

# Hybrid intelligent approach for short-term wind power forecasting in Portugal

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**Abstract:** 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, a hybrid intelligent approach is proposed for short-term wind power forecasting in Portugal. The proposed approach is based on the wavelet transform and a hybrid of neural networks and fuzzy logic. Results from a real-world case study are presented. A thorough comparison is carried out, taking into account the results obtained with other approaches. Conclusions are duly drawn.

**Key words:** Wind power; forecasting; neural networks; fuzzy logic; wavelet transform

## **1 Introduction**

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, representing about 25% of the total installed capacity in 2010. 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 [1].

The wind energy is free, so all wind-generated electric energy is accepted as it comes, i.e. as it is available. A major barrier to the integration of wind power into the grid is its variability [2]. Curtailment has been considered as a means of managing wind power integration into the grid. Hence, efforts should be made to predict the wind behaviour and the corresponding electric energy production.

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 vary from minutes for frequency considerations and to hours and days for operational reasons [3].

In the technical literature, several methods to predict wind power have been reported, which fall into two categories, 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 statistical method aims at finding the inherent structure within the measured power data. 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 [6] 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 data mining [7], neural networks (NN) [8, 9], fuzzy logic and neuro-fuzzy [10, 11], evolutionary algorithms [12], and some hybrid methods [13, 14]. 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, 8–12].

In this paper, a hybrid intelligent approach is proposed for short-term wind power forecasting in Portugal. The proposed approach is based on the wavelet transform (WT) and a hybrid of neural networks and fuzzy logic. The proposed approach is compared with persistence, ARIMA, NN and NNWT approaches, to demonstrate its effectiveness regarding forecasting accuracy and computation time.

## **2 Proposed approach**

The proposed approach to forecast short-term wind power is based on the WT and a hybrid of NN and fuzzy logic known as adaptive-network-based fuzzy inference system (ANFIS). The WT is used to decompose the wind power series into a set of constitutive series. Then, the future values of these constitutive series are forecasted using ANFIS. In turn, the ANFIS forecasts allow, through the inverse WT, reconstructing the future behaviour of the wind power series and therefore to forecast wind power.

## 2.1 Wavelet transform

The WT convert a wind power series in a set of constitutive series. These constitutive series present a better behaviour than the original wind power series, and therefore, they can be predicted more accurately. The reason for the better behaviour of the constitutive series is the filtering effect of the WT.

A brief summary of WT is presented hereafter. For the sake of simplicity, one-dimensional wavelets are considered to illustrate the related concepts.

A wavelet is a waveform of effectively limited duration that has an average value of zero. Comparing wavelets with sine waves (which are the basis of Fourier analysis), sinusoids do not have limited duration (they extend from minus to plus infinity). Moreover, where sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric.

Wavelet analysis is the breaking up of a signal into shifted and scaled versions of the mother wavelet. Signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid. Wavelet analysis does not use a time-frequency region (like the short-time Fourier transform), but rather a time-scale region. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, such as trends, breakdown points, discontinuities in higher derivatives and self-similarity. Furthermore, wavelet analysis can often compress or de-noise a signal without appreciable degradation [15]. These capabilities of WT can be useful in short-term wind power forecasting.

WTs can be divided in two categories: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The CWT  $W(a,b)$  of signal  $f(x)$  with respect to a mother wavelet  $\phi(x)$  is given by [15]:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(x) \phi\left(\frac{x-b}{a}\right) dx \quad (1)$$

where the scale parameter  $a$  controls the spread of the wavelet and translation parameter  $b$  determines its central position. The  $W(a,b)$  coefficient represents how well the original signal  $f(x)$  and the scaled/translated mother wavelet match. Thus, the set of all wavelet coefficients  $W(a,b)$  for all  $a, b$ , associated to a particular signal, is the wavelet representation of the signal with respect to the mother wavelet. Since the CWT is achieved by continuously scaling and translating the mother wavelet, substantial redundant information is generated. Therefore, instead of doing that, the mother wavelet can be scaled and translated using certain scales and positions usually based on powers of two. This scheme is more efficient and just as accurate as the CWT [16]. It is known as the DWT and defined as:

$$W(m,n) = 2^{-(m/2)} \sum_{t=0}^{T-1} f(t) \phi\left(\frac{t-n \cdot 2^m}{2^m}\right) \quad (2)$$

where  $T$  is the length of the signal  $f(t)$ . The scaling and translation parameters are functions of the integer variables  $m$  and  $n$  ( $a = 2^m, b = n \cdot 2^m$ );  $t$  is the discrete time index.

