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ORIGINAL ARTICLE

GA-based design of optimal discrete wavelet filters for efficient wind speed forecasting

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Abstract

Wind energy is getting more and more integrated into power grids, giving rise to some challenges because of its inherent intermittent and irregular nature. Wind speed forecasting plays a fundamental role in overcoming such challenging issues and, thus, assisting the power utility manager in optimizing the supply–demand balancing through wind energy generation. This paper suggests a new hybrid scheme WNN, based on discrete wavelet transform (DWT) combined with artificial neural network (ANN), for wind speed forecasting. More specifically, this work aims at designing the most appropriate discrete wavelet filters, best adapted to a one day ahead wind speed forecasting. The optimized DWT filters are intended to effectively preprocess the wind speed time series data in order to enhance the prediction accuracy. Using wind speed data collected from three different locations in the Magherbian region, the obtained simulation results indicate that the proposed approach outperforms other conventional wavelet-based forecasting structures regarding the wind speed prediction precision. Moreover, compared to the standard wavelet '*db4*' based approach, the optimized wavelet filter-based structure leads to a forecasting accuracy improvement, in terms of RMSE and MAPE index errors, that amounts to nearly 13% and 19%, respectively.

Keywords Wind power forecasting · Discrete wavelet transform · Genetic algorithm (GA) · Neural networks · Artificial intelligence

1 Introduction

Today, most of the energy supplies are covered by conventional electricity produced from fossil fuels, which are polluting and harmful to the environment. Thus, faced with growing needs for electrical energy, the global energy sector has to meet several challenges, especially climate change, inciting scientists to explore environmentally friendly solutions. Nowadays, renewable energies, considered as eco-friendly and very promising alternative solution because of their cleanness, endless and universally available energy sources, are occupying a more and more important place in the production of electrical energy. Among them, wind energy has experienced considerable growth and is regarded as an attractive alternative to conventional electric power [1]. Having numerous advantages, such as climate change mitigation, energy dependence reduction and contribution to sustainable development of many countries, wind energy could be considered as one of the cheapest forms of electricity in many markets. According to the statistics reported by the Global Wind Energy Council (GWEC), the cumulative installed capacity of global wind energy amounts to nearly 591.1 GW at the end of 2018 and will probably reach a capacity of about 817 GW by 2021 [2, 3]. However, due to the intermittency and random nature of wind energy production, many technical and economic challenges, such as energy generation planning and managing, arise [4]. Therefore, forecasting wind energy is crucial for optimizing power production and reducing the associated uncertainties. This will, effectively, facilitate and assist grid scheduling and electricity trading, thus ensuring an efficient supply/demand balance [5]. Wind speed forecasting can be very short-term forecasting (few minutes to 1 h ahead), short term (from 1 h to several hours ahead),

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medium term (from several hours to 1 week ahead) and long term (from 1 week to 1 year ahead) [6]. Recently, several wind forecasting techniques have been suggested for different time-scales, including physical, statistical, artificial intelligence and hybrids methods [6, 7]. The physical forecasting approaches use numerical weather prediction (NWP) to model the on-site conditions at the location of interest. Even though these techniques are efficient in wind prediction, they involve a large amount of numerical weather prediction data such as temperature, humidity, pressure and topological parameters [5]. Therefore, these methods are more appropriate for medium- and long-term forecasting horizons rather than for short-term prediction horizons [6]. The statistical approaches, quite simple compared to physical methods, employ historical time series data, at a given location, to model the wind speed signal for prediction purpose [6]. These approaches, based on probability, random process theory and statistics, use, generally, recursive linear models such as autoregressive (AR), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) as well as nonlinear models like NAR and NARMA, etc.[5, 6, 8]. Although statistical techniques outperform the physical approaches for very short and short time horizon wind speed prediction, yet their goodness of fit of nonlinear time series data could be further improved [9]. Artificial intelligence (AI)-based techniques, such as artificial neural networks (NNs), fuzzy logic, support vector machines (SVM), wavelet transformation and evolutionary computation like genetic (GA) and particle swarm optimization (PSO) algorithms, are commonly known for their effectiveness and abilities to handle nonlinear problems [6, 10–12]. Even though they are computationally costly, these machine learning methods, practically independent from the time series data, have recently gained much attention in prediction problems and wind speed forecasting issues [13].

To boost the forecasting efficiency, various hybrid methods have been suggested in the literature [3]. Involving the combination of different intelligent approaches with physical and statistical methods, the hybrid models tend to mix the advantages and characteristics of different methods with a view of achieving global optimum prediction performances [3, 13]. More specifically, the wavelet-based hybrid methods are among the most largely employed techniques, which employ the wavelet transform as a preprocessor for the time series data. It has been reported in the literature that several hybrid approaches, based on wavelet analysis, have been successfully implemented in various research works relevant to time series and wind energy forecasting. To predict hourly ozone concentrations, Salazar et al. [8] propose a forecasting scheme using the Haar discrete wavelet transform (HDWT) with ARIMA models. It has been shown that combining HDWT with ARIMA models leads to higher forecasting accuracies than those obtained by the simple application of the ARIMA models. In [14], a hybrid time series forecasting structure (PCA-WCCNN), combining neural network, wavelet transform (WT) and feature extraction based on principal component analysis (PCA), is examined. Priyanka and Ranjit [15] examine two wavelet-based neural network approaches, viz. wavelet-ANN and wavelet neural model (WNM) in order to forecast agricultural prices. Catalão et al. [16] examined the issue of using the wavelet transform in combination with artificial neural network for short-term wind energy forecasting in Portugal. The developed NNWT scheme, based on the db4 wavelet, has been compared against ARIMA, persistence and NN approaches and has exhibited relatively better performances. A hybrid scheme (W-SVM-GA) combining wavelet transform with SVM has been suggested in [17]. The underlined approach employed the genetic algorithm (GA) to optimize the SVM parameters in order to enhance the prediction accuracy. Compared with a persistent model and a SVM-GA approach without DWT, the proposed method shows relatively better results. Paras et al. [18] presented a hybrid intelligent algorithm using meteorological information for short-term wind energy production forecasting in the southern part of Alberta, Canada. The proposed technique (WT + NNPSO) employs DWT for data filtering with a PSO-optimized neural network. Using db4 as the mother wavelet, and compared with other soft computing models, the suggested scheme exhibits good performances in terms of wind power forecasts. In [9], the authors proposed a hybrid forecasting model named as the MOGWO–WPD-AdaBoost, where different discrete wavelets, namely db1, db3, db5, db7, db9, have been investigated according to their impact in preprocessing the training data. In [6], Aasim et al. suggested a wavelet-based technique called WT-ARIMA. The approach decomposes the wind speed data using the db2 based maximum overlap DWT. Compared to ARIMA and persistence methods, the proposed scheme presents better results in forecasting the wind speed. Berrezzek et al. [19] combined the discrete wavelet transform (DWT) with ANN for wind energy prediction in three different regions. Using various wavelet families, it has been found that the db4 mother wavelet gives relatively the best performances regarding the forecasting accuracy. In [20], the authors proposed a hybrid intelligent approach for wind power probabilistic forecasting using the krill herd optimization algorithm. The technique involves the 'db4' wavelet transform preprocessor combined with a single-hidden-layer feedforward neural networks (SLFNs).

