Hybrid Wavelet-PSO-ANFIS 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 it occurs today in Portugal, poses new challenges due to its intermittency and volatility. Wind power forecasting plays a key role in tackling these challenges. A novel hybrid approach, combining wavelet transform, particle swarm optimization, and an adaptive-network-based fuzzy inference system, is proposed in this paper for short-term wind power forecasting in Portugal. A thorough comparison is carried out, taking into account the results obtained with seven other approaches. Finally, conclusions are duly drawn.**

***Index Terms*—Forecasting, fuzzy logic, neural networks, swarm optimization, wavelet transform, wind power.**

I. Introduction

WIND generation is the fastest growing source of renewable energy [1], [2]. 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 [3], [4], and in 2006 was the second country in Europe with the highest wind power growth.

The wind energy is free, so all wind-generated electric energy is accepted as it comes, i.e., as it is available. However, the availability of the power supply generated from wind energy is not known in advance. Hence, the integration of a large share of wind power in an electricity system leads to some important challenges [5]. Wind power forecasting plays a key role in tackling these challenges [6].

Wind power prediction is a primary requirement for efficient large-scale integration of wind generation in power systems and electricity markets [7]–[12]. The time scales concerning short-term prediction are in the order of some days (for the forecast horizon) and from minutes to hours (for the time-step) [13].

In the technical literature, several methods to predict wind power have been reported, namely physical [14] and statistical methods. A comprehensive report on the state-of-the-art in short-term prediction of wind power can be found in [15].

The physical method requires a lot of physical considerations to reach the best prediction precision. Supercomputers are usually required to run numerical weather prediction (NWP) models [16]. 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 relationship of the on-line measured power data. For a statistical model, the historical wind power data may be used. The physical method has advantages in long-term prediction while the statistical method does well in short-term prediction [17].

The conventional statistical models are time-series-based models [18], including autoregressive (AR), and autoregressive integrated moving average (ARIMA) [19] models. The persistence models are considered as the simplest time-series models, but they can surpass many other models in very short-term prediction [17]. Particularly, persistence beats the NWP-based model for short prediction horizons (ca 3–6 hours) [15]. The persistence model is a useful first approximation for short-term wind power forecasting. A new reference model (NRM) was proposed in [20], which can be used instead of the persistence model.

Some new methods are catching researcher's attention, namely data mining [21], neural networks (NNs) [22]–[26], fuzzy logic and neuro-fuzzy (NF) [27]–[29], evolutionary algorithms [30], and some hybrid methods [31]–[33]. 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 intelligence methods outperformed others in short-term prediction [17].

In this paper, a novel hybrid approach is proposed for short-term wind power forecasting in Portugal. The proposed approach is based on the combination of wavelet transform (WT), particle swarm optimization (PSO), and adaptive-network-based fuzzy inference system (ANFIS). Our hybrid WPA approach is compared with persistence, NRM, ARIMA, NN, NNWT, NF, and wavelet-neuro-fuzzy (WNF) approaches, to demonstrate its effectiveness regarding forecasting accuracy and computation time.

The contributions of this paper are threefold:

1) to propose a novel hybrid approach for short-term wind power forecasting;
2) to improve forecasting accuracy, taking into account the results obtained with seven other approaches;
3) to offer a practical solution in terms of computational burden.

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This paper is organized as follows. Section II presents the proposed approach to forecast wind power. Section III provides the different criterions used to evaluate the forecasting accuracy. Section IV provides the numerical results from a real-world case study. Section V outlines the conclusions.

II. Proposed Approach

The proposed approach is based on the combination of WT, PSO, and ANFIS. The WT is used to decompose the wind power series into a set of better-behaved constitutive series. Then, the future values of these constitutive series are forecasted using ANFIS. The PSO is used to improve the performance of ANFIS, tuning the membership functions required to achieve a lower error. Finally, the ANFIS forecasts allow, through the inverse WT, reconstructing the future behavior of the wind power series, and therefore, to forecast wind power.

A. Wavelet Transform

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

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 [34]

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

where the scale parameter a controls the spread of the wavelet and translation parameter b determines its central position. DWT is more efficient and just as accurate as the CWT [35]. DWT is defined as

$$W(m,n) = 2^{-(m/2)} \sum_{t=0}^{T-1} f(t)\phi\left(\frac{t-n2^m}{2^m}\right) \tag{2}$$

where T is the length of the signal $f(t)$. The scaling and translation parameters are functions of the integer variables m and $n (a = 2^m, b = n2^m)$; 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) was developed by Mallat [36].

Multiresolution via Mallat's algorithm is a procedure to obtain "approximations" and "details" from a given signal. 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.

A 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 wavelength and smoothness, resulting in an appropriate behavior for short-term wind power forecasting. Similar wavelets have been considered by previous researchers for load forecasting [34], [35] and price forecasting [37], [38]. Also, three decomposition levels are considered, as in [38], since it describes the wind power series in a thorough and meaningful way.

