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Forecasting of wind speed using wavelets analysis and cascade-correlation neural networks

Van Giang Tran¹, Stéphane Grieu^{1,*}, Monique Polit¹, Quoc Tuan Tran² and Hoai Linh Tran³

¹ELIAUS Laboratory, University of Perpignan Via Domitia, Perpignan, France

²Grenoble Electrical Engineering Laboratory, Grenoble Institute of Technology, Grenoble, France

³Dept. of Electrical Engineering, Hanoi University of Technology, Hanoi, Vietnam

¹{vangiang.tran; grieu; polit}@univ-perp.fr; ²tuan.tran-quoc@g2elab.inpg.fr; ³linh-3i@mail.hut.edu.vn

Summary

The present paper focuses on developing and testing various reliable and robust tools with the aim of managing energy sources and promoting renewable energy for the city of Perpignan (south of France). In this sense, forecasting average wind speeds was the main objective of the work, leading to propose a forecast methodology including a (discrete) wavelet-based multi-resolution analysis of available historical data, used as training data, and an estimation of the coefficients of the wavelet decomposition in the original resolution, using trained Artificial Neural Networks (ANN), of the next day, next week or next month average wind speed. Then, the reconstruction of a forecasted daily, weekly or monthly average wind speed is performed by simply summing up the estimated coefficients. According to the nature (that is to say daily, weekly or monthly) of a to-be-predicted average wind speed and because the purpose of the proposed methodology is identifying patterns in time series data, only previous days, weeks or months average wind speeds were considered. Finally, and because of the accuracy of the predicted average wind speeds, one can consider that the obtained results by means of the proposed DWT-ANN methodology are satisfactory even very satisfactory.

1. Introduction

With the aim of surmounting the actual energy crisis (mainly caused by both the rarefaction of fossil fuels and excessive energy consumption), managing energy demand, promoting renewable energy and energy savings are worldwide concerns. Moreover, renewable energy is one of the ways allowing limiting both greenhouse gases emissions and the impact of climate change on environment and health. Renewable energy effectively uses natural resources such as sunlight, wind, rain or geothermal heat. Wind energy is actually one of the fastest-growing forms of electricity generation because wind is a clean, indigenous and inexhaustible energy resource that can generate enough electricity to power a lot of homes and businesses [1].

France enjoys an abundant wind potential, that is why its wind energy market has been progressing steadily in recent years. While in 2000, there were only 30 MW of wind generating capacity in France, the total installed capacity at the end of 2007 was 2454 MW, representing an annual growth rate of about 57% considering a total capacity. A further 3500 MW have been approved. The annual market also grew to 888 MW in 2007, making it the third largest annual market in Europe after Spain and Germany. The healthy growth of wind energy in France can be explained by the implementation in 2001 and 2002 of a feed-in tariff system which ensures a tariff of 8.2 ct €/kWh over a 10 year-period for wind farms. In July 2005, the law was amended to stipulate that wind farms must be built in "Wind Power Development Zones" in order to benefit from the above-mentioned tariff. According to industry groups, this law has, rather than promoting wind energy development, hampered the growth of the French market, since it resulted in longer and more complex administrative and grid connection procedures. In 2007, the French "Syndicat des Energies Renouvelables" suggested a wind power generation target of 25 GW by 2020, including 6 GW offshore, and one can suppose that this target will be adopted by the French government. The main difficulties facing wind energy deployment in France are the number of areas where wind farms are still forbidden, such as radar zones, natural protected areas and aviation paths. The lack of connection capacity is also a barrier in some areas, particularly in centre of France, near the Massif Central, and in the northern

* Corresponding author. Full address: ELIAUS Laboratory, University of Perpignan, 52 Avenue Paul Alduy, 66860, Perpignan, France; Tel.: +33 4 68 66 22 02; Fax: +33 4 68 66 22 87.

regions of Nord-Pas de Calais and Picardy, where the grid is saturated in some areas. Public opposition is another major issue, with various grassroots campaigners fighting against the implementation of wind farms, under the pretext of landscape protection [2].

