Paper

Application of Adaptive Neuro-Fuzzy Inference for Wind Power Short-Term Forecasting

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The increased integration of wind power into the electric grid, as nowadays occurs in Portugal, poses new challenges due to its intermittency and volatility. Hence, good forecasting tools play a key role in tackling these challenges. In this paper, an adaptive neuro-fuzzy inference approach is proposed for short-term wind power forecasting. Results from a real-world case study are presented. A thorough comparison is carried out, taking into account the results obtained with other approaches. Numerical results are presented and conclusions are duly drawn.

Keywords : wind power, forecasting, neural networks, fuzzy logic

1. Introduction

Wind energy is gaining increasing importance throughout the world [1], and wind-driven power resources have become increasingly important in the planning and operation of electric power systems.

In Portugal, the wind power goal foreseen for 2010 was established by the government as 3750 MW and that will constitute some 25% of the total installed capacity by 2010. This value has recently been raised to 5100 MW, by the most recent governmental goals for the wind sector. Hence, Portugal has one of the most ambitious goals in terms of wind power, and in 2006 was the second country in Europe with the highest wind power growth [2].

The wind energy is free, so all wind-generated electric energy is accepted as it comes, i.e. as it is available. However, the availability of the power supply generated from wind energy is not known in advance. Hence, the integration of a large share of wind power in an electricity system leads to some important challenges. Wind power forecasting plays a key role in tackling these challenges [3].

Short-term wind power forecasting is an extremely important field of research for the energy sector, as the system operators must handle an important amount of fluctuating power from the increasing installed wind power capacity. The time scales concerning short-term prediction are in the order of some days (for the forecast horizon) and from minutes to hours (for the time-step) [4].

In the technical literature, several methods to forecast wind power have been reported, namely physical and statistical methods.

The physical method requires a lot of physical considerations to reach the best prediction precision. For a physical model the input variables will be the physical or meteorology information [5].

The statistical method aims at finding the relationship of the on-line measured power data. For a statistical model the historical data of the wind farm may be used.

Physical method has advantages in long-term prediction while statistical method does well in short-term prediction [6].

Conventional statistical models are identical to the direct random time-series model, including auto regressive (AR), and auto regressive integrated moving average (ARIMA) [7] models. The persistence approach has proven to be a useful first approximation for short-term wind power forecasting and provides a benchmark against which to compare alternative technique.

In the recent years, some new methods are catching researcher's attention, namely neural networks (NN) [8]–[12], evolutionary algorithms [13], and some hybrid methods [14]–[16].

The accurate comparison of all the methods is quite difficult because these methods depend on different situations and the data collection is a formidable task. However, it has been reported that artificial-based models outperformed others in short-term prediction [6].

A hybrid of NN and fuzzy logic, also known as adaptive neuro-fuzzy inference system (ANFIS), has been used in several modeling and forecasting problems. For instance, it has been applied for hydraulic plant generation forecasting [17], tip speed ratio prediction in wind turbines [18], solar radiation data forecasting [19], load forecasting [20], price forecasting [21], and control systems [22].

In this paper, ANFIS is proposed for short-term wind power forecasting in Portugal, which is a new contribution. The proposed approach is compared with persistence, ARIMA and NN approaches, to demonstrate its effectiveness regarding forecasting accuracy and computation time.

This paper is organized as follows. Section 2 presents the proposed neuro-fuzzy (NF) approach to forecast wind power. Section 3 provides the different criterions used to evaluate the forecasting accuracy. Section 4 provides the numerical results from a real-world case study. Finally, Section 5 outlines the conclusions.

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2. Proposed Approach

NN are simple, but powerful and flexible tools for forecasting, provided that there are enough data for training, an adequate selection of the input-output samples, an appropriated number of hidden units and enough computational resources available. Multi-layered feedforward NN are specially suited for forecasting, implementing nonlinearities using sigmoid functions for the hidden layer and linear functions for the output layer [23].

Just like NN, a fuzzy logic system is a nonlinear mapping of an input vector into a scalar output, but it can handle numerical values and linguistic knowledge. In general, a fuzzy logic system contains four components: fuzzifier, rules, inference engine, and defuzzifier.

