Chapter

Optimization of the ANNs Models Performance in the Short-Term Forecasting of the Wind Power of Wind Farms

Sergio Velázquez-Medina and Ulises Portero-Ajenjo

Abstract

Due to the low dispatchability of wind power, the massive integration of this energy source in electrical systems requires short-term and very short-term wind farm power output forecasting models to be as efficient and stable as possible. A study is conducted in the present paper of potential improvements to the performance of artificial neural network (ANN) models in terms of efficiency and stability. Generally, current ANN models have been developed by considering exclusively the meteorological information of the wind farm reference station, in addition to selecting a fixed number of time periods prior to the forecasting. In this respect, new ANN models are proposed in this paper, which are developed by: varying the number of prior 1-h periods (periods prior to the prediction hour) chosen for the input layer parameters; and/or incorporating in the input layers data from a second weather station in addition to the wind farm reference station. It has been found that the model performance is always improved when data from a second weather station are incorporated. The mean absolute relative error (MARE) of the new models is reduced by up to 7.5%. Furthermore, the longer the forecast horizon, the greater the degree of improvement.

Keywords: Artificial neural networks (ANN), wind power forecasting, model performance, wind farm power output

1. Introduction

A major impediment to the large-scale integration of wind power in electrical systems is the low dispatchability of this energy source. The effects of variations in wind speed, and hence wind power, are not only observed on a year-to-year or season-to-season scale, but also on a within-day scale [1–5]. A strategy that can be employed to improve wind energy integration in electrical systems is to optimize the performance of short-term forecasting models of wind farm power production. This strategy is the focus of the present study.

The direct consequences of the low dispatchability of wind power on electrical systems can be both technical and economic. Supply and demand adjustments in electrical systems are made 24–36 hours in advance. Any mismatches that might arise between supply and demand forecasting are subsequently corrected on the day itself [6–9]. The mismatch correction as the result of imprecise forecasting entails additional costs for the electrical system [7, 10]. These extra costs are generally absorbed by the end user and/or electricity producer, with the latter thus burdened by an additional production cost.

Other strategies have been used to minimize the problem described above. One involves the direct estimation of the net energy demand of the electrical system, which can be understood as the difference between total demand and the energy generated by renewable sources. In [11–12], a model is proposed for direct forecasting of net energy demand which is validated with data from different electrical systems. Reference [13] compares a direct forecasting model of net energy demand with different indirect forecasting strategies.

In the electricity market, the matching of supply and demand is generally performed for 1 h periods. For this reason, in an analysis of model forecasting performance, it is very important to evaluate the error for 1 h periods, to study model performance for different forecast horizons, and to evaluate the stability of the error in the time horizon in which the forecasting is made.

Numerous studies can be found in the literature on the development of short-term forecasting models. Different techniques and approaches have been analyzed and proposed. In most cases, good performances for specific forecasting horizons have been obtained. The techniques that have been used range from simple heuristics [14–20] to systems which employ artificial intelligence [21–34]. The study developed in the present paper focuses on models which employ the technique of artificial neural networks (ANNs) to forecast wind farm power production [21, 22, 26], [27, 29–31, 33, 34].

In [34], the proposed forecasting model is developed on the basis of improvements made to the kriging interpolation method and empirical mode decomposition, using a new forecasting engine based on neural networks. To analyze the results, the mean absolute percentage error (MAPE), normalized mean absolute error (NMAE) and normalized root mean square error (NRMSE) metrics are used, calculated as the mean value in the forecasting horizons (24 h and 6 h). As in [34], models have been developed for different forecasting horizons [26, 27, 33]. However, an extensive analysis of the literature conducted by the authors of the present study has found that the models developed to date only consider a specific and fixed number of prior 1-*h* periods (periods prior to the prediction hour). It should also be noted that, in all the studies consulted, the meteorological data used as input layer parameters correspond exclusively to the reference weather station (WS) of the wind farm. In no case is the meteorological information used from additional WSs other than the reference WS of the wind farm. Finally, the metrics used to assess model performance in all these studies are obtained as the mean value of the forecasting time horizon. As previously stated, given that the matching of supply and demand in the electricity market is performed for 1 h periods, there is an additional interest in the study of the possible variation of the metrics within that time frame for each of the hourly periods.

The present study considers possible improvements, in terms of efficiency and stability, to the performance of ANN-based models for wind power forecasting. For this purpose, an analysis is made on the improvement of model performance of: ① varying the number of prior 1-*h* periods (periods prior to the forecasting hour) chosen for the ANN input layer parameters; and/or ② incorporating in the input layer data from a second weather station in addition to the data from the wind farm reference station. The analysis is undertaken for a wide range of forecasting horizons. Based on the above, a total of up to 175 ANN models are generated, and the results are compared by applying the models to two actual wind farms located in the Canary Islands, Spain.

The aim of this paper is to make the following original contributions to the scientific body of knowledge:

1. A study of improvement in the efficiency and stability of ANN models of varying the number of 1-*h* prior periods (periods prior to the prediction hour and hereinafter referred to as *n*), chosen for incorporation of the input layer parameters.

2. A study of improvement in ANN model performance of the additional incorporation in the input layer of meteorological data from WSs other than the wind farm reference station.

