Improved Wind Power Forecasting Using a Combined Neuro-fuzzy and Artificial Neural Network Model

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Abstract. The intermittent nature of the wind creates significant uncertainty in the operation of power systems with increased wind power penetration. Considerable efforts have been made for the accurate prediction of the wind power using either statistical or physical models. In this paper, a method based on Artificial Neural Network (ANN) is proposed in order to improve the predictions of an existing neuro-fuzzy wind power forecasting model taking into account the evaluation results from the use of this wind power forecasting tool. Thus, an improved wind power forecasting is achieved and a better estimation of the confidence interval of the proposed model is provided.

Keywords: Artificial neural networks, wind power forecasting, prediction error.

1 Introduction

Wind power is one of the dominant Renewable Energy Sources (RES) since, by the end of 2004, over 47 GW have been installed worldwide, 34 GW of which in Europe [1]. In Greece, the installed wind power capacity is 567 MW, 164.5 MW of which in the autonomous power systems of Greek islands [2]. The intermittent nature of wind power production forces the power systems operators maintaining significant percentage of spinning reserve to compensate for uncertainties in wind power product-ion. Sometimes, especially in autonomous power systems with increased wind power penetration, operators may even consider totally unreliable the wind power production leading the system to operate with excessive spinning reserve and thus increasing its operating cost.

In the past few years, there have been several studies on wind power forecasting. The simplest method of all, more suitable for shorter prediction horizon, is the persistence method, considering that the expected wind power production in the following few hours will be the same as the current hour. The accuracy of the persistence method is reduced as the prediction horizon is increased. Wind power forecasting methods include models based on statistical methods as presented in [3] and methods based on Artificial Neural Networks (ANN), e.g. Radial Basis Functions topology [4]

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or adaptive Fuzzy-Neural networks [5, 6]. Some efforts have been also made with time series and ARMA models, requiring however, transformation and standardization, given the non-Gaussian nature of the hourly wind speed distribution and the non-stationary nature of its daily evolution [7]. A more detailed literature overview of the developed wind power forecasting tools is described in [8]. Some of these methods use meteorological information, mainly wind speed, especially for longer period forecasts, provided by Numerical Weather Prediction (NWP) models like SKIRON and Hirlam.

The impact of improved wind forecasting tool with actual data for the last 4 months of 2001 has shown that improvement of wind forecasting errors has significant economic impact in the operation of the power system due to the reduction of spinning reserve requirements [9]. The reduction in the operating cost is about 1.8%-3.5% if a reliable forecast is used that allows the reduction of spinning reserve in the 50% of wind power production. The reduction in the operating cost is about 2.3%-5.3% if a reliable forecast is used that allows the reduction of spinning reserve in the 20% of wind power production. Therefore, the more reliable the wind power forecasting is, the more confident the operators of the power systems are for the wind power production forecast and thus, the spinning reserve requirements can be further reduced, leading to the reduction of the power system operating cost.

The developers of wind power forecasting models provide their end-users with the Mean Absolute Percentage Error (MAPE) index for their model expressed as a percentage of the installed wind power capacity. This index, however, does not give very much information neither about the performance of the wind power forecasting tool for different forecasting horizon nor about its performance for a variety of forecasted wind power values. Some wind power forecasting tools also provide as output the confidence interval of the wind power forecast based on the estimation of the weather stability and other parameters having to do with the forecasting model itself [10]. Such information helps the operators to estimate the range of the expected wind power production and thus the spinning reserve requirements to cope with the wind power production uncertainty.

In this paper, a method is proposed based on ANN, in order to improve the performance of an existing wind power forecasting tool. This method uses as inputs the outputs of the wind power forecasting model and trains the ANN using the results from the evaluation of the forecasting model. The output of the ANN is a new and improved wind power forecast. Moreover, an 85% confidence interval is provided to the operators for this improved wind power forecast.

The methodology followed to derive the improved wind power forecast is described in detail in Section 2. This methodology is applied to the wind power forecasting model developed within the MORE CARE framework [11, 12] that was executed off-line to produce wind power forecasts for a period with available meteorological data from SKIRON for the power system of Crete. Some information on the power system of Crete is provided in Section 3 concerning mainly the wind power. Section 4 presents results from the application of the proposed methodology to the power system of Crete evaluating the improved forecast obtained using as a criterion the change in the 85% interval and the MAPE. Conclusions are drawn in Section 5.

2 Improved Wind Power Forecasting

In this paper, an existing neuro-fuzzy wind power forecasting tool, considered as a black box, is combined with an ANN, whose general structure is shown in Fig. 1, in order to improve the accuracy of the wind power forecast.