NN have the advantage over the fuzzy logic models that knowledge is automatically acquired during the learning process. However, this knowledge cannot be extracted from the trained network behaving as a black box. Fuzzy systems, on the other hand, can be understood through their rules, but these rules are difficult to define when the system has too many variables and their relations are complex [24].

A combination of NN and fuzzy systems has the advantages of each of them. In a neuro-fuzzy system, neural networks extract automatically fuzzy rules from numerical data and, through the learning process, the membership functions are adaptively adjusted.

ANFIS is a class of adaptive multi-layer feedforward networks [25], applied to nonlinear forecasting where past samples are used to forecast the sample ahead. ANFIS incorporates the self-learning ability of NN with the linguistic expression function of fuzzy inference [20]. The ANFIS architecture is shown in Fig. 1.

The ANFIS network is composed of five layers. Each layer contains several nodes described by the node function. The node function is described next. Let O_i^j denote the output of the *i*th node in layer *j*.

In layer 1, every node *i* is an adaptive node with node function:

$$O_i^1 = \mu A_i(x), \quad i = 1, 2 \qquad (1)$$

or

$$O_i^1 = \mu B_{i-2}(y), \quad i = 3, 4 \qquad (2)$$

where x (or y) is the input to the *i*th node and A_i (or B_{i-2}) is a linguistic label associated with this node.

Thus, O_i^1 is the membership grade of a fuzzy set A ($= A_1$, A_2, B_1, or B_2) and it specifies the degree to which the given input x (or y) satisfies the quantifier A. The membership functions for A and B are usually described by generalized bell functions, e.g.:

$$\mu A_i(x) = \frac{1}{1 + \left| \frac{x - r_i}{p_i} \right|^{2q_i}} \qquad (3)$$

where (p_i, q_i, r_i) is the parameter set. As the values of these parameters change, the bell-shaped function varies accordingly, thus exhibiting various forms of membership functions on linguistic label A_i.

In fact, any continuous and piecewise differentiable functions, such as triangular-shaped membership functions, are also qualified candidates for node functions in this layer [26]. Parameters in this layer are referred to as premise parameters.

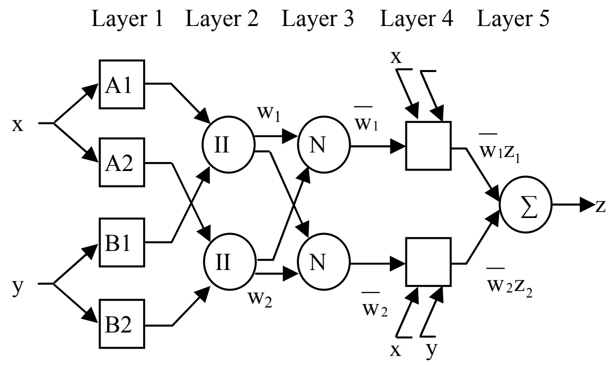

Fig. 1. ANFIS architecture.

In layer 2, each node $\prod$ multiplies incoming signals and sends the product out:

$$O_i^2 = w_i = \mu A_i(x)\, \mu B_i(y), \quad i = 1, 2 \qquad (4)$$

Hence, each node output represents the firing strength of a rule.

In layer 3, each node N computes the ratio of the *i*th rules's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \qquad (5)$$

The outputs of this layer are called normalized firing strengths.

In layer 4, each node computes the contribution of the ith rule to the overall output:

$$O_i^4 = \overline{w}_i\, z_i = \overline{w}_i\,(a_i x + b_i y + c_i), \quad i = 1, 2 \qquad (6)$$

where $\overline{w}_i$ is the output of layer 3 and (a_i, b_i, c_i) is the parameter set. Parameters of this layer are referred to as consequent parameters.

In layer 5, the single node $\sum$ computes the final output as the summation of all incoming signals:

$$O_i^5 = \sum_i \overline{w}_i\, z_i = \frac{\sum_i w_i\, z_i}{\sum_i w_i} \qquad (7)$$

Thus, an adaptive network is functionally equivalent to a Sugeno-type fuzzy inference system.

