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An artificial neural network approach for short-term wind power forecasting in Portugal

J P S Catalão[1], H M I Pousinho[1] and V M F Mendes[2]

[1]Department of Electromechanical Engineering, University of Beira Interior, R. Fonte do Lameiro, 6201-001 Covilha, Portugal. E-mail: catalao@ubi.pt; hmi-21@hotmail.com
[2]Department of Electrical Engineering and Automation, Instituto Superior de Engenharia de Lisboa, R. Conselheiro Emídio Navarro, 1950-062 Lisbon, Portugal. E-mail: vfmendes@isel.pt

This paper presents an artificial neural network approach for short-term wind power forecasting in Portugal. 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. The accuracy of the wind power forecasting attained with the proposed approach is evaluated against persistence and ARIMA approaches, reporting the numerical results from a real-world case study.

Keywords: Artificial Neural Networks; Forecasting; Wind Power

1. INTRODUCTION

Wind-driven power resources have become increasingly important in the planning and operation of electric power systems [1]. In Portugal, the wind power goal foreseen for 2010 was established by the government as 3750 MW, representing about 25% of the total installed capacity in 2010 [2]. This value has 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.

The wind energy is free, so all wind-generated electric energy is accepted as it comes, i.e. as it is available. However, its availability is not known in advance. Because of the increasing penetration of wind resources in power systems, efforts have been made to predict the wind behavior and the corresponding electric energy production [1].

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) [3].

In the technical literature, several methods to predict 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, such as description of orography, roughness, obstacles, pressure and temperature. The statis-

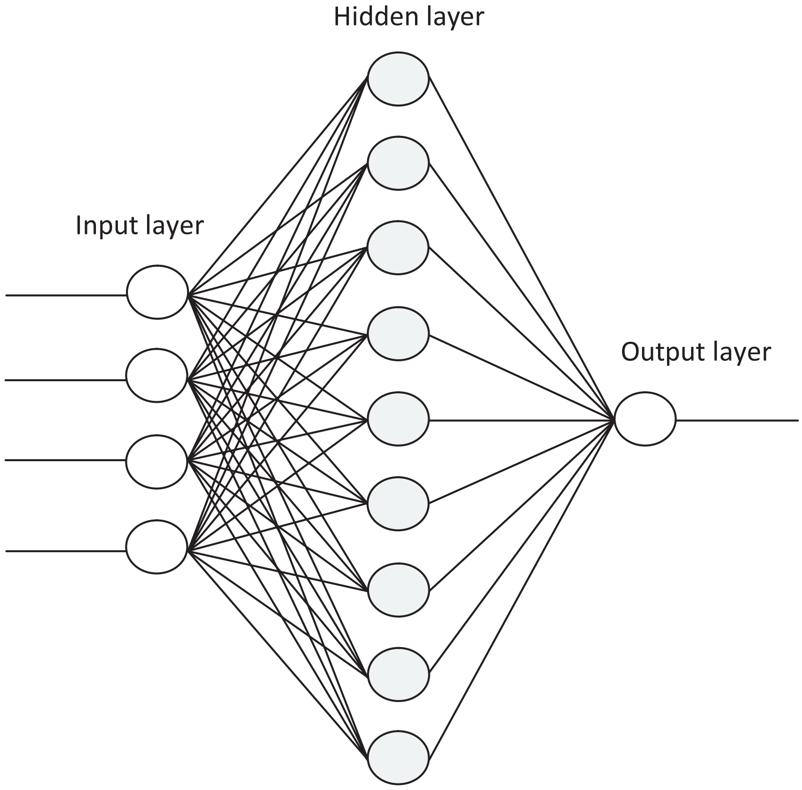

Figure 1 Generic example of a three-layered feedforward ANN model.

tical 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 [4].

Conventional statistical models are identical to the direct random time-series model, including auto regressive (AR), and auto regressive integrated moving average (ARIMA) [5] models. The persistence models are considered as the simplest time-series models. They can surpass many other models in very short-term prediction. In spite of the unstable forecasting efficiency, they have been widely used in practice [4]. 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 techniques.

In the recent years, some new methods are catching researcher's attention, namely methods based on artificial intelligence like artificial neural network (ANN) [6], fuzzy logic and neuro-fuzzy [7,8], evolutionary algorithms [9], and some hybrid methods [10,11]. 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 [4].

