DWT-based Wind Speed Forecasting Using Artificial Neural Networks in the region of Annaba

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***Abstract*— Global demand for electrical energy is in constant increase all over the world, leading to new kinds of energy from renewable resources, namely solar and wind power. Consequently, precise wind prediction is very important for efficient management of grid-connected wind farms. This article examines the use of wavelet analysis combined with neural networks to predict wind speed. The wavelet transform is employed to smooth the wind speed time series for better prediction using neural networks. Using the wind speed data of the region of Annaba situated in the east of Algeria, the obtained results show the db4 wavelet with 5-level decomposition outperforms all other wavelet families in terms of forecasting accuracy.**

***Keywords*— wind power forecasting, discrete wavelet transform, neural networks.**

I. Introduction

During recent years the wind energy is continuously and considerably growing throughout the worldwide where the capacity of the installed wind power will achieve approximately 903 GW at the end of 2023 [1]. In spite of its several environmental advantages, the inherent randomness of wind power rises major problems in managing electrical power plants. Wind energy forecasting is considered as a very important tool to ensure an efficient managing and scheduling of energy demand/supply balance. To handle the intermittency of wind energy, forecasting methods, over different time horizons, are needed. Several predicting approaches, comprising statistical, physical, intelligent and hybrid techniques have been developed [2], [4], [5]-[7]. Physical methods of forecasting, based on Numerical Weather prediction (NWP), are more appropriate for time horizons of several days [6]. Relatively simple compared with physical methods, the statistical approaches are based on time series models, and are usually used for short-term forecasts (many minutes to few hours) [6], [7]. Using artificial intelligence (AI), intelligent techniques are gaining more interest in prediction problems and wind energy forecasting issues [3], [7]. The hybrid methods deal with the combination of different intelligent methods and/or the physical and the statistical techniques [7], [8]. Recently, with the aim of boosting the precision of forecasting, various techniques have been introduced. Among them K–Nearest Neighbor (KNN), Autoregressive Moving Average (ARMA) and Support vector machine (SVM) prediction methods. Other techniques have been also developed such as, genetic algorithm (GA), fuzzy logic, artificial neural network (ANN), and discrete wavelet transform (DWT) based approaches [4], [7], [9], [10]-[15]. Particularly, wavelet analysis mixed with neural networks and different intelligent methods have been effectively employed in various research works concerning wind energy prediction. For short-term wind speed forecast, a hybrid technique, employing wavelet packet transform and ANN, has been suggested [15]. In [16], a short-term predicting scheme integrating DWT and SVM optimized using genetic algorithm, has been developed. The hybrid technique examined in [17] uses the db4 wavelet with neural networks trained by using the PSO optimization algorithm. In [18] a hybrid Neuro-wavelet wind energy forecasting approach is proposed, where the wavelets ***db1, db2*** and ***db3*** were employed to smooth the wind speed signal to improve the forecasting precision. The obtained data is, then, used for the training procedure of the neural network. This work examines the issue of combining the DWT with ANN for wind speed forecasting. More particularly, we look for the most appropriate standard wavelet for wind speed prediction.

The rest of this article is organized in the following way. In Section 2 DWT, utilized for time series decomposition, is described. Section 3 reviews the ANN employed in the procedure of forecasting. Section 4 presents the ANN-DWT hybrid approach. Sections 5 and 6 give respectively the obtained simulation results and some drawn conclusions.

II. Discrete Wavelet Decomposition

The wavelet analysis has two main largely applied decomposition algorithms: Continuous Wavelet Transformation (CWT) [10] and Discrete Wavelet Transformation (DWT). The CWT is generally given by:

$$CWT_X(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \qquad (1)$$

Where:

$x(t)$ represent the analyzed signal, $\psi_{a,b}(t)$ is the mother wavelet, $a > 0$ and b are the scale and shift parameters respectively:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (2)$$

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$\psi^*(t)$ is the complex conjugate of $\psi(t)$.