Both effects are analyzed for different forecasting horizons.

2. Methodology

Figure 1 shows the methodology followed in the present study for the implementation of different ANN models generated. It shows the combination of parameters which are considered for the input and output layer neurons in the generation process of different ANN models. The various parameters are defined as follows: t_i is the time instant on the basis of which the forecast is made, and V_{ti}, D_{ti} and P_{ti} are the wind speed, wind direction and the wind farm power output, respectively, in the instant t_i.

The following data are used in all the models: historical wind speed and direction data obtained from the wind farm reference WS, and historical power production

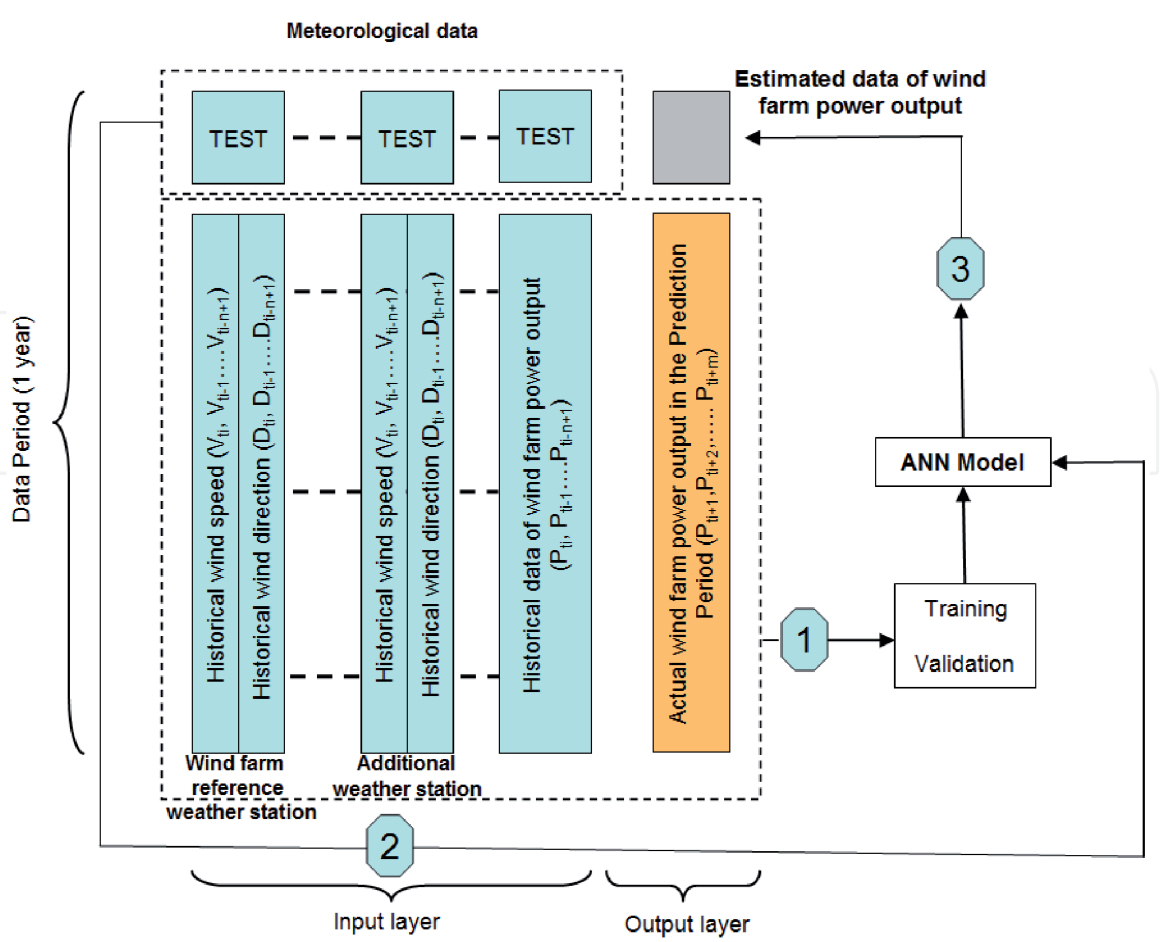

Figure 1.
Methodology to obtain forecasting models.

data of the wind farm. In some models, as will subsequently be explained, the historical wind speed and direction data of a second WS are used in addition to the data of the wind farm reference station.

The output layer is comprised of the power output values for different forecasting horizons.

The number of hours prior to the prediction hour, n, and the length of the forecasting horizon that is being forecasted, m, are variable.

2.1 Architecture of ANN employed

The ANNs used to generate the models are comprised of three layers with feedforward connections. For this purpose, multi-layer perceptron (MLP) topologies have been used [35, 36]. In order not to increase the length of the training period excessively, a single layer of hidden neurons is used. This architecture has been shown to have the capacity to satisfactorily approximate any continuous transformation [35, 36]. Various prior tests have been carried out to choose the number of hidden neurons, varying the number of input signals. It is found that using more than 20 neurons merely increases the time required for model training and validation without improving the results. It is therefore decided to use a total of 20 neurons in the hidden layer.

The architectures are trained using the backpropagation algorithm with sigmoidal activation function [31, 32]. The Levenberg–Marquardt algorithm is used to minimize the mean square error committed in the learning process [35, 37].