A fast DWT algorithm based on the four filters (decomposition low-pass, decomposition high-pass, reconstruction low-pass, and reconstruction high-pass filters), developed by Mallat [17], is considered in this paper. Multiresolution via Mallat's algorithm is a procedure to obtain "approximations" and "details" from a given signal. An approximation is a low-frequency representation of the original signal, whereas a detail is the difference between two successive approximations. An approximation holds the general trend of the original signal, whereas a detail depicts high-frequency components of it [16]. By successive decomposition of the approximations, Fig. 1, a multilevel decomposition process can be achieved where the original signal is broken down into lower resolution components.

One particular wavelet function of type Daubechies of order 4 (abbreviated as Db4) is used as the mother wavelet  $\phi(t)$ . This wavelet offers an appropriate trade-off between wave-length and smoothness, resulting in an appropriate behaviour for short-term wind power forecasting.

Similar wavelets have been considered by previous researchers for load forecasting [15, 16] and price forecasting [18, 19]. Also, three decomposition levels are considered, as in [19], since it describes the wind power series in a thorough and meaningful way.

## 2.2 ANFIS method

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. Also, NN have the well-known advantages of being able to approximate any nonlinear function and being able to solve problems where the input-output relationship is neither well defined nor easily computable, because NN are data-driven. 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 [20]. Hidden layer is a convention that is normally made to designate the internal layer to the network, i.e. the layer that is neither input nor output layer.

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. The fuzzifier converts a specific or exact ("crisp") input variable into a fuzzy representation, where membership functions give the degree of belonging of the variable to a given attribute. Fuzzy rules are of the type "if-then", and can be derived from numerical data or from expert linguistic. Mamdani and Sugeno inference engines are two of the main types of inference mechanisms. The Mamdani engine combines fuzzy rules into a mapping from fuzzy input sets to fuzzy output sets, while the Takagi-Sugeno type relates fuzzy inputs and crisp outputs. The defuzzifier converts a fuzzy set into a crisp number using the centroid of area, bisector of area, mean of maxima, or maximum criteria.

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 [21].

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, 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 [22].

The ANFIS architecture is shown in Fig. 2. 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:

$$O_i^1 = \mu A_i(x), \quad i = 1, 2 \quad (3)$$

or

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

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.:

$$\mu A_i(x) = \frac{1}{1 + \left| \frac{x - r_i}{p_i} \right|^{2q_i}} \quad (5)$$

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 [23]. Parameters in this layer are referred to as premise parameters.

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

$$O_i^2 = w_i = \mu_{A_i}(x) \mu_{B_i}(y), \quad i = 1, 2 \quad (6)$$

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' firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \quad (7)$$

The outputs of this layer are called normalized firing strengths.

In layer 4, each node computes the contribution of the  $i$ th rule to the overall output:

$$O_i^4 = \bar{w}_i z_i = \bar{w}_i (a_i x + b_i y + c_i), \quad i = 1, 2 \quad (8)$$

where  $\bar{w}_i$  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  $\Sigma$  computes the final output as the summation of all incoming signals:

$$O_i^5 = \sum_i \bar{w}_i z_i = \frac{\sum_i w_i z_i}{\sum_i w_i} \quad (9)$$

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. Thus, ANFIS uses a combination of the least-squares method (to determine consequent parameters) and the backpropagation gradient descent method (to learn the premise parameters). In the estimation process, for any given input vector, outputs are acquired by each node function, and the least square estimation is used to identify the conclusion parameters of fuzzy rules. Finally, output errors corresponding to each input data are calculated. While in the backpropagation stage, the error is transferred from the output node into the input node by the steepest descent method; and then, the parameters related to the shape of the membership functions are adjusted. When the error standard is satisfied or the established number of iterations is reached, the process is finished [22, 23]. The membership functions considered in this study are triangular-shaped. The number of membership functions is selected based on domain knowledge and computation time.

