Hybrid Evolutionary-Adaptive Approach to Predict Electricity Prices and Wind Power in the Short-Term

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***Abstract*—Nowadays, with the new paradigm shift in the energy sector and the advent of the smart grid, or even with the mandatory imposition for a gradual reduction of greenhouse gas emissions, the renewable producers, namely the wind power producers are faced with the competitiveness and deregulated structure that characterizes the liberalized electricity market. In a liberalized electricity market, the most important signal for all market players corresponds to the electricity prices. In this sense, accurate approaches for short-term electricity prices prediction are needed, and also for short-term wind power prediction due to the increasing share of wind generation. Hence, this paper presents a new hybrid evolutionary-adaptive approach for wind power and electricity market prices prediction, in the short-term, based on mutual information, wavelet transform, evolutionary particle swarm optimization and adaptive neuro-fuzzy inference system, tested on real case studies, proving its superiority in a comprehensive comparison with other approaches previously published in the scientific literature.**

Keywords—Forecasting; Market prices; Wind power; Neuro-fuzzy system; Evolutionary particle swarm optimization.

I. INTRODUCTION

The volatile and intermittent nature of wind power, associated with its increasing share in demand coverage, as occurs in some parts around the world, leads to the need for the development of forecasting approaches with enhanced capabilities where it is crucial to achieve higher accuracy and less uncertainty in wind power forecasts. Moreover, the computational burden should be kept low to enable fast operational decisions [1].

The wind power capacity connected to the electrical grid has sustained the highest growth [2] in comparison with other renewable sources and technologies. This expansion of wind energy has occurred due to the ratio between production and implementation costs, maintenance costs, the maturity of the technology and increasing production capacity [3]. However, due to the stochastic characteristic of wind power, its integration is responsible for the introduction of more variability, volatility and uncertainty in the system, which complicates substantially the proper management of all production and must be mitigated in order to reduce their impacts [4], [5]. Accordingly, wind power prediction approaches can be classified by time-scales, that is: very short (until few minutes), short (between few minutes till few days), and long (between few days till more than one week) terms [6].

Several wind power prediction approaches have been developed and presented in the scientific community in recent years, which can be split into physical and statistical approaches. The physical approaches use an extensive number of variables (temperature, pressure, etc.), presenting advantages in long-term prediction. Meanwhile, statistical approaches are able to find the relationship in specific structures included in measured data, showing advantages in short-term prediction [7].

Meanwhile, in a deregulated electricity market, the most important signal for all market players corresponds to the electricity price [8]. Several characteristics of market price series make their forecast harder than demand series, such as non-stationary behavior, high volatility and frequency, seasonality and calendar effect [9]. Accurate approaches for short-term electricity prices prediction are needed to assist producers in designing their offering strategies to achieve maximum profits, and to assist consumers in protecting themselves against elevated prices [10]. The electricity market prices prediction has grown to be one of the main research fields in power engineering [11], but the corresponding approaches or techniques have not yet reached the necessary maturity [12]. Furthermore, forecasting prices is indeed a crucial task for all market players [13] in their decision, especially with the advent of smart grids. Forecasting methodologies can also be divided in two groups: hard and soft computing approaches. The hard computing approaches require a precise modeling of the system, resulting in high computational requirements. Instead, the soft computing approaches use an auto learning mechanism from historical information identifying future patterns [14].

This paper provides a new hybrid evolutionary-adaptive approach (HEA) for wind power and electricity market prices prediction, in the short-term, based on mutual information (MI), wavelet transform (WT), evolutionary particle swarm optimization (EPSO) and adaptive neuro-fuzzy inference system (ANFIS). A comprehensive comparison with other methodologies previously published in the scientific literature is provided for demonstrating the enhanced forecasting accuracy and the reduced computational burden, testing on real case studies.

II. PROPOSED APPROACH

The HEA approach is a mixture of MI, WT, EPSO and ANFIS techniques. MI is employed in order to eliminate the randomness in the selection of data input. WT is employed to decompose the input data series into new constitutive data with better behavior. Forthcoming values are predicted with ANFIS.

EPSO brings on augmented ANFIS performance, by tuning membership functions to attain a lesser error. Finally, the inverse WT is used to reconstruct the previous results, obtaining then the final forecasting results.