To carry out the training and validation stages used to generate the model and the test stage of the network, the available annual data series for each parameter are divided into random and different subsets (**Figure 1**). The proportion of data selected for each of the stages is 75%, 15% and 10%, respectively.

As can be seen in **Figure 1**, the training and validation data subsets are used to generate the model. The test data subset is used to evaluate the performance of the model generated.

The 10-fold cross-validation technique is used for the process of model generation and evaluation. The test stage data subset is used in each of the iterations. The error assigned to each model is the arithmetic mean of those obtained in the test stage for each of the iterations.

The various studies are performed using neural network tools available in the MATLAB software package.

2.2 Study cases

1. *Case A: Comparison of efficiency and stability of different ANN models obtained when varying the number of periods prior to the prediction hour (n) chosen for incorporation of different parameters in the input layer*

The number of prior periods, n, and the number of forecast horizon periods, m, are study variables. The different combinations of n and m generate different models whose performances will be analyzed. For Case A, both n and m are permitted to take the values 3, 6, 12, 24 and 36. That is to say, five different models are generated for each forecasting horizon, and thus the total number of generated models is 25. This methodology is applied to the two wind farms of the study.

To study the models in terms of the stability of forecasting, the results obtained for each of the periods within the forecasting horizon, m, are compared.

Figure 2 shows the structure of the neural network for this study case. The number of neurons of the output layer depends on the forecasting horizon, and will thus

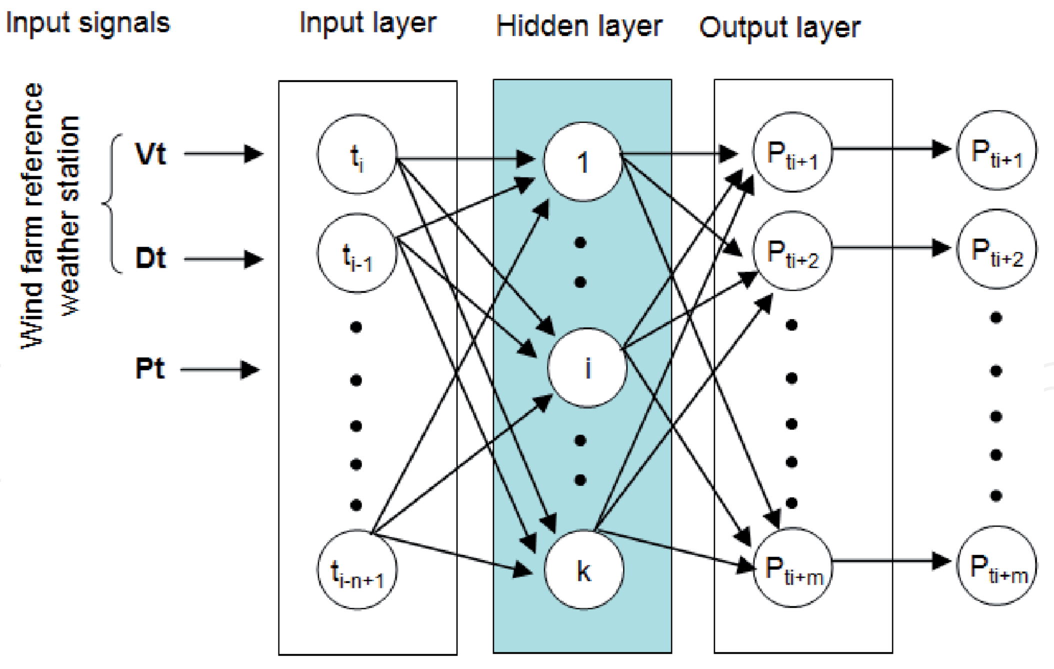

Figure 2.
Schematic representation of neural network for generation of forecasting models in case A.

fluctuate between 3 and 36 neurons. For the input layer, the number of neurons will also vary depending on the value of n, from 9 (n = 3) to 108 (n = 36) neurons.

2. *Case B: Comparison of performance of ANN models when additionally incorporating in the input layer the data from a second WS other than the reference station of wind farm.*

For Case B, both n and m could take the same values as indicated for Case A.

Figure 3 shows the structure of the neural network for the generation of models in Case B.

In Case B, the input layer of the ANN incorporates the data from a second WS in addition to that of the reference WS of the wind farm. To generate different models,