### 3 Forecasting accuracy evaluation

To evaluate the accuracy of the proposed hybrid wavelet-neuro-fuzzy (WNF) approach in forecasting wind power, different criteria are used. This accuracy is computed as a 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:

$$MAPE = \frac{100}{N} \sum_{h=1}^N \frac{|\hat{p}_h - p_h|}{\bar{p}} \quad (10)$$

$$\bar{p} = \frac{1}{N} \sum_{h=1}^N p_h \quad (11)$$

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:

$$SSE = \sum_{h=1}^N (\hat{p}_h - p_h)^2 \quad (12)$$

The SDE criterion is given by:

$$SDE = \sqrt{\frac{1}{N} \sum_{h=1}^N (e_h - \bar{e})^2} \quad (13)$$

$$e_h = \hat{p}_h - p_h \quad (14)$$

$$\bar{e} = \frac{1}{N} \sum_{h=1}^N e_h \quad (15)$$

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 [18].

Consistent with definition (10), daily error variance can be estimated as:

$$\sigma_{e,day}^2 = \frac{1}{N} \sum_{h=1}^N \left( \frac{|\hat{p}_h - p_h|}{\bar{p}} - (e_{day}) \right)^2 \quad (16)$$

$$e_{day} = \frac{1}{N} \sum_{h=1}^N \frac{|\hat{p}_h - p_h|}{\bar{p}} \quad (17)$$

## 4 Results

The proposed hybrid WNF 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 behaviour are deliberately not chosen. This results in an uneven accuracy distribution throughout the year that reflects reality.

Numerical results with the proposed hybrid WNF approach are shown in Figs. 3–6 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.

Table 1 presents the values for the criteria to evaluate the accuracy of the proposed hybrid WNF 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	$\sqrt{\text{SSE}}$	SDE
Winter	8.34	549.99	35.45
Spring	7.71	425.17	29.54
Summer	4.81	168.27	11.79
Fall	3.08	204.88	15.33

Table 2 shows a comparison between the proposed hybrid WNF approach and four other approaches (persistence, ARIMA, NN and NNWT), with respect to the MAPE criterion. The persistence approach states that the wind power forecast is the same as the last measured value [24].

Table 2: 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
NNWT	9.23	9.55	5.97	3.14	6.97
WNF	8.34	7.71	4.81	3.08	5.99

A good accuracy of the proposed hybrid WNF approach was ascertained. The MAPE has an average value of 5.99%.

The absolute values of forecast errors, considering NN, NNWT and WNF approaches, are shown in Figs. 7–10 respectively for the winter, spring, summer and fall days. The NN approach provides larger errors compared with NNWT and WNF approaches.

In addition to the MAPE, stability of results is another important factor for the comparison of forecast approaches. Table 3 shows a comparison between the proposed hybrid WNF approach and the four other approaches (persistence, ARIMA, NN and NNWT), regarding daily error variances. The average error variance is smaller for the proposed hybrid WNF approach, indicating less uncertainty in the predictions.

Table 3: 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
NNWT	0.0055	0.0083	0.0038	0.0012	0.0047
WNF	0.0046	0.0051	0.0021	0.0011	0.0032

Furthermore, the four plots of Fig. 11 provide average errors considering NN, NNWT and WNF approaches, for the four days analyzed.

The proposed hybrid WNF approach presents better forecasting accuracy over the other approaches. Moreover, the average computation time is less than 1 minute on a PC with 1 GB of RAM and a 2.0-GHz-based processor. Instead, supercomputers are usually required to run numerical weather prediction (NWP) models. Thus, the proposed approach offers a practical solution in terms of computational burden, which is important for real-life applications.