A. Mutual Information

The MI is based on the concept of entropy. This concept shows that random processes may have a complexity of such order that the signal cannot be compressed or reduced. To explain MI the entropy must be explained first. The entropy is derived from statistical physics, which was used as a quantity of the disorder state of a system. The discrete entropy $H(X)$ is mathematically described as [15]:

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

where X is a random discrete variable, with binomial probability $P(X_i)$. Furthermore, some results should be considered:

- If an event is equal to 0, that event does not occur;
- If an event is equal to 1, that event occurs;
- Considering the event: $X_1 = 0 \wedge X_2 = 1$, the individual entropy is equal to 0, i.e., $H(X_i) = 0$, if:

$$(P(X_1) = 0 \wedge P(X_2) = 1)\ (P(X_1) = 1 \wedge P(X_2) = 0) \quad (2)$$

and the individual entropy is equal to 1, i.e., $H(X_i) = 0$, if:

$$P(X_1) = 0.5 \wedge P(X_2) = 0.5 \quad (3)$$

By extending the definition of entropy for the case of joint distributions of random variables, where the value of a random discrete variable X is known, if the entropy of a random discrete variable Y is assumed to be known, (1) takes a new form:

$$H(Y/X) = -\sum_{i=1}^{n}\sum_{j=1}^{m} P(X_i, X_j)\log_2\big(P(Y_j/X_i)\big) \quad (4)$$

The conditional entropy $H(Y/X)$ quantifies the remaining uncertainty of Y when X is known [16]. MI has a strong connection with the individual entropy described in (1), and with the conditional entropy described in (4). The discrete MI measures the level of information between a set of information data which is described as:

$$MI(X,Y) = \sum_{i=1}^{n}\sum_{j=1}^{m} P(X_i, Y_j)\log_2\left(\frac{P(X_i, Y_j)}{P(X_i)P(Y_j)}\right) \quad (5)$$

The MI can be described as:

$$MI(X,Y) = MI(Y,X) = H(X) - H(X/Y) \quad (6)$$

Furthermore, in MI some results should be considered:

- If $MI(X,Y) \approx 1$, then the data are correlated.
- If $MI(X,Y) \approx 0$, then the data are not correlated.
- If $MI(X,Y) = 0$, then the data are independent.

Fig. 1 shows a simplified MI representation.

B. Wavelet Transform

The WT is normally used in pre-processing for understanding the non-stationary or time varying data [17], with sensibility to the irregularities of input data. WT is capable of showing the different aspects that constitute the data without losing the real signal content [18]. In other words, WT is able to reduce the noise of the input data (smoothing effect) without appreciable degradation.

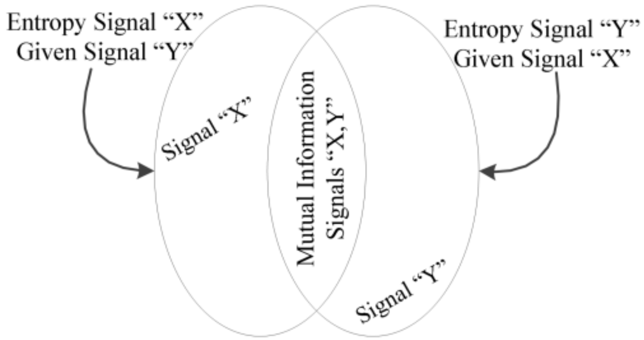

Fig. 1. Simplified MI Representation.

The discrete wavelet transform (DWT) is defined:

$$W(m,n) = 2^{-(m/2)}\sum_{t=0}^{T} f(t)\varphi\left(\frac{t - n2^m}{2^m}\right) \quad (7)$$

where T represents the signal length $f(t)$, the scaling and translation parameters given by $a = 2^m$ and $b = n2^m$ respectively, and the time step given by t.

A DWT algorithm is used based on four filters divided into two groups: the decomposition group and the reconstruction group formed in low-pass and high-pass filters.

Furthermore, the three level approximations and details of the original sets can be obtained via Mallat’s algorithm. Fig. 2 shows a general decomposition model of WT.