The present work takes part in a global development of reliable and robust tools allowing managing energy sources and promoting renewable energy for the city of Perpignan (south of France) [3,4]. Thus, forecasting daily, weekly and monthly average wind speed is of great interest. Previous work focused on testing, as a first approach, well-known tools in the field of forecasting such as the following Artificial Neural Networks (ANN): Multi-Layer Perceptrons (MLP), Elman Recurrent neural networks (ER) and Cascade-Correlation neural networks (CC) [5,6]. As a more in-depth approach and with the aim of improving the accuracy of the previously obtained results, a forecast methodology including a multi-resolution analysis, based on a Discrete Wavelet Transform (DWT) [7,8], of available historical data, used as training data, and an estimation of the coefficients of the wavelet decomposition in the original resolution of the next day, next week or next month average wind speed, using the above-mentioned trained Artificial Neural Networks (ANN), is proposed. Indeed, substituting the prediction task of the original time series of high variability by the prediction of its wavelet coefficients on different levels of lower variability is the main idea of the present work. Then, the reconstruction of a forecasted daily, weekly or monthly average wind speed is performed by simply summing up the estimated coefficients [9]. The present paper is focused, first, on introducing the study area, the available database and all the used tools and, secondly, on presenting the results of the prediction of the next day ($d + 1$), next week ($w + 1$) or next month ($m + 1$) average wind speed in Perpignan using the proposed DWT-ANN methodology. Finally, these forecast results have been compared with the preliminary results obtained using standalone artificial neural networks. An optimal choice of previous daily, weekly or monthly wind speeds to be taken into account was a major concern. Let us note, whatever the used ANN and according to both the nature of the to-be-predicted average wind speeds and the purpose of the proposed methodology, i.e. identifying patterns in time series data, that only previous days ($d, d - 1, d - 2, \dots$), weeks ($w, w - 1, w - 2, \dots$) or months ($m, m - 1, m - 2, \dots$) average wind speeds were considered.

2. Study area: the Perpignan city

The study area is the Perpignan city in southern France. Perpignan is around 150 km from Montpellier, 200 km from Toulouse or Barcelona (Spain) and 850 km from Paris. Its population is about 120 000 in the city proper and more than 300 000 in the metropolitan area. Because of its geographical localization and its proximity with the Mediterranean Sea, its population highly increases during the summer season. A typical Mediterranean climate is found in Perpignan: high temperature in summer and mild climate for the rest of the year. So, the weather is globally hot, with dry summers, mild and humid winters and just a few rainy days during the year. Perpignan is a very sunny and windy city and consequently an ideal place for developing the electricity production by means of photovoltaic solar cells and/or windmills.

3. Daily, weekly and monthly average wind speeds database

Perpignan's daily, weekly and monthly average wind speeds during years 1997 to 2006 allowed developing and testing the proposed DWT-ANN methodology. The available database is so composed of 3652 daily average wind speeds, 520 weekly average wind speeds and 120 monthly average wind speeds over the ten above-mentioned years. Figure 1 presents the time series of daily, weekly and monthly average wind speeds for 2005 [10]. A preliminary data analysis revealed the presence of cyclic dynamics in terms of trends and seasonality. 1997 to 2005 data have been used as training data and 2006 data as validation data [11].

4. Wavelet-based Multi-Resolution Analysis (WMRA) technique

4.1. Continuous Wavelet Transform (CWT)

The continuous wavelet transform is used with the aim of decomposing a signal into wavelets i.e. into highly localized (in time) small oscillations. Whereas the Fourier transform decomposes a given signal into infinite length sines and cosines, losing all time-localization

information, the CWT's basis functions are scaled and shifted versions of the time-localized mother wavelet. So, this mother wavelet is a continuous in both time and frequency function that can be considered as a source function from which scaled and translated basis functions are generated. The CWT is used to obtain a time-frequency representation of a signal that offers very good both time and frequency localization. Considering a mother wavelet $\Psi(t)$, one can obtain the following wavelet series $\Psi_{a,b}(t)$, where a is the scale factor and b is the translation factor according to the following expression [7,8]:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \Psi\left(\frac{t-b}{a}\right) \quad a, b \in R; a \neq 0 \quad [Eq. 1]$$

For any function $x(t) \in L^2(R)$, its continuous wavelet transform can be expressed as follows:

$$C_{a,b} = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \cdot \Psi^*\left(\frac{t-b}{a}\right) dt \quad [Eq. 2]$$

where Ψ^* is the complex conjugate of Ψ . $C_{a,b}$ is called the wavelet coefficient. The continuous wavelet coefficients can be used with the aim of reconstructing the function $x(t)$ in the following way [7,8,9]:

$$x(t) = \frac{1}{C_\Psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} C_{a,b} \Psi_{a,b}(t) \frac{da db}{a^2} \quad [Eq. 3]$$