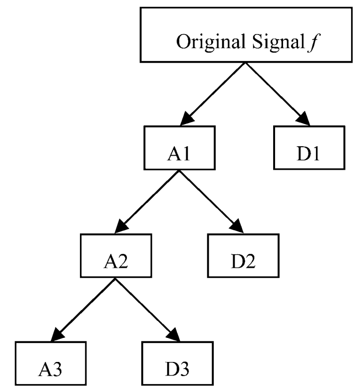

Fig. 1. Multilevel decomposition process.

B. Particle Swarm Optimization

PSO is a heuristic approach first proposed by Kennedy and Eberhart in 1995 [39] as an evolutionary computational method. The PSO algorithm is based on the biological and sociological behavior of animals searching for their food [40].

Empirical evidence has been accumulated to show that the algorithm is a useful tool for optimization [41]. PSO has been applied to many optimization problems in engineering, for instance [42].

Consider an optimization problem of D variables. A swarm of N particles is initialized in which each particle is assigned a random position in the D -dimensional hyperspace. Let x denote a particle's position and v denote the particle's flight velocity over a solution space.

The best previous position of a particle is *Pbest*. The index of the best particle among all particles in the swarm is *Gbest*. Velocity and position of a particle are updated by the following update rules:

$$\begin{aligned} v_i(t) &= \omega v_i(t-1) + \rho_1 \frac{(x_{\mathrm{Pbest}_i} - x_i(t))}{\Delta t} \\ &\quad + \rho_2 \frac{(x_{\mathrm{Gbest}} - x_i(t))}{\Delta t} \end{aligned} \tag{3}$$

$$x_i(t) = x_i(t-1) + v_i(t)\Delta t \tag{4}$$

where ω is an inertia weight, Δt is the time-step value, ρ_1 and ρ_2 are random variables defined as $\rho_1 = r_1 C_1$ and $\rho_2 = r_2 C_2$, with $r_1, r_2 \sim U(0,1)$, and C_1 and C_2 are positive acceleration constants. The time-step is necessary to make the algorithm dimensionally correct. Also, constants C_1 and C_2 are both set at 2.0, following the typical practice in [43].

Fig. 2 illustrates a search mechanism of a PSO technique using the velocity update rule (3) and the position update rule (4).

An inertia correction function called "inertia weight approach (IWA)" is also used in this work [43]. During the IWA, the inertia weight ω is modified according to the following equation:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{\mathrm{Itr}_{\max}} \mathrm{Itr} \tag{5}$$

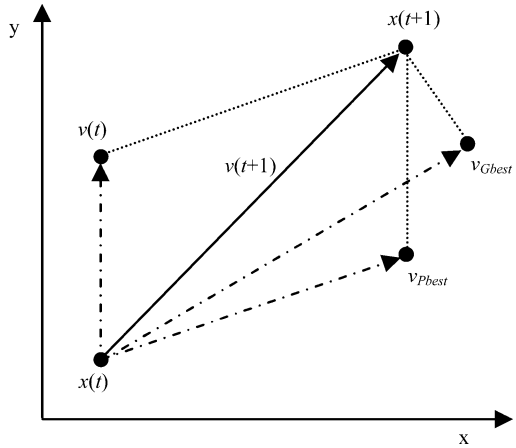

Fig. 2. Updating the position mechanism of PSO.

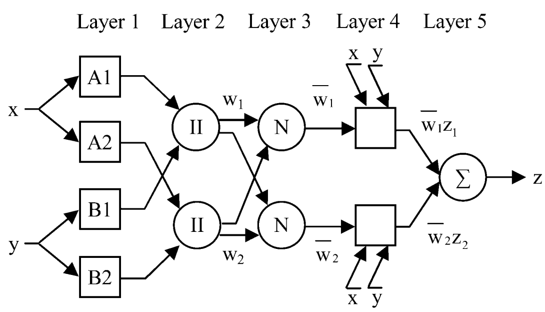

Fig. 3. ANFIS architecture.

where $\omega_{\max}$ and $\omega_{\min}$ are the initial and final inertia weights, $\mathrm{Itr}_{\max}$ is the maximum number of iteration, and Itr is the current number of iteration.

C. ANFIS

ANFIS is a class of adaptive multilayer 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 [44].

The ANFIS architecture is shown in Fig. 3. The ANFIS network is composed of five layers. Each layer contains several nodes described by the node function. Let O_i^j denote the output of the ith node in layer j.

In layer 1, every node i is an adaptive node with node function

$$O_i^1 = \mu A_i(x), \quad i = 1, 2 \tag{6}$$

or

$$O_i^1 = \mu B_{i-2}(y), \quad i = 3, 4 \tag{7}$$

where x (or y) is the input to the ith node and A_i (or B_{i-2}) is a linguistic label associated with this node. The membership functions for A and B are usually described by generalized bell functions, e.g.,

$$\mu A_i(x) = \frac{1}{1 + \left|\frac{x-r_i}{p_i}\right|^{2q_i}} \tag{8}$$

where $\{p_i, q_i, r_i\}$ is the parameter set. Any continuous and piecewise differentiable functions, such as triangular-shaped membership functions, are also qualified candidates for node functions in this layer [45]. Parameters in this layer are referred to as premise parameters.