Successful applications of ANNs have been reported in the technical literature [12–14]. ANNs 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 appropriate number of hidden units and enough computational resources available. ANNs have the well-known advantages of being able to approximate non-linear functions and being able to solve problems where the input-output relationship is neither well defined nor easily computable, because ANNs are data-driven. Three-layered feedforward ANNs are specially suited for forecasting, implementing nonlinearities using sigmoid functions for the hidden layer and linear functions for the output layer [15]. Hence, a three-layered feedforward ANN trained by the Levenberg-Marquardt algorithm is considered in this paper.

This paper presents a successful application of using an ANN approach to forecast short-term wind power in Portugal. Persistence and ARIMA approaches are also considered for comparison purposes. ANNs techniques are relatively easy to implement and show good performance being less time consuming than time series techniques.

This paper is structured as follows. Section 2 presents the ANN approach. Section 3 provides the different criterions used to assess the behavior of the proposed approach. Section 4 presents the numerical results. Finally, Section 5 outlines the conclusions.

2. ARTIFICIAL NEURAL NETWORK APPROACH

ANNs are highly interconnected simple processing units designed in a way to model how the human brain performs a particular task [16]. Each of those units, also called neurons, forms a weighted sum of its inputs, to which a constant term called bias is added. This sum is then passed through a transfer function: linear, sigmoid or hyperbolic tangent.

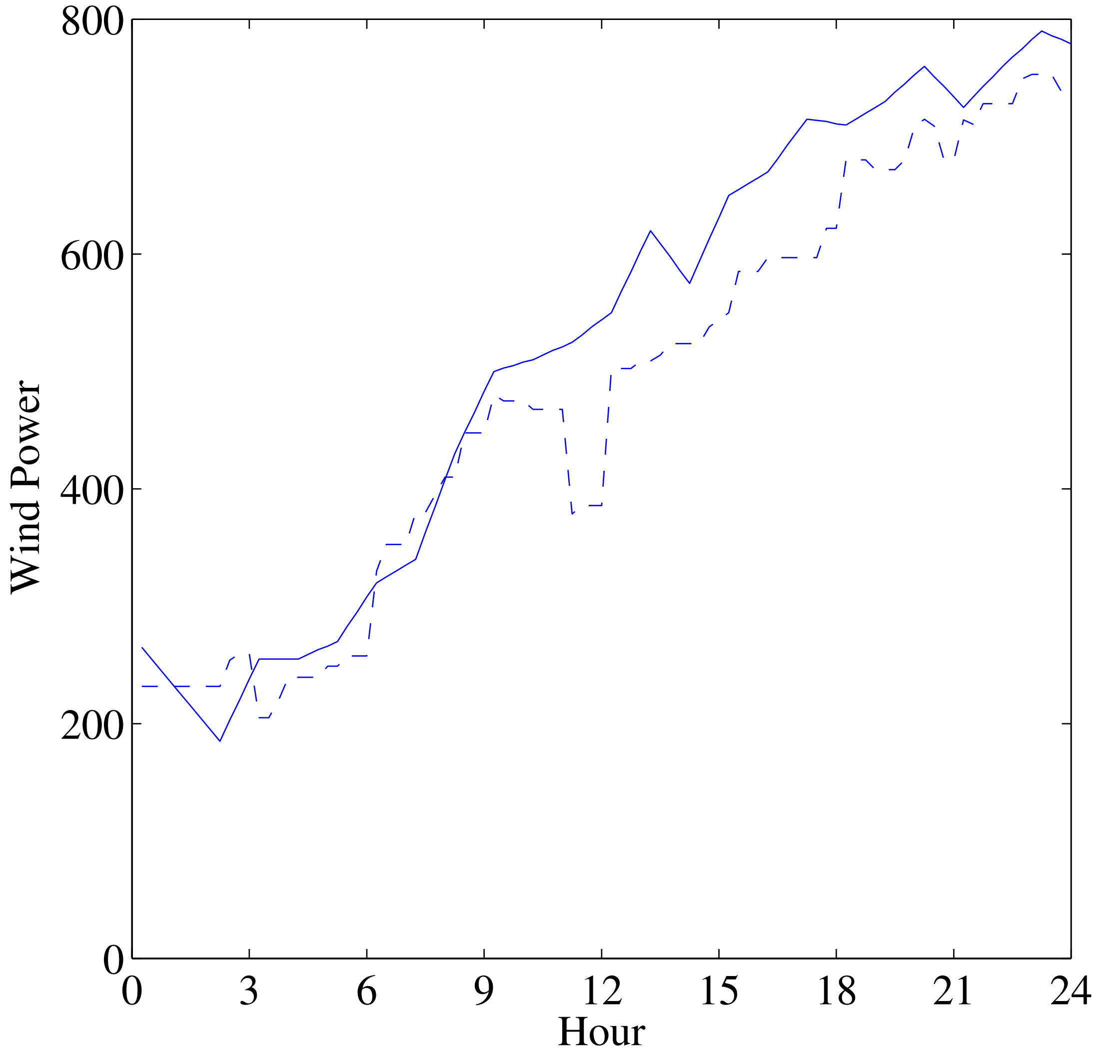

Figure 2 Winter day: actual wind power, solid line, together with the forecasted wind power, dashed line, in megawatt.