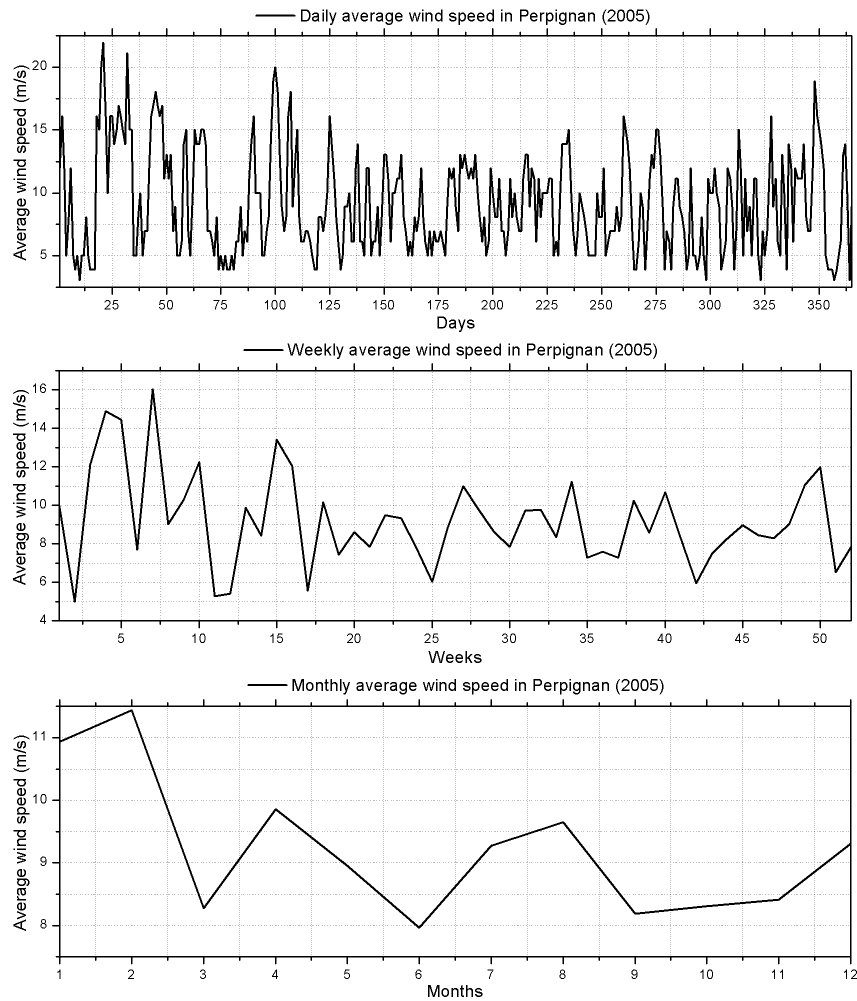


Figure 1. Time series of daily, weekly and monthly average wind speeds in Perpignan (2005).

4.2. Discrete Wavelet Transform (DWT) and multi-resolution analysis

Because translating the mother wavelet leads to redundant information, one can use, instead of the continuous wavelet transform, the discrete one. In this case, both scale (a) and translation (b) factors are restricted to only discrete values such that $a = a_0^m$ and $b = nb_0a_0^m$, where $a_0 > 1$, $b_0 \neq 0$, and $(m, n) \in \mathbb{Z}^2$. Basically, the discrete wavelet multi-resolution analysis, commonly based on Daubechies orthogonal wavelet basis, allows decomposing a signal into approximations (i.e. low frequency coefficients) and details (i.e. high frequency coefficients) using a filter bank composed of both low-pass (LP) and high-pass (HP) filters. This process can be repeated n times, producing n levels of decomposition, but decomposing (downsampling) the approximations (the low frequency coefficients) only. Indeed, the high frequency coefficients are neglected. So, a signal x can be first decomposed into an approximation A_1 and a detail D_1 (that is the level 1 of the decomposition). Then A_1 can be decomposed into an approximation A_2 and a detail D_2 (that is the level 2 of the decomposition) and so on. Considering n levels of decomposition, the reconstruction process allows recovering the initial signal x summing the n details D_1, D_2, \dots, D_n and the approximation A_n of level n . As an example, Figure 2 depicts the 3-level decomposition of a signal x and its reconstruction [7,8,9].

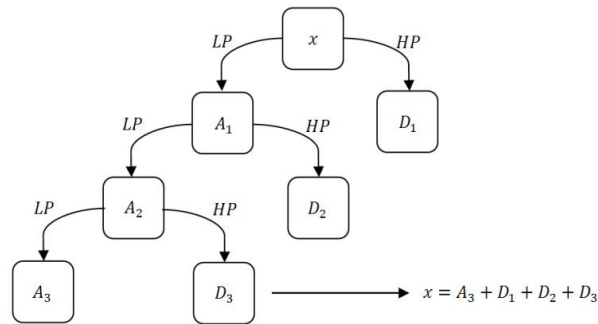


Figure 2. Multi resolution analysis leading to the 3-level decomposition of a signal.