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

$$O_i^2 = w_i = \mu A_i(x) \mu B_i(y), \quad i = 1, 2. \tag{9}$$

Each node output represents the firing strength of a rule.

In layer 3, each node N computes the ratio of the ith rules's firing strength to the sum of all rules' firing strengths

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \tag{10}$$

The outputs of this layer are called normalized firing strengths.

In layer 4, each node computes the contribution of the ith rule to the overall output

$$O_i^4 = \bar{w}_i z_i = \bar{w}_i (a_i x + b_i y + c_i), \quad i = 1, 2 \tag{11}$$

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 $\sum$ computes the final output as the summation of all incoming signals

$$O_i^5 = \sum_i \bar{w}_i z_i = \frac{\sum_i w_i z_i}{\sum_i w_i}. \tag{12}$$

Thus, an adaptive network is functionally equivalent to a Sugeno-type fuzzy inference system.

In this paper, ANFIS employs the PSO method to adjust the parameters of the membership functions, as in [46]. The PSO techniques have the advantage of being less computationally expensive for a given size of network topology. The membership functions considered in this study are triangular-shaped.

D. Hybrid Approach

In this section, the algorithm used to implement the proposed approach is described step-by-step.

As depicted in Fig. 4, wavelet techniques are implemented in the first and last stages. The actual time-series (wind power data) are first decomposed into a number of wavelet coefficient signals and one approximation signal.

The original wind power series is decomposed into four components by the WT and each subseries is separately predicted by the ANFIS. Finally, the predicted signals are recombined in the last stage to form the final predicted wind power series.

1) *First step:* Form a matrix with a set of historical wind power data, arranged in C columns of a matrix thereof. Each column of the array has an associated profile of wind power for a 3-hour interval with a time-step of 15 min (12 measured power values). In this first step, the matrix has four columns, corresponding to 12 hours.
2) *Second step:* Select a number of columns of the previous array so that the set of values derived from it represents the real input data.

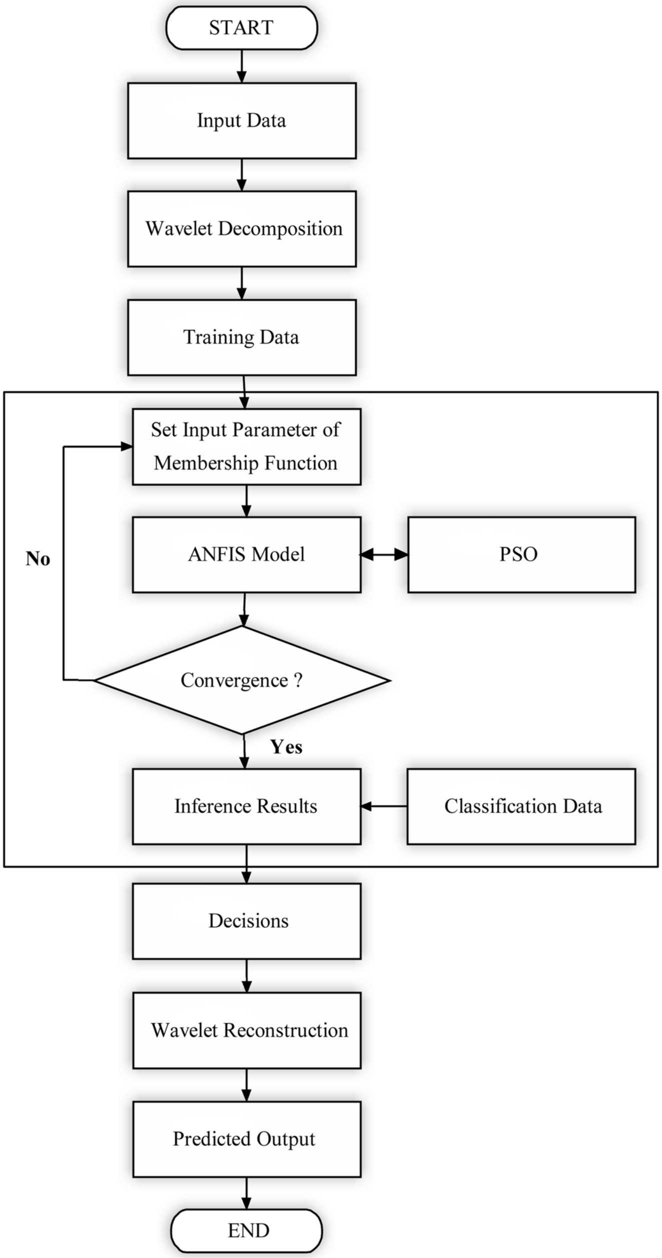

Fig. 4. Structure of the proposed wind power forecast strategy.