## 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, a hybrid WNF approach is proposed for short-term wind power forecasting, which is both novel and effective. The MAPE has an average value of 5.99%, outperforming persistence, ARIMA, NN and NNWT approaches, while the average computation time is less than 1 minute. Hence, the results presented confirm the considerable value of the proposed approach in forecasting wind power.

## 6 Acknowledgment

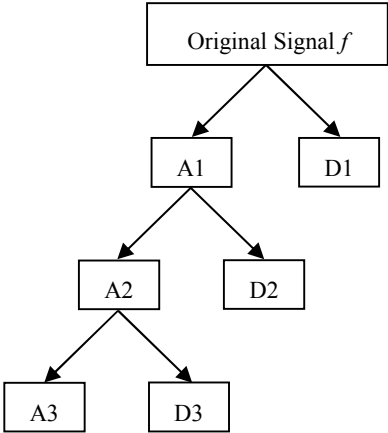
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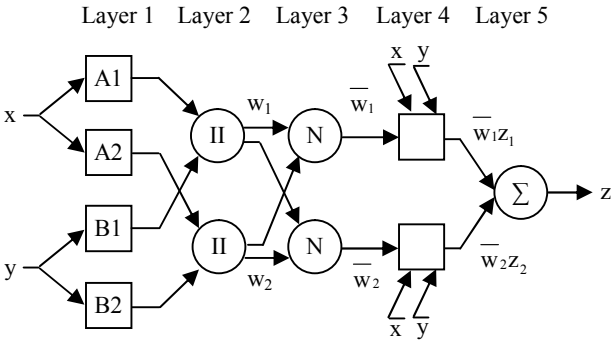
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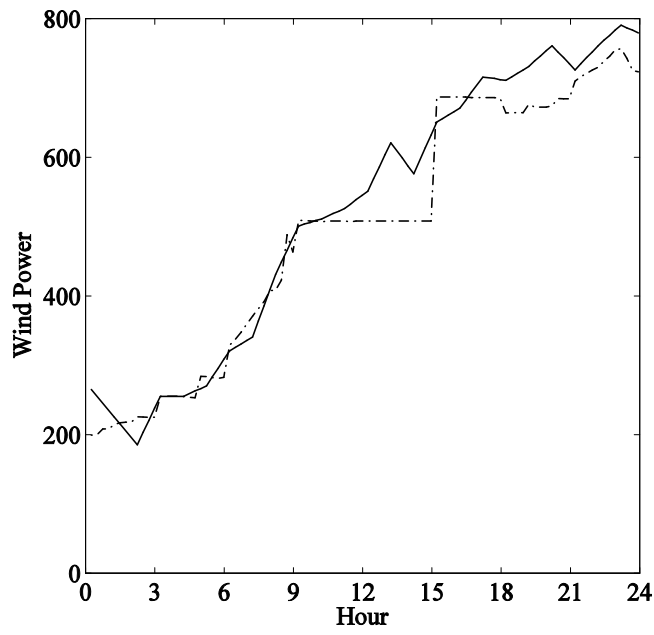
**Figure captions**



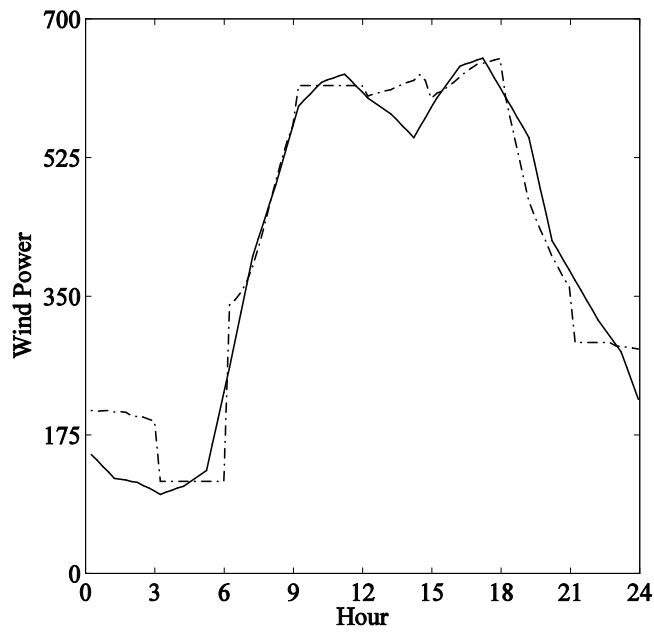
**Fig. 1** Multilevel decomposition process: the signal is divided into three levels, namely, a level of approximation (A) and details (D)