The approximations A_n are able to retain the general information given by the low-frequency representation and description of the high-frequency component. The details D_n are able to explain the difference between successive approximations. Finally, the fourth order of Daubechies mother wavelet function is used due to a better trade-off between length and smoothness.

C. Evolutionary Particle Swarm Optimization

EPSO incorporates a selection procedure to the original particle swarm optimization technique and the self-adapting properties for its parameters [19].

EPSO has some important features: *replication*: where each particle (data) is replicated; *mutation*: where each particle has its weight mutated; *reproduction:* where each mutated particle generates a new set of particles according with the movement rule; *evaluation:* where the improvement of each particle is computed; and *selection:* described by stochastic training, where the best particle is chosen to create a new particle [20].

The formulation of EPSO is composed of object parameters X and strategic weights parameters w, defined as:

$$X_i^{new} = X_i + V_i^{new} \quad (8)$$

$$V_i^{new} = w_{i0}^{*}V_i + w_{i1}^{*}(b_i - X_i) + w_{i2}^{*}(b_g^{*} - X_i) \quad (9)$$

Eqs. (8)-(9) are similar to the classical particle swarm optimization (PSO) algorithm, i.e. the movement rule keeps the inertia, memory and cooperation terms, which can be shown in Fig. 3. However, the weights undergo mutation, given by:

$$w_{ik}^{*} = w_{ik} + \tau N(0,1) \quad (10)$$

In (10), $N(0,1)$ is a random Gaussian variable with 0 mean and variance 1.

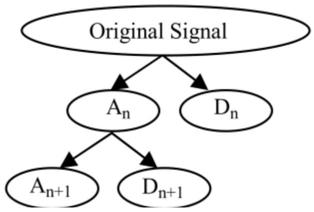

Fig. 2. Decomposition model of WT.

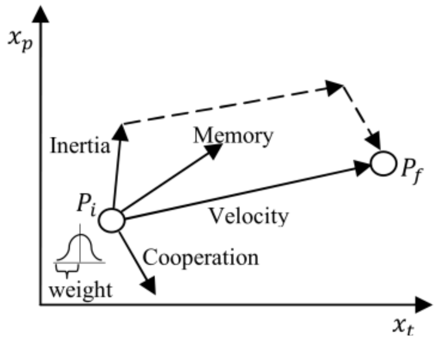

Fig. 3. EPSO movement rule.

Furthermore, the global position b_g^* is defined and changing according to:

$$b_g^* = b_g + \tau' N(0,1) \tag{11}$$

In (8)-(11) the parameters represent the position X_i, velocity V_i, best point b_i found at generation k, the learning parameters τ and the mutated parameter τ'. EPSO provides quicker convergence in comparison with the PSO algorithm because only the stronger particles survive in the evolutionary process [19], [20].

D. Adaptive Neuro-Fuzzy Inference System

ANFIS is a successful hybrid combination of neural network (NN) and fuzzy algorithms. This is possible due to the low computational requirements of well-structured NN architectures, which can be useful to deal with a large number of data, combined with a high response given by fuzzy algorithms. Furthermore, the NN algorithm has the self-learning capability that is combined with the fuzzy algorithm to self-adjust its parameters [21].

The general ANFIS architecture consists of fuzzification, rules, normalization data, desfuzzification, and signal reconstruction by the respective layers, i.e., composed by five layers, thus also called multi-layer feed-forward network, represented in general terms in Fig. 4. Each layer has a specific purpose:

- Layer1 is an adaptive layer where each node has a membership function node, with linguistic labels associated. Nodes A_n and B_n have a specific bell function [22]:

$$L1_i = \mu A_i(x), \qquad i = 1, 2 \tag{12}$$

or

$$L1_i = \mu B_{i-i}(y), \qquad i = 3, 4 \tag{13}$$

- Layer2 is responsible for the firing strength, where node Π_n computes the output signal with a multiplication of inputs signals:

$$L2_i = w_i = \mu A_i(x) \mu B_i(y), \qquad i = 1, 2 \tag{14}$$

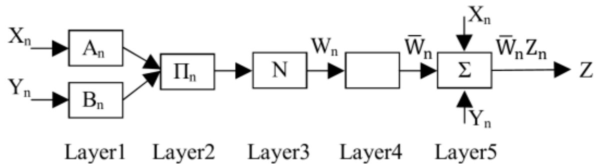

Fig. 4. General ANFIS architecture.