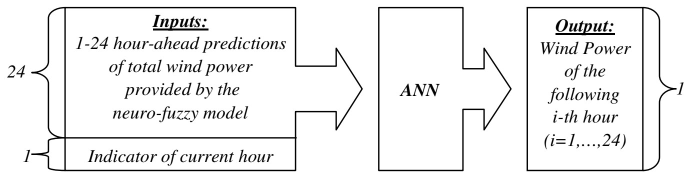

Fig. 1. General structure of the combined ANN and Neural –Fuzzy Network

The improved wind power forecasting methodology consists of the following 4 steps:

1. Creation of two independent Data Sets (DS) by off-line execution of the forecasting model,
2. Split of DS into Learning Set (LS) and Test Set (TS),
3. Creation and Training of the ANNs,
4. Evaluation of the ANN outputs and confidence interval derivation.

2.1 Preparation of the LS and TS

The DS for the ANN model is created as follows: The MORE CARE wind power prediction tool was run off-line for the last 4 months of 2001 providing forecasts for each hour at 24 hour steps. The next 24 hours forecasted values plus an indicator for the current hour are used as inputs for the DS, which consists of 663 time-series in our case study. This DS contains periods of various wind power production levels ranging from very low to very high wind power production.

To ensure more reliable results and to avoid confidence intervals with values below zero or above the wind power capacity, the DS is split into two major classes according to the forecasted values: the first one, with half the data contains values of 0-10 MW (DS1) and the second one with the rest available predictions has prediction values of 10-67.35 MW (DS2).

Each DS is split into a LS and TS. In our case, 2/3 of the data in each DS was used for training and 1/3 was used for the test. The TS data was used for estimating the confidence interval of the existing forecasting tool. Thus, an objective comparison with the same set of data can be performed.

2.2 Creation and Training of the ANNs

For each one of DS1 and DS2 and for each hour, an ANN has been developed, thus a total number of 48 ANNs has been used.

After the training procedure, the neural network is able to learn (generalize) the input-output relationship and thus to predict the wind power to any input vector outside the training set.However, good generalization depends on the network structure. In particular, small size networks are not able to approximate complicated input-output relationships. On the other hand, recent studies on learning versus generalization network capabilities including the VC dimension [13] indicate that an unnecessarily large network size heavily deteriorating generalization. In our approach, we adopt a back-propagation variant [14] in a constructive framework [15], which begins with a small size network and subsequently adds neurons to improve the network performance. A validation data set has been also used during training to control learning with respect to the generalization ability of the network.

In Table 1, the results of different extensively studied ANN architectures for a variety of hour-ahead predictions are presented. The selected architecture is the one with the minimum MAPE during the whole prediction horizon. In the specific study, the optimal ANN structure for both classes was the one consisting of 3 hidden layers of 13 neurons each, namely 25-13-13-13-1. In Fig. 2, the performance of the selected ANN architecture for different number of epochs is examined as far as MAPE is concerned. According to this figure, the optimal number of epochs was 15.

Table 1. MAPE of TS in the 10-67.35 MW class for different ANN architectures

ANN architecture	MAPE of 10-67.35 MW class		
	1 hour ahead prediction	12 hour ahead prediction	24 hour ahead prediction
25-13-1	10.72%	12.68%	11.27%
25-25-1	10.05%	11.86%	10.74%
25-13-13-1	9.59%	12.06%	10.44%
25-25-25-1	10.01%	11.69%	10.41%
25-13-13-13-1	9.40%	11.66%	10.22%

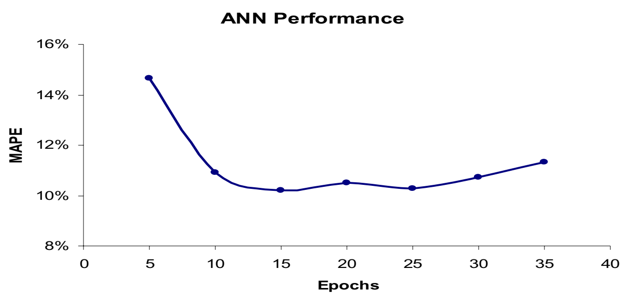

Fig. 2. Performance of the 25-13-13-13-1 ANN architecture for the MAPE estimation of the 24^{th} hour ahead prediction

2.3 Evaluation of the ANN Output and Confidence Interval Derivation

The output of the ANN is the improved wind power prediction for each studied interval. In order to evaluate the performance of the ANN, the MAPE is calculated comparing the outputs of the improved wind power forecast with the actual wind power production from the wind parks of Crete for the period of study; i.e. 4 last months of 2001. The MAPE index for the ANN is calculated as follows:

$$e_r = \left(\frac{P_f - P_a}{P_i} \right) \cdot 100\% \tag{1}$$

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} |e_r| \tag{2}$$

where e_r is the wind power prediction error, P_f is the forecasted wind power provided by the ANN, P_a is the actual wind power, P_i is the total installed wind power capacity and N is the number of hours studied (for our application N=24). For the island of Crete, P_i=67.35 MW, for the year 2001. Negative values of e_r mean underestimation of the ANN output, while positive mean overestimation.

