Short-term wind power forecasting using adaptive neuro-fuzzy inference system combined with evolutionary particle swarm optimization, wavelet transform and mutual information

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Abstract

The non-stationary and stochastic nature of wind power reveals itself a difficult task to forecast and manage. In this context, with the continuous increment of wind farms and their capacity production in Portugal, there is an increasing need to develop new forecasting tools with enhanced capabilities. On the one hand, it is crucial to achieve higher accuracy and less uncertainty in the predictions. On the other hand, the computational burden should be kept low to enable fast operational decisions. Hence, this paper proposes a new hybrid evolutionary-adaptive methodology for wind power forecasting in the short-term, successfully combining mutual information, wavelet transform, evolutionary particle swarm optimization, and the adaptive neuro-fuzzy inference system. The strength of this paper is the integration of already existing models and algorithms, which jointly show an advancement over present state of the art. The results obtained show a significant improvement over previously reported methodologies.

Keywords: Forecasting, wind power, evolutionary particle swarm optimization, neuro-fuzzy system, mutual information, wavelet transform.

1. Introduction

Recently, with the new paradigm shift in the energy sector, and the impositions for a gradual reduction of greenhouse gas emissions, producers are faced with delivering electricity using clean energy sources, in competitive deregulated electricity markets [1]-[2].

In this context, wind power sources have had the biggest jump in exploration and implementation within the electricity grid [3]-[4], in comparison with other clean energy technologies [5]. This worldwide expansion of wind energy has occurred due to the ratio between production and implementation costs, maintenance costs, the maturity of technology, and increasing production capacity [6]. However, due to the stochastic characteristic of wind power sources [7]-[9], its integration is responsible for the introduction of more variability, volatility, and uncertainty in system operation, which complicates the proper management of all production sources [10]-[11].

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The behavior of wind farms depends on the quality and variation of wind speed, the weather conditions, total wind power capacity connected to the electricity grid, scheduled maintenance [12]-[13], and the wind power acceptance in electrical framework when it is available [14].

Portugal is one of the countries with the fastest growth in wind power production, and by 2020 it hopes to achieve an installed capacity of 8500 MW [15]. Thus, it becomes important to minimize the volatility and intermittent impacts of wind power [16]-[17], which can be accomplished by the scientific community in presenting new ideas for predicting wind power behavior [18]-[20]. Wind power forecasting tools represent a very important field of research for system operators, in order to reduce fluctuating power and optimize the installed wind power resources [21].

Wind power forecasting can be classified by time-scales, that is: very short-term, short-term and long-term (of the order of multiple days) [22]. Several wind power forecasting methodologies have been developed and described in the technical literature in recent years, which can be split into physical and statistical methodologies [23].

Physical methodologies need an extensive number of physical specifications, and their inputs are also physical variables, such as orography, pressure and temperature, presenting advantages in long-term forecasting [24]. Statistical methodologies try to establish inherent relationships within the measured data, which can have advantages in short-term forecasting [25]-[26]. Some statistical methodologies are based on auto regressive techniques, i.e., auto regressive integrated moving average (ARIMA) [27]. Persistence and new reference model (NRM) [28] are also time-series models that can provide a valuable first approximation, and inclusively are able to beat numerical weather prediction (NWP) models for very short-term horizons (between few seconds till 6 hours ahead).

Soft computing methodologies have become very popular recently, using an auto learning process from historical sets to identify future patterns, such as neural networks (NNs) [29]-[30], NNs with wavelet transform (WT), i.e., NNWT [31]; adaptive WT with NN (AWNN) [32], neuro-fuzzy (NF) systems [33]-[34], evolutionary algorithms [35], and some hybrid methods, such as wavelet-neuro-fuzzy (WNF) and particle swarm optimization (PSO)-WT-NF (WPA) [36].