- In Layer3, each node N computes the measurement of firing rules strength with the sum of every firing strength rules:

$$L3_i = \overline{w_i} = \frac{w_i}{w_i + w_{i+1}}, \qquad i = 1, 2 \tag{15}$$

- In Layer4, every node measures the contribution of each rule for the global input, and where $\{a_i, b_i, c_i\}$ are parameters sets:

$$L4_i = \overline{w_i} z_i = \overline{w_i}(a_i x + b_i y + c_i), \qquad i = 1, 2 \tag{16}$$

- Finally, Layer5 computes the sum of all inputs in this node:

$$L5_i = \sum \overline{w_i} z_i = \frac{\sum_i w_i z_i}{\sum_i w_i} \tag{17}$$

In this work, the ANFIS employs the least-squares and back-propagation gradient descent algorithm.

E. Hybrid Evolutionary-Adaptive Approach

The HEA approach is described in successive steps. Fig. 5 provides the structure of the HEA approach in the form of a detailed flowchart.

- Step 1. Initialize the HEA approach with an historical data matrix of wind power or electricity market prices, considering the previous days/weeks.
- Step 2. The matrix will be normalized in $\{0, 1\}$ intervals, to find the set of historical data in the same scale, which will be later used by the MI in candidate selections.
- Step 3. Constitute data groups for the MI. The number of these groups is defined by combinatorial optimization in order to avoid compromising the computational burden.
- Step 4. Compute the entropy and conditional entropy of each group by using (4).
- Step 5. Compute MI given by (6) of each group.
- Step 6. Compute the best group subset data. The best group found will be recombined in original data. These selected data will be inputs for the WT.
- Step 7. Train the ANFIS with the previous constitutive data. The optimization of the membership function parameters is achieved by EPSO. Table I shows the parameters considered for MI, ANFIS and EPSO. The inference rules of ANFIS are put into automatic mode to achieve the best performance.
- Step 8. Until the best results or convergence are not reached:
  - Step 8.1. Jump to Step 7 in case of electricity market prices prediction. When the best results are found or convergence is reached, the inverse WT is applied and the output of the approach is attained, that is, the electricity prices are forecasted for the next week.

- Step 8.2. Jump to Step 1 in case of wind power prediction. When the best results are found or convergence is reached, the inverse WT is applied and the output of the approach is attained, that is, the wind power data are forecasted for the next three hours. This is repeated eight times with new and refreshing sets of historical wind power data.

- Step 9. Compute the forecasting errors with different criteria to validate the proposed HEA approach.