It is believed that the design of optimal wavelets for a specific application could significantly boost the performances. Sherlock and Monro have successfully used this approach to obtain optimal wavelets for the compression of fingerprint [21]. Daamouche et al., using the PSO algorithm, optimized wavelet filters for classification of hyperspectral images [22] and ECG signals [23]. To the best of our knowledge, all the reported research works have not examined the issue of designing specific wavelets adapted to wind speed time series forecasting. The present work suggests a novel hybrid forecasting scheme, where the question of the design of the most suitable wavelet filters combined with ANN for wind speed prediction is addressed. Using the genetic algorithm, the wavelet filter design optimization is accomplished based on the Sherlock and Monro [24] iterative algorithm that allows parameterizing the space of orthonormal wavelet filters, which is adapted from the Vaidyanathan parameterization of perfect reconstruction two-channel filter banks [25]. The rest of this paper is structured as follows. Section 2 introduces the basic concepts of the wavelet transform, the polyphase representation of wavelet filter, the genetic algorithm and the neural networks. In Section 3, the proposed forecasting scheme along with the wavelet filter design process is presented. Section 4 gives and discusses the forecasting results with a comparative analysis. Finally, the conclusion remarks are provided in Sect. 5.

2 Methodology

2.1 DWT and wavelet design

The wavelet transform (WT) is an efficient signal processing tool that can be divided into two types: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). Adopting a mother wavelet $\psi(t)$, the CWT of a function $x(t)$ may be expressed as [26]:

$$\mathrm{CWT}(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right)\mathrm{d}t \tag{1}$$

where $*$ denotes the complex conjugate and a and b are the scale and translation coefficients, respectively. A more computationally efficient form of the CWT is the DWT given by [26]:

$$\mathrm{DWT}(j,k) = \frac{1}{\sqrt{2^j}} \int x(t)\psi^{*}\left(\frac{t-k2^j}{2^j}\right)\mathrm{d}t \tag{2}$$

where $a = 2^j$ and $b = k2^j$ are the dyadic sampling of the dilation and translation coefficients, respectively, and $(j,k) \in \mathbb{Z}^2$ represent the decomposition level and the translation factor, respectively. Generally, DWT is performed by employing the recursive Mallat multiresolution algorithm [27] through the use a pair of a low-pass (LP) and high-pass (HP) quadrature mirror filters (QMF), with impulse responses given by $h(n)$ and $g(n) = (-1)^n h(1-n)$, respectively [26]. The design of these two wavelet filters is usually conducted using the mother wavelet $\psi(t)$ and its corresponding scaling function $\phi(t)$ [26]:

$$\begin{cases} \phi(t)) = \sqrt{2}\sum_n h(n)(2t-n) \\ \psi(t) = \sqrt{2}\sum_n g(n)(2t-n) \end{cases} \tag{3}$$

Practically, the DWT decomposition, at level M, of a time series sequence $x(t) = (x_1, x_2, x_3, \ldots, x_K)$ is implemented by letting the signal go through M LP and HP wavelet filters $h(n)$ and $g(n)$, giving rise to one approximation A_M coefficient vector and M detail coefficient vectors $D_j (1 \le j \le M)$ expressed by Eq. (4) [28], and depicted in Fig. 1, for the case of $M = 3$.

$$\begin{aligned} \boldsymbol{x}(\boldsymbol{t}) &= \boldsymbol{A_M}(\boldsymbol{t}) + \sum_{j=1}^{M} \boldsymbol{D_j}(\boldsymbol{t}) \\ &= \sum_n \boldsymbol{a_{M,n}}(\boldsymbol{t}-\boldsymbol{n}) + \sum_{j=1}^{M}\sum_n \boldsymbol{d_{j,n}}\boldsymbol{\psi}(2^j\boldsymbol{t}-\boldsymbol{n}) \end{aligned} \tag{4}$$

It can be shown that the approximation and detail coefficients can be recursively calculated by [26]:

$$\begin{cases} \boldsymbol{a_{m,n}} = \sum_k \boldsymbol{h}[\boldsymbol{k}-2\boldsymbol{n}]\boldsymbol{a_{m-1,n}} \\ \boldsymbol{d_{m,n}} = \sum_k \boldsymbol{g}[\boldsymbol{k}-2\boldsymbol{n}]\boldsymbol{a_{m-1,n}} \end{cases} \tag{5}$$

Generally, the design of optimum wavelet depends on the problem under consideration and can be tackled in various ways. In this regard, Sherlock and Monro [24], based on Vaidyanathan factorization [25], devised an attractive polyphase method [29] allowing the determination of the coefficients of a filter bank. This algorithm enables the generation of any orthonormal perfect reconstruction FIR filters of any specific length. A brief explanation of the method is described. Let $H_0(z)$ be the $\mathbb{Z}$ transform, written in terms of even and odd powers of z, of

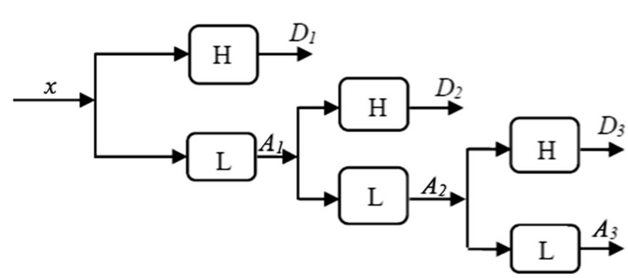


Fig. 1 DWT decomposition at level three

a low-pass analysis FIR filter with $2N$ coefficients $\{h_i\}$, expressed by [24]:

$$\begin{aligned} H_0(z) &= \sum_{i=0}^{2N-1} h_i z^{-i} \\ &= \sum_{i=0}^{N-1} h_{2i} z^{-2i} + z^{-1} \sum_{i=0}^{N-1} h_{2i+1} z^{-2i} \\ &= H_{00}\left(z^2\right) + z^{-1} H_{01}\left(z^2\right) \end{aligned} \tag{6}$$

where $H_{00}(z)$and$H_{01}(z)$ are the polyphase components of $H_0(z)$. The polyphase matrix of a two-channel filter bank may be formulated as [24]:

$$H_{poly}(z) = \begin{pmatrix} H_{00}(z) & H_{01}(z) \\ H_{10}(z) & H_{11}(z) \end{pmatrix} \tag{7}$$

With $H_{10}(z)$ and $H_{11}(z)$ representing the polyphase components of the high-pass analysis filter. Vaidyanathan suggested the following polyphase matrix factorization [25]:

$$H_{poly}(z) = \begin{pmatrix} c_0 & s_0 \\ -s_0 & c_0 \end{pmatrix} \prod_{i=1}^{N-1} \begin{pmatrix} 1 & 0 \\ 0 & z^{-1} \end{pmatrix} \begin{pmatrix} c_i & s_i \\ -s_i & c_i \end{pmatrix} \tag{8}$$

where $c_i = \cos(\theta_i)$ and $s_i = \sin(\theta_i)$. Sherlock et al. [24] reformulated the factorization leading to a recursive calculation of the low-pass filter coefficients:

$$\begin{cases} h_0^{(k+1)} = c_k h_0^k \\ h_{2i}^{(k+1)} = c_k h_{2i}^{(k)} - s_k h_{2i-1}^{(k)} \; i = 1, 2, \ldots, k-1 \\ h_{2k}^{(k+1)} = -s_k h_{2k-1}^{(k)} \end{cases}$$

where $h_0^{(1)} = c_0$ and $h_1^{(1)} = s_0$, and the odd filter coefficients $\{h_{2i+1}\}$ are defined by:

$$\begin{cases} h_1^{(k+1)} = s_k h_0^{(k)} \\ h_{2i+1}^{(k+1)} = s_k h_{2i}^{(k)} + c_k h_{2i-1}^{(k)} \quad i = 1, 2, \ldots, k-1 \\ h_{2k+1}^{(k+1)} = c_k h_{2k-1}^{(k)} \end{cases} \tag{10}$$