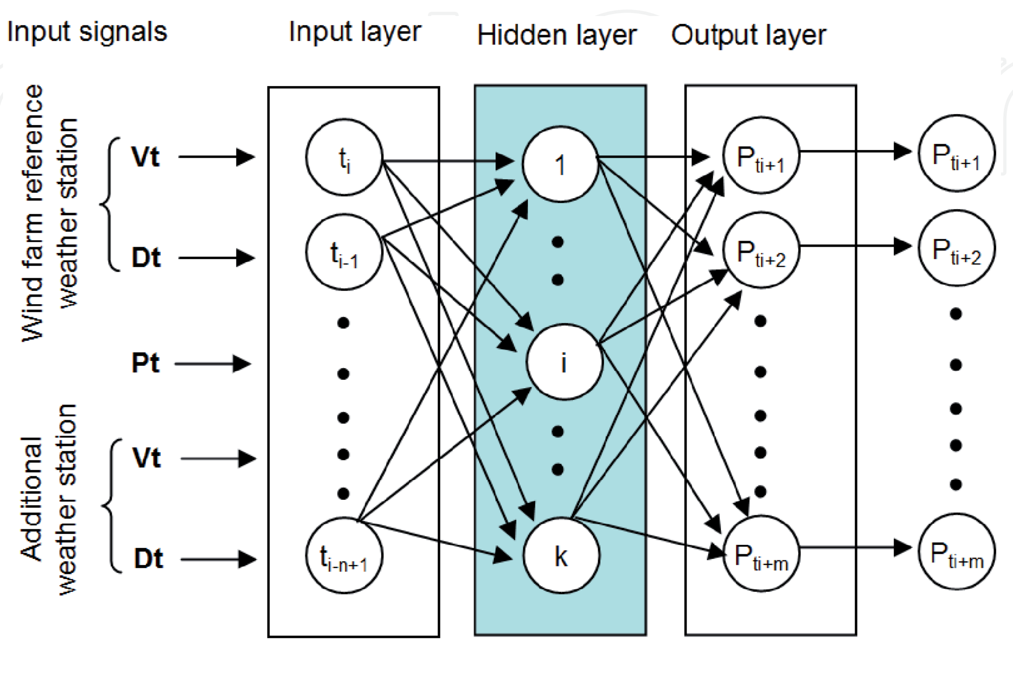

Figure 3.
Schematic representation of neural network for generation of forecasting models in case B.

Code	Height (magl)	Latitude (north)	Longitude (west)	Altitude (m)
WS1	40	27°54′08”	15°23′17”	16
WS2	10	27°51′36”	15°23′13”	3
WS3	10	28°27′10”	13°51′54”	24
WS4	10	28°57′07”	13°36′00”	10
WS5	13	28°01′36”	15°23′16”	5
WS6	10	28°07′30”	15°40′37”	472
WS7	10	27°56′08”	15°25′24”	186
WS8	10	28°02′35”	16°34′16”	51
WS9	40	29°05′47”	13°30′21”	457

Table 1.
Weather stations used in study.

the data of the reference WS of each wind farm (WS1 and WS9) are combined with the data of each of the seven other weather stations, WS-2 to WS-8 (**Table 1**). Therefore, for Case B, 175 different models are generated (25 × 7). After applying these models to each wind farm, their results are then compared.

The number of neurons in the input layer also varies, depending on the value of n, from 15 (n = 3) to 180 (n = 36).

The variation in the number of output layer neurons is the same as in Case A.

2.3 Metrics used to compare the different models

To compare the performance of the different models generated for Cases A and B, metrics (1) and (2) were used:

$$MARE = \frac{1}{m}\sum_{j=1}^{m}\frac{1}{(T-r)}\sum_{i=1}^{T-r}\left(\frac{\left|P_j-\hat{P}_j\right|}{P_j}\right)_i = \frac{1}{m}MARE_j \tag{1}$$

$$R = \frac{1}{m}\sum_{j=1}^{m}\frac{\sum_{i=1}^{T-r}\left(P_{j_i}-\overline{P_j}\right)\times\left(\hat{P}_{ji}-\overline{\hat{P}_j}\right)}{\sqrt{\left[\sum_{i=1}^{T-r}\left(P_{ji}-\overline{P_j}\right)^2\right]\times\left[\sum_{i=1}^{T-r}\left(\hat{P}_{ji}-\overline{\hat{P}_j}\right)^2\right]}} = \frac{1}{m}\sum_{j=1}^{m}R_j \tag{2}$$

where: MARE is the mean absolute relative error for the forecast horizon; T is the number of data in the test stage (see **Figure 1**); r = T-m-n; $MARE_j$ is the mean absolute relative error for the forecasting period j; P_j and $\hat{P}_j$ are the actual and estimated wind farm power output in the forecasting period j, respectively; R is the mean value of Pearson's coefficient of correlation between the estimated and actual wind farm power output for the forecast horizon; and R_j is the mean Pearson correlation coefficient between the estimated and actual wind farm power output values for the forecasting period j.

The combined use of the two previous metrics is considered sufficient for the evaluation of the performance of the models and they have been widely used [38–41]. Alternatively, for the evaluation of future models, combinations of other metrics could be used [42]. For example, a combination of the Normalized Mean Absolute Error (NMAE) and the Index of Agreement (IoA) could be used.

3. Materials

The meteorological data (wind speed and direction) recorded by nine WSs located in four of the seven islands of the Canary Archipelago (**Table 1**) are used in this study. The mean hourly wind speed and direction data from 2008 are used in all cases. The heights of the WSs are expressed in metres above ground level (magl).

To validate and compare the results obtained with the different models, information corresponding to two wind farms (WF) located on two of the seven islands of the Canary Archipelago is used. **Tables 2** and **3** shows the geographic coordinates of the wind turbines (WT) of the two wind farms (WF1 and WF2). The hourly wind farm power output data for 2008 are used for this study.

