6 h, while output of the wind power prediction models is normally required every hour. Weather forecasts constitute therefore the main source of uncertainty, since they depend on the spatial and temporal resolution of the NWP model. Inaccurate NWPs, especially in short-term horizons, make wind power prediction extremely difficult. There is no doubt, however, that NWPs are indispensable for short-term, as well as for the long-term horizons and their accuracy contributes critically to the accuracy of wind power predictions. The main contribution of the proposed method is that it uses artificial neural networks (ANNs) combined with a fuzzy logic model in order to optimize the use of the NWPs. Fig. 1 outlines the structure of the system.

The overall system consists of three models: the preliminary wind power prediction model, a model that provides a fuzzy index about the reliability of the numerical weather predictions (the main input data to the system), and the final wind power prediction model. The first model, which provides an initial prediction of power, comprises a combination of a self-organized map and three radial basis neural networks. The second model consists of a fuzzy logic model and two radial basis neural networks, and the final prediction is given by three radial basis neural networks. These models are described in more detail in the following subsections. The structure of the overall wind power prediction model is shown in Fig. 2.

In order to explain the proposed method better, wind power data from the Klim wind farm, which is located at the northwestern part of Jutland, 8 km from the north coast and 50 km west of the city Aalborg, is used. The farm contains 35 600-kW turbines, and its total rated capacity is 21 MW [21]. The wind data and the power production data sets cover the period from January 1, 1999 to February 28, 2001. NWP data from the Danish HIRLAM model have been used. This model with horizontal grid resolution 16 km (0.15°) provides weather forecasts in three levels (29, 30, and 31) relative to the atmospheric pressure. For this application, forecasts at level 30 are used. These data comprise the training sets. The fact that there is no specific numerical weather prediction model for offshore wind farms reduces the accuracy of a wind power-forecasting tool [22]. Also complex interactions and influences to the wind smoothing due to the short distance of the farm with the shore should be noted.

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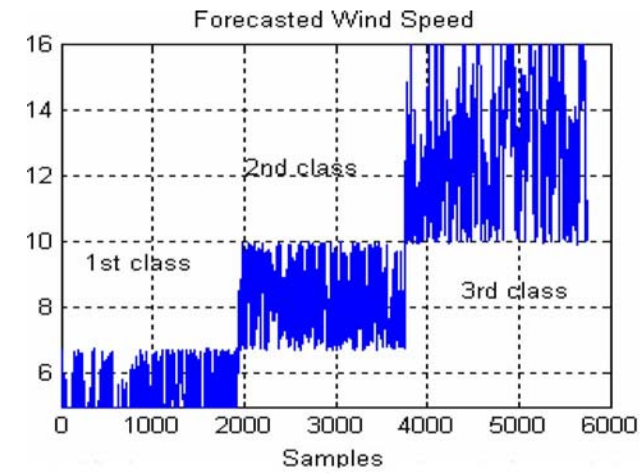

Fig. 3. Classification of the input NWP data according to the forecasted wind speed for one-hour-ahead prediction.

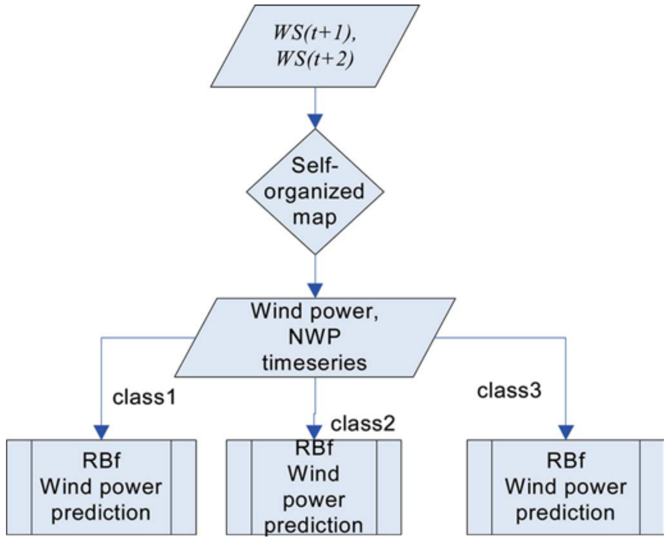

Fig. 4. Structure of the initial wind power prediction model.