3) *Third step:* Decompose the input data using the WT tool available in MATLAB. The operation mode of this process is to decompose the vector with the input data selected. The decomposition is made from the choice of basis functions (wavelet family of functions), and the number of levels wanted to split the series. The signal is divided into three levels, namely, a level of approximation (A) and details (D). Fig. 1 illustrates the decomposition process. The wavelet function used is the Db4 type, which offers a good approach and ability to use a relatively small number of coefficients, making the code faster. Subsequently, in the level of decomposition, the detail series (for high frequencies) obtained is analyzed, so that they make a selection of coefficients in this series. This selection procedure is known as thresholding, because the purpose is to eliminate the coefficients smaller than a given value, with the aim of improving signal quality by removing noise. Finally, there is the process of reconstruction of the series (from the series of approximate level with the N series about the modified thresholding process—levels 1 to N).

4) *Fourth step:* Get the signal from the Wavelet reorganized so that it can be submitted to the entrance of the ANFIS structure.

5) *Fifth step:* Train the ANFIS with the data from the implementation of the previous step. The ANFIS uses a combination of the least-squares method (to determine consequent parameters) and the backpropagation gradient descent method (to learn the premise parameters). The training process allows the system to adjust its parameters as inputs/outputs submitted. The knowledge acquired through the learning process is tested by applying new data that it has never seen before, called the testing set. The network should be able to generalize and have an accurate output for this unseen data [47]. It is undesirable to overtrain the network, meaning that it would only work well on the training set, and would not generalize well to new data outside the training set. Thus, very large training sets should not be used to avoid overtraining during the learning process. The PSO is used to train the parameters associated with the membership functions of fuzzy inference system. This process allows obtaining more accurate results.

6) *Sixth step:* Create a vector with N-dimension, where N equals the number of membership functions. This vector contains the parameters of membership function and will be optimized by PSO algorithm. The fitness function is defined as the mean squared error.

7) *Seventh step:* Define the parameters associated with the PSO algorithm (Table I). Parameters are initialized randomly in the first stage and then are being updated using the PSO algorithm. In each iteration, one of the parameters of membership function is being updated; i.e., in the first iteration, for example, p_i is updated, then in the second iteration, q_i is updated, and then after updating all parameters again the first parameter update is considered, and so on [48]. These parameters are grouped in a vector that is being updated iteration to iteration. The PSO algorithm used to optimize parameters of membership functions is

TABLE I
PARAMETERS OF PSO

Parameters	Value
Number of particles	25
Number of iterations	2000
Cognitive acceleration C_1	2.0
Social acceleration C_2	2.0
Initial inertia weight $\omega_{\min}$	0.9
Final inertia weight $\omega_{\max}$	0.4

described below: i) initialize the population positions and speeds. For each particle, the position and velocity vectors are randomly initialized with the same size as presented by the size of the problem. ii) Assess the ability of the individual particle (*Pbest*). If the value is better than the current value of the individual particle, *Pbest* reset the current position of the particle and update the individual value. If the best of all the particles of individual values is better than the overall value of current *Gbest*, reset the location of the best particles. iii) Measure the fitness of each particle (*Pbest*) and store the particles with the best value of fitness (*Gbest*). iv) Modify the speed based on the position *Pbest* and *Gbest*. v) Update the particles. vi) End if the condition is verified. If the current iteration number reaches the maximum default number or the result reached a minimum error set, then stop the iteration and collect the best solution.

8) *Eighth step:* Extract the output of the ANFIS using the parameters found by the PSO.
9) *Ninth step:* Use wavelet again to reconstruct the wind power series forecast given by ANFIS. The final output corresponds to the prediction of our hybrid WPA approach.

III. Forecasting Accuracy Evaluation

To evaluate the accuracy in forecasting wind power, the mean absolute percentage error (MAPE) is considered.

The MAPE criterion is defined as follows:

$$\mathrm{MAPE} = \frac{100}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \tag{13}$$

$$\bar{p} = \frac{1}{N}\sum_{h=1}^{N} p_h \tag{14}$$

where $\hat{p}_h$ and p_h are, respectively, the forecasted and actual wind power at period h, $\bar{p}$ is the average wind power of the forecasting horizon, and N is the number of forecasted periods. For daily MAPE, N is equal to 24.

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 the prediction is [37].

Consistent with definition (13), daily error variance can be estimated as

$$\sigma^2_{e,\mathrm{day}} = \frac{1}{N}\sum_{h=1}^{N}\left(\frac{|\hat{p}_h - p_h|}{\bar{p}} - (e_{\mathrm{day}})\right)^2 \tag{15}$$

$$e_{\mathrm{day}} = \frac{1}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}}. \tag{16}$$

Additionally, the normalized mean absolute error (NMAE) criterion is taken into account, given by

$$\mathrm{NMAE} = \frac{1}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{p_{\mathrm{inst}}} \tag{17}$$

where p_{inst} is the installed wind power capacity.