Multilayer perceptrons are the best known and most widely used kind of ANN. The units are organized in a way that defines the network architecture. In feedforward networks, units are often arranged in layers: an input layer, one or more hidden layers and an output layer.

Fig. 1 shows the architecture of a generic three-layered feedforward ANN model.

In order to find the optimal network architecture, several combinations were evaluated. These combinations include networks with different number of hidden layers, different number of units in each layer and different types of transfer functions. The configuration chosen consists of a one hidden layer that uses a hyperbolic tangent sigmoid transfer function and a one unit output layer with a pure linear transfer function. This configuration has been proven to be a universal mapper, provided that the hidden layer has enough units [17]. On one hand, if there are too few units, the network will not be flexible enough to model the data well and, on the other hand, if there are too many units, the network may over-fit the data. The number of units in the hidden layer was chosen by trial and error. The best results were produced with nine hidden units.

Forecasting with ANNs involves two steps: training and learning. Training of feedforward networks is normally performed in a supervised manner. It is assumed that a training set is available, given by the historical data and containing both inputs and the corresponding desired outputs, which is presented to the network. The adequate selection of inputs for ANN training is highly influential to the success of training. In the learning process an ANN constructs an input-output mapping, adjusting the weights and biases at each iteration based on the minimization of some error measure between the output produced and the desired output. The error minimization process is repeated until an acceptable criterion for convergence is reached.

The most common learning algorithm is the backpropagation algorithm, in which the input is passed layer through layer until the final output is calculated, and it is compared to the real output to find the error. The error is then propagated back to the input adjusting the weights and biases in each layer. The standard backpropagation learning algorithm is a steepest descent algorithm that minimizes the sum of square errors. However, the standard backpropagation learning algorithm tends to converge slowly [18,19]. An algorithm that trains an ANN 10 to 100 times faster than the standard backpropagation algorithm