For a filter of length $2N$, the LP coefficients $\{h_0, h_1, \ldots, h_{2N-1}\}$ are determined using Eqs. (9) and (10) in terms of N random angular parameters $\{\theta_0, \theta_1, \ldots, \theta_{N-1}\}$ chosen in the interval$[0, 2\pi[$. The coefficients of the HP filter are found by flipping and sign-alternating as [24]:

$$g_i = (-1)^{i+1} h_{2N-1-i} \tag{11}$$

2.2 Genetic algorithm

Genetic algorithm (GA), suggested by John Holland et al. at the end of 1960s, is a powerful stochastic algorithm of nonlinear global optimization that is inspired by natural selection mechanism, and based on the principles of evolution and natural selection mechanisms: survival of the fittest. It is very appropriate for optimizing complex problems due to its simplicity and robustness, and it has been largely used in various optimization fields such as forecasting [3, 17]. Initially, GA begins with a set of random solutions (chromosomes or individuals) called initial population. The fitness of each chromosome is evaluated with respect to a predefined cost function. After specific operations, including selection, crossover, and mutation, chromosomes with lower fitness are discarded and a new population is obtained. These operations are iterated until the solution satisfies certain stopping criteria. In other words, GA begins searching from several points and progresses toward an optimal solution. In this paper, the genetic optimization algorithm is utilized to look for the appropriate angular parameters $\theta_i^{'}s$ relevant to the polyphase representation of the wavelet filters to enhance the neural network based wind speed prediction accuracy.

2.3 Neural networks

Artificial neural networks (ANN), based on biological neurons, are complex intelligent structures known to be a powerful tool providing good solutions to problems that cannot be solved analytically and represent an attractive technique in handling nonlinear problems such as time series forecasting [3, 30]. It is made up of a number of interconnected simple processing elements, called neurons, designed in a manner to model the human brain way of thinking to perform a specific task. Each of those elements constitutes a weighted sum of its inputs, to which a constant bias is added. This sum is then fed to an activation function, and output data are transferred to other neurons. Generally, ANN is composed of an input layer, hidden layers and an output layer, where each layer is fully connected to the adjacent layer via interconnection weights w_{ij}. Figure 2 depicts the adopted architecture of the ANN

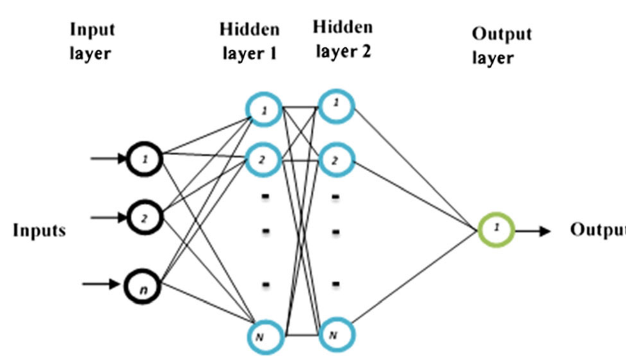


Fig. 2 Structure of the neural network

having n inputs, two hidden layers with N neurons each and one output layer. Multilayer perceptrons (MLP) feedforward back propagation neural network (BPNN) are among the most widely used types of ANN having a relatively simple structure making it easily realizable. In this work, dealing with wind speed forecasting, all the weights w_{ij} among the network layers are properly adjusted with respect to the prediction accuracy. A MLP feedforward network, trained using Levenberg–Marquardt algorithm, is adopted, where the transfer functions used for the hidden and output layers are tangent sigmoid '*tansig*' and Log sigmoid '*logsig*', respectively.

3 The proposed intelligent hybrid forecasting scheme

3.1 Overview of the prediction scheme

This work suggests the use of discrete wavelet transform (DWT) and neural network for wind speed forecasting. In order to assess the proposed wind speed forecasting scheme, daily wind speed data from 2007 to 2018 for three Magherbian regions, namely Annaba, Sidi Bouzid and Tetouan, have been collected and employed [31]. Generally, data preprocessing plays a crucial role in improving the wind speed prediction accuracy [17]. In this study, the preprocessing phase is mostly based on wavelet analysis. To underline the importance of using the DWT, Figs. 3 and 4 show, respectively, the average daily wind speed and the DWT decomposition at level $L = 5$ for the region of Annaba. It is noteworthy that the approximation coefficient A_5 (Fig. 4), representing about 91% of the total energy of the wind speed signal, shows a smooth and slowly varying curve that could lead to a prediction with noticeable error reduction.

The proposed forecasting structure (WNN) based on DWT and ANN is shown in Fig. 5, where the wind speed signal undergoes the following preprocessing steps:

- The collected wind speed signal outliers are detected and discarded for appropriate NN training.
- Wind speed data are averaged to obtain daily mean speeds.
- DWT is applied on the time series data to diminish the wind speed inherent fluctuations and boost further the forecasting accuracy.

Using the genetic algorithm, the wavelet filters are optimized and an L-level DWT decomposition is applied to the preprocessed wind speed sequence to generate L detail coefficients $\{D_1, D_2, \ldots, D_L\}$ and an approximation coefficient A_L. Note that each DWT transformed coefficient has its own neural network for prediction. Thus, for a decomposition level equal to L, the number of NNs to use as predictors is $L + 1$.

The adopted hybrid forecasting approach uses w previous daily average wind speeds, corresponding to days $d, d-1, \ldots, d-w+1$, to predict day d + 1) average wind speed. Thus, the number of inputs for each NN is dictated by the number of previous days employed to forecast the average wind speed of the next day. In other words, this proposed hybrid WNN forecasting scheme accomplishes a one-step prediction with a lag equal to w.

Using the $(L+1)$ NNs, estimates of the approximation coefficient $\hat{A}_L$ and the L detail coefficients $\{\hat{D}_1, \hat{D}_2, \ldots, \hat{D}_L\}$ are computed, and then the wind speed sequence $\hat{x} = (\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_K)$ is reconstructed:

$$\hat{x} = \hat{D}_1 + \hat{D}_2 + \ldots + \hat{D}_L + \hat{A}_L \tag{12}$$

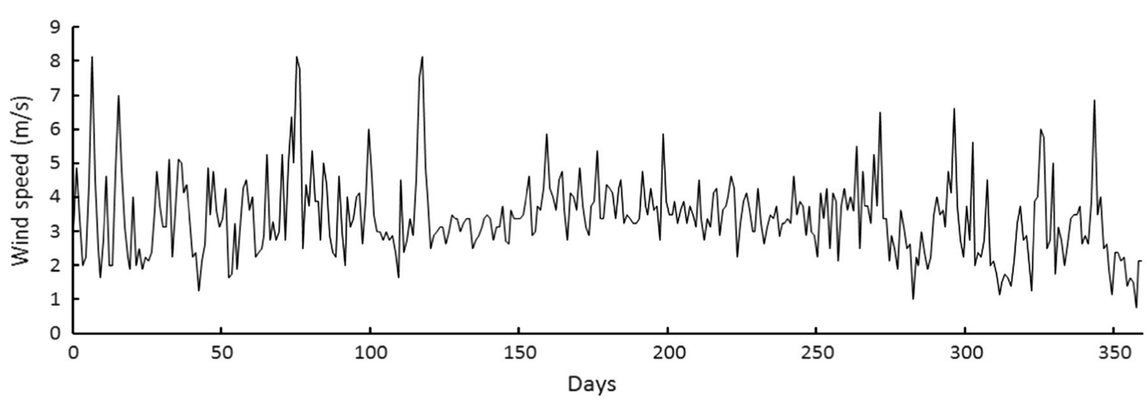


Fig. 3 Average daily wind speed data for the region of Annaba, year 2018

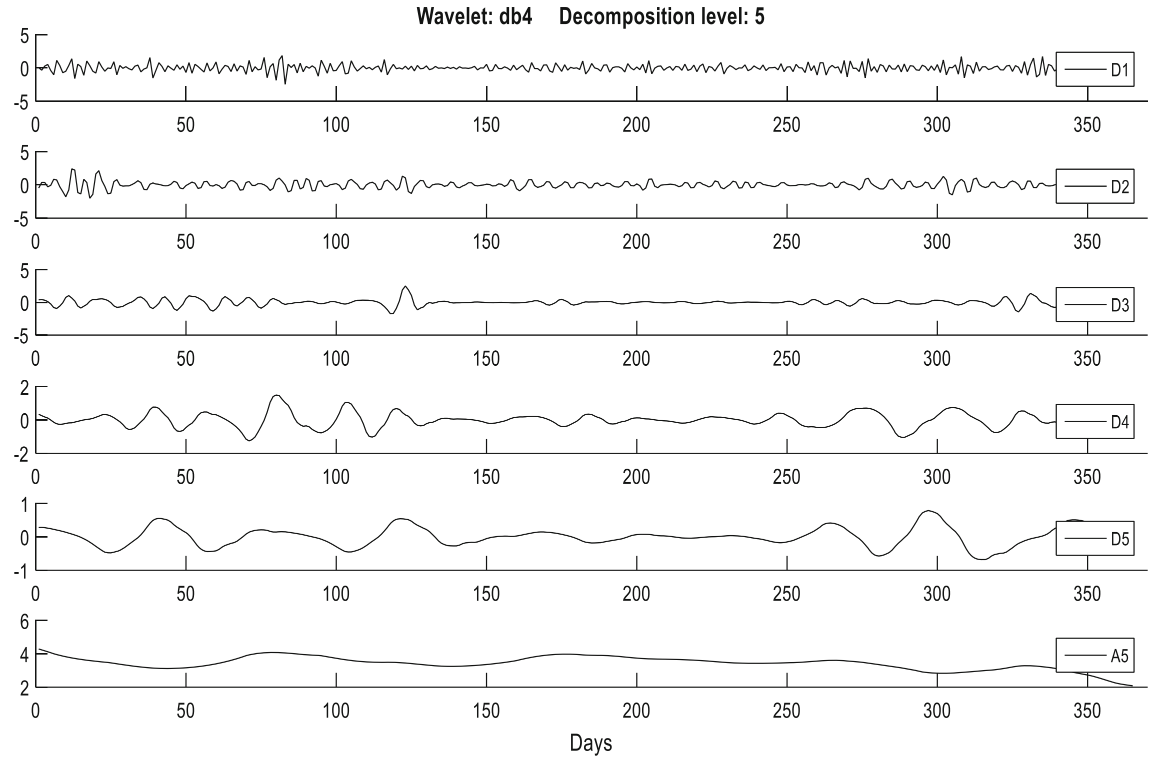


Fig. 4 DWT decomposition at level 5 of wind speed signal, Annaba, year 2018

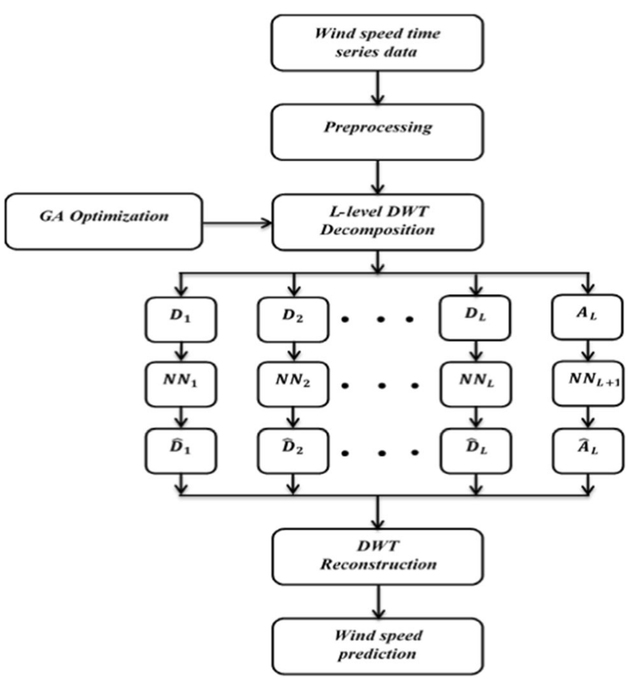


Fig. 5 The WNN hybrid forecasting scheme

3.2 Wavelet filter design process

Wavelets, essentially developed for general-purpose signal processing algorithms, have been widely and successfully utilized in different signal analysis problems, including wind energy forecasting. Furthermore, it has been revealed that a higher wind speed prediction precision could be obtained when wavelet transform is employed in the preprocessing phase. It is believed that the wavelet performances could be enhanced further if the wavelet filters are designed with respect to the prediction accuracy. Thus, based on the polyphase representation described in Sect. 2.1, we suggest to design the wavelet filters using the GA algorithm, where the chromosomes are represented by the free parameters θ_i, and the wind speed forecasting accuracy is considered as the objective function. The flowchart of Fig. 6 outlines, for a fixed pair of filter order and decomposition level (N, L), the wavelet filter optimization process. Thus, the WNN scheme design steps are carried out as follows:

1. Initialize the wavelet filter order N_{min}.
2. Initialize the DWT decomposition level L_{min}.
3. Generate an initial random population of 25 chromosomes, where each chromosome is made up of an angular position vector $\{\theta_0, \theta_1, \ldots, \theta_{N-1}\}$ randomly chosen within $[0, 2\pi[$.
4. For each chromosome calculate the corresponding fitness function as follows:

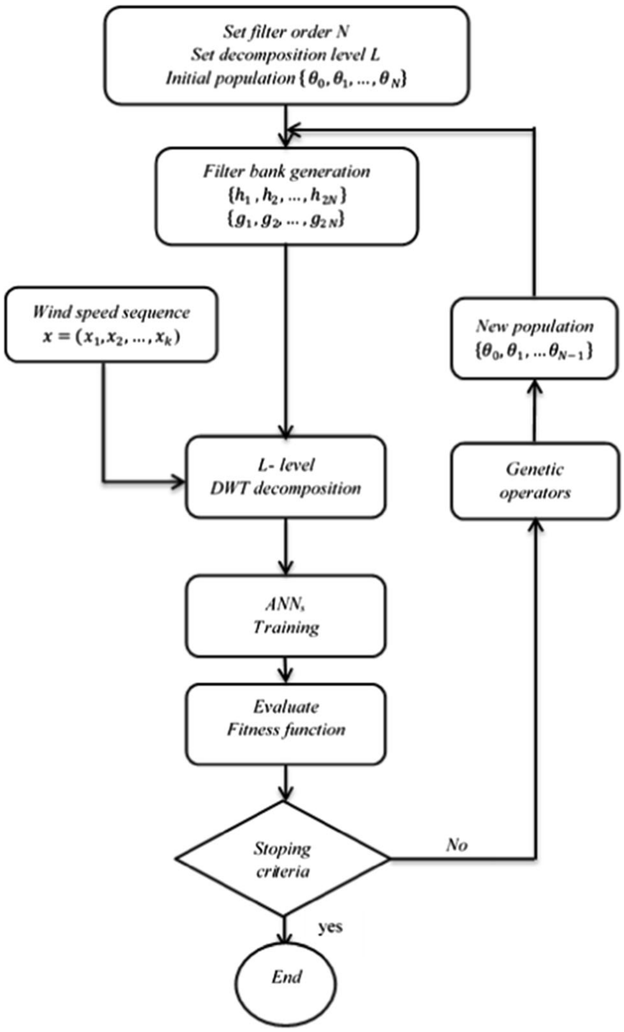


Fig. 6 Wavelet filter design flowchart

a. Determine the HP filter coefficients $\{g_1, g_2, \ldots, g_{2N}\}$ using Eq. (11): $g_i = (-1)^{i+1} h_{2N-1-i}$.
b. Using the derived LP and HP analysis filters apply the *L-level* DWT decomposition to the wind speed sequence $x = (x_1, x_2, \ldots, x_K)$ to generate the detail and approximation coefficients $\{D_1, D_2, \ldots, D_L, A_L\}$.
c. Train the $(L + 1)$ *NNs*, and apply each generated coefficient to its corresponding *NN* to obtain the $(L + 1)$ estimated coefficients $\{\hat{D}_1, \hat{D}_2, \ldots, \hat{D}_L, \hat{A}_L\}$.
d. Estimate the wind speed time series sequence $\hat{x} = (\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_K)$ using Eq. (12).
e. Evaluate the cost function given by the mean square error (*MSE*):

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

5. Create the next generation: Using the roulette wheel mechanism, a proportion of individuals in the current population are selected according to their objective function. Then, the next generation is created using genetic operators, namely crossover, mutation and reproduction. Scattered crossover with a crossover fraction set to 0.8 is employed. A Gaussian mutation and an elitism mechanism are also considered. The iteration procedure is repeated until one of the stopping criteria is achieved.
6. The above steps 4 and 5 are repeated until a certain termination condition is satisfied. Note that when there is no more significant enhancement in the forecasting accuracy, during 20 consecutive iterations, convergence is considered.
7. Update the decomposition level:

   $L_{\min} \leftarrow L_{\min} + 1.$
8. Repeat steps 3–6.
9. Update the filter order $N_{\min} \leftarrow N_{\min} + 1$
10. Iterate steps 3–6.

Finally, the pair of values (N, L) belonging to the intervals $[N_{\min}, N_{\max}]$ and $[L_{\min}, L_{\max}]$ leading to the best forecasting accuracy is considered.

4 Simulations Results and discussion

To assess the performances of a given forecasting model, numerous error measures are employed. In this study, the predicting accuracy of the proposed WNN scheme is evaluated using the root mean square error (RMSE) and the mean absolute percentage error (MAPE) whose expressions are, respectively, given by Eqs. (13) and (14):

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{N}} \tag{13}$$

$$\text{MAPE} = \frac{100\%}{N} \sum_{i=1}^{N} \left| \frac{x_i - \hat{x}_i}{x_i} \right| \tag{14}$$

where x_i and $\hat{x}_i$ represent the measured and estimated wind speed data, respectively. Note that, in all the executed simulations, and in order to avoid the effect of random initialization, the neural network training process is repeated 20 times and the best results are considered.

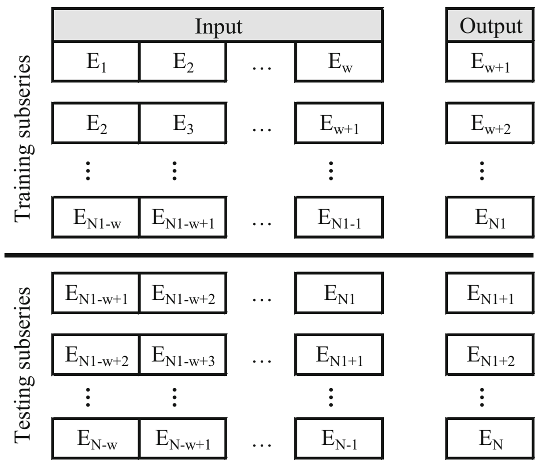


Fig. 7 Training and testing data format

4.1 Dataset setup

In this work, using the collected data (years 2007–2018) of the three regions (Annaba, Sidi Bouzid and Tetouane) [31], where years 2007–2017 data (4015 samples) are used for training the neural network, and the remaining 365 samples of year 2018 are employed for testing the *NN*. For training and testing the neural network predictor, the dataset selection technique is explained in the following. If the forecasting is based on a lag of *wdays*, then the *NN* has *w* inputs. Let $\{E_i, i = 1, 2, \ldots, N\}$ be the entries of every *L-level* DWT transformed coefficient $\{D_1, D_2, \ldots, D_L, A_L\}$ of size *N*, where *N1* samples are used for training and the remaining samples for testing. Figure 7 illustrates the adopted strategy to create the training and testing subseries of the $(L + 1)$ *NNs*.

4.2 Parameter selection and forecast results

Firstly, for the one-step-ahead forecasts, we have conducted a thorough investigation using a variable length lag of *w* days, practically all the standard orthogonal wavelets with different DWT decomposition levels. It has been found that the Daubechies wavelet '*db4*' with a decomposition level $L = 5$ and a sliding window *w* = *5* outperforms all the other schemes in terms of forecasting accuracy [19]. Reporting only certain wavelets who exhibit good performances, Table 1 and Figs. 8 and 9 show clearly that '*db4*' with $(L, w) = (5, 5)$ surpasses mostly all the other wavelets in terms of RMSE and MAPE errors. Moreover, the prediction performances using '*db4*' is confirmed as shown in Fig. 10 for the region of Annaba, where the predicted wind speed is in a good agreement with the actual wind speed.