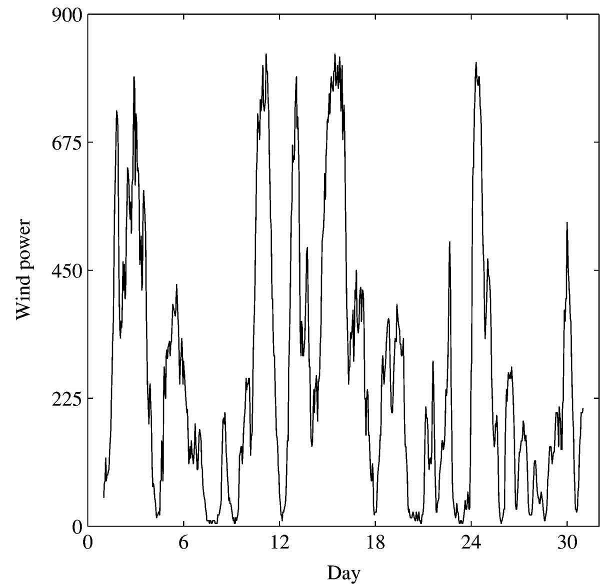

Fig. 5. Wind power profile in Portugal, January 2008, in megawatts.

IV. Results

The hybrid WPA approach has been applied for the prediction of the whole wind power in Portugal. The numerical results presented take into account the wind farms that have telemetry with the National Electric Grid (REN). Historical wind power data are the only inputs for training the ANFIS. For the sake of clear comparison, no exogenous variables are considered. The wind power profile in Portugal, at January 2008, is shown in Fig. 5.

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 min (48 measured power values: the first 36 values are used for training, while the last 12 values are used for testing). This procedure is repeated until the next 24 hour 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 behavior are deliberately not chosen. This results in an uneven accuracy distribution throughout the year that reflects reality.

Numerical results with the hybrid WPA approach are shown in Figs. 6–9, respectively, for the winter, spring, summer, and fall days.

Table II shows a comparison between the hybrid WPA approach and seven other approaches (Persistence, NRM, ARIMA, NN, NNWT, NF, and WNF), regarding the MAPE criterion.

The proposed approach presents better forecasting accuracy: the MAPE has an average value of 4.98%. Improvement in the average MAPE of the proposed approach with respect to the seven previous approaches is 73.9%, 73.8%, 51.8%, 31.4%, 28.6%, 25.0%, and 16.9%, respectively.

In addition to the MAPE, stability of results is another important factor for the comparison of forecast approaches.

Table III shows a comparison between the hybrid WPA approach and seven other approaches (Persistence, NRM,

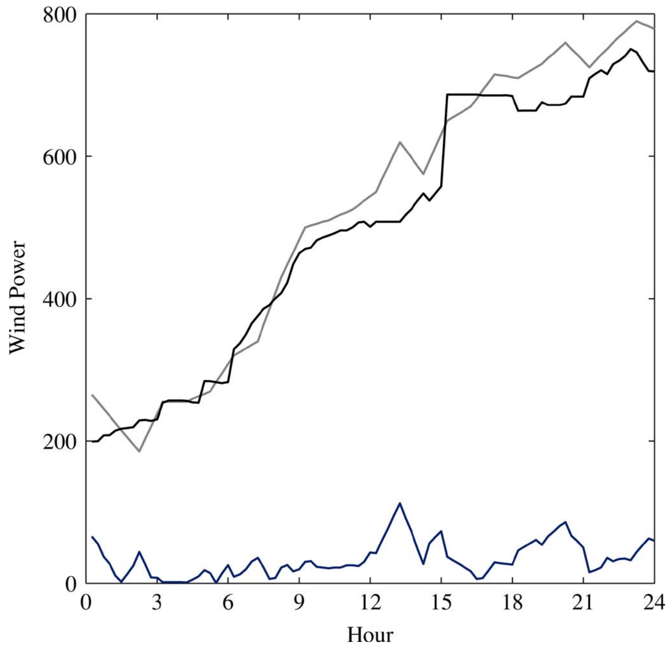

Fig. 6. Winter day: actual wind power (gray line) together with the forecasted wind power (black line), in megawatts; absolute value of forecast errors (bottom, blue line).

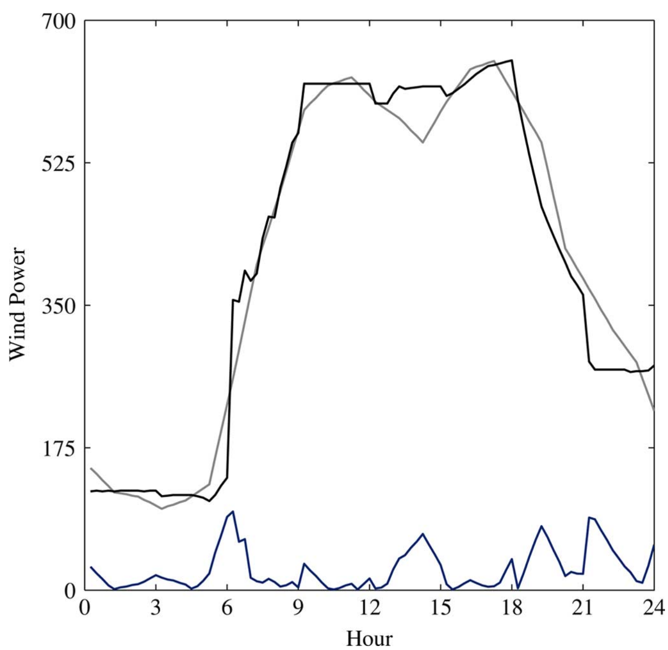

Fig. 7. Spring day: actual wind power (gray line) together with the forecasted wind power (black line), in megawatts; absolute value of forecast errors (bottom, blue line).

