Electricity prices forecasting by a hybrid evolutionary-adaptive methodology

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Abstract

With the restructuring of the electricity sector in recent years, and the increased variability and uncertainty associated with electricity market prices, it has become necessary to develop forecasting tools with enhanced capabilities to support the decisions of market players in a competitive environment. Hence, this paper proposes a new hybrid evolutionary-adaptive methodology for electricity prices forecasting in the short-term, i.e., between 24 and 168 hours ahead, successfully combining mutual information, wavelet transform, evolutionary particle swarm optimization, and the adaptive neuro-fuzzy inference system. In order to determine the accuracy, competence and proficiency of the proposed methodology, results from real-world case studies using real data are presented, together with a thorough comparison considering the results obtained with previously reported forecasting tools. Not only is the accuracy an important factor, but also the computational burden is relevant in a comparative study. The results show that it is possible to reduce the uncertainty associated with electricity market prices prediction without using any exogenous data, just the historical values, thus requiring just a few seconds of computation time.

Keywords: Forecasting, market prices, mutual information, wavelet transform, evolutionary particle swarm optimization, neuro-fuzzy.

1. Introduction

1.1. Aims and Difficulty

In a deregulated electricity market, the most important signal for all market players corresponds to the price. The evolution from a vertically integrated structure to a deregulated framework increased the complexity of electricity market prices behaviour [1, 2]. Several characteristics of electricity market prices series make their forecast harder than demand series, such as non-stationary behaviour, high volatility and frequency, seasonality and the calendar effect [3]. An accurate tool for short-term electricity market prices forecasting is needed to assist producers in designing their offering strategies to the electricity market to achieve maximum profits [4, 5], on the one hand, and to assist consumers in protecting themselves against elevated prices and for planning purposes, on the other [6, 7]. Forecasting electricity market prices has grown to be one of the main research areas in power engineering [8-10], but the corresponding tools or techniques have not yet reached maturity [11]. Predicting electricity market prices is indeed a crucial task for all market players [12] in their decision making, especially with the advent of smart grids [13], or even with the mitigation commitment of green house gases emissions around the world [14].

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1.2. Literature Review

In recent years, several forecasting methodologies have been described in the specialized literature. These can be divided in two groups: hard and soft computing methodologies [15]. In hard computing, some known methodologies can be found, such as auto regressive integrated moving average (ARIMA) [16], wavelet transform (WT) with ARIMA [17], and transfer function models [18]. These methodologies usually need a large number of physical data, requiring also the exact modelling of the system, and result in high computational burden. In soft computing, the methodologies use an auto learning process from historical sets to identify future patterns. Thus, a new soft computing methodology was developed in this paper. Several methodologies can be found in the specialized literature, such as neural network (NN) [19], NN model based on similar days (SDNN) [20], fuzzy NN (FNN) [21], weighted nearest neighbours (WNN) [22], a modification of WNN called pattern sequence-based forecasting (PSF) [23], adaptive wavelet NN (AWNN) [6], hybrid intelligent systems (HIS) [24], NN with WT (NNWT) [25], WT with ARIMA and radial basis function NN (RBFN) [15], Elman network or simple recurrent network (SRN) [26], cascaded neuro-evolutionary algorithms (CNEA) [27], cascaded NN (CNN) [28], hybrid neuro-evolutionary system (HNES) [29], and other hybrids [30].

Existing features selection algorithms include correlation analysis [31], mutual information [27] and modified relief [32], among other combinations and two stage techniques [33]. More recently, there are some interesting methodologies published in this field of knowledge, such as WT combined with chaotic least squares support vector machine (CLSSVM) and exponential generalized autoregressive conditional heteroskedastic (EGARCH) model (WT+CLSSVM+EGARCH) [34], singular spectrum analysis (SSA) method [35], a combination technique based on wavelet transform fuzzy, firefly algorithm and fuzzy ARTMAP (WT+FF+FA) [36], a recursive dynamic factor analysis combined with Kalman filter (RDFA+KF) [37], and a derived methodology by integrating the kernel principal component analysis, combined with the local informative vector machine, derived from a local regression method (KPCA+IVM) [38].