In this paper, a new hybrid evolutionary-adaptive (HEA) methodology is tested for forecasting wind power, based on MI-mutual information, WT, EPSO-evolutionary particle swarm optimization, and ANFIS-adaptive neuro-fuzzy inference system. The HEA methodology is tested on a real case study using wind power data from Portugal. The object of the study is short-term prediction in wide area forecasting. To prove its superior forecasting accuracy and reduced computational burden, a comparison study will take into account persistence, NRM, ARIMA, NN, NNWT, NF, WNF, and WPA methodologies. This paper is organized in five sections: the proposed methodology (Section 2), forecasting accuracy validation (Section 3), case study (Section 4), and finally conclusions (Section 5).

2. Proposed methodology

The HEA methodology results from the innovative combination of MI, WT, EPSO and ANFIS. The MI is used to eliminate the randomness in the selection of wind power series as inputs, increasing the robustness of the methodology and helping to decrease the final forecasting error [37]. MI is a nonlinear feature selection technique that is more adequate for wind power series than a correlation analysis [23, 38]. MI-based techniques in [23] outperform correlation analysis, which is a linear feature selection method, while wind power is a nonlinear mapping function of its input variables. The WT is employed to decompose the sets of wind power into new constitutive sets with better behavior. Then, the forthcoming values of those constitutive sets are predicted with the ANFIS. EPSO brings on augmented ANFIS performance by tuning their membership functions to attain a lesser error. Comparatively to a classical PSO, the evolutionary concepts behind of EPSO can make a real difference in terms of convergence properties. EPSO is self-adaptive, more robust and less sensitive to parameter initialization, comparatively to classical PSO. The evolutionary characteristics of EPSO and the adaptive characteristics of ANFIS complement each other perfectly. Finally, the inverse WT is used to reconstruct the signal, obtaining then the final forecasting results.

2.1 Mutual Information

The MI is based on the concept of entropy. In the case where variable X is a random discrete variable, for example, $(X_1, \ldots, X_n)$, with distribution probabilities $P(X_n)$, the entropy $H(X)$ is given by [39]-[40]:

$$H(X) = -\sum_{i=1}^{n} P(X_i)\log_2\big(P(X_i)\big) \tag{1}$$

The conditional entropy is defined as:

$$H(Y/X) = -\sum_{i=1}^{n}\sum_{j=1}^{m} P(X_i, Y_j)\log_2\left(P(Y_j/X_i)\right) \tag{2}$$

The conditional entropy $H(Y/X)$ quantifies the remaining uncertainty of Y when X is known. The joint and conditional entropies are related by:

$$H(X,Y) = H(X) + H(Y/X) = H(Y) + H(X/Y) \tag{3}$$

The MI measures the level of information between a set of information data. The discrete expression is defined as:

$$MI(X,Y) = \sum_{i=1}^{n}\sum_{j=1}^{m} P(X_i, Y_j)\log_2\left(\frac{P(X_i, Y_j)}{P(X_i)P(Y_j)}\right) \tag{4}$$

The MI may be given as:

$$MI(X,Y) = MI(Y,X) = H(X) - H(X\,/\,Y) \tag{5}$$

To ensure the convergence of the HEA methodology, the bounds of MI are very important to guarantee the best performance of the ANFIS. MI helps to determine the best sets of candidates that will be inputs for training the ANFIS tool [41]. Fig. 1 shows a simplified representation about MI.

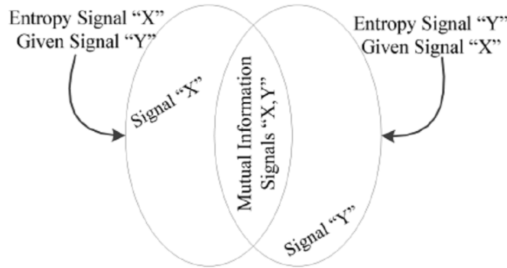


Fig. 1. Simplified MI representation.