Stations WS1 and WS9 (**Table 1**) are the reference weather stations of wind farms WF1 and WF2, respectively. The WS1 and WS9 data and the wind power production values are provided by the respective owners of the wind farms. The data from the seven additional WSs used in the study are provided by the Canary Islands Technological Institute (Spanish initials: ITC), a publicly owned R&D company run by the Regional Government of the Canary Islands and Spain's State Meteorological Agency (Spanish initials: AEMET).

Table 4 shows the results obtained for the coefficients of linear correlation (3) between the mean hourly wind speeds of the different WSs.

$$CC = \frac{\sum_{i=1}^{NG}\left(V_i - \overline{V}\right)\times\left(V_i' - \overline{V'}\right)}{\sqrt{\sum_{i=1}^{NG}\left(V_i - \overline{V}\right)^2}\times\sqrt{\sum_{i=1}^{NG}\left(V_i' - \overline{V'}\right)^2}} \quad (3)$$

where *CC* is the Pearson's coefficient of correlation between the wind speeds of two WSs; *NG* is the total number of data of the series. In this case, as a series of hourly data equivalent to one year is available, *NG* is equal to 8760. V_i and V_i' are the speeds at instant i of the two WSs subject to correlation; $\overline{V}$ and $\overline{V'}$ are the mean wind speeds of the two WSs subject to correlation for the available data series.

Code	*x* (m)	*y* (m)	*z* (m)
WF1-WT1	461764	3086314	3
WF1-WT2	461839	3086301	1
WF1-WT3	461681	3086067	5
WF1-WT4	461753	3086038	2

Table 2.
Geographic coordinates of wind turbines in WF1.

Code	*x* (m)	*y* (m)	*z* (m)
WF2-WT1	645043	3219819	486
WF2-WT2	645147	3219752	478
WF2-WT3	645186	3219638	473
WF2-WT4	645264	3219548	464
WF2-WT5	645333	3219462	456
WF2-WT6	645403	3219369	448
WF2-WT7	645406	3219213	440
WF2-WT8	645554	3219194	425
WF2-WT9	645664	3219133	405

Table 3.
Geographic coordinates of wind turbines in WF2.

No.	Coefficient of linear correlation								
	WS1	**WS2**	**WS3**	**WS4**	**WS5**	**WS6**	**WS7**	**WS8**	**WS9**
WS1	1.00	0.84	0.27	0.34	0.74	0.73	0.77	0.50	0.51
WS2	0.81	1.00	0.19	0.25	0.79	0.74	0.87	0.44	0.54
WS3	0.27	0.19	1.00	0.70	0.16	0.16	0.18	0.16	0.11
WS4	0.34	0.25	0.70	1.00	0.20	0.21	0.22	0.20	0.11
WS5	0.74	0.79	0.16	0.20	1.00	0.49	0.78	0.21	0.44
WS6	0.73	0.74	0.16	0.21	0.49	1.00	0.61	0.62	0.54
WS7	0.77	0.87	0.18	0.22	0.78	0.61	1.00	0.39	0.46
WS8	0.50	0.44	0.16	0.20	0.21	0.62	0.39	1.00	0.35
WS9	0.51	0.54	0.11	0.11	0.44	0.54	0.46	0.35	1.00

Table 4.
Coefficient of linear correlation between wind speeds of different weather stations in 2008.

4. Results and discussion

The discussion of the results centres on the two cases proposed in the methodology. For the various figures corresponding to the results, t-3 indicates that 2 periods prior to the forecasting period are chosen in addition to the forecasting period (t_i, t_i-1, t_i-2), and t + 3 indicates a forecasting horizon of 3 periods, $t_i + 1$, $t_i + 2$, $t_i + 3$, starting from the period for which the forecasting is being made, and so on for all combinations.

4.1 Discussion of results for case A

Figures 4 and **5** show the results for the MARE and R metrics for the 25 generated models. In practically all cases, the MARE and R values improve as n increases. The only exception is for case t-36 in comparison with t-24, where the improvement is minimal or not observed. In addition, the degree of improvement increases as m increases (t + 12, t + 24 and t + 36).

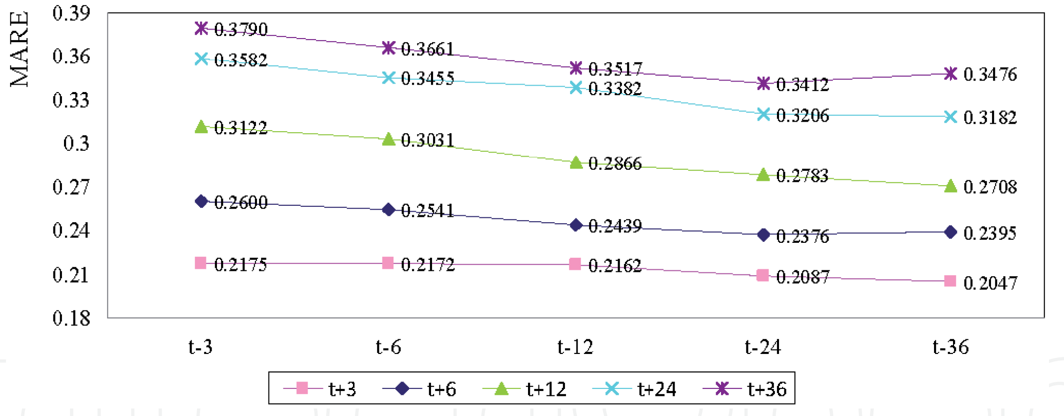

Figure 4.
MARE results in case A.