The ANFIS considered in this study uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. ANFIS uses a combination of the least-squares method (to determine consequent parameters) and the backpropagation gradient descent method (to learn the premise parameters). The training process allows the system to adjust its parameters as inputs/outputs submitted. The training process stops whenever the designated number of times is reached or the objective of training error is achieved. The number of epochs used is 20. The knowledge acquired through the learning process is tested by applying new data that it has never seen before, called the testing set. The network should be able to generalize and have an accurate output for this unseen data. It is undesirable to overtrain the network, meaning that it would only work well on the training set, and would not generalize well to new data outside the training set. Thus, very large training sets should not be used to avoid overtraining during the learning process.

The ANFIS architecture and training parameters used in this study are shown in Table I.

Table I. ANFIS architecture and training parameters

	Architecture	Training parameters
Number of layers	5	-
Number of inputs and output	Input: 2/ Output: 1	-
Type of membership functions	Triangular-shaped	-
Learning rule	-	Hybrid learning algorithm: Backpropagation for parameters (p_i, q_i, r_i) and least square errors for parameters (a_i, b_i, c_i)
Number epochs	-	20
Momentum constant	-	0.98
Sum-squared error	-	0.001

The proposed NF approach is studied comparatively to persistence, ARIMA and NN approaches. The persistence approach assumes that the predicted value of the next step in the future is the last measured value. The ARIMA approach is developed using SPSS software. Parameter estimation is performed with the aid of this software. The configuration considered corresponds to an ARIMA (1,2,1). The NN approach is developed using MATLAB. The configuration considered corresponds to a three-layered feed-forward network: one input layer with four units, one hidden layer with nine units considering hyperbolic tangent sigmoid transfer function, and one output layer with one unit considering pure linear transfer function. A scaled conjugate gradient algorithm is employed for training, and the training epoch is set to 100.

3. Forecasting Accuracy Evaluation

To evaluate the accuracy of the proposed NF approach in forecasting wind power, different criterions are used. This accuracy is computed in function of the actual wind power that occurred.

The mean absolute percentage error (MAPE) criterion, the sum squared error (SSE) criterion, and the standard deviation of error (SDE) criterion, are defined as follows.

The MAPE criterion is defined as follows:

$$MAPE = \frac{100}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \quad (8)$$

$$\bar{p} = \frac{1}{N}\sum_{h=1}^{N} p_h \quad (9)$$

where $\hat{p}_h$ and p_h are respectively the forecasted and actual wind power at hour h, $\bar{p}$ is the average wind power of the forecasting period and N is the number of forecasted hours.

The SSE criterion is given by:

$$SSE = \sum_{h=1}^{N}(\hat{p}_h - p_h)^2 \quad (10)$$

The SDE criterion is given by:

$$SDE = \sqrt{\frac{1}{N}\sum_{h=1}^{N}(e_h - \bar{e})^2} \quad (11)$$

$$e_h = \hat{p}_h - p_h \quad (12)$$

$$\bar{e} = \frac{1}{N}\sum_{h=1}^{N} e_h \quad (13)$$

where e_h is the forecast error at hour h and $\bar{e}$ is the average error of the forecasting period.

A measure of the uncertainty of a model is the variability of what is still unexplained after fitting the model, which can be measured through the estimation of the variance of the error. The smaller this variance, the more precise is the prediction [27].

Consistent with definition (8), daily error variance can be estimated as

$$\sigma^2_{e,day} = \frac{1}{24}\sum_{h=1}^{24}\left(\frac{|\hat{p}_h - p_h|}{\bar{p}} - (e_{day})\right)^2 \quad (14)$$

$$e_{day} = \frac{1}{24}\sum_{h=1}^{24}\frac{|\hat{p}_h - p_h|}{\bar{p}} \quad (15)$$

4. Numerical Results

The proposed NF approach has been applied for wind power forecasting in Portugal. Historical wind power data are the main inputs for training. For the sake of clear comparison, no exogenous variables are considered. Our forecaster predicts the value of the wind power subseries for 3 hours ahead, taking into account the wind power data of the previous 12 hours with a time-step of 15 minutes. This procedure is repeated until the next 24 hours values are predicted. The following days are randomly selected: July 3, 2007, October 31, 2007, January 14, 2008, and April 2, 2008, corresponding to the four seasons of the year. Hence, days with particularly good wind power behavior are deliberately not chosen. This results in an uneven accuracy distribution throughout the year that reflects reality.