2.2 Wavelet Transform

Non-stationary behavior in a time series arises from instability in the mean and variance of the series. The WT is used in non-stationary or time varying sets [42], being sensitive to the irregularities of input sets [43]. WT tools are capable of illustrating different aspects in the sets without losing the signal [44], reducing the noise of the sets without degradation. The discrete wavelet transform (DWT) is defined [13] as:

$$W(m,n) = 2^{-(m/2)} \sum_{t=0}^{T-1} f(t)\, \varphi\left(\frac{t-b}{a}\right) \tag{6}$$

In (6) the variable T represents the signal length $f(t)$, the parameters of scaling and translation of φ are given by $a = 2^m$ and $b = n2^m$, respectively, and the time step is given by t. The DWT algorithm used in this work is based on four filters divided into two groups: the decomposition in low and high pass filters, and the reconstruction in low and high filters. The approximations (A_n) and details (D_n) of the original sets can be obtained via Mallat's algorithm. Fig. 2 shows a three-level decomposition model of WT [13], used in this work. Also, the 4th Daubechies function is chosen as mother function due to better trade-off among length and smoothness [36].

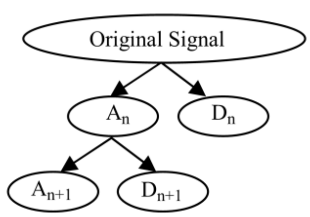


Fig. 2. Level decomposition model of WT.

2.3 Evolutionary Particle Swarm Optimization

EPSO corresponds to a meta heuristic method where rules and optimization concepts are contained in the evolutionary strategies and self-adaptive properties [45]. Each particle is described by object parameters and strategic parameters [46]-[47]. Hence, the formulation of EPSO is composed of object parameters X and strategic parameters w that correspond to the weights. The movement rule of EPSO is defined as [48]:

$$X_i^{new} = X_i + V_i^{new} \tag{7}$$

$$V_i^{new} = w_{i0}^{*}\, V_i + w_{i1}^{*}\,(b_i - X_i) + w_{i2}^{*}\,(b_g^{*} - X_i) \tag{8}$$

Equations (7) and (8) are similar to their classical PSO algorithm, as shown in Fig. 3. The difference is related to the weights w_{ik}^{*}, which undergo mutation given as:

$$w_{ik}^{*} = w_{ik} + \tau N(0{,}1) \tag{9}$$

where $N(0{,}1)$ is a randomly Gaussian variable. The global best b_g^{*} is changed according to:

$$b_g^{*} = b_g + \tau' N(0{,}1) \tag{10}$$

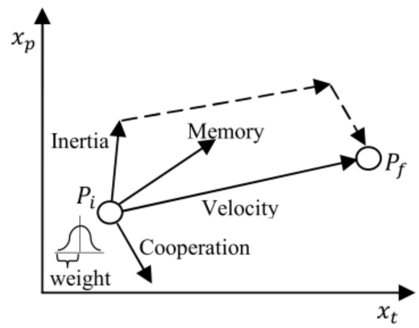


Fig. 3. Movement rule of a particle.

2.4 Adaptive Neuro-Fuzzy Inference System

ANFIS is a combination of NN and fuzzy algorithms: NN has the capability of self-learning which is essential for the fuzzy system to auto-adjust accordingly with the proposed problem. Due to the self-learning process, the membership functions are adjusted in an adaptive form [49]-[50]. The general ANFIS architecture is composed by 5 layers, thus also called multi-layer feed-forward network, represented in general terms in Fig. 4.

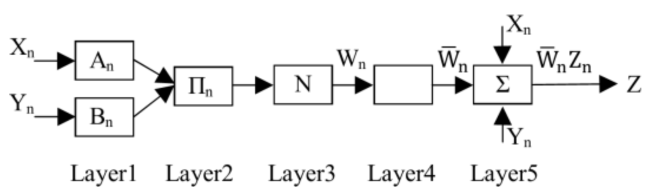


Fig. 4. General ANFIS architecture [50].

A triangular membership function is considered in this manuscript as a node function due to being a continuous and piecewise differentiable function [36]. The ANFIS used in this paper employs the least-squares and back-propagation gradient descent method. EPSO assists in the tuning of the membership function parameters [36].

2.5 Hybrid Evolutionary–Adaptive Methodology

The HEA methodology will now be described in successive steps. Fig. 5 illustrates the structure of the HEA methodology in the form of a flowchart.