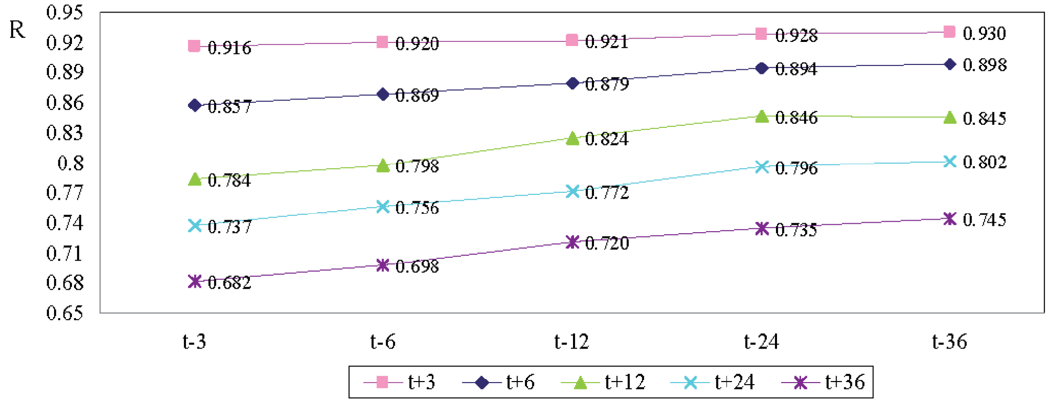

Figure 5.
R results in case A.

For the forecasting horizons $t + 12$, $t + 24$, $t + 36$, the maximum improvements obtained for MARE between the values for $n = 3$ and $n = 36$, are 13.3%, 11.2% and 10%, respectively. For the same cases but for R, the corresponding improvements are 7.9%, 8.9% and 9.2%, respectively.

To study the forecasting stability, an analysis has been made of the specific case of forecasting horizon $t + 24$, in which the number of periods to forecast is significant. **Figure 6** shows, for this specific case and differentiated according to n, the results of the variation of the relative error in the different forecasting periods, $MARE_j$. It can be seen how the relative error stabilizes earlier as n increases.

The forecasting stability is analyzed for all the forecasting horizons (**Figure** 7). This analysis is made on the basis of the standard deviation of relative error in the forecasting horizon:.

$$SDV = \sqrt{\frac{\sum_{j=1}^{m}\left(MARE_j - MARE\right)^2}{m-1}} \tag{4}$$

where SDV is the mean standard deviation of the MARE for a forecasting time horizon m.

It can be seen in **Figure** 7 that for all the forecasting horizons, the SDV/MARE value decreases significantly as the number of prior hours n increases. This significant improvement in the stability of models is observed even for the lowest forecasting horizons. Only for the particular case of forecasting horizon $t + 3$ and when the horizon passes from t-24 to t-36, no improvement is observed.

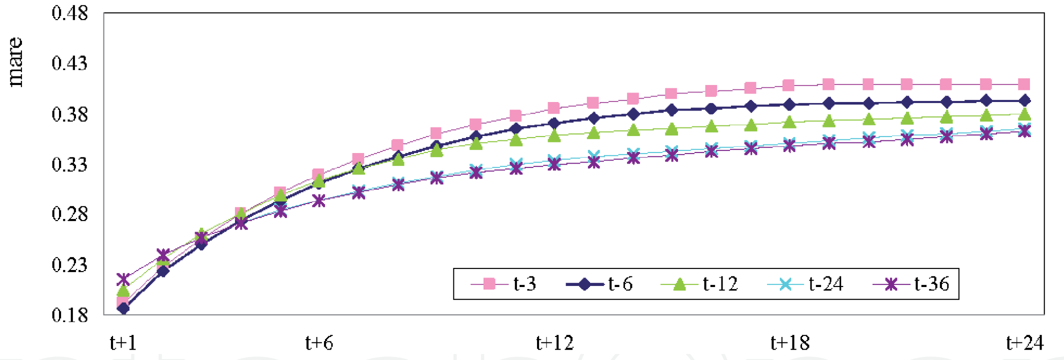

Figure 6.
MARE variation of different prediction periods: Case of a forecasting horizon t + 24.