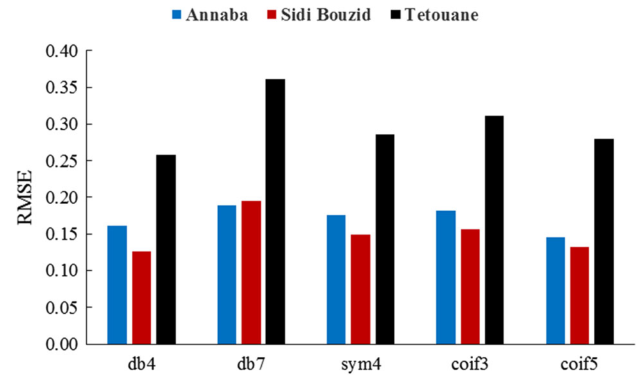


Fig. 8 RMSE values for various wavelets

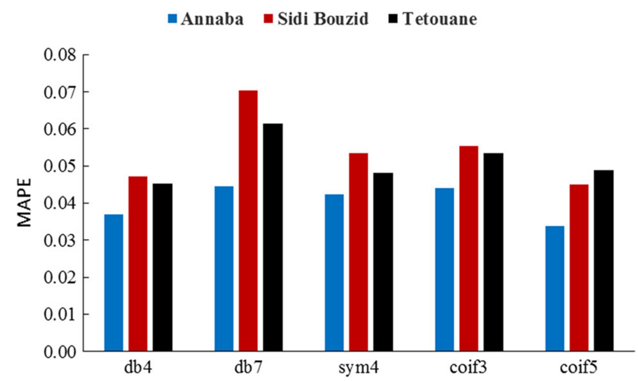


Fig. 9 MAPE values for various wavelets

Table 1 RMSE and MAPE values using the 5-level DWT decomposition for various wavelets

	db4		*db7*		*sym4*		*coif3*		*coif5*	
	RMSE	MAPE (%)	RMSE	MAPE (%)	RMSE	MAPE (%)	RMSE	MAPE (%)	RMSE	MAPE (%)
Annaba	0.1612	3.71	0.1891	4.44	0.1763	4.24	0.1819	4.41	0.1454	3.39
Sidi Bouzid	0.1265	4.71	0.1946	7.05	0.1494	5.35	0.1569	5.55	0.1317	4.50
Tetouane	0.2576	4.51	0.3616	6.15	0.2859	4.81	0.3113	5.35	0.2804	4.88

Fig. 10 Measured and estimated wind speed using the '*db4*' wavelet with 5-level decomposition for Annaba region

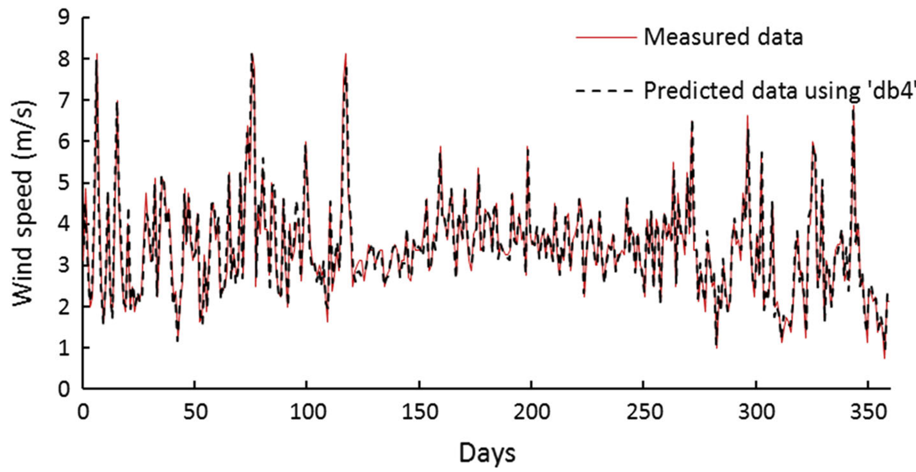


Table 2 RMSE and MAPE versus decomposition level

Decomposition level	Annaba		Sidi Bouzid		Tetouane	
	RMSE	MAPE (%)	RMSE	MAPE (%)	RMSE	MAPE (%)
1	0.3144	7.27	0.2460	8.64	0.5124	8.02
2	0.1814	4.42	0.1460	5.64	0.3535	6.16
3	0.1706	4.01	0.1331	4.81	0.4537	5.83
4	0.1909	4.51	0.1493	5.39	0.3055	5.15
5	0.1612	3.71	0.1265	4.71	0.2576	4.51
6	0.1760	4.31	0.1393	4.85	0.2814	4.84
7	0.1848	4.23	0.1263	4.46	0.2678	4.93
8	0.1832	4.30	0.1395	5.04	0.3007	5.34
9	0.1760	4.00	0.1259	4.81	0.2484	4.66
10	0.2074	4.80	0.1311	4.64	0.2710	4.68

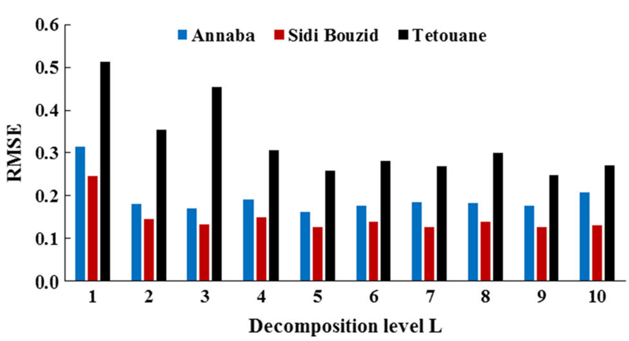


Fig. 11 RMSE versus decomposition level

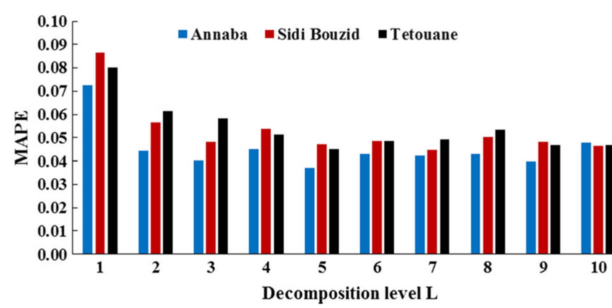


Fig. 12 MAPE versus decomposition level

Knowing that, in our proposed WNN predicting structure, the DWT decomposition level L not only imposes the number of NNs (equal to $L + 1$) to be employed, but also does affect the forecasting accuracy. The RMSE and MAPE values versus the decomposition level L, reported in Table 2 and Figs. 11, 12, indicate that a decomposition level $L = 5$, is indeed an optimal choice for our suggested scheme.

Using '*db4*' DWT decomposition with $L = 5$, several experimental simulations have been carried out with different prediction lags. Consequently, from the obtained results shown in Table 3 and Figs. 13, 14, it can be

Table 3 RMSE values in terms of the prediction lag

Lag w	Annaba		Sidi Bouzid		Tetouane	
	RMSE	MAPE (%)	RMSE	MAPE (%)	RMSE	MAPE (%)
1	0.7666	18.03	0.7222	24.87	1.3913	24.68
2	0.4938	11.57	0.453	16.37	0.883	14.82
3	0.3128	7.02	0.2789	9.96	0.5394	9.35
4	0.2199	5.32	0.1899	6.9	0.3529	6.31
5	0.1612	3.71	0.1265	4.71	0.2576	4.51
6	0.1672	3.85	0.1349	4.71	0.2857	4.36
7	0.188	4.68	0.1382	5.21	0.2821	4.62
8	0.1651	3.85	0.1326	4.35	0.2400	4.03

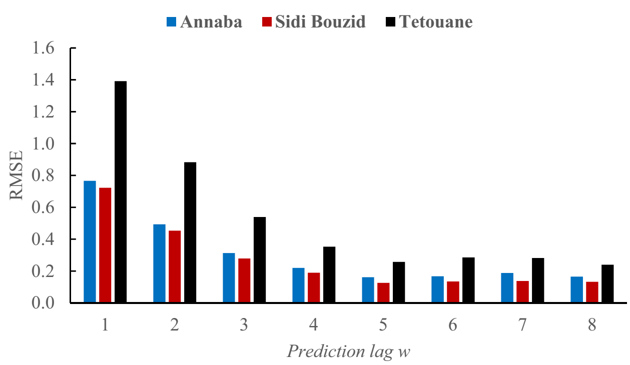


Fig. 13 RMSE versus prediction lag w

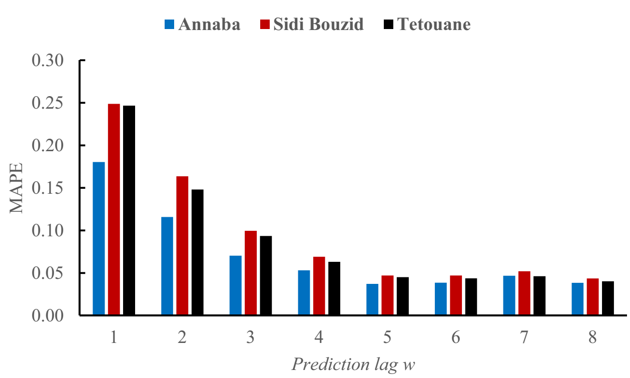


Fig. 14 MAPE versus prediction lag w

concluded that, effectively, a lag of $w = 5$ seems to be an appropriate choice for our proposed prediction approach.