1.3. Motivation and Contribution

In this paper, a new hybrid evolutionary–adaptive (HEA) methodology is proposed for short-term electricity market price forecasting, based on mutual information (MI), WT, evolutionary particle swarm optimization (EPSO), and the adaptive neuro-fuzzy inference system (ANFIS). The HEA methodology is tested on real case studies using electricity market prices from the Spanish and Pennsylvania-New Jersey-Maryland (PJM) electricity markets. To prove its superior forecasting accuracy and reduced computational burden, a comprehensive comparison with others methodologies previously published in the specialized literature was undertaken. The comparison (illustrated in tabular form) will take into account AWNN [6], wavelet-PSO-ANFIS (WPA) methodology [12], RBFN [15], ARIMA [16], wavelet-ARIMA [17], NN [19], SDNN [20], FNN [21], WNN [22], PSF [23], HIS [24], NNWT [25], SRN [26], CNEA [27], CNN [28], HNES [29], other hybrids [30, 33, 36] and mixed models [39].

The new proposed HEA methodology, which combines relevant techniques (MI, WT, EPSO and ANFIS) for the first time ever in electricity market prices forecasting, allows a timely and improved prediction with low computational effort, avoiding the use of exogenous data such as load, oil prices, among others, using instead just the historical values of electricity market prices available from public domain, which is an important new contribution to the field.

1.4. Layout of the paper

The remainder of this paper is partitioned as follows: Section 2 describes the proposed methodology in detail, i.e., all techniques that compose the proposed methodology and structure, Section 3 provides the forecasting accuracy validation, which supports the comparative results obtained, Section 4 presents the case studies with real-world historical data in different time horizons from Spanish and PJM markets, and finally, in Section 5 the conclusions are drawn.

2. Proposed Methodology

The HEA methodology results from the innovative combination of MI, WT, EPSO and ANFIS. MI eliminates the randomness in the selection of electricity market prices sets as inputs, increasing the robustness of the methodology and helping to decrease the final forecasting error. Furthermore, MI is a nonlinear feature selection algorithm, more adequate for electricity market prices (non-stationary, time varying and irregular sets), instead of using a simple linear correlation analysis for input selection that can compromise the selection of the best candidates [27]. The WT is employed to decompose the electricity price sets into new constitutive sets with better behavior without losing the real behavior of input data signal. Then, the forthcoming values of those constitutive sets are predicted with the ANFIS. The EPSO brings on augmented ANFIS performance by tuning their membership functions to attain a lesser error. The evolutionary concepts can make a real difference in terms of convergence properties, i.e., the EPSO is self-adaptive, more robust and less sensitive to parameter initialization, comparatively to 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. This concept shows that random processes may have a complexity of such order that the signal cannot be compressed or reduced. The entropy is derived from statistical physics, which was used as a measure of the disorder state of a system. The entropy $H(X)$ is mathematically described as [27]:

$$H(X) = -\int P(X)\log_2(P(X))dX \quad (1)$$

where X is a random continuous variable with distribution probability $P(X)$.

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:

$$H(X) = -\sum_{i=1}^{n} P(X_i)\log_2(P(X_i)) \quad (2)$$

The following examples should be considered:

- "A given event is equal to 0", when this event does not occur;
- "A given event is equal to 1", when this event occurs;
- Consider the events: $X_1 = 0 \wedge X_2 = 1$;

The individual entropy is equal to 0, that is, $H(X_n) = 0$, if:

$$(P(X_1) = 0 \wedge P(X_2) = 1) \vee (P(X_1) = 1 \wedge P(X_2) = 0) \quad (3)$$

and the individual entropy is equal to 1, that is, $H(X_n) = 1$, if:

$$P(X_1) = 0.5 \wedge P(X_2) = 0.5 \quad (4)$$

By extending the definition of entropy for the case of joint distributions of random variables, where the value of a random continuous variable X is known, if the entropy of a random continuous variable Y is assumed to be known, (1) takes a new approach [28]:

$$H(X,Y) = -\iint P(X_n, Y_m)\log_2(P(X_n, Y_m)) \quad (5)$$

In the case where variables X and Y are random discrete variables, the joint entropy $H(X, Y)$ is given by:

$$H(X,Y) = -\sum_{i=1}^{n}\sum_{j=1}^{m} P(X_i, Y_j)\log_2\left(P(X_i, Y_j)\right) \quad (6)$$