A. Preliminary Wind Power Prediction Model

The system requests as inputs two forecasted wind speeds obtained by NWPs, corresponding to the hour wind power is predicted and to the next hour. The second value of wind speed corresponding to the next hour is used in order that the predictors recognize the trend of the wind speed to increase or decrease. Also in order to make more effective the performance of the applied RBfs, the range of wind speed values used is reduced to the cut-in limit and to the speed that corresponds to the nominal power of wind turbine. Under the cut-in limit, the produced wind power is set to zero, and when the wind speed is above the rated wind speed, wind power production is set to its maximum (nominal) value. In this way, the neural networks are only trained for cases, when wind speed is high enough to produce power and lower than the value corresponding to constant wind farm output. Thus, neural networks perform better for our application, when they are trained with a data subset corresponding to a more restricted range of wind speeds. In the same way, in order to make the best use of NWPs, the preliminary wind power prediction model separates the time-series of the forecasted wind speed in three sets according to the speed's magnitude (small, medium, high) applying a self-organized map. This is a Kohonen neural network that consists of three neurons in its single layer, and it classifies the wind speed values in three classes. Fig. 3 shows the classified forecasted values of wind speed used for the one-hour-ahead wind power prediction.

Based on this division of the forecasted wind speeds, the remaining data for wind power prediction, namely, past value of wind power, wind direction, and the hour of the day for which the prediction is made, are grouped according to the wind speed's class in three sets. Each set trains a separate RBf network. RBfs were chosen because, as shown by several tests, they perform better for our particular application than other kinds of neural networks, e.g., multilayer perceptrons or Elman networks [18].

Fig. 4 shows the structure of the initial wind power prediction model.

The input of each RBf network has the following form:

$$\mathrm{P(t+1)} = f(\mathrm{P(t)}, \mathrm{WS(t+1)}\\ \mathrm{WS(t+2)}, \mathrm{WD(t+1)}, \mathrm{H(t+1)}) \quad (1)$$

where $\mathrm{P(t+1)}$ is the output of the model, $\mathrm{P(t)}$ is the wind power production, WS is the wind speed provided by NWPs, WD is the wind direction provided by NWPs in "rad," and H is the hour for which prediction is made.

A radial basis neural network consists of two layers. In the hidden layer, the training set is divided in universes and the kernels of each universe comprise the weighted matrix. This procedure is accomplished by the use of Euclidean distance of each vector of the training set. By trial and error, it is proved that the applied RBf networks perform better with 13 neurons. For example, networks with 12 neurons perform 0.98% worse for one hour ahead, 1.45% for 18 h ahead, 0.92% for 36 h ahead, while networks with 14 neurons perform 0.26% worse for one hour ahead, 0.67% for 18 h ahead, and 1.41% for 36 h ahead. In the validation period, the output of the hidden layer has the following form:

$$a = f\left(\sum_{j=1}^{n} (IW_{i,j} - Pj)^2 b\right) \quad (2)$$

where f is a Gaussian function; $\mathrm{IW_{i,j}}$ is the weighted matrix and b the bias; $\mathrm{P_j}$ is the input vector; n is the size of the input vector; and i is the number of neurons. The second layer of the RBf network is linear and is trained by the actual wind power values (target vector). In Fig. 5, the structure of an RBf network is shown.

The combination of unsupervised learning in the hidden layer and supervised in the second layer makes RBf networks capable to handle nonlinear problems, like wind power prediction. The effectiveness of the RBf network can be enhanced by allowing some input variables of the network to have more influence on its output, by proper selection of their normalization factors.

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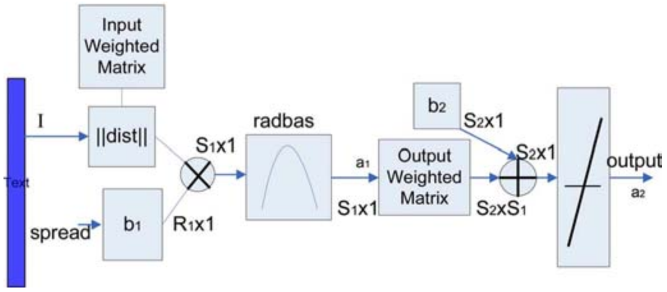

Fig. 5. RBf architecture.