5. Artificial Neural Networks (ANN)

5.1. Multi-layer Perceptron (MLP) neural network

The Perceptron, the simplest neural network, is only able to classify data into two classes. Basically it consists of a single neuron with a number of adjustable weights. It uses an adaptative learning rule. Given a problem which calls for more than two classes, several Perceptrons can be combined: the simplest form of a layered network just has an input layer of source nodes connected to an output layer of neurons. The single-layer Perceptron can only classify linearly separable problems. For non-separable problems it is necessary to use more layers. A multi-layer network has one or more hidden layers and is fully connected. The multi-layer Perceptron consists of one layer of linear output neurons and only one hidden layer of nonlinear neurons. Because intermediate neurons not directly connected to output neurons learn very slowly, more than one hidden layer proved to cause slower convergence during the learning phase. Based on the principle of generalization versus convergence, both number of hidden neurons and iterations completed during the training phase were optimized [12,13]. The multi-layer Perceptron learns using an algorithm called backpropagation. During this iterative process, input data are repeatedly presented to the network. For each presentation, the network output is compared to the desired output and an error is computed. This error is fed back to the network and used to adjust the weights such that it decreases and the model gets closer and closer to produce the desired output [14,15].

5.2. Elman Recurrent (ER) neural network

Feedforward neural networks have been successfully used to solve problems that require the computation of a static function. In the real world however, one encounters many problems

which cannot be solved by learning a static function because the function being computed changes with each input received. It should be clear from the architecture of feedforward neural networks that past inputs have no way of influencing the processing of future inputs. This situation can be rectified by the introduction of feedback connections in the network. Now network activation produced by past inputs can cycle back and affect the processing of future inputs. The class of neural networks which contain feedback connections are called Recurrent Neural Networks (RNN). The Elman network commonly is a 2-layer network with feedback from the first-layer output to the first layer input. This recurrent connection allows the Elman network to both detect and generate time-varying patterns. It has non-linear neurons in its recurrent layer and linear neurons in its output layer. This combination allows 2-layer networks with these transfer functions to approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fit increases in complexity [16].

5.3. Cascade-Correlation (CC) neural network

To build feed-forward neural networks, a cascade-correlation learning algorithm which generates hidden neurons as they are needed can be used. A cascade network differs from fully connected feedforward neural networks exploiting a fixed architecture in the way that cascade networks start learning with only one neuron. During the learning phase, the algorithm automatically adds and trains new neurons creating a multi-layer structure. The number of hidden neurons increases step-by-step while the training error decreases. As a result, the training algorithm grows the neural network of a near optimal complexity which can generalize well. So, the first idea is to build up the cascade architecture by adding new neurons together with their connections to all the inputs as well as to the previous hidden neurons. This configuration is not changed at the following layers. The second idea is to learn only the newly created neuron by fitting its weights so that to minimize the residual error of the network. The advantages of this kind of ANN are well known. First, no structure being predefined, the network is automatically built up from the training data. Secondly, it learns very fast because of each of its neurons is trained independently to each other. However, cascade-correlation networks can be over-fitted in the presence of noisy features [5,6].

6. Forecast procedure

As previously noted, Perpignan's daily, weekly and monthly average wind speeds covering years 1997 to 2006 have been used for formalizing and testing the proposed wind speed forecast procedure. All the available daily, weekly and monthly time series have been decomposed into 5-level wavelets by means of the described (discrete) wavelet-based multi-resolution analysis. Every decomposition leads to 5 details (i.e. high frequency coefficients) D_1, D_2, D_3, D_4 and D_5 and an approximation (i.e. low frequency coefficient) A_5 of level 5. As example, Figure 3 depicts the 5-level decomposition of the 2005 (one of the nine years used as training data) daily, weekly and monthly average wind speed time series. Let us note that the optimal level of decomposition proved to be 5: for a too low (i.e. < 5) or a too high (i.e. > 5) number of levels, the forecast accuracy clearly deteriorates. Using a sliding window, which size depends on the number of previous daily average wind speeds taken into account, the 5-level decomposed 1997 to 2005 daily time series have been scanned during the ANNs' training phase with the aim of predicting, over the whole year 2006, the wavelet coefficients of the next day ($d + 1$) average wind speed. The same procedure was used with the 5-level decomposed 1997 to 2005 weekly and monthly time series respectively for predicting, again over the whole year 2006, the wavelet coefficients of both the next week ($w + 1$) and next month ($m + 1$) average wind speeds. At different levels, a notable difference of variability can be observed: the higher is the wavelet level, the lower is the variability of the coefficients. So, substituting the prediction task, using neural networks, of the original daily, weekly or monthly time series of high variability by the prediction of its wavelet coefficients on different levels of lower variability is the main idea of the work [3,4]. Then, the reconstruction of a forecasted daily, weekly or monthly average wind speed is performed by simply summing up the estimated coefficients. Because the wavelet coefficients are of lower variability, one can expect improving the forecast accuracy. Whatever the used ANN and according to both the nature of the to-be-predicted

average wind speeds and the purpose of the proposed DWT-ANN methodology, i.e. identifying patterns in time series data, only previous days ($d, d - 1, d - 2, \dots$), weeks ($w, w - 1, w - 2, \dots$) or months ($m, m - 1, m - 2, \dots$) average wind speeds were considered for predicting the next day ($d + 1$), next week ($w + 1$) or next month ($m + 1$) average wind speed. So, many examples of such dependencies for consecutive days, weeks and months were analyzed: 2 to 9 previous daily, weekly or monthly average wind speeds were considered.