Step 1: The HEA methodology is initialized with a matrix of historical wind power data considering the previous 12 hours, with a time step of 15 minutes. The historical wind power data date back to 2007 and 2008, available in [51]. To allow a fair comparison with the results already obtained using other methodologies, the same data of 2007 and 2008 were selected, each corresponding to a different season (winter, spring, summer and fall). Moreover, for a clear comparison, only historical data sets of wind power are used, i.e., no exogenous sets are taken into account, which also allows a reduced overall computational time.

Step 2: The previous matrix of historical data is normalized in $\{0,1\}$ intervals, to find the set of historical wind power data in the same scale, that will be later used by the MI in future candidate selections.

Step 3: Constitute data groups for the MI. The number of those groups is defined by combinatorial optimization in order to avoid compromising the computational burden. The formation of groups must be performed in a balanced way; otherwise, this could compromise the ANFIS performance.

Step 4: Compute the entropy and conditional entropy of each group, where $P(X_n)$ is given by a binomial distribution function.

Step 5: Compute the MI of each group.

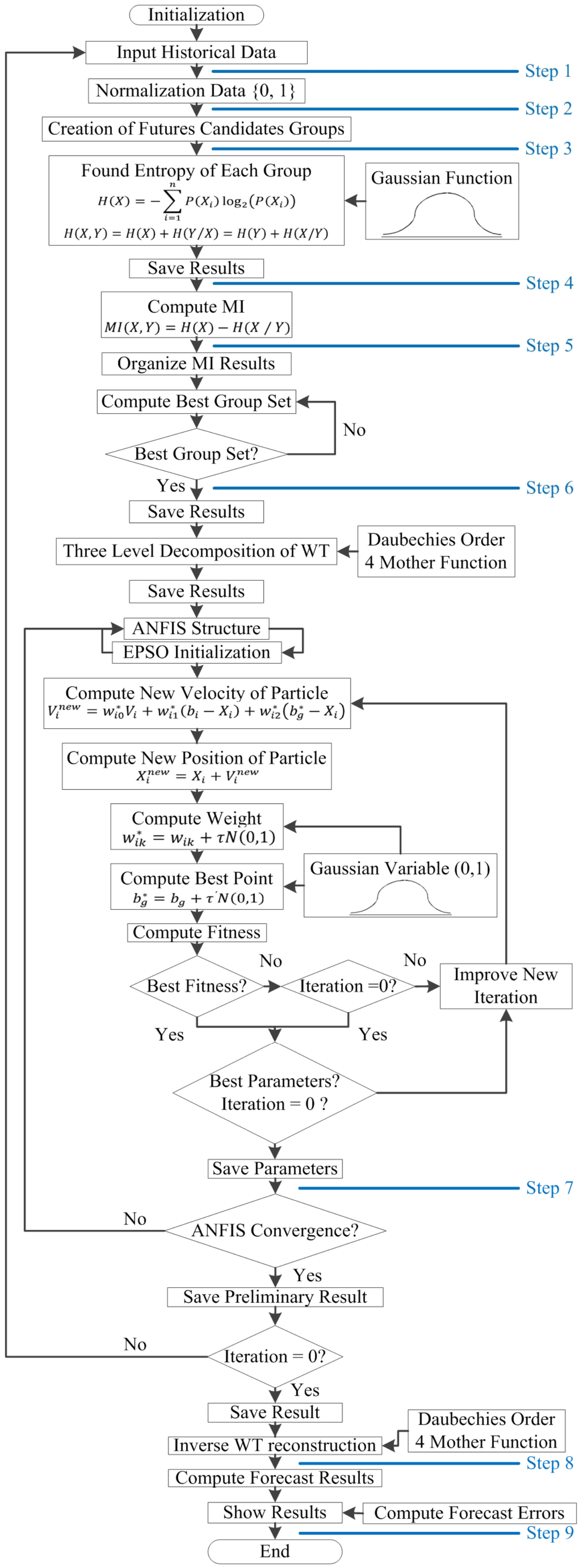
Step 6: Compute the best group subset data. The best group found will be recombined in wind power data-sets. These selected sets will be inputs for the WT.