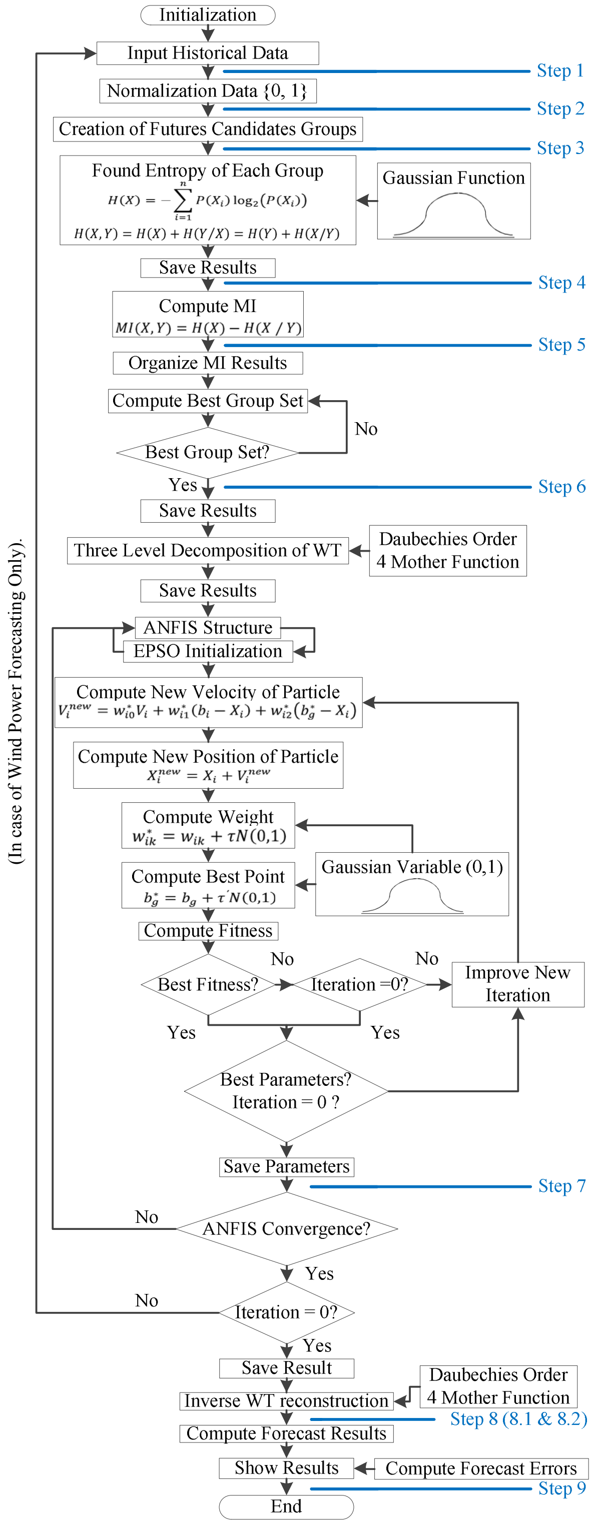

Fig. 5. Flowchart of proposed HEA approach.

III. Forecasting Accuracy Validation

To compare the proposed HEA approach with other approaches used in wind power and electricity market prices prediction, the mean absolute percentage error (MAPE) criterion is commonly used.

The MAPE criterion is given as:

$$MAPE = \frac{100}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \tag{18}$$

$$\bar{p} = \frac{1}{N}\sum_{h=1}^{N} p_h \tag{19}$$

where $\hat{p}_n$ is the data forecast at hour h, p_h is the real data at hour h, $\bar{p}$ is the average value for the forecasting horizon, and N is equal to the number of observed points. The uncertainty of the HEA approach is also evaluated using the error variance estimation. The smaller the value for this criterion, the more exact the approach is.

The error variance criterion is given by:

$$\sigma_{e,t}^2 = \frac{1}{N}\sum_{h=1}^{N}\left(\frac{|\hat{p}_h - p_h|}{\bar{p}} - e_t\right)^2 \tag{20}$$

$$e_t = \frac{1}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \tag{21}$$

IV. Case Studies

A. *Short-term Wind Power Prediction*

The HEA approach has been applied to forecast the wind power for 3 hours ahead in Portugal. The historical data of wind power data date back to 2007 and 2008, available in [23]. To allow a fair comparison with the results already obtained using other published approaches, the same data of 2007 and 2008 were selected, each corresponding to a different season. Moreover, for a clear comparison, only historical data of wind power is used, i.e., no exogenous data are taken into account. The HEA approach predicts the wind power data in Portugal for 3 hours ahead considering a time step of 15 minutes. This process is repeated eight times to show the consistency and validity of the wind power predictions obtained in each season.

Numerical results with the HEA approach are provided in Fig. 6 and Fig. 7 corresponding to the winter and fall seasons, illustrative of the obtained forecasts. Table II provides a thorough comparative study between the HEA approach and eight other previously published methodologies, namely persistence, new reference model (NRM), auto regressive integrated moving average (ARIMA), NN, NN with wavelet transform (NNWT), neuro-fuzzy (NF), wavelet-neuro-fuzzy (WNF) and wavelet-PSO-ANFIS (WPA), regarding the MAPE criterion. The enhancements between HEA and the other approaches are 80.4%, 80.4%, 63.9%, 48.6%, 46.5%, 43.8%, 37.7% and 25.1%, respectively, that is, always above 25%, which is very significant for wind power forecasting. Moreover, Table III provides a thorough comparative study between the HEA approach and the eight other approaches, regarding the daily error variance criterion. The enhancements between HEA and the other approaches are 94.8%, 94.8%, 85.0%, 76.5%, 74.5%, 72.1%, 62.5% and 42.9%, respectively, that is, always above 40%, again notable.