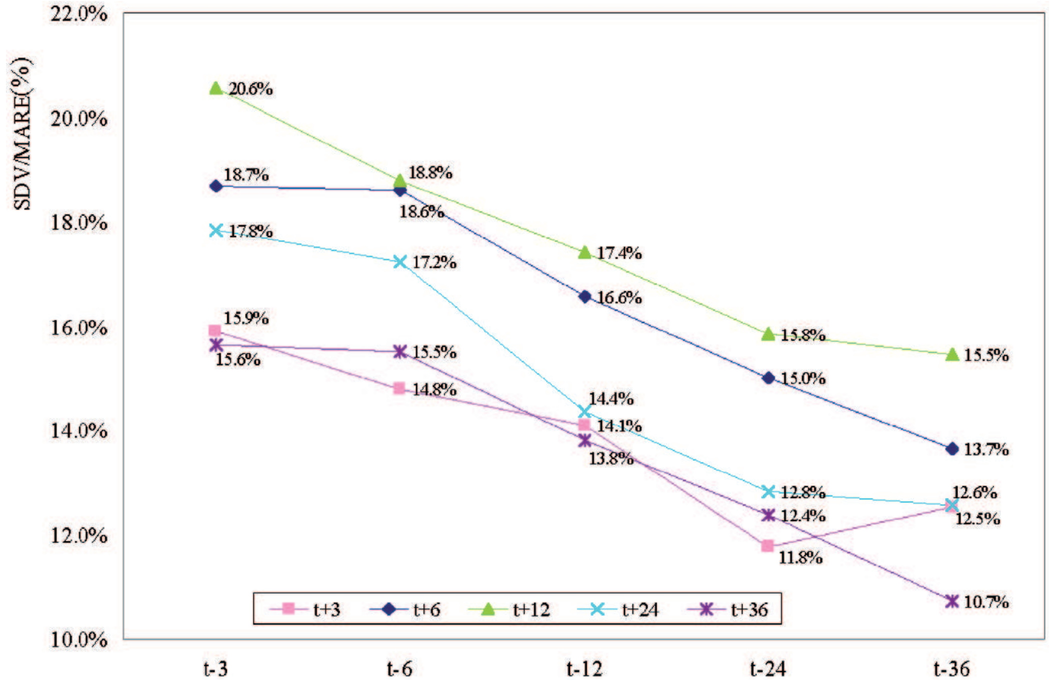

Figure 7.
Stability of relative error SDV in forecasting horizon.

By way of example, we will now proceed to analyze the specific cases of the forecasting models $t + 12$ and $t + 24$. To date, in the ANN models studied in the literature, the number of prior periods n chosen to generate the models has always been fixed. Assume that the n chosen for a standard model is 12. In this case, the MARE value is 0.2866 for the $t + 12$ model and 0.3382 for the $t + 24$ model (**Figure 4**). The corresponding values for the stability of the relative error are 17.4% and 14.4% (**Figure 7**), respectively. According to the analysis made with Case A, the performance of these models can be improved by choosing a higher value of n. If n is 24, the MARE values decrease to 0.2783 and 0.3206, respectively (**Figure 4**). Similarly, for an n of 24, the stability of the relative error in the forecasting improves to the values of 15.8% and 12.8%, respectively (**Figure 7**).

4.2 Discussion of results for case B

For the analysis of Case B, the MARE and R results of this case, with two WSs, are compared with those of Case A, with one WS. For this purpose, (5) and (6) are used.

$$\Delta\, MARE = \frac{1}{7}\sum_{p=1}^{7}\frac{MARE_{p_{(with\,2\,WSs)}} - MARE_{(with\;1\,WS)}}{MARE_{(with\,1\,WS)}}\times 100\% \tag{5}$$

$$\Delta\, R = \frac{1}{7}\sum_{p=1}^{7}\frac{R_{p_{(with\,2\,WSs)}} - R_{(with\,1\,WS)}}{R_{(with\,1\,WS)}}\times 100\% \tag{6}$$

It can be seen in **Figures 8** and **9** how all the models generated for Case B obtain an additional improvement in performance to that already obtained for Case A. This additional improvement is in relation to ANN models developed to date which always use exclusive data from a single WS.

It can also be observed that, in general, the degree of improvement increases as m increases. This degree of improvement slows down for forecasting horizons longer than 24 hours.

The maximum additional improvements in model performance are seen in forecasting horizons $t + 24$ and $t + 36$ (7.5% and 5.5% for MARE and 3.7% and 5.4% for R, respectively). Even for the shortest forecasting horizons, $t + 3$ and $t + 6$, the maximum improvements in the MARE metric are significant (3% and 4.9%, respectively).

Continuing with the specific example proposed in the analysis of results for Case A (using models $t + 12$ and $t + 24$), **Figure 10** shows the additional improvements in performance that can be obtained through the incorporation in the input layer of data from a second WS (Case B).

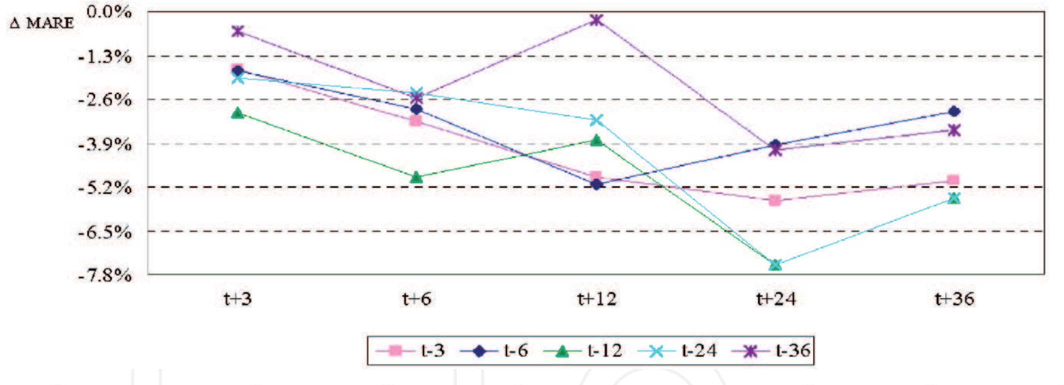

Figure 8.
Comparison of MARE results for cases A and B.