Step 7: Training the ANFIS with the previous constitutive sets. The optimization of membership function parameters is achieved by EPSO.

Step 8: Until the best results or convergence are not reached, jump to *Step 1*. When the best results are found or convergence is reached, the inverse WT is applied and the output of the methodology is reached.

Step 9: Compute the wind power forecasting errors with different criteria to validate the methodology, comparing the results obtained with other results already available in the specialized literature.

Table 1 shows the parameters considered for MI, ANFIS and EPSO. The inference rules of ANFIS are put into automatic mode to achieve the best performance. This is done according to the nature of the data, which requires a large number of inference rules to obtain the best results [36].



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144 Fig. 5. Flowchart of the proposed methodology.

Table 1
Parameters of MI, ANFIS and EPSO

	Parameters	Type or Size
MI	Best Lower Bound of Set	0.20
	Best Upper Bound of Set	0.86
ANFIS	Membership Functions	2–7
	Necessary Iterations or Epoch	2–25
	Type of Membership Functions	Triangular–format
EPSO	Fitness Acceleration	2
	Sharing Acceleration	2
	Initial Inertia Weight of Population	0.9
	Final Inertia Weight of Population	0.4
	Population Size	96
	Maximum Generation	192
	Number of New Particles	12
	Generation for Each New Particle	2
	Necessary Iterations	192
	Minimum Value of New Position	5
	Maximum Value of New Position	2000

3. Forecasting accuracy evaluation

To compare the proposed methodology with other methodologies used for wind power forecasting, previously published in the specialized literature, the mean absolute percentage error (MAPE) criterion is commonly used. This criterion is given as:

$$MAPE = \frac{100}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \quad (11)$$

$$\bar{p} = \frac{1}{N}\sum_{h=1}^{N} p_h \quad (12)$$

where $\hat{p}_h$ is the wind power data forecast at hour h, p_h is the actual wind power data at hour h, $\bar{p}$ is the average value for the forecasting horizon.

The uncertainty of the proposed methodology is also evaluated using the error variance estimation. The smaller the value for this criterion, the more exact the methodology is. In accordance with the MAPE criterion, the error variance criterion is given by:

$$\sigma_{e,t}^2 = \frac{1}{N}\sum_{h=1}^{N}\left(\frac{|\hat{p}_h - p_h|}{\bar{p}} - e_t\right)^2 \quad (12)$$

$$e_t = \frac{1}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \quad (13)$$

Moreover, the normalized mean absolute error (NMAE) criterion is determined by:

$$NMAE = \frac{100}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{P_{ins}} \quad (14)$$

while P_{ins} corresponds to the wind power capacity installed ($P_{ins} = 2700MW$ in this work).

Furthermore, the normalized root mean square error (NRMSE) is used [23], [52], [53] determined by:

$$NMAE = \sqrt{\frac{1}{N}\sum_{h=1}^{N}\left(\frac{\hat{p}_h - p_h}{P_{ins}}\right)^2} \times 100 \tag{15}$$

4. Case study

The HEA methodology 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 Portuguese TSO (REN). Our forecaster predicts the value of the wind power subseries for 3-h ahead taking into account the wind power data of the previous 12 hours with a time step of 15 minutes.

Numerical results with HEA methodology are provided in Figures 6 to 9 for the four seasons of the year, correspondingly. The prediction bias may be considered rather neutral, in the sense that when the errors start to go more in the positive side, the methodology immediately corrects itself and drives them to the negative side to compensate, and vice-versa. This behaviour is associated to the evolutionary characteristics of EPSO, on the one hand, and the adaptive characteristics of ANFIS, on the other hand.

Table 2 provides a comparative study between the HEA methodology and eight other previously published methodologies, regarding the MAPE criterion. The MAPE criterion using HEA methodology has an average value of only 3.75%, the lowest one of all. The MAPE enhancements between HEA and the other methodologies are 80.3%, 80.3%, 63.7%, 48.3%, 46.2%, 43.5%, 37.4% and 24.7%, respectively, always above 24%, which is significant.