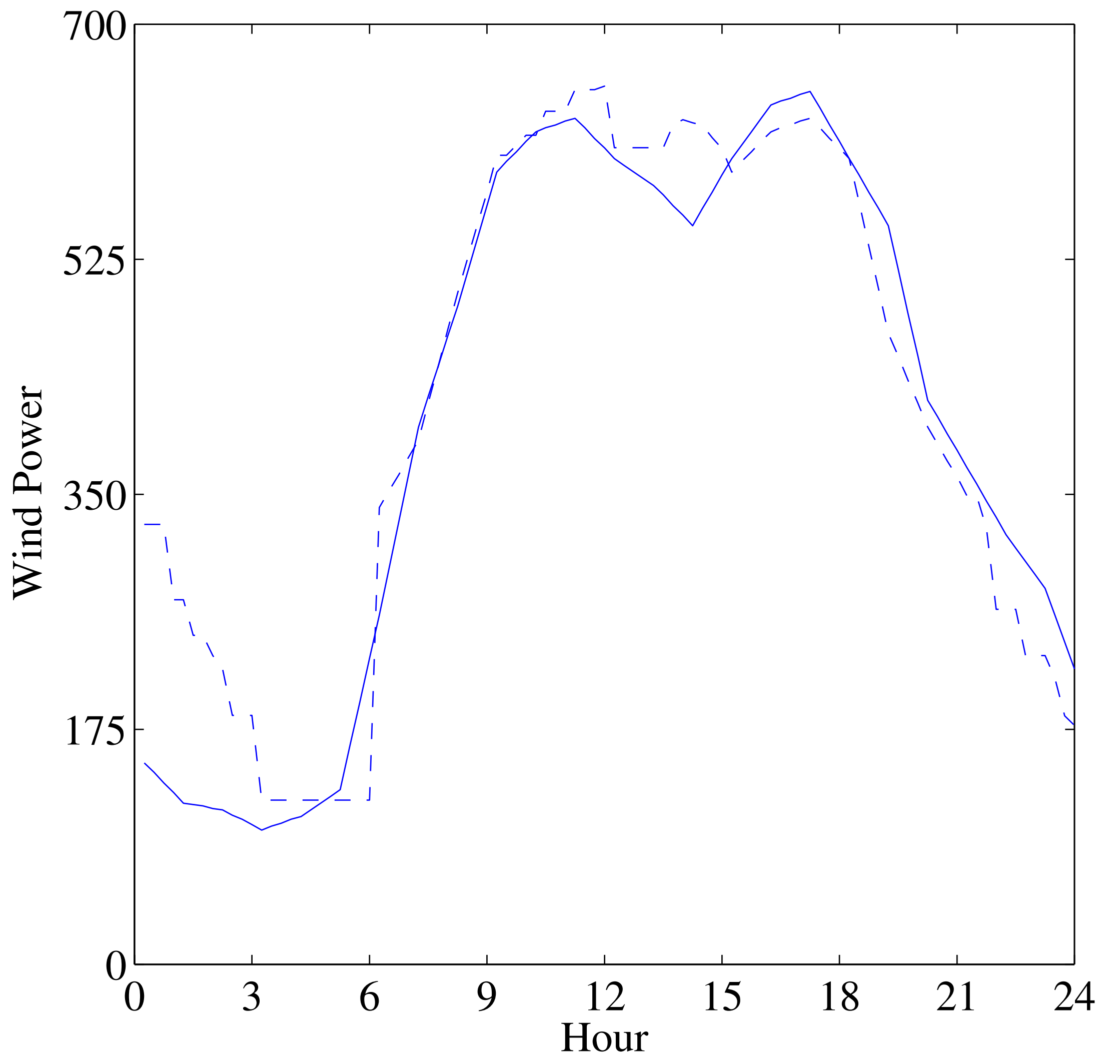

Figure 3 Spring day: actual wind power, solid line, together with the forecasted wind power, dashed line, in megawatt.

is the Levenberg-Marquardt algorithm [19]. A three-layered feedforward ANN trained by the Levenberg-Marquardt algorithm is considered in this paper, as in [20].

3. FORECASTING ACCURACY EVALUATION

To evaluate the accuracy of the ANN 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 given by:

$$\mathrm{MAPE} = \frac{100}{N} \sum_{h=1}^{N} \frac{|\hat{p}_h - p_h|}{\overline{p}} \tag{1}$$

$$\overline{p} = \frac{1}{N} \sum_{h=1}^{N} p_h \tag{2}$$

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

The SSE criterion is given by:

$$\mathrm{SSE} = \sum_{h=1}^{N} (\hat{p}_h - p_h)^2. \tag{3}$$

The SDE criterion is given by:

$$\mathrm{SDE} = \sqrt{\frac{1}{N} \sum_{h=1}^{N} (e_h - \overline{e})^2} \tag{4}$$