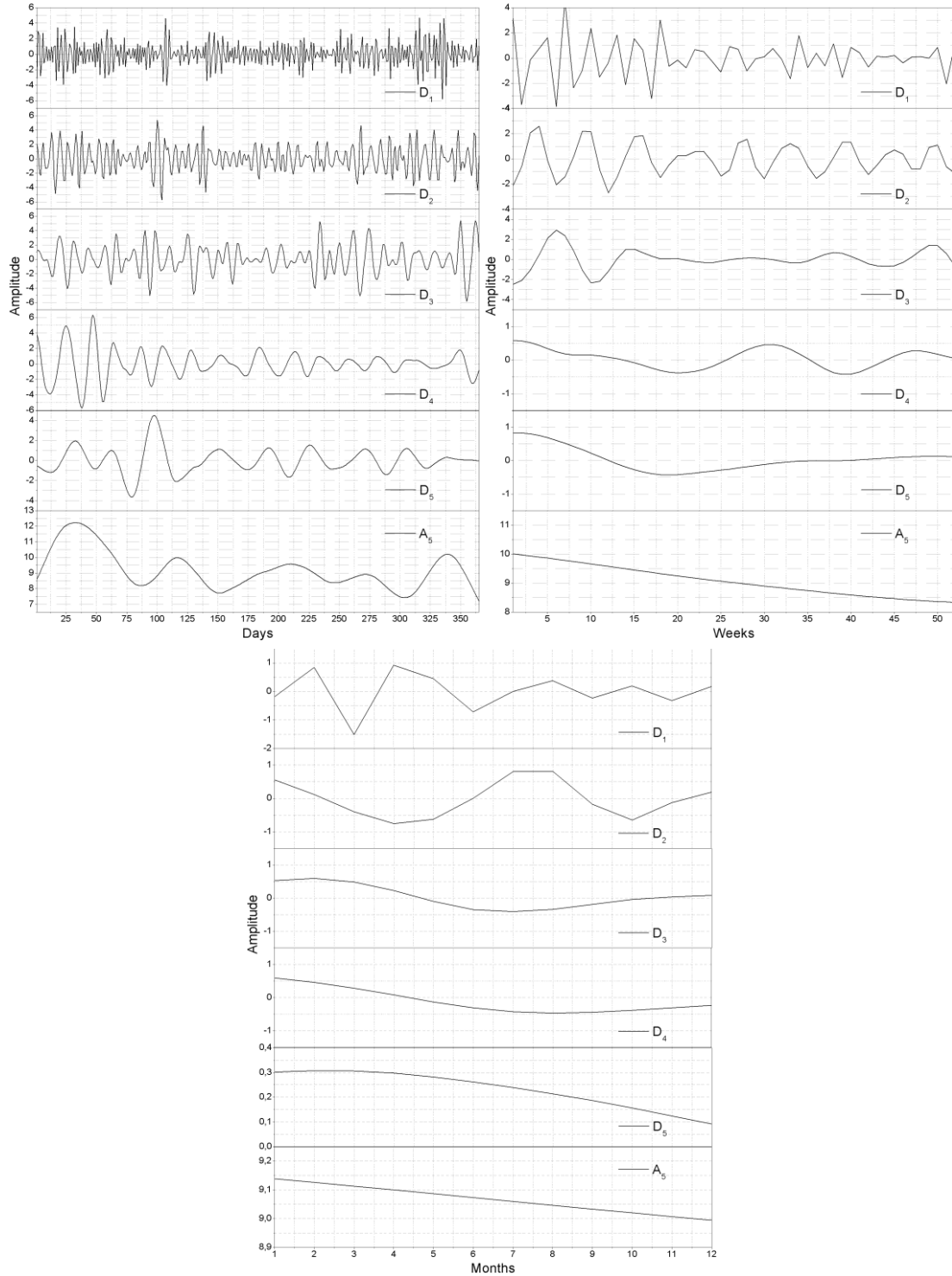


Figure 3. 5-level decomposition of the 2005 daily, weekly and monthly average wind speed time series.

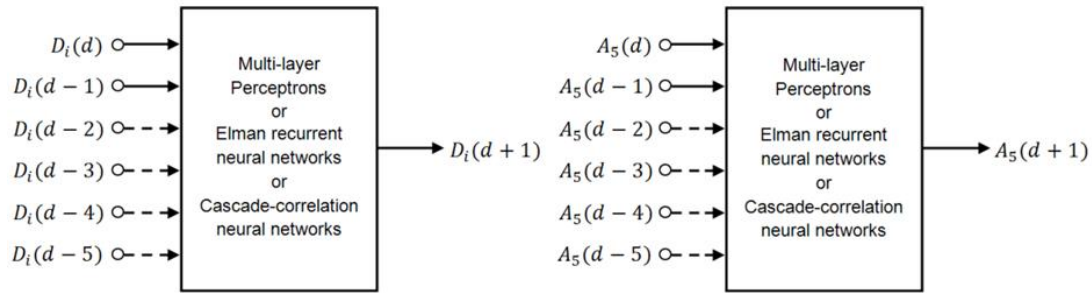


Figure 4. ANN structure for estimating $D_i(d + 1)$, with $i = 1, 2, \dots, 5$, and $A_5(d + 1)$.