Table 3 provides a comparative study between the HEA methodology and the eight other methodologies, regarding the error variance criterion. The average value is only 0.0013, again the lowest one of all, indicating lesser uncertainty in the forecasts. The error variance enhancements between HEA and the other methodologies are 94.4%, 94.4%, 83.8%, 74.5%, 72.3%, 69.8%, 59.4% and 38.1%, respectively, always above 38%, even more significant since it is related to the uncertainty in the forecasts, representing a major improvement. Table 4 shows the NMAE criterion comparative results between the HEA methodology and the eight other methodologies. The enhancements between HEA methodology and the other methodologies regarding the NMAE criterion are 83.1%, 83.0%, 69.0%, 55.1%, 53.3%, 51.1%, 46.5% and 36.3%, respectively, always above 35%, again significant.

Furthermore, Table V shows the NRMSE criterion results of the HEA methodology for the four seasons. The NRMSE criterion using the HEA methodology has an average value of 2.66%.

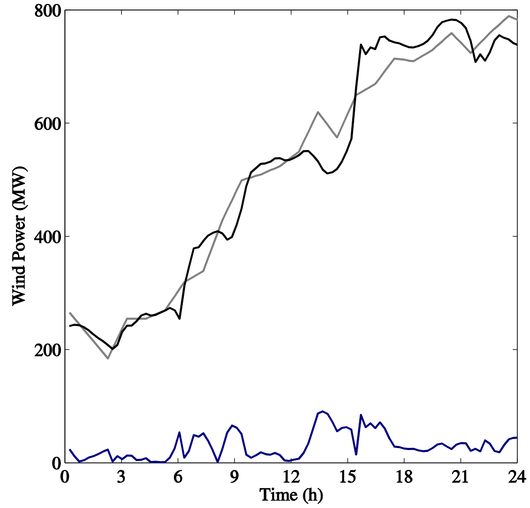

Fig. 6. Measured and predicted results (15-min intervals) for the Winter season: Gray and black lines represent actual and forecasted wind power, respectively, while dark-blue line represents errors in absolute value.

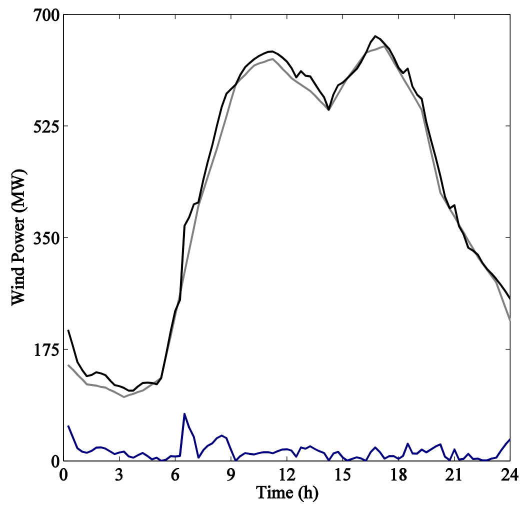

Fig. 7. Measured and predicted results (15-min intervals) for the Spring season: Gray and black lines represent actual and forecasted wind power, respectively, while dark-blue line represents errors in absolute value.

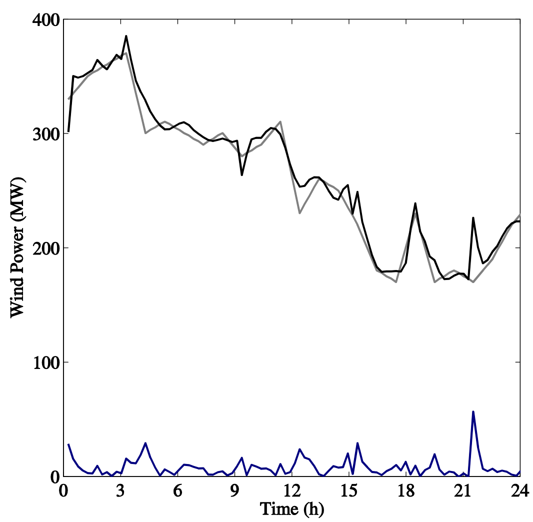

Fig. 8. Measured and predicted results (15-min intervals) for the Summer season: Gray and black lines represent actual and forecasted wind power, respectively, while dark-blue line represents errors in absolute value.