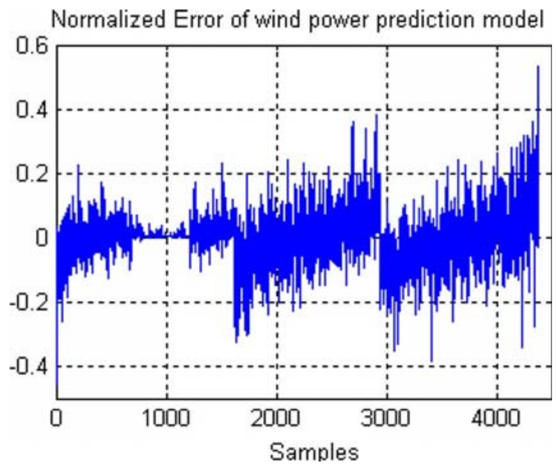

Fig. 6. Normalized hourly errors for one-hour ahead of the preliminary wind power prediction model.

The most important information is provided by the NWPs, especially for forecasting horizons over 6 h ahead. The input variables of wind speed and wind direction are therefore used with higher order of magnitude than the other variables (past value of wind power and hour of prediction). Especially the wind speed value, which corresponds to the prediction hour, is set one order of magnitude higher than the other wind speed variable and the wind direction. It should be noted that in short-term prediction, until 6 h ahead, the previous wind power has greater importance than in longer horizons, and it is therefore expressed in MW. This is because the model runs iteratively and uses the previous power prediction as past wind power. As the prediction horizon increases, the error in power prediction increases; therefore, for long-term predictions, past wind powers are expressed in GW. In this way, the same RBf structure is used for both short-term and long-term predictions. A typical normalization of the RBf input has the following form:

$$\begin{aligned}\mathrm{P}(\mathrm{t}+1) = f(&\mathrm{P}(\mathrm{t}), \mathrm{WS}(\mathrm{t}+1)*20\\ &\mathrm{WS}(\mathrm{t}+2)*10, \mathrm{WD}(\mathrm{t}+1), \mathrm{H}(\mathrm{t}+1)/480). \quad (3)\end{aligned}$$

Fig. 6 shows the hourly errors produced by the preliminary wind power prediction model for the one-hour-ahead wind power prediction of Fig. 4, normalized by the wind park installed capacity. A maximum error of 40% to 50% is shown.

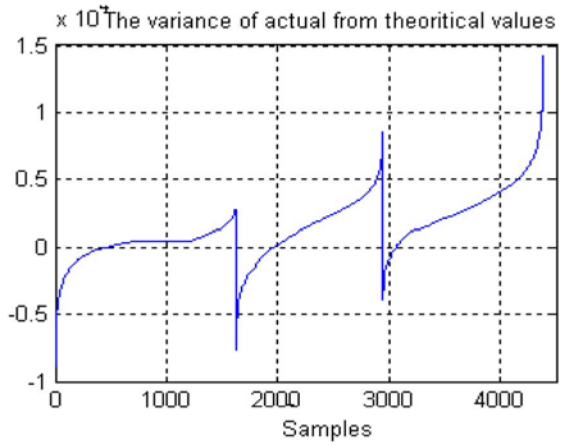

Fig. 7. Normalized errors of the "theoretical" wind power predictions provided by the power curve and forecasted wind speed classified by wind class in ascending order.

B. NWP's Quality Estimator

As discussed in the previous section, the performance of the wind power prediction model depends critically on the quality of the NWPs. Cases where weather forecasts deviate from actual values of the wind speed have a profoundly negative effect on the quality of the forecasts. This is clearly shown by observing the errors obtained, when the wind power values are simply calculated from the wind speed forecasted by the NWPs and the wind turbine power curve (power versus wind speed). We call these wind power predictions "theoretical values." Fig. 7 shows the normalized errors of this very simple prediction, based purely on the NWP of the hour wind speed is predicted and the power curve. The errors are classified by wind class and in ascending order. As before, the errors are normalized by the installed capacity of the wind farm.