Using discrete $a = 2^m$ and $b = n.2^m$, the DWT can be given [17] :

$$dwt_x(m,n) = 2^{-\left(\frac{m}{2}\right)} \sum_{t=0}^{T-1} x(t)\psi\left(\frac{t-n2^m}{2^m}\right) \qquad (3)$$

Mallat has developed an efficient recursive approach for the DWT implementation, referred to as Mallat multiresolution signal decomposition [17]. Thus, the sequence $x(t) = (x_1, x_2, x_3 \ldots, x_N)$ to be decomposed at M^{th} level DWT decomposition passes across M high-pass and low-pass filters, giving rise to M detail coefficient vectors D_m and only one approximation coefficient vector A_M respectively (m: level of decomposition; $1 \le m \le M$). Fig. 1 illustrates a three-level decomposition for this multiresolution analysis given by:

$$x(t) = A_M(t) + \sum_{m=1}^{M} D_m(t)$$

$$= \sum_n a_{M,n}\varphi_{M,n}(t) + \sum_{m=1}^{M}\sum_n d_{m,n} \quad \psi_{m,n}(t) \qquad (4)$$

Where $a_{M,n}$ and $d_{M,n}$ represent the approximation and detail coefficients respectively. The signal is decomposed for dyadic scales extending from $m=1$ to a specified scale $m = M$. The decomposition coefficients could be iteratively obtained through a pair of low-pass and high-pass filters whose impulse response are $h[n]$ and $g[n]$ respectively [19] :

$$\begin{cases} a_{m+1,n} = \sum_k h[k-2n]a_{m,n} \\ d_{m+1,n} = \sum_k g[k-2n]a_{m,n} \end{cases} \qquad (5)$$

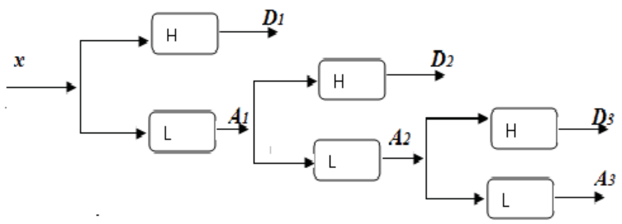

Fig. 1. Third level Wavelet decomposition.

The signal is reconstructed by adding up the obtained decomposed components as:

$$x = A_3 + D_3 + D_2 + D_1 \qquad (6)$$

This article focuses on determining the discrete wavelet, amongst different wavelet families, best adapted to wind speed forecasting. The wavelets considered in this work are:

- Daubechies: db1-db10,
- symlet: sym1-sym10,
- coiflet : coif1-coif5,
- biorthogonal (bior) wavelets.

III. Artificial Neural Networks (ANN)

Artificial neural networks (ANN) are among the popular supervised machine learning techniques widely used in the manipulation of problems with nonlinearities such as time series predicting [2], [8], [17].

An artificial neural network (ANN), made up of several neurons connected together like brain cells, is a numerical model seeking to imitate the functions of biological neural networks. Generally, ANN is composed of three types of layers:

- One input layer,
- One or more hidden layers,
- One output layer.

Each layer is entirely linked to the adjacent layer by weights w_{ij} as illustrated in Fig. 2. For future value estimation, time series data are supplied to the ANN to adequately train the network by tuning the weights w_{ij}. In this paper, non-linear auto regressive (NAR) feedforward networks are used. The NN training is conducted using the Levenberg-Marquardt algorithm.

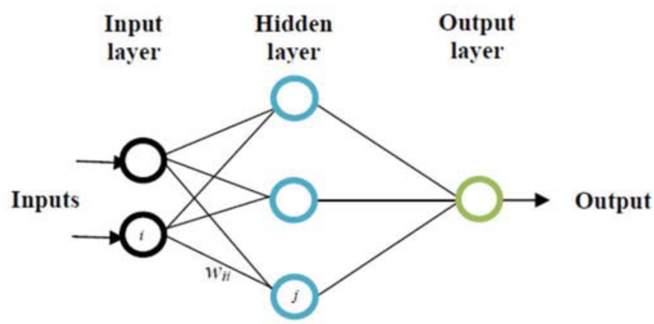

Fig. 2. Neural network structure

IV. Outline of the Forecasting Procedure

To assess the considered wind speed forecasting scheme, average daily wind speed from 2007 to 2018 for the region of Annaba, has been collected [20]. The eleven years from 2007 to 2017 have been used for training the network, whereas the data of 2018 were utilized for testing. Using most of the existing standard discrete wavelets, the DWT, with different levels of decomposition, is applied to the wind speed signals. Carrying out all the discrete wavelet decomposition tests, it is worth pointing out that the 5-level decomposition leads to the highest prediction accuracy compared to all the other levels. Figs. 3 and 4 show, for the city of Annaba during 2018, respectively the daily wind speed time series and the DWT decomposition at level 5 which produces an approximation coefficient A_5 and 5 detail coefficients D_1, D_2, D_3, D_4 *and* D_5 . Moreover, to show up the advantage of the DWT use, it is worth mentioning that the approximation coefficient A_5 , depicted in Fig. 4, reveals a slow variation curve very suitable for prediction. Furthermore, it can be easily verified that the energy of the coefficient A_5 represents approximately 91% of the total energy of the signal.