Overestimation of wind power, leads to lack of energy unless sufficient spinning reserve has been committed to the power system. Thus, the higher the overestimation of the forecasting model, the higher the spinning reserve that should be maintained, leading to more units to be committed for the same load and thus the higher the operating cost. On the other hand, underestimation of wind power has as an impact that the committed units operate in lower efficiency operating points increasing their operating cost.

After the evaluation of the improved wind power forecast tool is complete, an 85% confidence interval of the forecasting error is derived in order to help the operators to determine their spinning reserve policy as far as wind power forecast uncertainty is concerned.

3 Crete Power System

Crete is the largest isolated power network in Greece with significant wind power penetration around 10% of the annual island demand since 2000. The instantaneous wind power penetration has reached 39% during some valley hours in winter and early spring [9]. The installed wind power capacity on the island is currently 105.15 MW. There are also installed 690 MW of various thermal units, such as diesel, gas turbines, steam turbines and one combined cycle unit in three power plants.

Public Power Corporation (PPC) is the operator of this power system and is obliged to buy at specific price (90% of the retail low voltage price), the energy produced by the wind park installations. Thus, the improved wind power forecasting and the estimation of its confidence interval are significant, especially during low load periods, when slow response units, steam turbines and combined cycle units operate to avoid committing surplus units or not having enough units to compensate for unit loss.

In our study, data from the last 4 months of 2001 was used, when the installed wind power capacity was 67.35 MW.

4 Results

In Table 2, the MAPE for both the existing neuro-fuzzy wind power forecasting model and the proposed methodology are presented for the TS data. In all cases, especially in the 0-10 MW class, the proposed methodology offers much better results.

Table 2. Comparison of TS MAPE for the 0-10 MW class and for the 10-67.35 MW class for the existing wind power forecasting tool (neuro-fuzzy model) and the proposed model (ANN)

Estimation (Hours ahead)	0-10 MW class MAPE on test test		10-67.35 MW class MAPE on test test	
	Neuro-fuzzy model	Improved model (ANN)	Neuro-fuzzy model	Improved model (ANN)
1	19.10%	9.04%	18.10%	9.40%
2	21.70%	11.88%	15.38%	9.54%
3	20.74%	11.53%	16.71%	9.37%
4	21.93%	11.22%	16.70%	11.16%
5	22.27%	12.32%	15.41%	10.03%
6	21.07%	11.29%	15.43%	10.46%
7	23.40%	11.88%	15.63%	10.69%
8	25.58%	14.56%	15.36%	10.43%
9	20.82%	11.37%	16.64%	11.27%
10	21.53%	13.53%	18.53%	11.16%
11	21.46%	12.10%	16.94%	11.02%
12	24.44%	14.37%	17.52%	11.66%
13	23.79%	14.01%	15.30%	11.21%
14	23.14%	12.48%	15.45%	10.82%
15	23.49%	11.53%	16.59%	11.61%
16	24.01%	12.29%	17.12%	11.23%
17	28.10%	14.57%	17.68%	10.00%
18	24.20%	12.18%	17.00%	9.94%
19	22.54%	13.70%	15.48%	11.05%
20	23.67%	11.73%	15.53%	9.51%
21	23.30%	13.45%	17.41%	10.33%
22	23.16%	13.84%	16.46%	9.99%
23	22.40%	13.12%	19.44%	8.96%
24	24.32%	12.79%	17.52%	10.22%

The MAPE differences range from 8.00% (10^{th} hour estimation) to 13.53% (17^{th} hour estimation) for the 0-10 MW class and from 4.09% (13^{th} hour estimation) to 10.48% (23^{rd} hour estimation) for the 10-67.35 MW class.

In Tables 3 and 4, the 85% confidence intervals, expressed as 7.5% and 92.5% percentiles (ptl) on the test set for the two classes of wind power forecasting values are presented, according to both the outputs of the existing model and the proposed method, respectively.