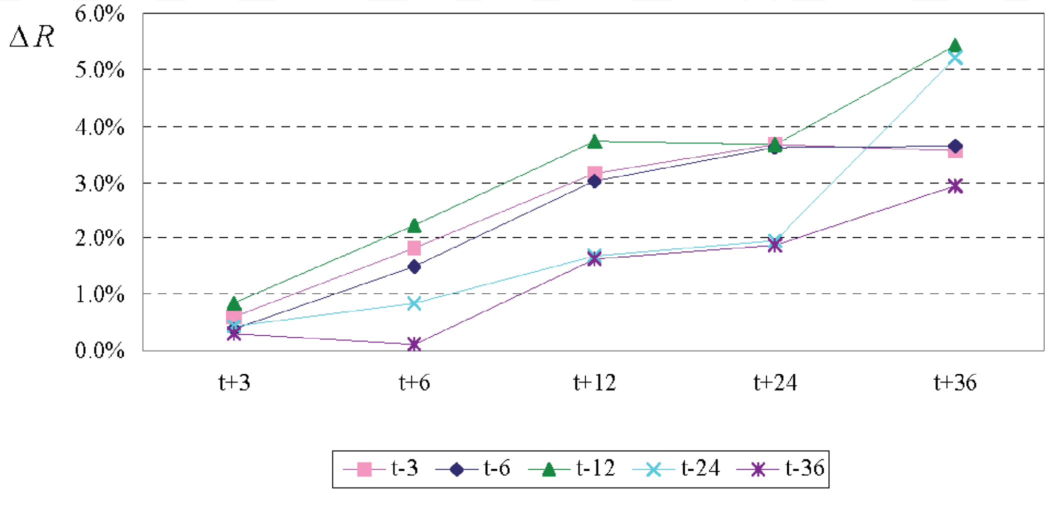

Figure 9.
Comparison of results obtained for R for cases A and B.

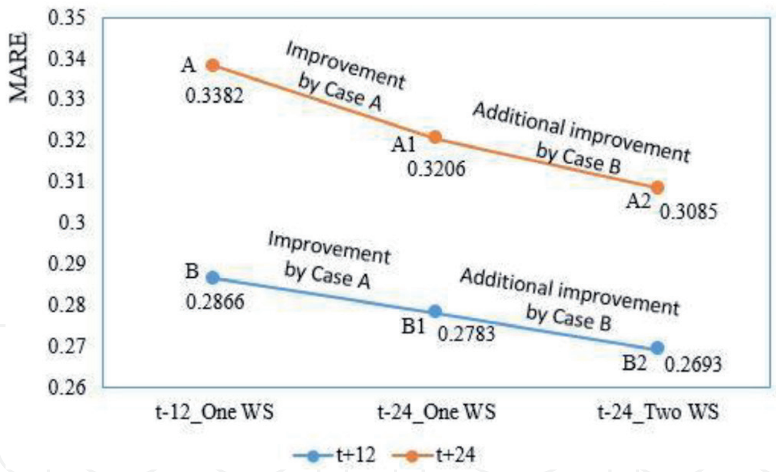

Figure 10.
Improvements in error for two specific models due to implementation of cases A and B.

Points A and B represent the error obtained when using a fixed n of 12 and only data from the reference WS of the wind farm. Points A1 and B1 represent the improvements obtained in the error when n is increased to 24. Points A2 and B2 represent the additional improvements obtained in the error when, in Case B, the data from a second WS are incorporated in the input layer of the ANN. For the two specific examples given, the overall improvements obtained by combining Cases A and B amount to 8.78% and 6.04%, respectively.

5. Conclusion

A series of interesting conclusions can be drawn from the results of this study with respect to possible improvements in the performance of ANN models for the short-term forecasting of wind farm power output.

The performance of the new ANN models generated for each forecast horizon improves with the increase in the number of prior 1-h periods (periods prior to the prediction hour), n, chosen for incorporation of the input layer parameters. For the forecasting horizons $t + 12$, $t + 24$ and $t + 36$, the maximum improvements obtained for MARE are 13.3%, 11.2% and 10%, respectively; and for R, the corresponding improvements are 7.9%, 8.9% and 9.2%, respectively.

A study is also made of the stability of the mean relative error for the different forecasting periods and for each forecasting horizon m. As n increases the stability of the error in the forecasting improves significantly for all forecasting horizons.

Additionally, in all the new models generated, the incorporation in the input layer of ANN of meteorological data from a second WS also improves the performance of the traditional models generated exclusively with data from the reference station of the wind farm. In general terms, the degree of improvement in model performance increases with m, attaining improvements in the MARE and R of up to 7.5% and 5.4%, respectively.

In view of the conclusions drawn from the present study, the original contributions described in this manuscript could be implemented in existing ANN models to optimize their results.

Acknowledgements

This research has been co-funded by ERDF funds, INTERREG MAC 2014-2020 programme, within the ENERMAC project (MAC/1.1a/117). No funding sources

had any influence on study design, collection, analysis, or interpretation of data, manuscript preparation, or the decision to submit for publication.

Conflict of interest

The authors declare no conflict of interest.

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