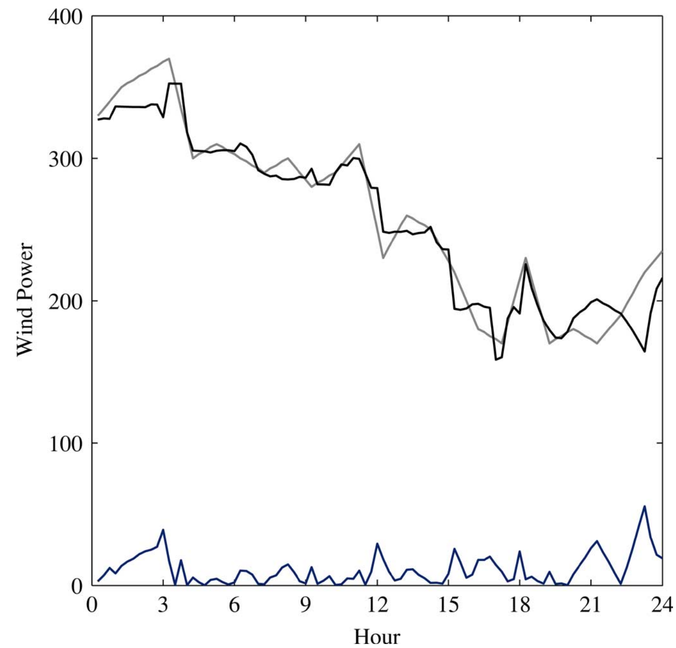

Fig. 8. Summer day: actual wind power (gray line) together with the forecasted wind power (black line), in megawatts; absolute value of forecast errors (bottom, blue line).

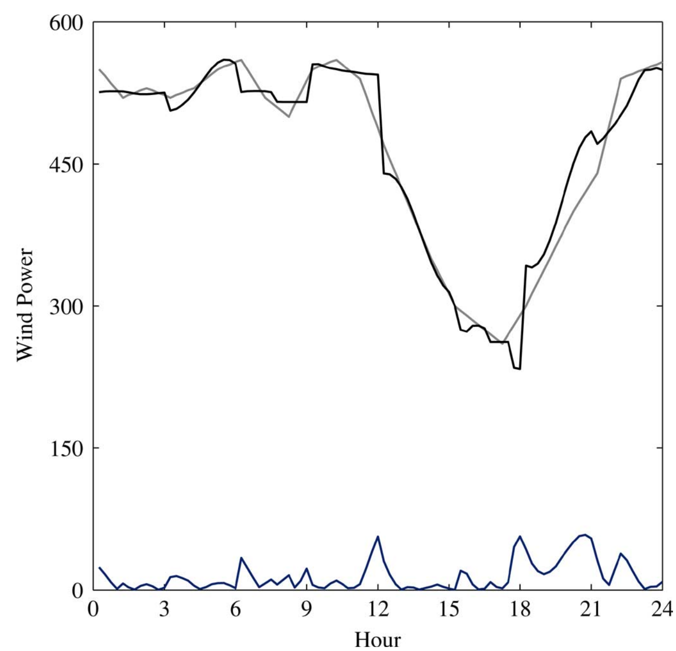

Fig. 9. Fall day: actual wind power (gray line) together with the forecasted wind power (black line), in megawatts; absolute value of forecast errors (bottom, blue line).

ARIMA, NN, NNWT, NF, and WNF) regarding daily error variance.

Note that the average error variance is smaller for the hybrid WPA approach, indicating less uncertainty in the predictions. Improvement in the average error variance of the proposed approach with respect to the seven previous approaches is 91.0%, 90.9%, 73.8%, 58.8%, 55.3%, 51.1%, and 34.4%, respectively.

Table IV illustrates the performance evaluation by the use of the NMAE criterion, considering the hybrid WPA approach and seven other approaches (Persistence, NRM, ARIMA, NN, NNWT, NF, and WNF).

The performance in terms of NMAE of the hybrid WPA approach is shown in Fig. 10, for the winter and spring days, and in Fig. 11, for the summer and fall days.

Regarding this NMAE criterion, the hybrid WPA approach experienced an average error representing 2.37% of the installed wind power capacity for its 3-hours ahead predictions, over the whole forecasting horizon.