TABLE I. PARAMETERS OF MI, ANFIS AND EPSO

	Parameters	Type or Size	
		Wind Power	*Market Prices*
MI	Best Lower Bound of Set	0.20	0.15
	Best Upper Bound of Set	0.86	0.65
ANFIS	Membership Functions	2-7	
	Necessary Iterations	2-25	3-50
	Membership Function	Triangular format	
EPSO	Fitness Acceleration	2	
	Sharing Acceleration	2	
	Initial Inertia of Population	0.9	
	Final Inertia of Population	0.4	
	Population Size	96	168
	Maximum Generation	192	326
	Number of New Particles	12	168
	Generation for New Particle	2	
	Necessary Iterations	192	326
	Min. Value of New Position	5	20
	Max. Value of New Position	2000	120

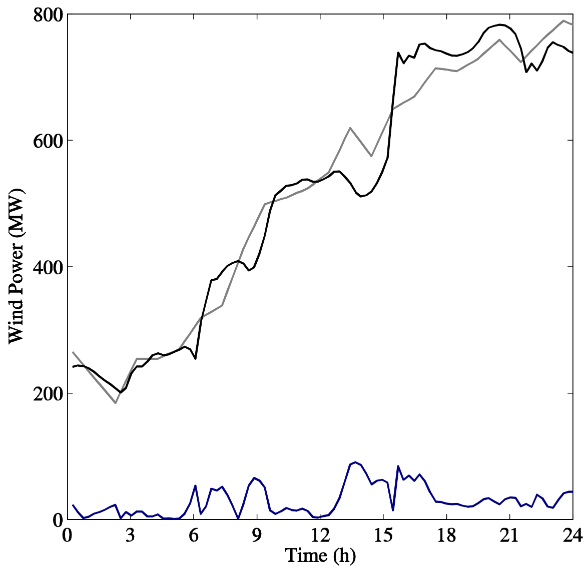

Fig. 6. Real (gray line), forecasted (black line) and error in absolute value (dark-blue line) of wind power results for winter season in Portugal.

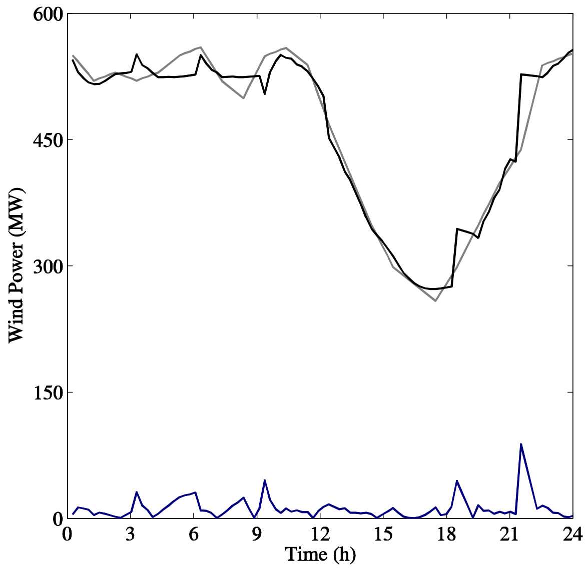

Fig. 7. Real (gray line), forecasted (black line) and error in absolute value (dark-blue line) of wind power results for fall season in Portugal.

TABLE II. COMPARATIVE MAPE RESULTS FOR WIND POWER PREDICTION

	Winter season	Spring season	Summer season	Fall season	Average
Persistence [24]	13.89	32.40	13.43	16.49	19.05
NRM [25]	13.87	32.38	13.43	16.43	19.03
ARIMA [24]	10.93	12.05	11.04	7.35	10.34
NN [24]	9.51	9.92	6.34	3.26	7.26
NNWT [26]	9.23	9.55	5.97	3.14	6.97
NF [27]	8.85	8.96	5.63	3.11	6.64
WNF [28]	8.34	7.71	4.81	3.08	5.99
WPA [25]	6.47	6.08	4.31	3.07	4.98
HEA	5.74	3.41	3.13	2.62	3.73