By comparing Figs. 6 and 7, it can be seen that the largest errors provided by the initial wind power prediction model also appear in corresponding wind speed samples with the largest errors in the predicted "theoretical" values of wind power. It should be noted that the influence of wind direction in the prediction is not considered in calculating the "theoretical" wind power values, and this is one of the main reasons for the errors obtained in these calculations. In the following, the effect of wind direction in the quality of the wind speed predictions provided by NWPs is considered. From the correlation of the wind power production with the wind speed and the wind direction, it can be proven that, when the forecasted wind direction is between defined limits, NWPs can be considered as relatively accurate. This is because usually, strong winds that are most difficult to be predicted come from known directions due to the topography of the area where the wind park is located.

For the prediction of the cases in which the "theoretical" power values differ significantly from the actual wind power values, two RBf networks are applied for each class of wind speeds, separately.

One network receives as inputs the two values of wind speed provided by NWPs, which correspond to the hour that wind power is predicted and to the next hour. The other network receives as input the forecasted wind direction and the prediction's hour. The networks are trained in order to predict the

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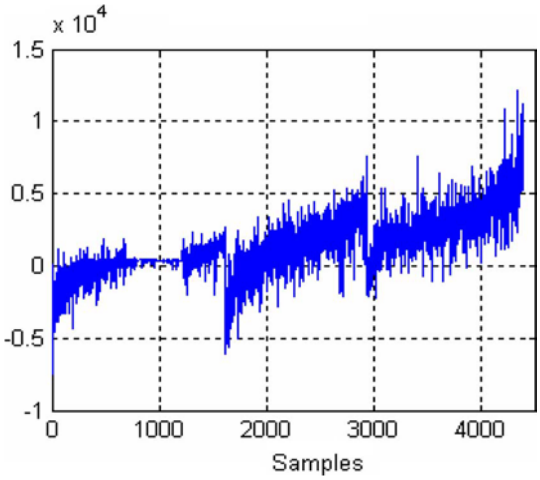

Fig. 8. Difference between the preliminary wind power prediction and the output of the RBf network trained with forecasted wind speeds.

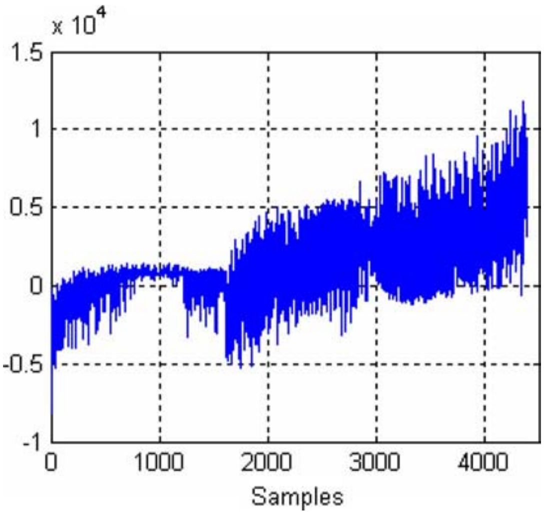

Fig. 9. Difference between the preliminary wind power prediction and the output of the RBf network trained with forecasted wind direction and the prediction hour.

"theoretical" value of power that is calculated from the power curve. Comparison of the outputs of these RBf networks with the output of the preliminary wind power prediction model identifies the "poor" NWPs. Fig. 8 shows the difference between the preliminary wind power prediction model and the output of the first RBf trained with forecasted wind speed values and Fig. 9 the difference with the second RBf trained with the forecasted wind direction and the prediction hour.

Comparing Figs. 8 and 9 with Fig. 7, it is easy to see that, using as parameters these two differences, inaccurate wind speed forecasts can be identified. To achieve this, a fuzzy logic-based model is applied to identify "poor" NWPs. The fuzzy model receives as inputs the differences between the RBf network outputs and the preliminary predictions, as displayed in Figs. 7 and 8 and the wind direction. The model estimates the quality of the NWPs, when the differences take high values and the wind direction is outside predefined limits.

Each input of the fuzzy model (linguistic variable) takes values from the three fuzzy sets (small, medium, and high).