**Fig. 2** ANFIS architecture

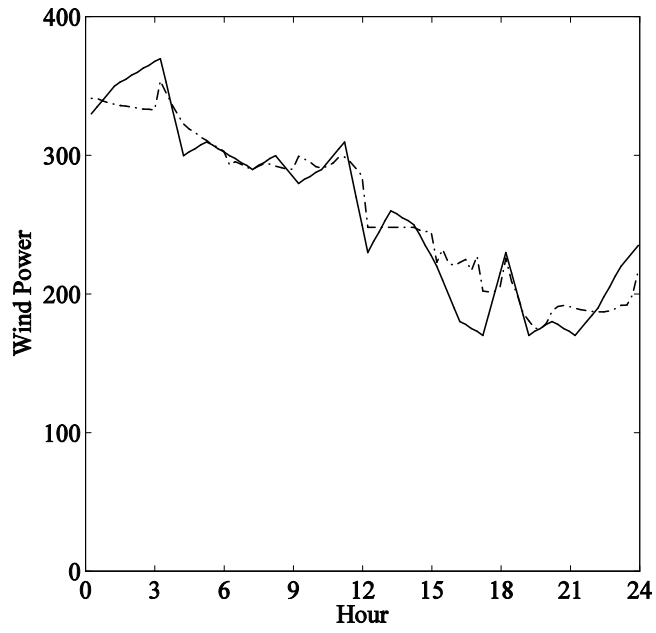


**Fig. 3** Winter day: actual wind power, solid line, together with the forecasted wind power, dash-dot line, in megawatt

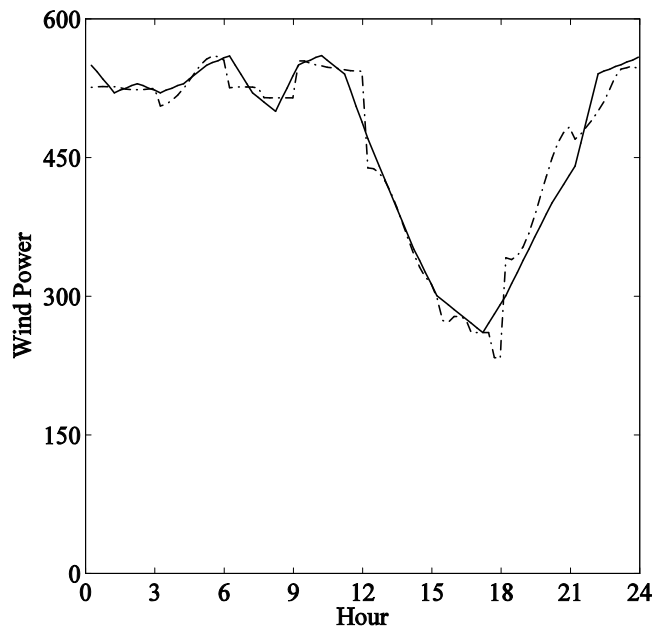


**Fig. 4** Spring day: actual wind power, solid line, together with the forecasted wind power, dash-dot line, in megawatt