TABLE III. COMPARATIVE DAILY ERROR VARIANCE

	Winter season	Spring season	Summer season	Fall season	Average
Persistence [24]	0.0074	0.0592	0.0085	0.0179	0.0233
NRM [25]	0.0074	0.0590	0.0079	0.0180	0.0231
ARIMA [24]	0.0025	0.0164	0.0090	0.0039	0.0080
NN [24]	0.0044	0.0106	0.0043	0.0010	0.0051
NNWT [26]	0.0055	0.0083	0.0038	0.0012	0.0047
NF [27]	0.0041	0.0086	0.0038	0.0008	0.0043
WNF [28]	0.0046	0.0051	0.0021	0.0011	0.0032
WPA [25]	0.0021	0.0035	0.0016	0.0011	0.0021
HEA	0.0019	0.0012	0.0010	0.0008	0.0012

B. Short-term Electricity Market Prices Prediction

The HEA approach has also been applied to forecast the Spanish electricity market prices for the next 168 hours. The historical data of electricity prices date back to 2002, available in [29]. To allow a fair comparison with the results already obtained using other published approaches, the same four test weeks of 2002 were selected, each corresponding to a different season. Moreover, for a clear comparison, only historical data were used, i.e., no exogenous data are taken into account. The HEA approach predicts the electricity prices for 168 hours ahead considering a time step of 1 hour. The previous six weeks or 42 days are the input sets. The output corresponds directly to an output with 168 values, equal to the prediction horizon.

Numerical results with the HEA approach are provided in Fig. 8 and Fig. 9 corresponding to the winter and summer seasons, illustrative of the obtained forecasts. Table IV provides a thorough comparative study between the HEA approach and fourteen other previously published methodologies, namely ARIMA, NN, wavelet-ARIMA, fuzzy-NN (FNN), hybrid intelligent system (HIS), adaptive wavelet NN (AWNN), NNWT, radial basis function NN (RBFN), cascaded neuro evolutionary algorithms (CNEA), cascaded NN (CNN), hybrid neuro evolutionary system (HNES), MI+CNN, WPA and MI-MI+CNN, regarding the MAPE criterion. The enhancements between HEA and the other approaches are 58.0%, 53.1%, 48.5%, 44.4%, 40.0%, 38.1%, 37.1%, 27.2%, 21.4%, 19.9%, 18.7%, 18.5%, 17.6% and 15.6%, respectively, that is, always above 15%, which is very significant for electricity price forecasting. Moreover, Table V provides a thorough comparative study between the HEA approach and the fourteen other approaches, regarding the weekly error variance criterion. The enhancements between HEA and the other approaches are 83.7%, 78.6%, 76.6%, 72.2%, 68.8%, 59.5%, 58.3%, 58.3%, 57.1%, 54.5%, 44.4%, 28.6%, 28.6% and 28.6%, respectively, that is, always above 25%, again notable.

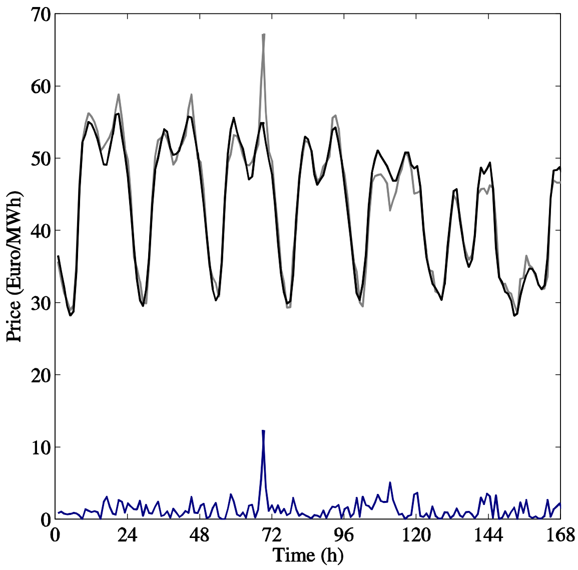

Fig. 8. Real (gray line), forecasted (black line) and error in absolute value (dark-blue line) of electricity price results for winter season in Spanish market.