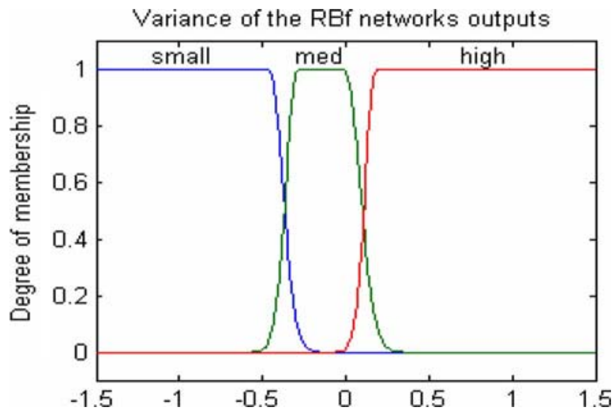

Fig. 10. Fuzzy sets of the difference between the preliminary wind power prediction model and the output of the first RBf network trained with forecasted wind speeds.

Fig. 10 shows the participation in the three fuzzy sets of the difference between the preliminary wind power prediction model and the output of the first RBf trained with forecasted wind speed values.

The proposed fuzzy model can be expressed by 27 rules of the type

$$\text{"IF x1 is A1 and } \times 2 \text{ is A2} \ldots \text{THEN y is Bi"} \tag{4}$$

where $\mathrm{x_i}$ are the inputs variables ($\mathrm{i} = 1 \ldots 3$), $\mathrm{A_i}, \mathrm{B_i}$ are the fuzzy sets, and y is the output of the model taking values between $0 \ldots 1$.

The fuzzy sets are modeled using Gaussian functions

$$\mu \mathrm{A}_i(x_i) = \exp\left(-\left(\frac{x_i - a_i}{b_i}\right)^2\right). \tag{5}$$

The output of the fuzzy model ranges between 0 and 1 and provides a quality index of the numerical weather predictions. Similar fuzzy models are applied for each class of wind speed.

C. *Final Wind Power Prediction*

For each class of wind speed separately, an RBf network is trained with the same data like the RBf networks of the initial wind power prediction model and also the output of the fuzzy model. These networks have the same structure as the RBf networks that provide the initial wind power prediction. Namely, they have 13 neurons in their hidden layer, and they are trained with the same training set to which the quality index of the forecasted wind speed is added. Also the input normalization is implemented in the same manner for short-term prediction and for long-term horizons.

III. Results From Application to the Klim Wind Farm

The proposed system is applied to the Klim wind farm. The following figures present the system performance in the period from March 2001 to April 2003. The weather forecasts cover a 48-h horizon and are updated four times per day. The proposed

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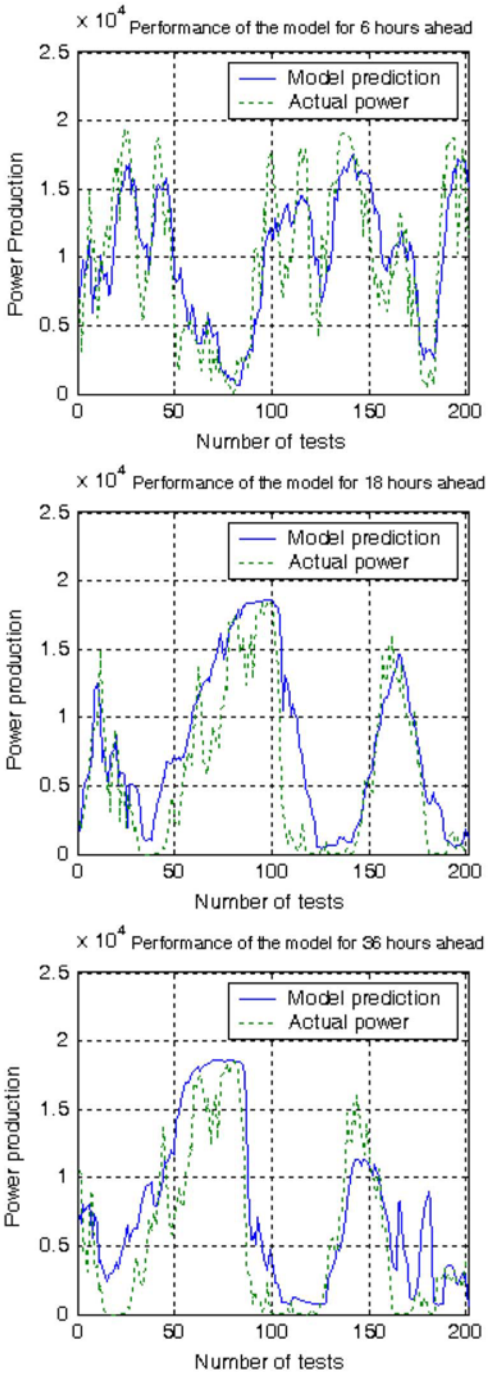