For estimating, for the next day, the next week or the next month, the wavelet coefficients of each decomposition level, artificial neural networks have been used. One neural network is required for each of the details D_1, D_2, D_3, D_4 and D_5 . An additional one is needed for estimating the approximation A_5 of level 5. So, instead of one neural network allowing estimating the average wind speed of the next day, the next week or the next month, a total of 6 trained networks had to be used for estimating 6 coefficients. Figure 4 presents the ANN structure used for estimating the wavelet coefficients on i^{th} level for the average wind speed of the next day i.e. $D_i(d + 1)$, with $i = 1, 2, \dots, 5$ and A_5 . The same structure is used for estimating the wavelet coefficients on i^{th} level for the average wind speed of the next week and the next month [3,4].

7. Forecast results

7.1. Forecast of the next day ($d + 1$) average wind speed

The forecast results obtained using the proposed DWT-ANN methodology (DWT-MLP, DWT-ER or DWT-CC) are given in Table 1. Mean relative errors have been calculated over the whole estimated daily average wind speeds for year 2006. These results allow, first, highlighting the generalization ability of the various ANN used and, secondly, specifying the optimal number of previous average wind speeds to be taken into account. Table 1 also remembers previously obtained results using the standalone neural networks with the aim of quantifying the impact of the wavelet-based multi-resolution analysis on the forecast results obtained when using the DWT-ANN methodology.

Table 1. Forecast of the next day ($d + 1$) average wind speed.

Previous daily average wind speeds taken into account	Methodology	Predicted d+1-day average wind speed (MRE (%))
$d, d-1$	MLP / DWT-MLP	12.13 / 10.36
	ER / DWT-ER	13.67 / 12.41
	CC / DWT-CC	12.37 / 10.15
$d, d-1, d-2$	MLP / DWT-MLP	13.87 / 10.70
	ER / DWT-ER	13.85 / 11.13
	CC / DWT-CC	12.18 / 10.14
$d, d-1, d-2, d-3$	MLP / DWT-MLP	12.41 / 7.69
	ER / DWT-ER	14.64 / 12.40
	CC / DWT-CC	12.29 / 7.37
$d, d-1, d-2, d-3, d-4$	MLP / DWT-MLP	12.84 / 5.22
	ER / DWT-ER	12.61 / 10.11
	CC / DWT-CC	13.55 / 5.17
$d, d-1, d-2, d-3, d-4, d-5$	MLP / DWT-MLP	13.05 / 4.42
	ER / DWT-ER	14.45 / 12.35
	CC / DWT-CC	10.93 / 3.98
$d, d-1, d-2, d-3, d-4, d-5, d-6$	MLP / DWT-MLP	13.06 / 3.69
	ER / DWT-ER	13.76 / 11.27
	CC / DWT-CC	10.10 / 3.01
$d, d-1, d-2, d-3, d-4, d-5, d-6, d-7$	MLP / DWT-MLP	14.32 / 4.30
	ER / DWT-ER	15.32 / 10.89
	CC / DWT-CC	12.23 / 3.19
$d, d-1, d-2, d-3, d-4, d-5, d-6, d-7, d-8$	MLP / DWT-MLP	14.10 / 5.70
	ER / DWT-ER	15.02 / 12.61
	CC / DWT-CC	13.41 / 3.60

Taking a look at Table 1 allows coming to some conclusions. First, whatever the number of previous daily average wind speeds taken into account, the best accuracy is given by the DWT-CC methodology. Using this methodology, the mean relative error, when estimating over the whole year 2006 (used as validation data) the average wind speed of the next day ($d + 1$) in Perpignan city, ranges between 3.01% and 10.15%. Without any doubts, cascade-correlation neural networks present the best generalization ability. On the other hand, the worst accuracy is given by the DWT-ER methodology: according to the previous daily average wind speeds taken into account, the mean relative error ranges between 10.11% and 12.61%. Elman recurrent neural networks are, in this case, of much worse generalization ability. The DWT-MLP methodology provides intermediate accuracy. Overall, and whatever the used methodology, the obtained results can be considered as very satisfactory.