TABLE II
COMPARATIVE MAPE RESULTS

	Winter	Spring	Summer	Fall	Average
Persistence	13.89	32.40	13.43	16.49	19.05
NRM	13.87	32.38	13.43	16.43	19.03
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
NF	8.85	8.96	5.63	3.11	6.64
WNF	8.34	7.71	4.81	3.08	5.99
WPA	6.47	6.08	4.31	3.07	4.98

TABLE III
DAILY FORECASTING ERROR VARIANCE

	Winter	Spring	Summer	Fall	Average
Persistence	0.0074	0.0592	0.0085	0.0179	0.0233
NRM	0.0074	0.0590	0.0079	0.0180	0.0231
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
NF	0.0041	0.0086	0.0038	0.00075	0.0043
WNF	0.0046	0.0051	0.0021	0.0011	0.0032
WPA	0.0021	0.0035	0.0016	0.0011	0.0021

TABLE IV
COMPARATIVE NMAE RESULTS

	Winter	Spring	Summer	Fall	Average
Persistence	7.64	12.15	4.98	10.88	8.91
NRM	7.62	12.14	4.98	10.84	8.90
ARIMA	6.01	4.52	4.09	4.85	4.87
NN	5.22	3.72	2.35	2.15	3.36
NNWT	5.07	3.58	2.21	2.07	3.23
NF	4.86	3.36	2.09	2.05	3.09
WNF	4.58	2.89	1.78	2.03	2.82
WPA	3.56	2.28	1.60	2.02	2.37

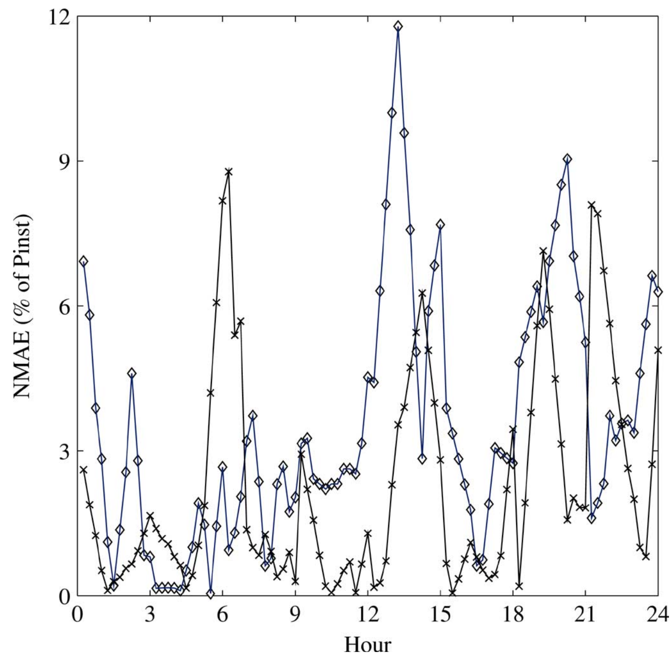

Fig. 10. Performance in terms of NMAE of the hybrid WPA approach, for the winter (◇) and spring (×) days.

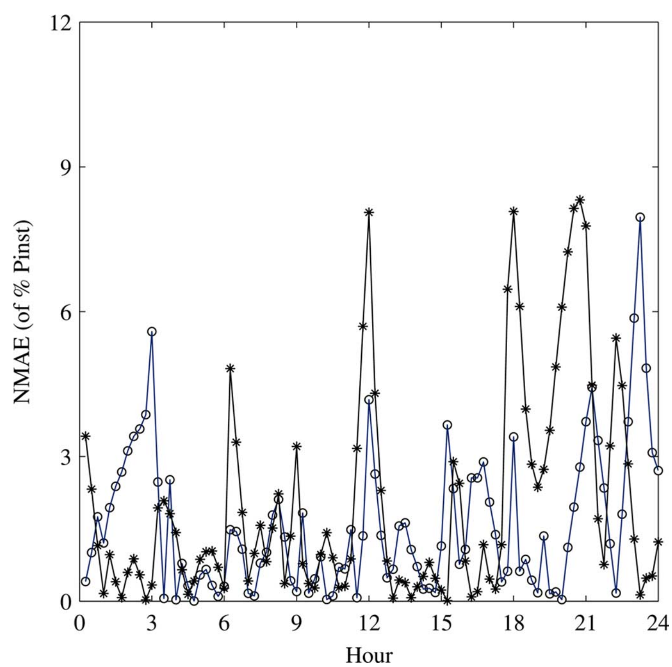

Fig. 11. Performance in terms of NMAE of the hybrid WPA approach, for the summer (○) and fall (∗) days.

The four plots of Fig. 12 provide average errors considering NRM, NN, NF, WFN, and the hybrid WPA approach, for the four days analyzed.

In Fig. 12, the 24 hours of each day have been divided into three intervals (1–8, 9–16, and 17–24 hours) to further elucidate the forecast performance of the proposed approach in comparison with the other approaches.

It can be seen that the performance of the proposed approach is generally better. The interval 1–8 hours for the spring day [Fig. 12(b)] is especially hard to predict, due to a sudden increase in wind power noticeable in Fig. 7 around hour 6. The proposed approach presents a much smaller error within this interval, reflecting its enhanced forecasting abilities.

For a more thorough comparison between the different models used, statistically representative results for the year of 2009 are presented thereafter, in Tables V and VI.