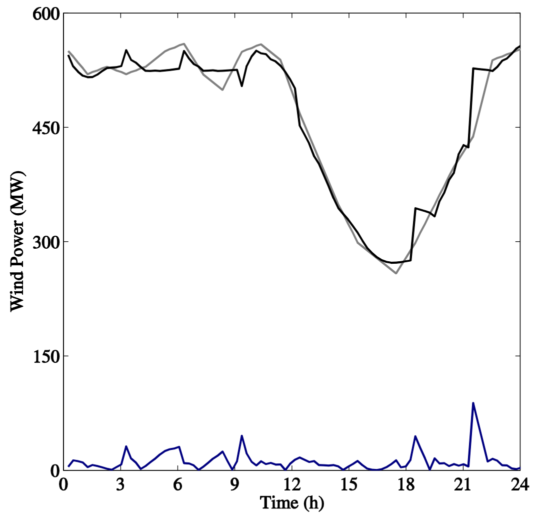

Fig. 9. Measured and predicted results (15-min intervals) for the Fall season: Gray and black lines represent actual and forecasted wind power, respectively, while dark-blue line represents errors in absolute value.

Table 2
MAPE Outcomes for all Methodologies

	Winter season	Spring season	Summer season	Fall season	Average
Persistence [29]	13.89	32.40	13.43	16.49	19.05
NRM [36]	13.87	32.38	13.43	16.43	19.03
ARIMA [29]	10.93	12.05	11.04	7.35	10.34
NN [29]	9.51	9.92	6.34	3.26	7.26
NNWT [31]	9.23	9.55	5.97	3.14	6.97
NF [33]	8.85	8.96	5.63	3.11	6.64
WNF [19]	8.34	7.71	4.81	3.08	5.99
WPA [36]	6.47	6.08	4.31	3.07	4.98
HEA	5.74	3.49	3.13	2.62	3.75

Table 3
Error variance outcomes for all methodologies

	Winter season	Spring season	Summer season	Fall season	Average
Persistence [29]	0.0074	0.0592	0.0085	0.0179	0.0233
NRM [36]	0.0074	0.0590	0.0079	0.0180	0.0231
ARIMA [29]	0.0025	0.0164	0.0090	0.0039	0.0080
NN [29]	0.0044	0.0106	0.0043	0.0010	0.0051
NNWT [31]	0.0055	0.0083	0.0038	0.0012	0.0047
NF [33]	0.0041	0.0086	0.0038	0.0008	0.0043
WNF [19]	0.0046	0.0051	0.0021	0.0011	0.0032
WPA [36]	0.0021	0.0035	0.0016	0.0011	0.0021
HEA	0.0019	0.0015	0.0010	0.0008	0.0013

Table 4
Comparative NMAE results

	Winter season	Spring season	Summer season	Fall season	Average
Persistence [29]	7.64	12.15	4.98	10.88	8.91
NRM [36]	7.62	12.14	4.98	10.84	8.90
ARIMA [29]	6.01	4.52	4.09	4.85	4.87
NN [29]	5.22	3.72	2.35	2.15	3.36
NNWT [31]	5.07	3.58	2.21	2.07	3.23
NF [33]	4.86	3.36	2.09	2.05	3.09
WNF [19]	4.58	2.89	1.78	2.03	2.82
WPA [36]	3.56	2.28	1.60	2.02	2.37
HEA	2.73	1.48	0.74	1.10	1.51

Table 5
NRMSE results

	Winter season	Spring season	Summer season	Fall season	Average
HEA	3.60	3.18	1.78	2.07	2.66

Statistically demonstrative results for a full year (2009) using the HEA methodology are provided in Table 6 and Table 7 concerning the MAPE and NMAE criterions, respectively. The HEA methodology clearly outperforms all other methodologies.