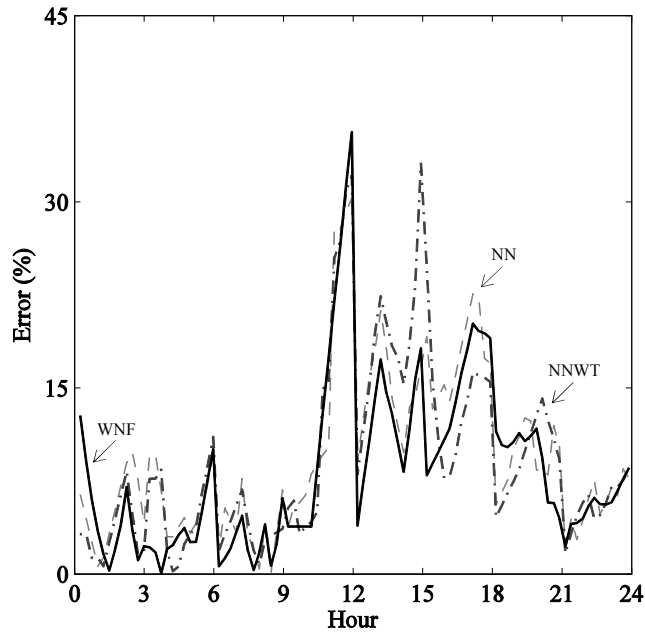




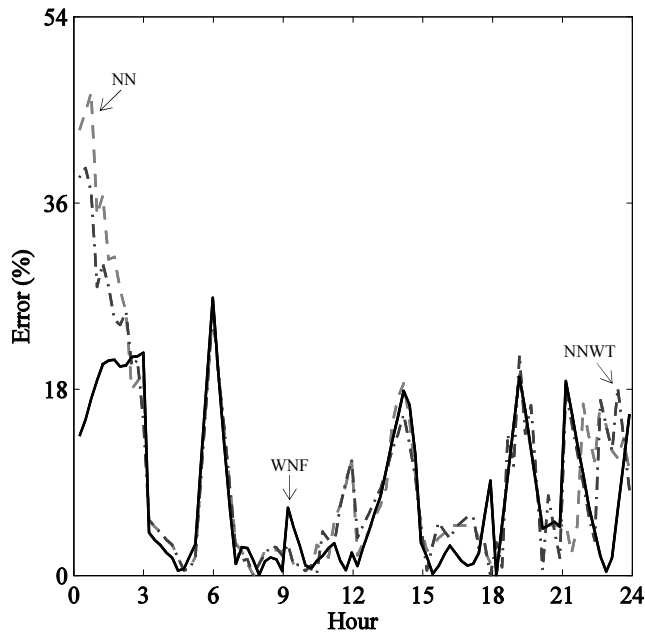
**Fig. 5** Summer day: actual wind power, solid line, together with the forecasted wind power, dash-dot line, in megawatt



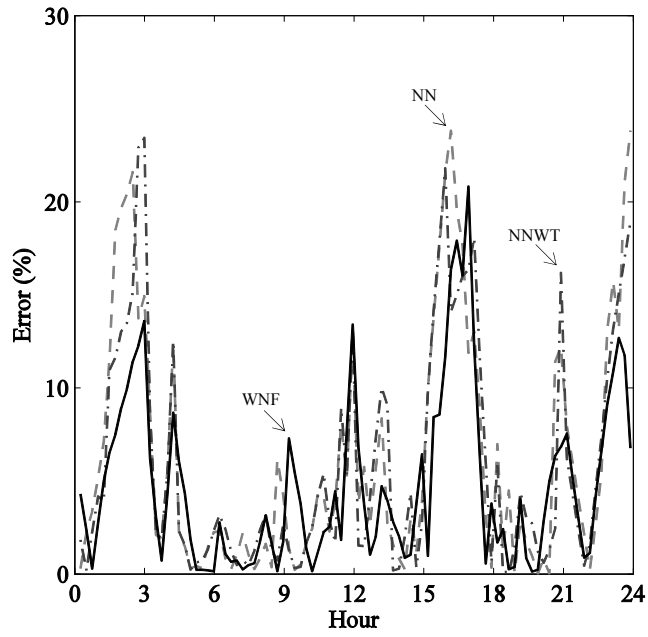
**Fig. 6** Fall day: actual wind power, solid line, together with the forecasted wind power, dash-dot line, in megawatt