Fig. 11. Actual estimated power production in kW for 6, 18, 36 h ahead.

model provides wind power predictions every hour ahead using NWPs for 2 h ahead. This means that at the hour before updated NWPs are provided, NWPS for 42 h ahead only are available. Hourly wind power forecasts therefore cover a 41-h horizon.

Fig. 11 shows indicative results from the performance of the model 6, 18, and 36 h ahead.

Distributions of the normalized errors for four different look-ahead times are shown in Fig. 12. As shown, the larger percentage of errors is concentrated between −10% and 10% in short-term look-ahead times. In longer term horizons, zero error is obtained between 20% and 25%, and the distribution of the maximum errors is less than 1%.

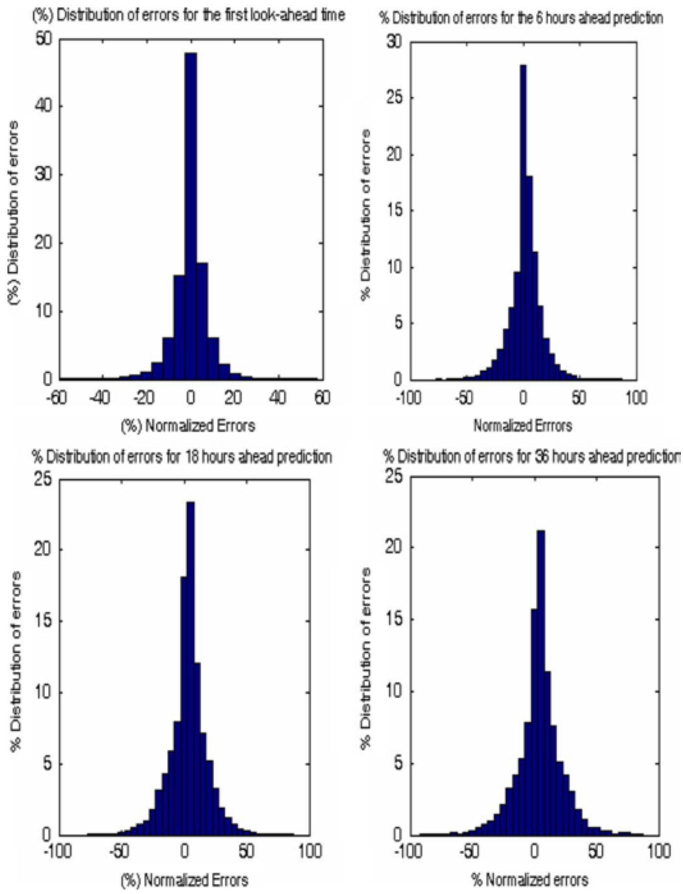

Fig. 12. Distributions of normalized errors for the predictions 1, 6, 18, and 36 h ahead, respectively.

For the evaluation of the performance of the system, improvement over the persistence model is calculated. Persistence is a simple forecasted method, which considers that the wind power production remains unchanged for all look-ahead times. This naïve predictor performs surprisingly well, and it is hard to be outperformed for the first look-ahead times. Therefore, a classical benchmark model to test the performance of a wind power forecasting tool is the persistence model [11]. In the following figures, it is shown that the proposed method performs better than persistence for all look-ahead times. The normalized mean absolute error (NMAE) ranges between 5% and 14%, while the NMAE of the persistence reaches 24%. The normalized root mean square error (NRMSE) is always less than 20%, while the respective criterion for persistence reaches 34%.

Fig. 13 shows the NMAE and Fig. 14 the NRMSE of the proposed method compared to the one of persistence.