Although the MAPE results have slightly worsened for all methodologies, the NMAE results have improved significantly

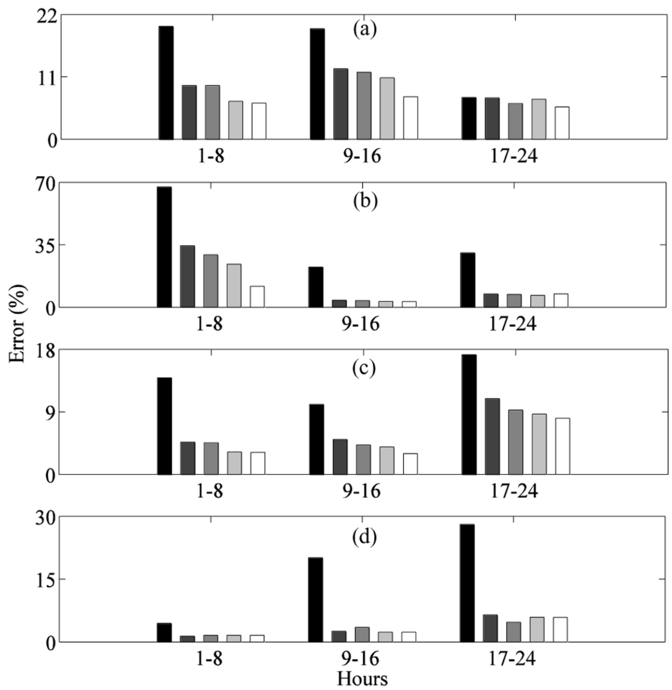

Fig. 12. Average errors within three time intervals, considering NRM, NN, NF, WNF, and the hybrid WPA approach, for the days analyzed: (a) Winter, (b) Spring, (c) Summer, and (d) Fall.

TABLE V
REPRESENTATIVE MAPE RESULTS FOR THE YEAR OF 2009

	Persistence	NRM	ARIMA	NN	NNWT	NF	WNF	WPA
January	17.44	16.83	16.03	13.62	12.22	10.69	8.16	6.71
February	22.84	22.81	20.56	14.55	12.92	11.68	8.64	7.05
March	19.70	18.99	13.01	12.04	11.05	8.76	7.51	6.19
April	22.77	22.53	13.26	9.43	9.19	8.78	7.82	6.57
May	17.20	16.78	11.98	9.86	8.85	8.29	6.87	5.94
June	36.70	36.37	27.96	14.18	12.52	11.60	8.85	7.23
July	21.30	20.86	15.98	13.53	12.28	11.16	8.42	7.06
August	13.94	13.55	11.94	8.42	7.48	6.18	5.09	4.66
September	24.51	24.20	16.65	10.60	10.28	9.95	8.28	7.33
October	26.45	26.16	18.58	12.92	11.28	10.44	8.67	7.26
November	17.16	16.88	14.47	12.72	12.15	11.36	8.65	6.99
December	16.90	16.86	12.14	10.03	9.54	8.98	7.02	5.99
Average	21.41	21.07	16.05	11.83	10.81	9.82	7.83	6.58

due to the ever-increasing installed wind power capacity. Besides, the hybrid WPA approach still clearly outperforms all other approaches.

The proposed approach is both novel and effective for short-term prediction of wind power. The average computation time required by the hybrid WPA approach for each forecasted day is less than 1 min using MATLAB on a PC with 1 GB of RAM and a 2.0-GHz-based processor. Hence, the proposed approach presents not only better forecasting accuracy, but also an acceptable computation time, which is important for real-life applications.

TABLE VI
REPRESENTATIVE NMAE RESULTS FOR THE YEAR OF 2009

	Persistence	NRM	ARIMA	NN	NNWT	NF	WNF	WPA
January	3.23	3.12	2.97	2.53	2.26	1.98	1.51	1.24
February	8.34	8.37	7.51	5.31	4.71	4.27	3.16	2.58
March	1.91	1.84	1.26	1.17	1.07	0.85	0.73	0.60
April	4.07	4.02	2.37	1.69	1.64	1.57	1.40	1.17
May	5.91	5.76	4.11	3.39	3.04	2.85	2.36	2.04
June	7.86	7.79	5.99	3.04	2.68	2.48	1.89	1.55
July	4.05	3.96	3.04	2.57	2.33	2.12	1.60	1.34
August	4.73	4.60	4.05	2.86	2.54	2.10	1.73	1.58
September	4.85	4.79	3.29	2.10	2.03	1.97	1.64	1.45
October	5.36	5.31	3.77	2.62	2.29	2.12	1.76	1.47
November	7.02	6.90	4.08	5.20	4.97	4.65	3.54	2.86
December	5.54	5.53	3.98	3.29	3.13	2.95	2.30	1.97
Average	5.24	5.17	3.87	2.98	2.72	2.49	1.97	1.65

V. CONCLUSION

A novel hybrid approach was proposed in this paper for short-term wind power forecasting in Portugal. The proposed approach is based on the combination of wavelet transform, particle swarm optimization, and an adaptive-network-based fuzzy inference system. The application of the proposed approach to wind power forecasting is both novel and effective. The average MAPE and NMAE results outperform seven other approaches, while the average computation time is acceptable. Hence, the presented results validate the proficiency of the proposed approach in short-term wind power forecasting.

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