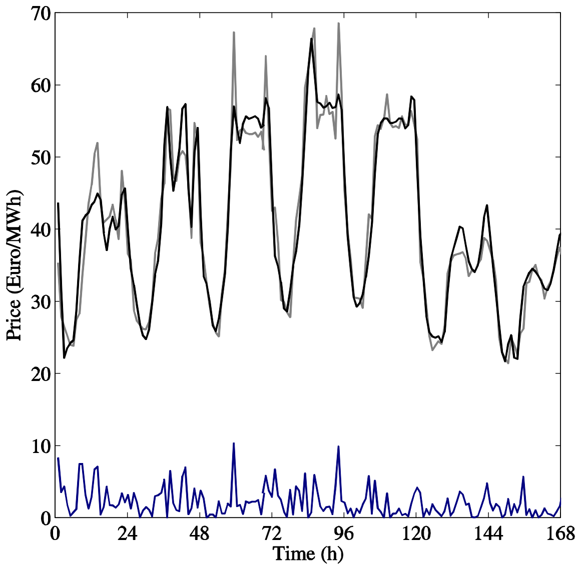

Fig. 9. Real (gray line), forecasted (black line) and error in absolute value (dark-blue line) of electricity price results for summer season in Spanish market.

TABLE IV. COMPARATIVE MAPE RESULTS FOR ELECTRICITY PRICES PREDICTION

	Winter	Spring	Summer	Fall	Average
ARIMA [30]	6.32	6.36	13.39	13.78	9.96
NN [31]	5.23	5.36	11.40	13.65	8.91
Wavelet-ARIMA [32]	4.78	5.69	10.70	11.27	8.11
FNN [33]	4.62	5.30	9.84	10.32	7.52
HIS [34]	6.06	7.07	7.47	7.30	6.97
AWNN [35]	3.43	4.67	9.64	9.29	6.75
NNWT [36]	3.61	4.22	9.50	9.28	6.65
RBFN [14]	4.27	4.58	6.76	7.35	5.74
CNEA [15]	4.88	4.65	5.79	5.96	5.32
CNN [37]	4.21	4.76	6.01	5.88	5.22
HNES [38]	4.28	4.39	6.53	5.37	5.14
MI+CNN [39]	4.51	4.28	6.47	5.27	5.13
WPA [13]	3.37	3.91	6.50	6.51	5.07
MI–MI+CNN [39]	4.29	4.20	6.31	5.01	4.95
HEA	3.04	3.33	5.38	4.97	4.18

TABLE V. COMPARATIVE WEAKLY ERROR VARIANCE

($\times 10^{-4}$)	Winter	Spring	Summer	Fall	Average
ARIMA [30]	3.4	2.0	15.8	15.7	9.2
NN [31]	1.7	1.8	10.9	13.6	7.0
Wavelet-ARIMA [32]	1.9	2.5	10.8	10.3	6.4
FNN [33]	1.8	1.9	9.2	8.8	5.4
AWNN [35]	1.2	3.1	7.4	7.5	4.8
NNWT [36]	0.9	1.7	7.4	4.9	3.7
HIS [34]	3.4	4.9	2.9	3.1	3.6
CNEA [15]	3.6	2.7	4.3	3.9	3.6
CNN [37]	1.4	3.3	4.5	4.8	3.5
RBFN [14]	1.5	1.9	4.7	4.9	3.3
WPA [13]	0.8	1.3	5.6	3.3	2.7
MI+CNN [39]	1.4	1.4	3.3	2.2	2.1
HNES [38]	1.3	1.5	3.3	2.2	2.1
MI–MI+CNN [39]	1.4	1.4	3.2	2.3	2.1
HEA	0.8	1.1	2.6	1.4	1.5

V. CONCLUSION

A new hybrid evolutionary-adaptive approach, called HEA, was proposed for short-term wind power and electricity prices prediction. The added value of the proposed work was the novel combination of relevant techniques (MI, WT, EPSO and ANFIS) applied for the first time ever in wind power and electricity prices prediction in the short-term time horizon. The CPU time was less than one minute on average in all cases studied, working with MATLAB on a standard PC with 1.8 GHz processor and 1.5 GB of RAM. Hence, an excellent trade-off between computational time and MAPE results was achieved, which is of the utmost importance for real-life and real-time power system operations, avoiding also the use of exogenous data such as load, using instead just the historical values of wind power and electricity market prices available from public domain. Hence, not only was the training time practically negligible, but also the accuracy was higher and the uncertainty was lower in the cases presented.

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