Using both the DWT-CC and the DWT-MLP methodologies, the optimal number of previous daily average wind speeds to be taken into account seems to be equal to 7 ($d, d - 1, \dots, d - 6$), while it seems to be equal to 5 ($d, d - 1, \dots, d - 4$) when using the DWT-ER methodology. Resorting to the DWT-CC methodology, considering more than the six previous daily average wind speeds proved to be unnecessary and had a significant negative impact on the accuracy of the obtained forecast results. Thus, in this case, one can suppose that the correlations between the next day ($d + 1$) average wind speed and average wind speeds of previous days exceeding 7 ($> d - 6$) is weak or changing significantly. Finally, let us note that whatever both the used methodology and the number of previous daily average wind speeds taken into account, the impact of the wavelet-based multi-resolution analysis on the obtained forecast results is very positive: mean relative errors are, in all the cases, significantly reduced.

7.2. Forecast of the next week ($w + 1$) average wind speed

As when predicting the next day ($d + 1$) average wind speed, the best overall accuracy is given by the DWT-CC methodology. However, taking a look at Table 2, one can observe that the forecast accuracy given by both the DWT-CC and DWT-MLP methodologies is comparable. Indeed, using the DWT-CC methodology, the mean relative error observed, when predicting over the whole year 2006 the average wind speed of the next week ($w + 1$) in Perpignan city, ranges between 2.77% and 5.11%, while it ranges between 2.98% and 5.45% when using the DWT-MLP methodology. Again, the worst accuracy is given by the DWT-ER methodology: according to the previous weekly average wind speeds taken into account, the observed mean relative error ranges between 5.60% and 9.82%.

Table 2. Forecast of the next week ($w + 1$) average wind speed.

Previous weekly average wind speeds taken into account	Methodology	Predicted $w+1$ -week average wind speed (MRE (%))
$w, w-1$	MLP / DWT-MLP	12.78 / 4.53
	ER / DWT-ER	10.85 / 8.45
	CC / DWT-CC	12.05 / 3.53
$w, w-1, w-2$	MLP / DWT-MLP	11.01 / 5.45
	ER / DWT-ER	13.39 / 6.13
	CC / DWT-CC	9.68 / 4.99
$w, w-1, w-2, w-3$	MLP / DWT-MLP	12.60 / 5.05
	ER / DWT-ER	12.32 / 9.04
	CC / DWT-CC	9.23 / 5.11
$w, w-1, w-2, w-3, w-4$	MLP / DWT-MLP	10.83 / 3.54
	ER / DWT-ER	10.50 / 5.94
	CC / DWT-CC	8.53 / 4.62
$w, w-1, w-2, w-3, w-4, w-5$	MLP / DWT-MLP	7.68 / 3.47
	ER / DWT-ER	11.28 / 9.82
	CC / DWT-CC	9.46 / 4.30
$w, w-1, w-2, w-3, w-4, w-5, w-6$	MLP / DWT-MLP	10.06 / 4.41
	ER / DWT-ER	11.94 / 9.20
	CC / DWT-CC	10.18 / 3.98
$w, w-1, w-2, w-3, w-4, w-5, w-6, w-7$	MLP / DWT-MLP	10.30 / 3.60
	ER / DWT-ER	11.89 / 8.49
	CC / DWT-CC	9.35 / 3.27
$w, w-1, w-2, w-3, w-4, w-5, w-6, w-7, w-8$	MLP / DWT-MLP	8.30 / 2.98
	ER / DWT-ER	8.82 / 5.60
	CC / DWT-CC	7.71 / 2.77

Whatever the used methodology, the optimal number of previous weekly average wind speeds to be taken into account seems to be equal to 9 ($w, w - 1, \dots, w - 8$). However, taking another look at Table 2, one can observe that the impact of the previous average wind speeds taken into account is less significant than when predicting the next day ($d + 1$) average wind speed. Finally, let us note that, again, whatever both the used methodology and the number of previous weekly average wind speeds taken into account, the impact of the wavelet-based multi-resolution analysis on the obtained forecast results is very positive: mean relative errors are, in all the cases, significantly reduced.

7.3. Forecast of the next month ($m + 1$) average wind speed

As when predicting the next day ($d + 1$) or the next week ($w + 1$) average wind speed, the best overall accuracy is given by the DWT-CC methodology. Even if all the methodologies used provide very good accuracy, the worst accuracy is again given by the DWT-ER methodology. Indeed, using the DWT-CC methodology, the mean relative error observed, when predicting over the whole year 2006 the average wind speed of the next month ($m + 1$) in Perpignan city, ranges between 0.41% and 2.44%, while it ranges between 0.93% and 2.81% and between 2.99% and 4.99% when using the DWT-MLP and DWT-ER methodologies, respectively.