$$e_h = \hat{p}_h - p_h \tag{5}$$

$$\overline{e} = \frac{1}{N} \sum_{h=1}^{N} e_h \tag{6}$$

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

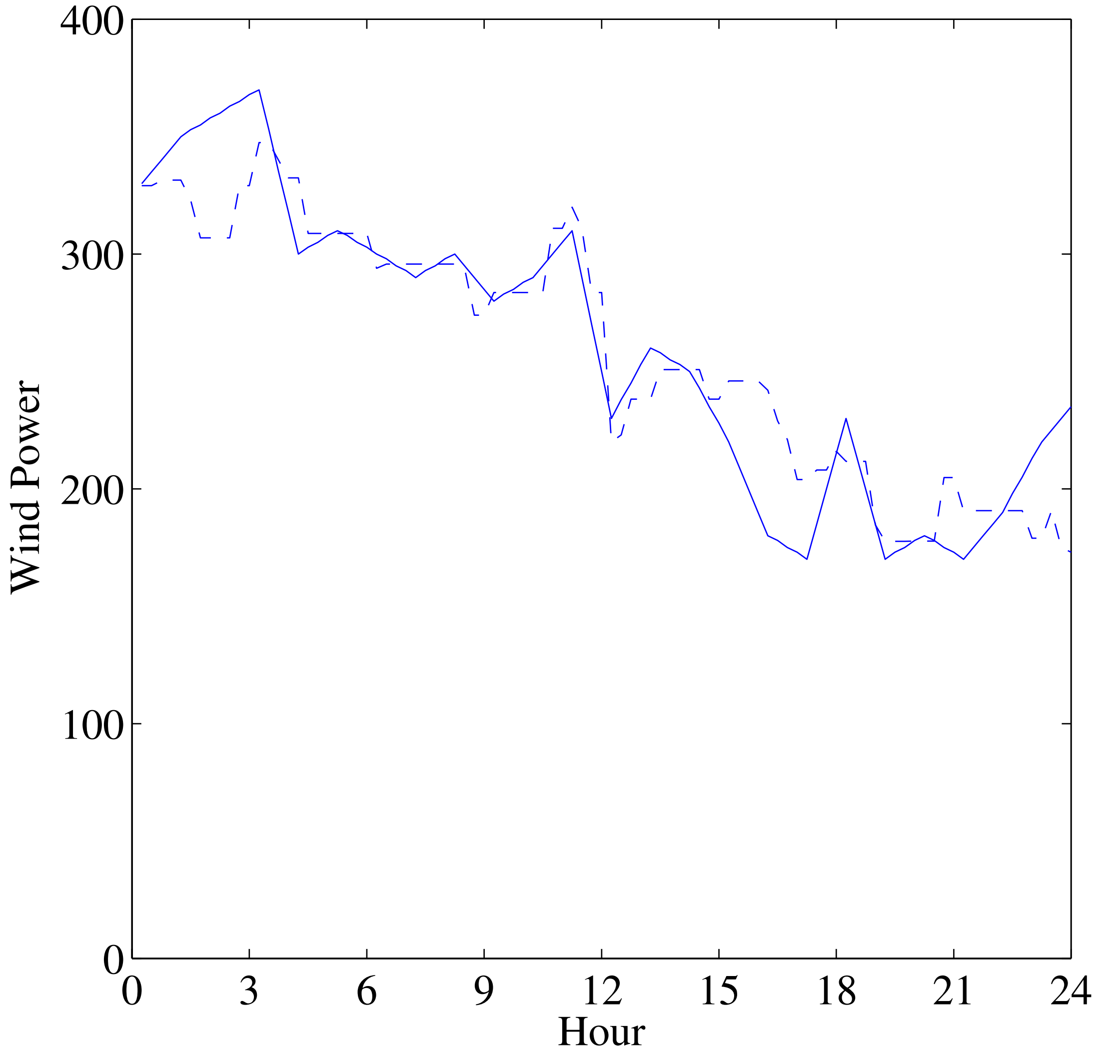

Figure 4 Summer day: actual wind power, solid line, together with the forecasted wind power, dashed line, in megawatt.

4. NUMERICAL RESULTS

The proposed ANN approach has been applied for wind power forecasting in Portugal. Historical wind power data are the main inputs to train the ANN proposed in this paper. For the sake of clear comparison, no exogenous variables are considered.

The forecast horizon is one day with a time-step of fifteen minutes. 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 ANN approach are shown in Figs. 2–5 respectively for the winter, spring, summer and fall days. Each figure shows the actual wind power, solid line, together with the forecasted wind power, dashed line.

Table 1 presents the values for the criterions to evaluate the accuracy of the proposed ANN 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 1 Statistical analysis of the daily forecasting error.

Day	$MAPE$	$\sqrt{SSE}$	SDE
Winter	9.51%	593.71	34.78
Spring	9.92%	578.13	42.49
Summer	6.34%	232.56	17.11
Fall	3.26%	207.10	14.85

A good accuracy of the proposed ANN approach was ascertained. The MAPE has an average value of 7.26%. Moreover, the average computation time is less than 5 seconds. All the cases have been run on a PC with 1 GB of RAM and a 2.0-GHz-based processor.

Table 2 shows a comparison between the ANN approach and two other approaches, persistence and ARIMA, for the MAPE criterion. The persistence approach assumes that the predicted value of the next step in the future is the last measured value.

The average MAPE value for a persistence approach is 19.05%, while the average MAPE value for the ARIMA approach is 10.34%. Hence, the proposed ANN approach provides a powerful tool of easy implementation for forecasting wind power, enhancing forecasting accuracy over persistence and ARIMA approaches.