4.3 Wavelet design forecasting results

Recall that the obtained optimal WNN predicting structure uses '*db4*', a decomposition level $L = 5$ and a lag of $w = 5$ days. This work aims at improving the forecasting accuracy by designing wavelet filters appropriate to wind speed signals. Thus, using the design process explained in Sect. 3.2 and illustrated by the flowchart of Fig. 6, the obtained simulation results show that wavelet filters of order 8, whose obtained coefficients are reported in Table 4, with a decomposition level $L = 5$ and a predicting lag of $w = 5$ days lead to the highest forecasting accuracy with respect to other WNN schemes (with different decomposition level L and lag w).

The performances of the designed WNN scheme are compared to the '*db4*'-based WNN system in terms of the RMSE and MAPE error values. To compute the error difference e_{dif} between the two schemes, we have proposed to use the following formula:

$$e_{dif} = \frac{e_{dw} - e_{db4}}{e_{dw}} \times 100\% \tag{15}$$

where e_{dw} and e_{db4} denote the RMSE or the MAPE error value of the 'designed wavelets' and the '*db4*' based

Table 4 Designed Low-pass wavelet filter coefficients for the three regions

	Designed wavelet filter coefficients							
Annaba	− 0.06283	− 0.02158	0.67564	0.72742	0.09842	− 0.01075	− 0.00413	0.01201
Sidi Bouzid	0.00044	0.00212	− 0.02418	− 0.07734	0.48112	0.83477	0.24972	− 0.05245
Tetouane	0.00768	0.00159	− 0.10575	0.17525	0.79779	0.56591	0.00739	− 0.03565

Table 5 RMSE and MAPE values for the '*db4*' and 'designed wavelets'-based WNN schemes for the three regions

	RMSE		MAPE (%)	
	db4	Designed wavelets	*db4*	Designed wavelets
Annaba	0.161[2]	0.149	3.71	3.16
Sidi Bouzid	0.1265	0.097	4.71	3.53
Tetouane	0.2576	0.2385	4.51	3.79

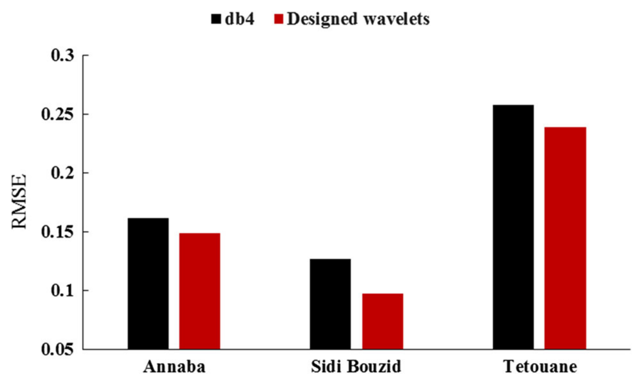


Fig. 15 Comparison between RMSE values for the '*db4*' and 'designed wavelets' based WNN schemes

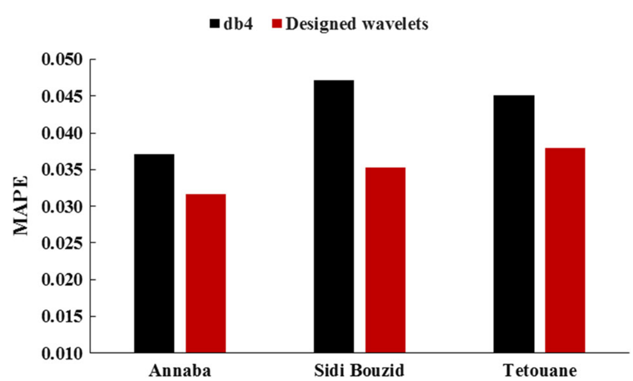


Fig. 16 Comparison between MAPE values for the '*db4*' and 'designed wavelets' based WNN schemes

forecasting structures, respectively. From the obtained results, presented in Table 5 and depicted in Figs. 15, 16, the superiority of the designed wavelets can be easily observed, where an average error difference in RMSE and MAPE of nearly 13% and 19% respectively, is achieved. Furthermore, to illustrate the efficiency of the proposed forecasting scheme, the estimated and the measured wind speeds, using the designed wavelets, for the three regions are depicted in Fig. 17. It can be easily noticed that the forecasted and the actual speed data curves show a high degree of similarity for the entire year 2018. In addition, to further verify the effectiveness of the suggested method over the '*db4*' based approach, Figs. 18, 19, 20 present a closer look, for one month forecasting period, for the three considered regions, where a noticeable improvement in the forecasting accuracy, with respect to the '*db4*' based structure, can be easily observed.

5 Conclusion

A novel hybrid approach based on discrete wavelet transform and artificial neural networks has been presented for wind speed forecasting. More particularly, this work examines the issue of optimizing the DWT filters combined with ANN in order to boost further the wind speed predicting accuracy. Using wind speed data collected from three different Magherbian regions during 2007–2018, the assessment of the proposed forecasting model is conducted in terms of wind speed predicting precision through error indices, namely the RMSE and MAPE. Some conclusions and contributions of this research are summarized as follows.

(1) The new proposed scheme is based on the design of wavelet filters, best adapted to wind speed signal, using the polyphase wavelet filter representation.

(2) The DWT filters, intended to preprocess the wind speed signal, are optimized using the genetic algorithm with respect to the wind speed forecasting accuracy.

(3) A deep investigation has clearly shown that the '*db4*' wavelet with a decomposition level $L = 5$, practically, outperforms almost all the other standard discrete wavelets.

(4) It has been confirmed that the neural network predictor could lead to higher predicting accuracy if the signal is effectively preprocessed.