Taking a look at Table 3, one can observe, because, first, of the nature of the prediction task (i.e. concerning monthly values) and because, secondly, of the very good results obtained when directly predicting the next month ($m + 1$) average wind speed using standalone neural networks, that the impact on the forecast results of both the previous average wind speeds taken into account and the wavelet-based multi-resolution analysis is less significant than when predicting the next day ($d + 1$) or even the next week ($w + 1$) average wind speed. However, substituting the prediction task of the original time series of high variability by the prediction of its wavelet coefficients on different levels of lower variability stills improving the accuracy of the predicted values. The optimal number of previous monthly average wind speeds to be taken into account seems to be equal to 2 ($m, m - 1$) when using the DWT-ER methodology, while it seems to be equal to 8 ($m, m - 1, \dots, m - 7$) and 9 ($m, m - 1, \dots, m - 8$) when using the DWT-MLP and DWT-CC methodologies, respectively.

Table 3. Forecast of the next month ($m + 1$) average wind speed.

Previous monthly average wind speeds taken into account	Methodology	Predicted $m+1$ -month average wind speed (MRE (%))
$m, m-1$	MLP / DWT-MLP	3.33 / 2.81
	ER / DWT-ER	3.54 / 2.99
	CC / DWT-CC	3.23 / 2.17
$m, m-1, m-2$	MLP / DWT-MLP	3.84 / 2.78
	ER / DWT-ER	5.24 / 4.66
	CC / DWT-CC	2.92 / 2.44
$m, m-1, m-2, m-3$	MLP / DWT-MLP	4.29 / 2.26
	ER / DWT-ER	4.33 / 3.15
	CC / DWT-CC	4.69 / 1.62
$m, m-1, m-2, m-3, m-4$	MLP / DWT-MLP	3.29 / 2.24
	ER / DWT-ER	5.06 / 4.81
	CC / DWT-CC	4.60 / 1.25
$m, m-1, m-2, m-3, m-4, m-5$	MLP / DWT-MLP	4.39 / 1.84
	ER / DWT-ER	6.74 / 4.28
	CC / DWT-CC	4.84 / 1.63
$m, m-1, m-2, m-3, m-4, m-5, m-6$	MLP / DWT-MLP	5.14 / 1.70
	ER / DWT-ER	4.47 / 3.46
	CC / DWT-CC	4.51 / 1.24
$m, m-1, m-2, m-3, m-4, m-5, m-6, m-7$	MLP / DWT-MLP	6.65 / 0.93
	ER / DWT-ER	5.49 / 3.73
	CC / DWT-CC	5.22 / 0.91
$m, m-1, m-2, m-3, m-4, m-5, m-6, m-7, m-8$	MLP / DWT-MLP	3.30 / 1.34
	ER / DWT-ER	4.64 / 4.99
	CC / DWT-CC	3.95 / 0.41

8. Conclusions

The present work takes part in a global development of reliable and robust tools with the aim of both efficiently managing energy sources and promoting renewable energy for the city of

Perpignan (south of France). In this sense, forecasting daily, weekly and monthly average wind speeds in Perpignan is of paramount interest. So, a forecast methodology including a multi-resolution analysis, based on a Discrete Wavelet Transform (DWT), of available historical data, used as training data, and an estimation of the coefficients of the wavelet decomposition in the original resolution of the next day ($d + 1$), next week ($w + 1$) or next month ($m + 1$) average wind speed, using trained Artificial Neural Networks (ANN), is proposed. Indeed, substituting the prediction task of the original time series of high variability by the prediction of its wavelet coefficients on different levels of lower variability is the main idea of the present work. Then, the reconstruction of a forecasted daily, weekly or monthly average wind speed is performed by simply summing up the estimated coefficients. An optimal choice of previous daily, weekly or monthly wind speeds to be taken into account was a major concern. Let us note, according to both the nature of the to-be-predicted average wind speeds and the purpose of the proposed methodology, i.e. identifying patterns in time series data, that only previous days ($d, d - 1, d - 2, \dots$), weeks ($w, w - 1, w - 2, \dots$) or months ($m, m - 1, m - 2, \dots$) average wind speeds were considered. Whatever the nature of the estimated average wind speed and the number of previous daily, weekly or monthly wind speeds taken into account, the best accuracy is always given by the DWT-CC methodology. Cascade-correlation neural networks proved, after being correctly trained using historical data, to be of best generalization ability. Whatever both the used methodology and the previous daily, weekly or monthly average wind speeds taken into account, the impact of the wavelet decomposition on the obtained forecast results is very positive: mean relative errors are, in all the cases, reduced. As expected, predicting a monthly average wind speed is easier than predicting a weekly average wind speed while predicting a weekly average wind speed is easier than predicting a daily average wind speed. However, let us note that in all the considered cases, the obtained results by means of the proposed DWT-ANN methodology are satisfactory even very satisfactory.

Future work will now focus on specifying a maximal forecast horizon and on integrating a forecast module based on the present work in a virtual power plant with the aim of managing energy sources and promoting renewable energy for the city of Perpignan.

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