Numerical results with the proposed NF approach are shown in Figs. 2 to 5 respectively for the winter, spring, summer and fall days. Each figure shows the actual wind power, solid line, together with the forecasted wind power, dash-dot line.

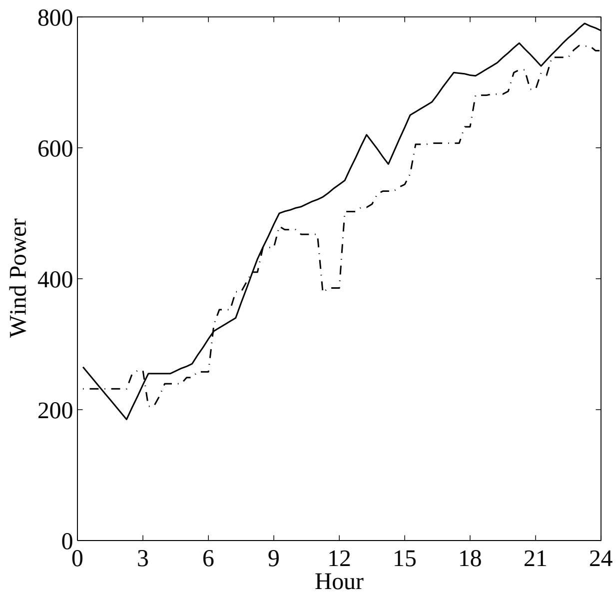

Fig. 2. Winter day: actual wind power (solid line) together with the forecasted wind power (dash-dot line), in megawatt.

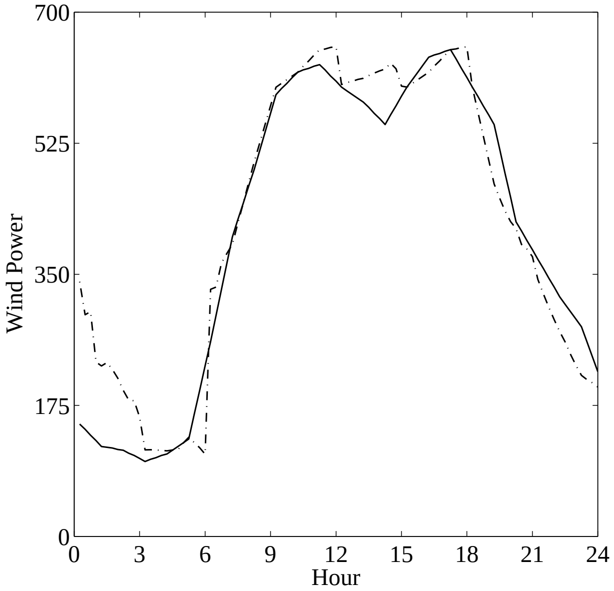

Fig. 3. Spring day: actual wind power (solid line) together with the forecasted wind power (dash-dot line), in megawatt.

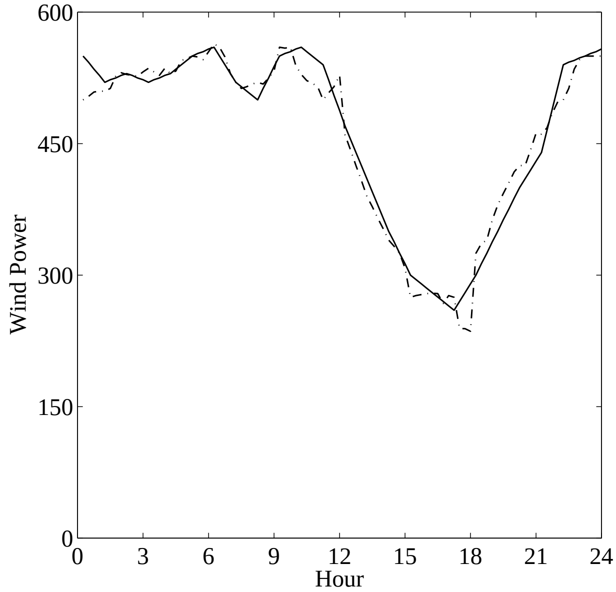

Fig. 5. Fall day: actual wind power (solid line) together with the forecasted wind power (dash-dot line), in megawatt.