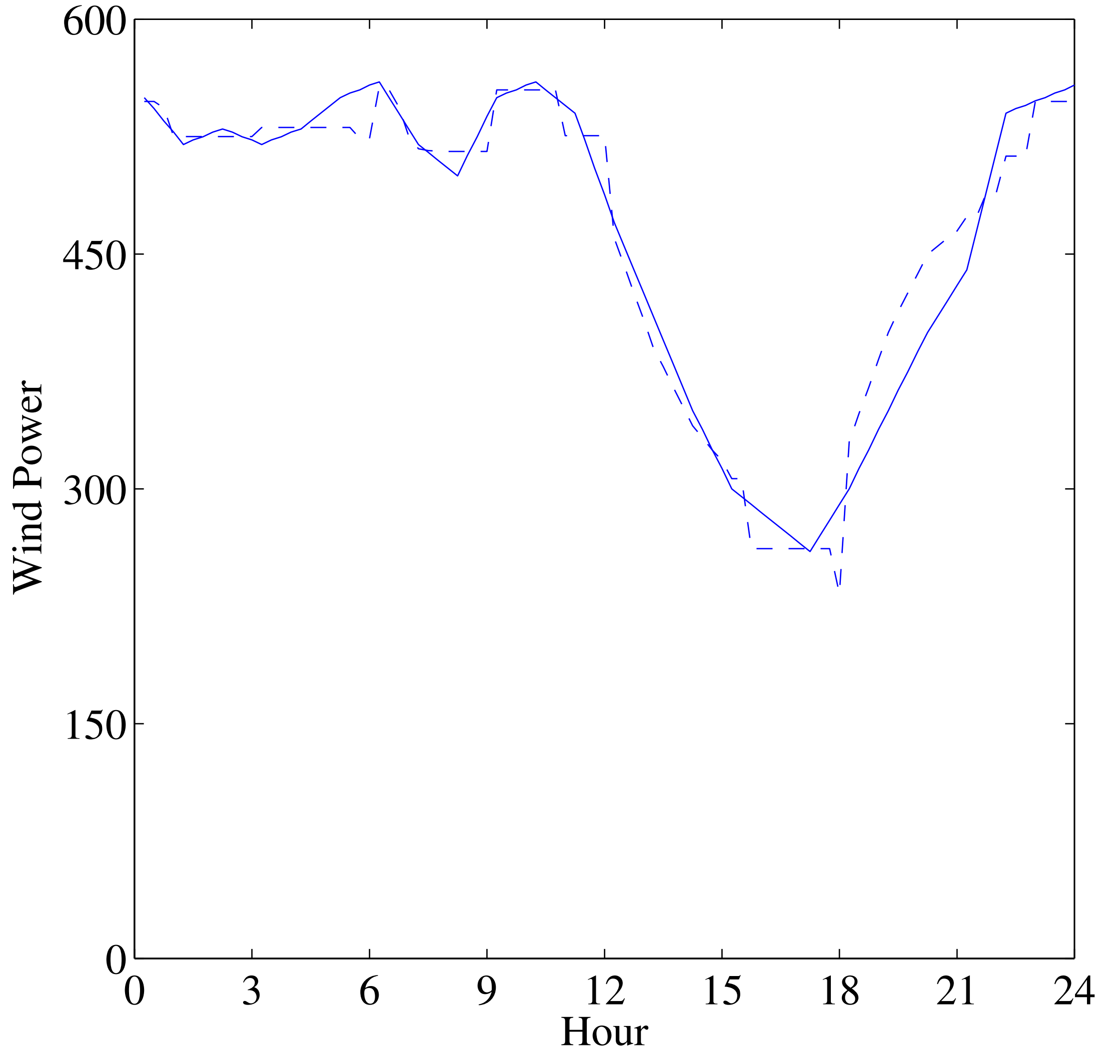

Figure 5 Fall day: actual wind power, solid line, together with the forecasted wind power, dashed line, in megawatt.

Table 2 Comparative MAPE results.

Day	Persistence	ARIMA	ANN
Winter	13.89%	10.93%	9.51%
Spring	32.40%	12.05%	9.92%
Summer	13.43%	11.04%	6.34%
Fall	16.49%	7.35%	3.26%

5. CONCLUSIONS

A three-layered feedforward ANN trained by the Levenberg-Marquardt algorithm is considered in this paper for short-term wind power forecasting in Portugal. The configuration chosen consists of a one hidden layer that uses a hyperbolic tangent sigmoid transfer function and a one unit output layer with a pure linear transfer function. The number of units in the hidden layer was chosen by trial and error. The best results were produced with nine hidden units. Historical wind power data are the main inputs to train the ANN proposed in this paper. For the sake of clear comparison, no exogenous variables are considered. The MAPE has an average value of 7.26% with the ANN approach, outperforming persistence and ARIMA approaches. Hence, the results presented confirm the considerable value of the proposed ANN approach in short-term wind power forecasting.

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