The improvement or skill [10] of the proposed system with respect to persistence performance is given by the expression

$$\mathrm{skill}(k) = \frac{\mathrm{NMAE}_P(k) - \mathrm{NMAE}_{RBf}(k)}{\mathrm{NMAE}_P(k)} * 100\% \quad (6)$$

and is shown in Fig. 15 for both criteria.

The improvement of the proposed system w.r.t. persistence is shown to reach up to 46% for both criteria. Also both criteria remain above 40% for forecasts after 10 h ahead, while based

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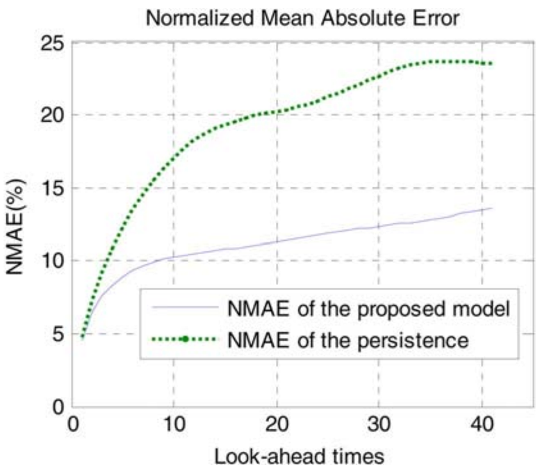

Fig. 13. NMAE of the proposed method (broken line) versus NMAE of persistence (continuous line) for various look-ahead times.

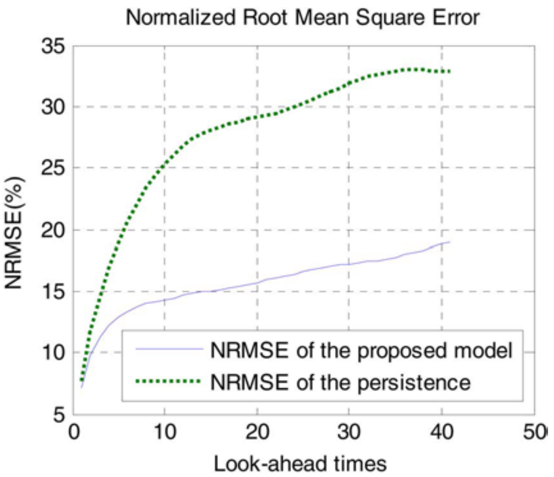

Fig. 14. NRMSE of the proposed method (broken line) versus NRMSE of persistence (continuous line) for various look-ahead times.

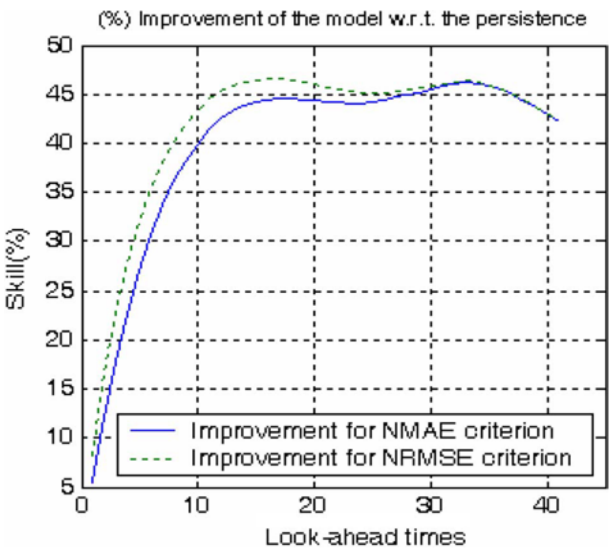

Fig. 15. Improvement of the proposed system with respect to persistence for both criteria, NMAE (continuous line) and RMSE (broken line), for various look-ahead times.

on the NRMSE criterion, the proposed method outreaches 30% after 5 h ahead.