Table II presents the values for the criterions to evaluate the accuracy of the proposed NF approach in forecasting wind power. The first column indicates the day, the second column presents the MAPE, the third column presents the square root of the SSE, and the fourth column presents the SDE.

Table III shows a comparison between the proposed NF approach and three other approaches (persistence, ARIMA, and NN), regarding the MAPE criterion. A good accuracy of the proposed NF approach was ascertained. The MAPE has an average value of 6.64%. The proposed approach the two advantages against the other existing methods in this study. First, it reduces possible difficulties in the modeling and analysis of complex data. Second, it is appropriate for incorporating the qualitative aspects of human experience within its mapping rules.

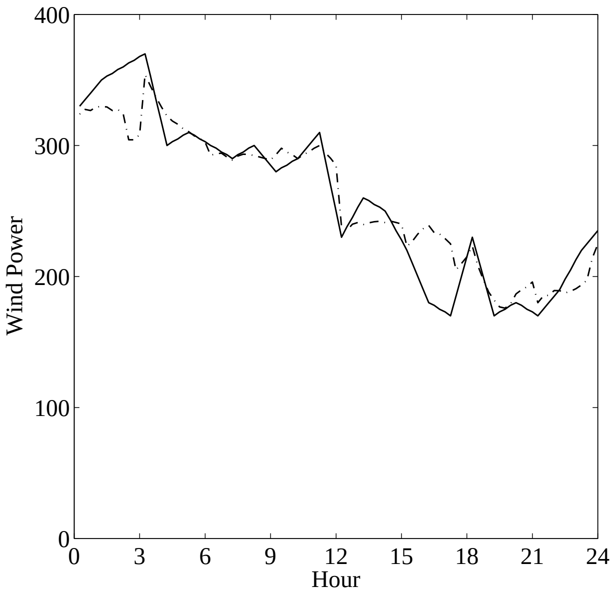

Fig. 4. Summer day: actual wind power (solid line) together with the forecasted wind power (dash-dot line), in megawatt.

The absolute values of forecast errors, considering ARIMA, NN and NF approaches, are shown in Figs. 6 to 9 respectively for the winter, spring, summer and fall days. The proposed NF approach provides smaller errors compared with ARIMA and NN approaches.

In addition to the MAPE, stability of results is another important factor for the comparison of forecast approaches. Table IV shows a comparison between the proposed NF approach and the three other approaches (Persistence, ARIMA and NN), regarding daily error variances. The average error variance is smaller for the proposed NF approach, indicating less uncertainty in the predictions. Improvement in the average error variance of the proposed NF approach with respect to the three other approaches is 81.5%, 46.3% and 15.7%, respectively.

Table II. Statistical analysis of the daily forecasting error

Day	MAPE	$\sqrt{\text{SSE}}$	SDE
Winter	8.85	558.93	33.47
Spring	8.96	520.42	38.15
Summer	5.63	211.73	15.93
Fall	3.11	187.61	12.82

Table III. Comparative MAPE results

	Winter	Spring	Summer	Fall	Average
Persistence	13.89	32.40	13.43	16.49	19.05
ARIMA	10.93	12.05	11.04	7.35	10.34
NN	9.51	9.92	6.34	3.26	7.26
NF	8.85	8.96	5.63	3.11	6.64