The proposed methodology provides significant reduction to each confidence interval range and much smaller underestimated values, so the power system operator can estimate the wind power production more accurately avoiding committing more units than necessary. More specifically, in the 0-10 MW class, the existing model's lowest underestimating errors are always under -40%, while in the proposed model the corresponding values only once exceed -30%. In the 10-67.35 MW class, the underestimation error differences are smaller, but in almost every case are over 10%.

Table 3. 85% confidence interval (c.i.) for the estimated error of 0-10 MW class and 10-67.35 MW class of the wind power forecasting tool (neuro-fuzzy model)

Estimation	0-10 MW class		10-67.35 MW class	
(Hours ahead)	7.5% ptl	92.5% ptl	7.5% ptl	92.5% ptl
1	-41.80%	2.04%	-42.75%	14.80%
2	-46.52%	0.99%	-40.18%	15.96%
3	-42.52%	3.26%	-35.79%	14.87%
4	-46.38%	1.56%	-43.21%	13.47%
5	-48.88%	2.15%	-31.54%	20.46%
6	-42.88%	0.98%	-33.81%	17.85%
7	-50.01%	0.44%	-31.40%	20.88%
8	-50.09%	0.93%	-32.43%	13.35%
9	-44.91%	7.22%	-35.25%	17.70%
10	-48.35%	8.37%	-35.28%	19.20%
11	-48.08%	8.59%	-36.97%	21.60%
12	-52.55%	7.90%	-42.85%	19.36%
13	-50.71%	8.08%	-33.40%	16.28%
14	-48.77%	2.60%	-30.44%	26.17%
15	-52.14%	5.45%	-33.30%	22.94%
16	-50.47%	7.77%	-35.33%	23.81%
17	-54.43%	0.64%	-34.35%	25.29%
18	-53.52%	2.95%	-31.31%	26.49%
19	-49.90%	6.19%	-28.21%	23.93%
20	-51.27%	7.98%	-29.53%	24.03%
21	-49.34%	2.07%	-33.38%	26.60%
22	-50.36%	8.47%	-27.19%	32.02%
23	-51.51%	3.19%	-31.55%	27.59%
24	-53.64%	1.92%	-30.99%	30.92%

For both classes, smaller differences of the confidence intervals' largest overestimation values are observed, especially in the 0-10 MW class, where for some estimations the initial model gives slightly better results.

Figs. 3 and 4 provide the difference in the forecast and actual operation for specific values of the studied period for the existing neuro-fuzzy model and the proposed ANN model. For each case, the minimum and maximum value of the wind power is also displayed, as it results from the upper and lower boundary of the 85% confidence interval. The reference date is the 28/12/2001 and prediction time 12:00. This prediction time-series offers wide variation of the predicted values from the neuro-fuzzy model, the input data of the ANN model, ranging between 5.18 MW and 45.23 MW. Thus a more representative analysis of models' performance can be done. The selected time-series also provides acceptable number of data for both classes of wind power prediction of the initial model (8 data from the 0-10 MW class and 16 data from 10-67.35 MW class). The comparison of Figs. 3 and 4 proves that the performance of the proposed ANN is much better than the existing model, since the ANN wind power estimation is much more accurate, while its 85% confidence interval is significantly narrower.

Table 4. 85% confidence interval (c.i.) for the estimated error of 0-10 MW class and 10-67.35 MW class of the proposed ANN

Estimation	0-10 MW class		10-67.35 MW class	
(Hours ahead)	7.5% ptl	92.5% ptl	7.5% ptl	92.5% ptl
1	-13.12%	1.36%	-14.94%	6.64%
2	-21.88%	3.18%	-15.56%	10.57%
3	-9.50%	0.70%	-16.73%	6.25%
4	-14.83%	1.31%	-18.17%	4.00%
5	-15.91%	1.81%	-15.72%	8.64%
6	-20.91%	2.83%	-16.32%	6.84%
7	-25.95%	2.07%	-15.90%	6.88%
8	-33.77%	1.88%	-20.45%	9.11%
9	-20.40%	1.87%	-16.48%	10.23%
10	-16.93%	4.43%	-22.03%	6.50%
11	-21.77%	1.90%	-15.97%	9.65%
12	-25.00%	1.54%	-20.39%	7.32%
13	-20.07%	3.54%	-17.29%	9.60%
14	-21.21%	2.46%	-15.86%	12.14%
15	-18.18%	0.80%	-20.65%	13.39%
16	-20.30%	1.95%	-20.03%	9.82%
17	-27.83%	5.50%	-21.10%	8.88%
18	-19.05%	2.62%	-11.62%	8.42%
19	-19.19%	2.81%	-17.35%	10.46%
20	-19.20%	2.88%	-14.00%	8.46%
21	-15.55%	2.32%	-20.10%	8.01%
22	-20.42%	5.06%	-17.02%	8.36%
23	-19.44%	2.92%	-16.32%	6.40%
24	-28.20%	2.69%	-14.99%	12.34%