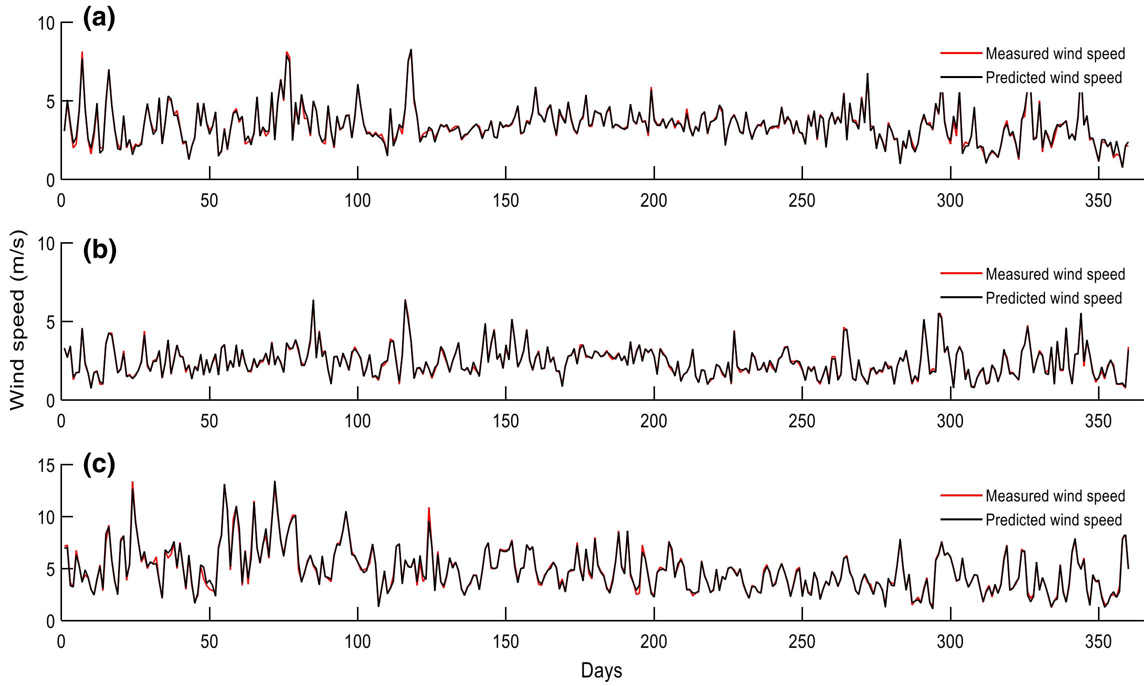
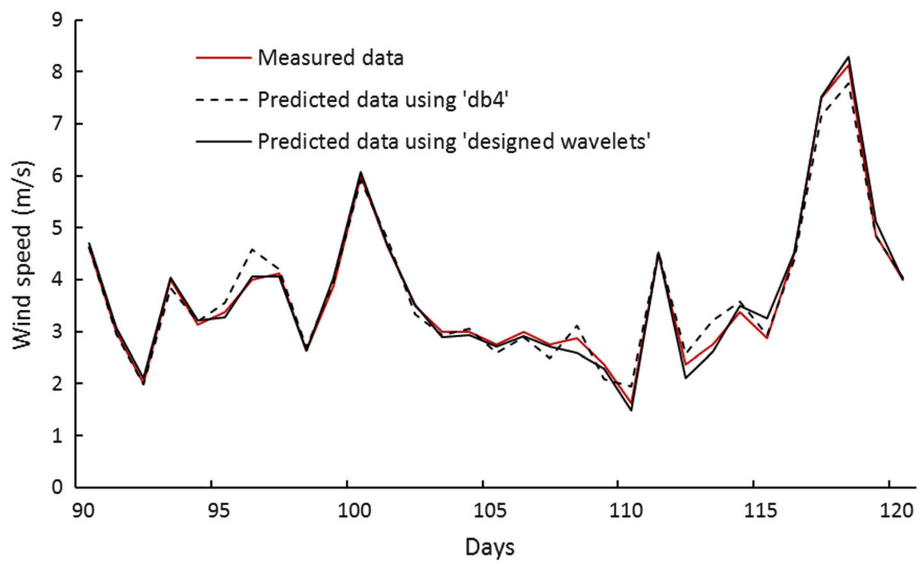


Fig. 17 Wind speed forecasting using designed wavelets for the year 2018, **a** Annaba, **b** Sidi Bouzid, **c** Tetouane

Fig. 18 Wind speed forecasting using designed wavelets for the region Annaba during one month



(5) Using the PSO optimized wavelet filters for preprocessing the wind speed signal, the developed WNN scheme is compared to the ‘*db4*’ based predicting system. The obtained simulation results show that the new suggested forecasting approach surpasses the ‘*db4*’ based structure, where an enhancement, in terms of the error metrics RMSE and MAPE of about 13% and 19%, respectively, is achieved.

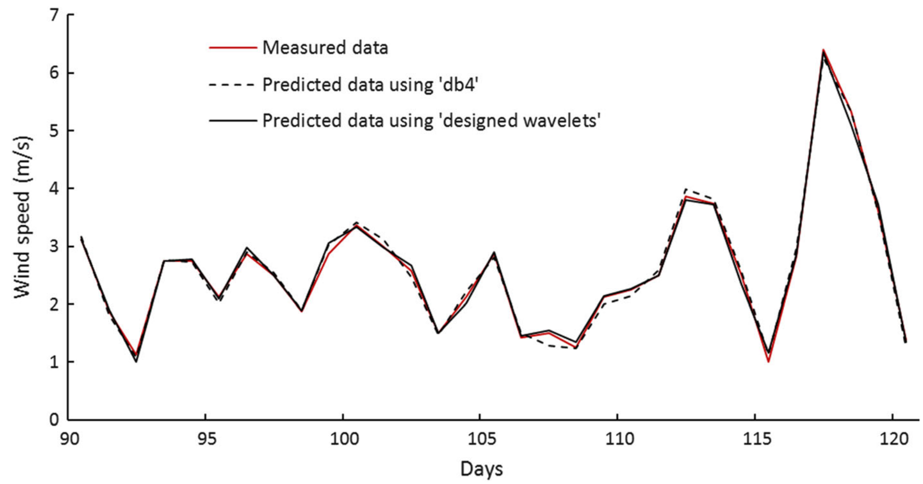


Fig. 19 Wind speed forecasting using designed wavelets for the region of Sidi Bouzid during one month

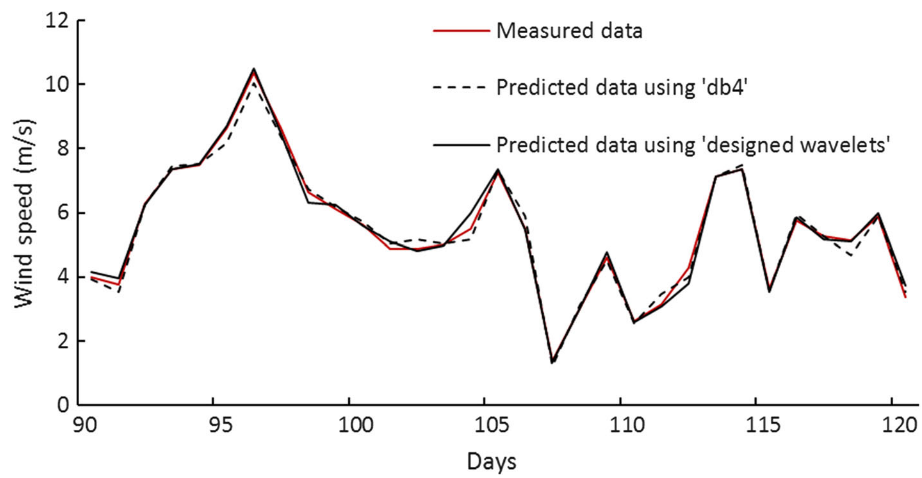


Fig. 20 Wind speed forecasting using designed wavelets for the region of Tetouane during one month

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Compliance with ethical standards

Conflict of interest The authors declare that there is no conflict of interests regarding the publication of this paper.

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