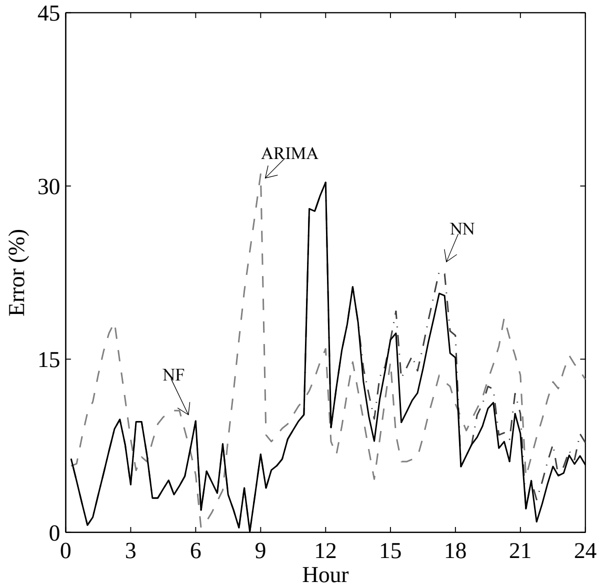

Fig. 6. Winter day: absolute value of forecast errors considering ARIMA (dashed line), NN (dash-dot line) and NF (solid line) approaches.

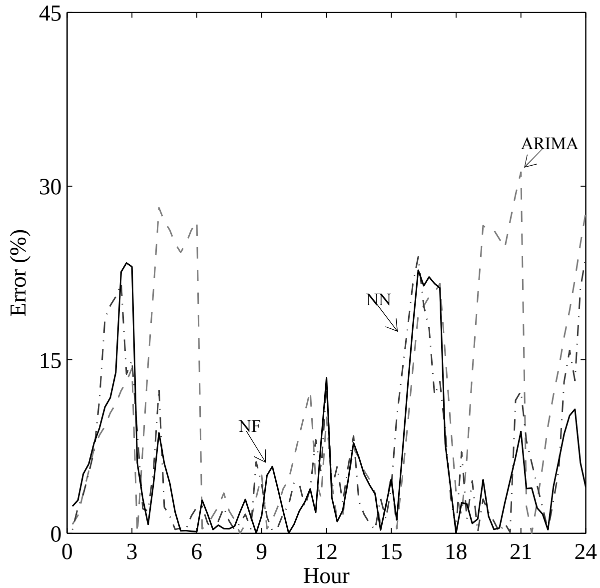

Fig. 8. Summer day: absolute value of forecast errors considering ARIMA (dashed line), NN (dash-dot line) and NF (solid line) approaches.

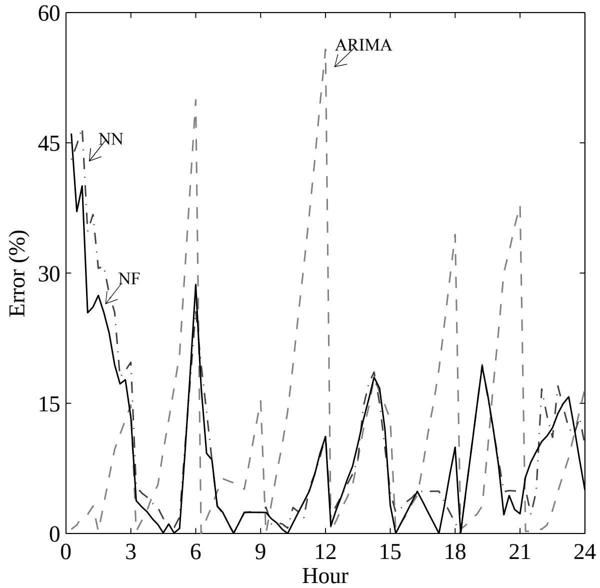

Fig. 7. Spring day: absolute value of forecast errors considering ARIMA (dashed line), NN (dash-dot line) and NF (solid line) approaches.

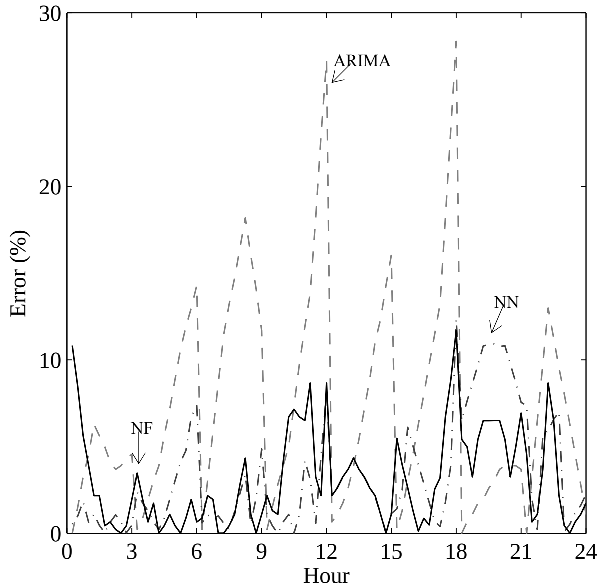

Fig. 9. Fall day: absolute value of forecast errors considering ARIMA (dashed line), NN (dash-dot line) and NF (solid line) approaches.