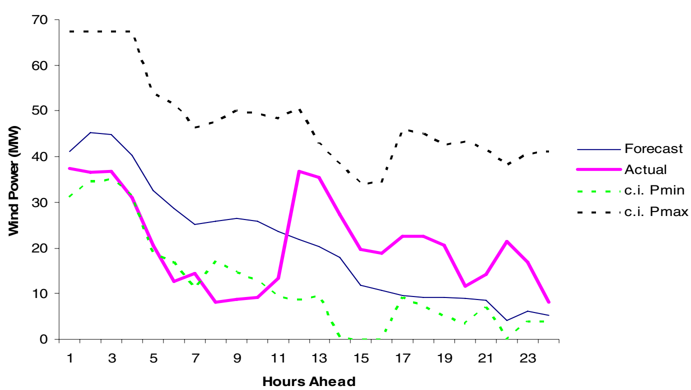

Fig. 3. Forecast versus actual wind power and min/max boundaries of 85% confidence intervals for the existing neuro-fuzzy model for the 28/12/2001 at 12:00

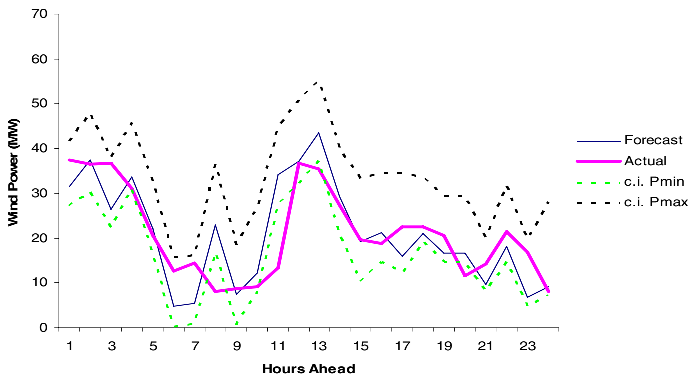

Fig. 4. Forecast versus actual wind power and min/max boundaries of 85% confidence intervals for the proposed ANN model for the 28/12/2001 at 12:00

The economic impact of the improvements of the wind power forecasting, especially for confidence interval, is due to the reduction of spinning reserve requirements to compensate for the wrong estimation of wind. It is considered that the spinning reserve requirements is given by the following equation:

$$Spin\_res = 0.1 \cdot load\_forec + conf\_interval \cdot wind\_power \tag{3}$$

where *conf_interval* is the 92.5% percentile (ptl) values used corresponding to the larger user-defined acceptable wind underestimation level, *load_forec* is the forecasted load and *wind_power* is the installed wind power capacity.

The impact of reduced spinning reserve is shown in Table 5 for two characteristic days corresponding to the two classes of the test sets and for different loading conditions. During Day 1, low loading, the wind power forecast never exceeded 10 MW, while during Day 2, high loading, the wind power forecast was always over 10 MW so the corresponding data should be used from Tables 3 and 4.

It can be seen that there are significant savings in the operating cost during medium to high wind power conditions during high load conditions reaching 1.00%. This is due to the fact that the more expensive gas turbines are committed for less time, or less of these units are required.

Table 5. Characteristic days used for indicating the impact of improved wind power confidence interval

Day	Total daily demand (MWh)	Average Wind Power Production (MW)	Characterization	Percentage Savings
Day 1	5197.4	1.3	Low Load, Low Wind Production	0.05%
Day 2	7396.5	26.6	High Load, Medium Wind Production	1.00%

5 Conclusions

This paper proposes a combined neuro-fuzzy and ANN model for wind power forecasting. The output of an existing neuro-fuzzy wind power prediction tool is used as input to the proposed ANN structure. It is shown that the proposed ANN model exploits the past performance of the neuro-fuzzy model and provides more accurate wind power forecasting values. More specifically, the proposed method offers significant improvements in all crucial information for power system operators, concerning wind power prediction and its uncertainty estimation, providing narrower confidence intervals for the predicted wind power. Thus the operator can very quickly and very accurately have improved wind power forecast with narrower confidence intervals based on the initial wind power forecast provided by the Neuro-fuzzy tool or any other wind power forecasting algorithm. Thus, the power systems operators have at their disposal much more accurate information on the expected wind power in the following few hours, that can be used as inputs for the economic scheduling functions of the power systems. Reduction of the uncertainty concerning wind power, especially for autonomous power systems helps in increasing the confidence of the power systems operators on wind power and its further exploitation.

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