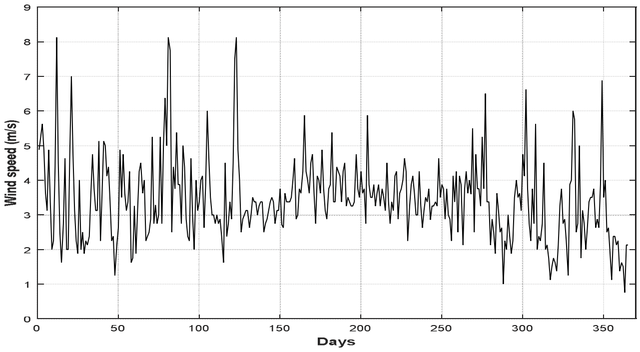

Fig. 3. Average wind speed signal (year 2018: Annaba)

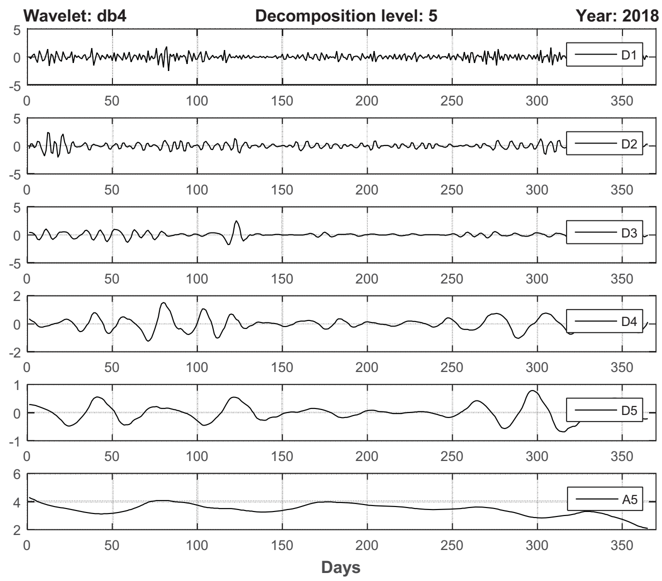

Fig. 4. Approximation and detail coefficients of average wind speed signal

For the adopted combined approach, using the DWT and an ANN as shown in Fig. 5, the following points are took into account:

- The wind speeds of the five past days {*d*, *d-1, d-2, d-3, d-4*} are fed to the NN to estimate the next day (*d+1*).
- One neural network, having two hidden layers composed of 10 neurons each, is determined for each set of approximation and detail coefficients $\{D_1, D_2, D_3, D_4, D_5, A_5\}$ as illustrated in Fig. 6.
- From the 4375 samples of the wind speed representing the period 2007-2018, 4015 and 360 data samples are employed to train and test the network respectively.

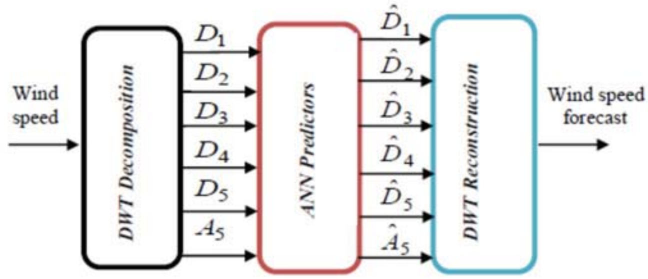

Fig. 5. The Wavelet-based ANN structure

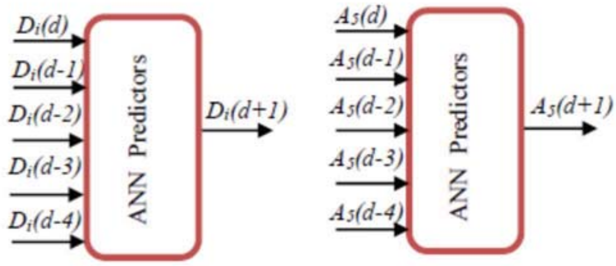

Fig. 6. ANN estimator of Di(d+1) and A_5(d+1)

The present work examines a hybrid scheme combining the discrete wavelet transform with artificial neural network (WANN) to forecast a one day ahead wind speed.