Furthermore, the HEA methodology presents a relatively low computational burden; the CPU time is less than 40 seconds per iteration, on average, working with MATLAB on a standard PC with 1.8 GHz processor and 1.5-GB of RAM. Not only is the training time almost negligible, but also the accuracy is higher and the uncertainty is lower.

Table 6
Comparative MAPE outcomes for 2009

	Persist. [29]	NRM [36]	ARIMA [29]	NN [29]	NNWT [31]	NF [33]	WNF [19]	WPA [36]	HEA
January	17.44	16.83	16.03	13.62	12.22	10.69	8.16	6.71	6.14
February	22.84	22.81	20.56	14.55	12.92	11.68	8.64	7.05	6.05
March	19.70	18.99	13.01	12.04	11.05	8.76	7.51	6.19	5.61
April	22.77	22.53	13.26	9.43	9.19	8.78	7.82	6.57	5.55
May	17.20	16.78	11.98	9.86	8.85	8.29	6.87	5.94	4.52
June	36.70	36.37	27.96	14.18	12.52	11.60	8.85	7.23	6.98
July	21.30	20.86	15.98	13.53	12.28	11.16	8.42	7.06	7.02
August	13.94	13.55	11.94	8.42	7.48	6.18	5.09	4.66	4.58
September	24.51	24.20	16.65	10.60	10.28	9.95	8.28	7.33	5.55
October	26.45	26.16	18.58	12.92	11.28	10.44	8.67	7.26	7.20
November	17.16	16.88	14.47	12.72	12.15	11.36	8.65	6.99	5.10
December	16.90	16.86	12.14	10.03	9.54	8.98	7.02	5.99	5.43
Average	21.41	21.07	16.05	11.83	10.81	9.82	7.83	6.58	5.81

Table 7
Comparative NMAE outcomes for 2009

	Persist. [29]	NRM [36]	ARIMA [29]	NN [29]	NNWT [31]	NF [33]	WNF [19]	WPA [36]	HEA
January	3.23	3.12	2.97	2.53	2.26	1.98	1.51	1.24	1.16
February	8.34	8.37	7.51	5.31	4.71	4.27	3.16	2.58	2.24
March	1.91	1.84	1.26	1.17	1.07	0.85	0.73	0.60	0.55
April	4.07	4.02	2.37	1.69	1.64	1.57	1.40	1.17	0.99
May	5.91	5.76	4.11	3.39	3.04	2.85	2.36	2.04	1.59
June	7.86	7.79	5.99	3.04	2.68	2.48	1.89	1.55	0.72
July	4.05	3.96	3.04	2.57	2.33	2.12	1.60	1.34	0.69
August	4.73	4.60	4.05	2.86	2.54	2.10	1.73	1.58	1.55
September	4.85	4.79	3.29	2.10	2.03	1.97	1.64	1.45	1.09
October	5.36	5.31	3.77	2.62	2.29	2.12	1.76	1.47	1.35
November	7.02	6.90	4.08	5.20	4.97	4.65	3.54	2.86	1.98
December	5.54	5.53	3.98	3.29	3.13	2.95	2.30	1.97	1.81
Average	5.24	5.17	3.87	2.98	2.72	2.49	1.97	1.65	1.31

5. Conclusions

A new hybrid evolutionary-adaptive methodology, called HEA, was tested for short-term (3-h ahead with 15-min intervals) wind power predictions in the Portuguese system. The HEA methodology results from the valuable joint characteristics of WT (bringing a filtering effect handling non-stationary sets), EPSO (bringing evolutionary optimization), and ANFIS (bringing an adaptive architecture), considering also MI in the selection of the best input data (increasing the robustness of the methodology). For a fair and clear comparative study, identical test cases used by other methodologies were considered, also without exogenous variables. The application of the proposed HEA methodology was revealed to be accurate and effective, helping to reduce the uncertainty associated with wind power. The average MAPE value was only 3.75% for an average error variance of 0.0013 and a NRMSE of 2.66%. In addition, the low computational burden is a reality, providing wind power forecast results in less than 40 seconds per iteration. Hence, the proposed HEA methodology presents the best trade-off between computational time and accuracy, which is crucial for real-life and real-time applications.

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