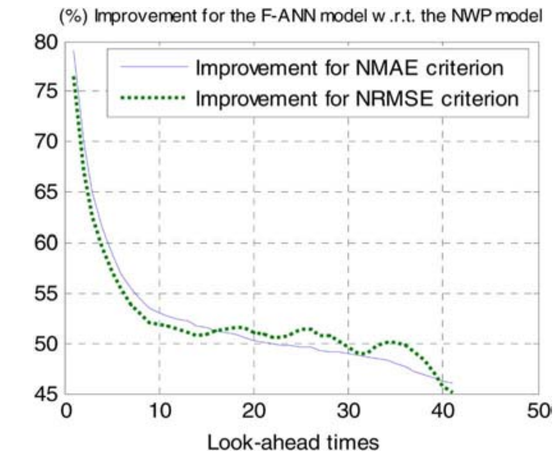

Fig. 16. Improvement of the proposed system with respect to NWP model for both criteria, NMAE (continuous line) and RMSE (broken line), for various look-ahead times.

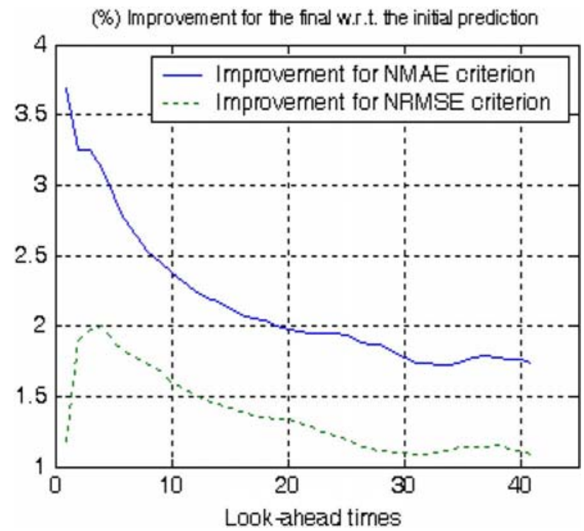

Fig. 17. Improvement over the preliminary forecasting results obtained by the NWP quality index for the NMAE criterion (continuous line) and NRMSE (broken line).

The proposed model is also compared to the NWPs' performance showing superior performance, as shown in Fig. 16. In this case, the wind power is estimated directly from the forecasted wind speed transformed by the equivalent power curve of the wind farm.

Finally, it is interesting to investigate the effects of the improvement obtained by the RBf-fuzzy model that estimates the NWPs quality. This is shown in Fig. 17, comparing the performance of the final results to the results of the initial prediction model. It is shown that the performance of the initial prediction model is improved for all look-ahead times and reaches 4% for the NMAE criterion.

In [20] and [21], the performance of eight state-of-the-art statistical wind power prediction models applied on the same wind farm is compared. From this comparison, it can be seen that the proposed model outperforms most of them and provides results close to the ones of the best models. Given the difficulties encountered in offshore wind farm predictions, the performance of the proposed method is considered very satisfactory.

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IV. Conclusion

In this paper, a combination of neural networks and fuzzy logic techniques are applied for an accurate estimation of a wind farm's output. A self-organized map classifies the input data to three classes, depending on the magnitude of the wind speed of the hour of prediction and of the next hour. For each class, a different RBf network provides a preliminary prediction. This prediction is compared with the output of two RBf networks, which are trained to forecast the theoretical value of wind power, as obtained by the NWPs and the wind turbine power versus wind speed curve. This comparison uses a fuzzy model to provide a quality indicator of the wind speeds provided by NWPs by correlating them to the wind direction. This is exploited by an RBf network to provide the final prediction. Results from the application of the proposed method to an actual offshore wind farm show that it can be used effectively for operational planning in 1–48 h ahead.

Acknowledgment

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George Sideratos was born in Chios, Greece, in 1976. He received the diploma in electrical and computer engineering from the National Technical University of Athens (NTUA), Athens, Greece. He is currently pursuing the Ph.D. degree at the School of Electrical and Computer Engineering of NTUA.

His research interests include wind power and artificial intelligence techniques.

Nikos D. Hatziargyriou (SM'79) was born in Athens, Greece, in 1954.

He is a Professor in the Power Division of the Electrical and Computer Engineering Department of the National Technical University of Athens (NTUA), Athens, Greece. His research interests include dispersed and renewable generation, artificial intelligence techniques in power systems, and modeling and digital techniques for power system analysis and control.

Mr. Hatziargyriou is a member of CIGRE SCC6 and of the Technical Chamber of Greece.

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