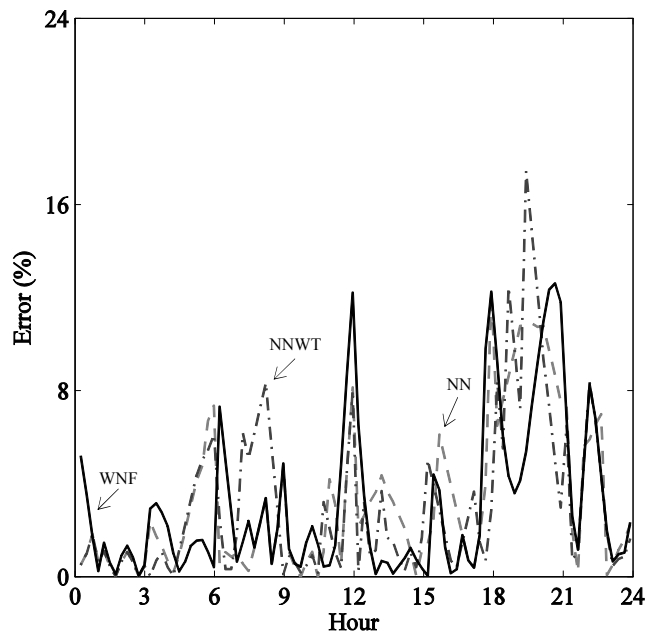
**Fig. 7** Winter day: absolute value of forecast errors considering NN (dashed line), NNWT (dash-dot line) and WNF (solid line) approaches



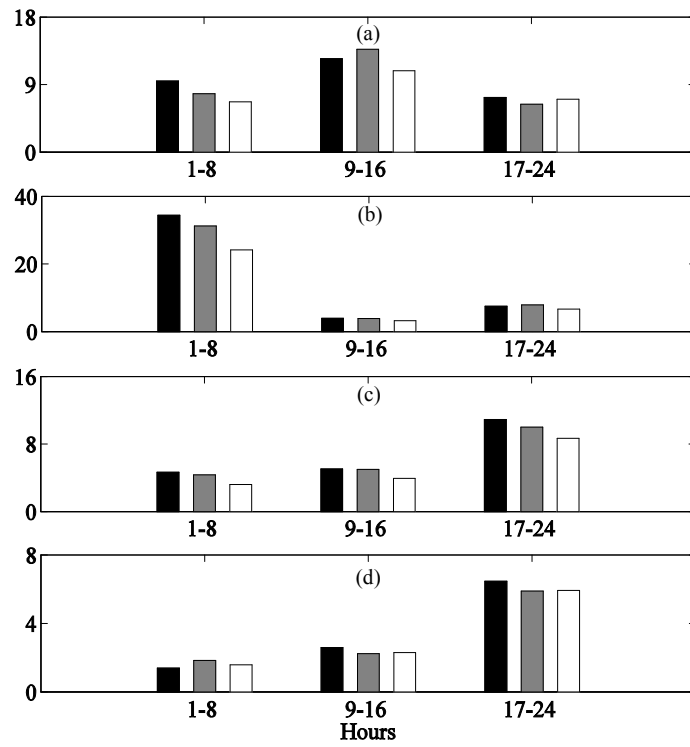
**Fig. 8** Spring day: absolute value of forecast errors considering NN (dashed line), NNWT (dash-dot line) and WNF (solid line) approaches



**Fig. 9** Summer day: absolute value of forecast errors considering NN (dashed line), NNWT (dash-dot line) and WNF (solid line) approaches



**Fig. 10** Fall day: absolute value of forecast errors considering NN (dashed line), NNWT (dash-dot line) and WNF (solid line) approaches



**Fig.11** Average errors within three time intervals, considering NN (black rectangle), NNWT (grey rectangle) and WNF (white rectangle) approaches for the days analyzed: (a) Winter, (b) Spring, (c) Summer, and (d) Fall