Furthermore, the four plots of Fig. 10 provide hourly errors for the four days, considering ARIMA, NN and NF approaches, respectively.

Overall, the performance of the proposed NF approach is generally better than the performance of ARIMA and NN approaches. Moreover, the average computation time required by the proposed NF approach is less than 5 seconds, using MATLAB on a PC with 1 GB of RAM and a 2.0-GHz-based processor.

Hence, the proposed NF approach provides a powerful tool of easy implementation for short-term wind power forecasting.

Table IV. Daily forecasting error variance

	Winter	Spring	Summer	Fall	Average
Persistence	0.0074	0.0592	0.0085	0.0179	0.0233
ARIMA	0.0025	0.0164	0.0090	0.0039	0.0080
NN	0.0044	0.0106	0.0043	0.0010	0.0051
NF	0.0041	0.0086	0.0038	0.0008	0.0043

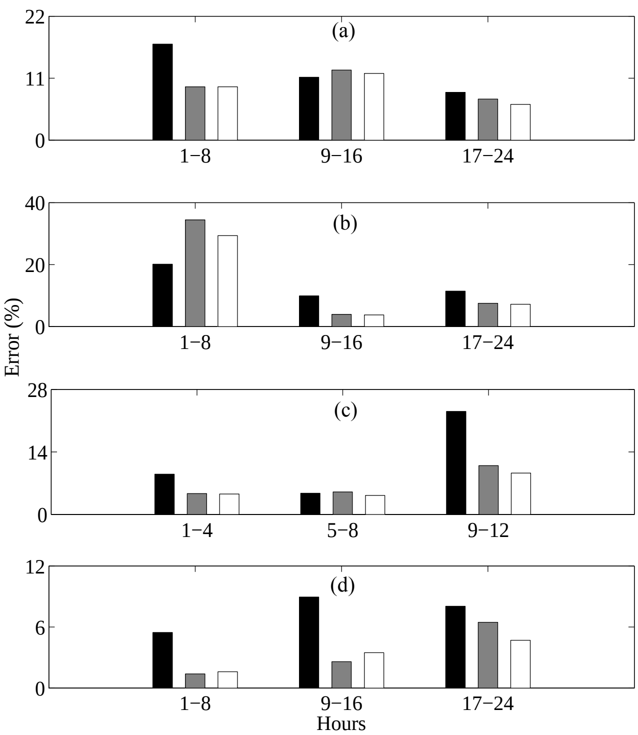

Fig. 10. Hourly errors corresponding to ARIMA (black rectangle), NN (grey rectangle) and NF (white rectangle) approaches for the days analyzed: (a) Winter, (b) Spring, (c) Summer, and (d) Fall.

The proposed approach can be applied in other problems related with electricity markets. For instance, to predict electricity prices in order to support informed decision-making by market agents.

5. Conclusions

As the penetration level of wind power in power systems increases, the accurate prediction of the wind behaviour and the corresponding electric energy production will be increasingly important. In this paper, an adaptive neuro-fuzzy inference approach is proposed for short-term wind power forecasting in Portugal. The proposed NF approach outperforms persistence, ARIMA and NN approaches, regarding the MAPE criterion and the average error variance. Moreover, the average computation time is less than 5 seconds. Hence, the results confirm the considerable value of the proposed NF approach in forecasting wind power.

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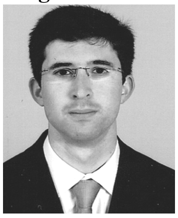

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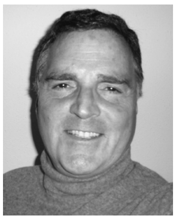

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