Generally, the effectiveness assessment of a predictive model, several error criteria are employed [12], [13], [20]. The mean square error (MSE) is adopted to evaluate the forecasting performance of the considered scheme.

V. Simulation Results and Discussion

The process to determine the optimal wavelet best adapted for wind speed prediction proceeds as follow:

1) The wind speed data from 2007 to 2018 are transformed using a 5-level DWT, to get the coefficients $\{D_1, D_2, D_3, D_4, D_5, A_5\}$.

2) Once the six NNs are accurately trained, the approximation coefficient $\hat{A}_5$ *and the five detail coefficient* $\{\hat{D}_1, \hat{D}_2, \hat{D}_3, \hat{D}_4, \hat{D}_5\}$ *are calculated.*

3) The estimation of the wind speeds for year 2018 is accomplished by:

$$\hat{x} = \hat{A}_5 + \hat{D}_1 + \hat{D}_2 + \hat{D}_3 + \hat{D}_4 + \hat{D}_5 \quad (7)$$

Where $\hat{x} = (\hat{x}_1, \hat{x}_2, \hat{x}_3, \ldots, \hat{x}_N)$ represents the estimated wind speed data series.

4) To select the optimal wavelet according to the forecasting precision, the mse is computed:

$$mse = \|x - \hat{x}\|^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \quad (8)$$

5) Steps 1-4 are performed using all the wavelets.

Firstly, employing all the wavelets, the fifth decomposition level has been found to be the most optimal one that that leads practically to the highest wind speed prediction precision. To overcome the inherent influence of initial weight random assignment when training the NN, the simulation procedure is executed a hundred times with different initializations and the best results will be saved.

Among all the used wavelets, the db4, db7, sym4, coif3, coif5 and bior3.7 wavelets have performed better in terms of ***mse*** as reported in Table1. Moreover, it can be noted that the db4, with the least number of filter coefficients, presents a forecasting performance with a ***mse*** of almost 0.026. Fig. 7 depicts the measured and the predicted wind time series curves, where it can be seen that they nearly coincide, indicating that the proposed scheme may accurately predict a one-day ahead wind speed.

TABLE I. THE *MSE* VALUES USING A 5-LEVEL DWT DECOMPOSITION.

	Wavelet type					
	db4	**db7**	**Sym4**	**Coif3**	**Coif5**	**bior3.7**
mse	0.026	0.035	0.026	0.028	0.022	0.039

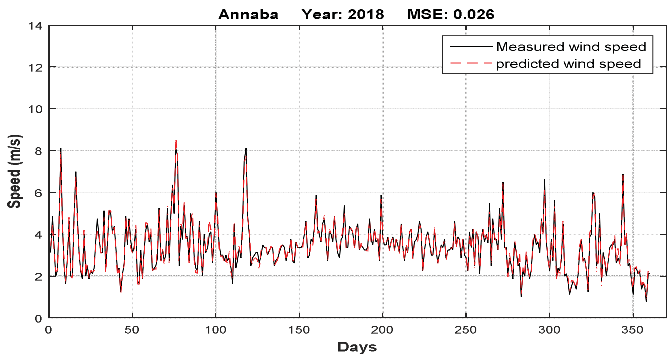

Fig. 7. Forecasting results using DWT db4 at decomposition level 5.

VI. CONCLUSION

Wind speed forecasting is very important in electric power management. Accordingly, various research works have suggested different methods for predicting the speed of wind, where different studies have proven that their efficiency rely a lot on the data preprocessing phase. This works examines the issue of forecasting one-ahead average daily wind speed using DWT combined with ANN. The DWT decomposes the wind speed signal into several sub-series to obtain a smooth signal and hence improve the precision of forecasting. Different wavelets, namely Daubechies, Coiflet and Symlet, have underwent tests using the wind speed values gathered from 2007 to 2018 in the region of Annaba. The obtained results show that, the DWT ***db4*** at decomposition level 4 is relatively more suitable for wind speed prediction. Moreover, using the MSE index error, the suggested approach reveals good performance for average daily wind speed prediction.

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