However, it is not possible to compute (6) directly, so a new concept is necessary, which measures the level of uncertainty of the random discrete variable Y after having observed the value of random discrete variable X. The conditional entropy is defined as:

$$H(Y/X) = -\sum_{i=1}^{n}\sum_{j=1}^{m} P(X_i,Y_j)\log_2\left(P(Y_j/X_i)\right) \tag{7}$$

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

$$H(X,Y) = H(X) + H(Y/X) = H(Y) + H(X/Y) \tag{8}$$

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

$$MI(X,Y) = \sum_{i=1}^{n}\sum_{j=1}^{m} P(X_i,Y_j)\log_2\left(\frac{P(X_i,Y_j)}{P(X_i)P(Y_j)}\right) \tag{9}$$

The MI results can be described by the following points:

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

MI has a strong connection with the individual entropy described in (2), with the conditional entropy described in (7), as well as with (8), so the MI in (9) can be expressed as:

$$MI(X,Y) = H(X) - H(X\ /\ Y) \tag{10}$$

$$MI(X,Y) = MI(Y,X) \tag{11}$$

To ensure the convergence of the HEA methodology, the bounds of MI are very important to guarantee the best performance of the ANFIS. The MI helps to determine the best sets of candidates that will be inputs for training the ANFIS architecture [40].

2.2. Wavelet Transform

The WT is commonly used to understand the non-stationary or time varying sets [41], being sensitive to the irregularities of input sets [42].

WT tools are capable of illustrating different aspects in the sets that are beyond the capacities of other tools without losing the signal [43], reducing the noise of the sets (smoothing effect) without appreciable degradation. The discrete wavelet transform (DWT) is defined:

$$W(m,n) = 2^{-(m/2)}\sum_{t=0}^{T-1} f(t)\,\varphi\left(\frac{t-n2^m}{2^m}\right) \tag{12}$$

In (12) the variable *T* represents the signal length *f(t)*, the parameters of scaling and translation are given by

$a = 2^m$ and $b = n2^m$, respectively, and the time step is given by t. A DWT algorithm is used based on four filters divided into two groups: the decomposition in low-pass and high-pass filters and the reconstruction in low-pass and high-pass filters. The approximations and details of the original sets can be obtained via Mallat algorithm. Furthermore, Fig. 1 shows a three-level decomposition model of WT. The approximations are able to retain the general information of the original sets, that is, the low-frequency representation and description of the high-frequency component. The details are able to explain the difference between successive approximations. The fourth order Daubechies is chosen as the mother wavelet function due to a better trade-off between smoothness and length, as explained in [12].

2.3. Evolutionary Particle Swarm Optimization

EPSO is a meta-heuristic method where rules and optimization concepts are contained in the evolutionary strategies and self-adaptive properties [44]. It is usual to call by generation, the data with alternative solutions, and by individuals the particles data. Each particle is described by object parameters (the value of the variables describing the solution) and strategic parameters (the mutation coefficients of each variable, angle of correlation of mutation variables, or similar) [45].

In EPSO it should be noted the following ideas [46]:

- Each particle (data) is replicated as many times as necessary.
- The weight parameter of the particles is transformed.
- The object parameters of each particle are transformed into a new generated particle by strategic parameters.
- The new mutated particles generate new particles.
- For a group constituted by old particles and new particles, the best fit should lead to the generation of a new population of particles.

Hence, the formulation of EPSO is composed of an object parameters X and strategic parameters w that correspond to the weights. The movement rule of EPSO is defined as [47]:

$$X_i^{new} = X_i + V_i^{new} \tag{13}$$

$$V_i^{new} = w_{i0}^* V_i + w_{i1}^* (b_i - X_i) + w_{i2}^* (b_g^* - X_i) \tag{14}$$

Equations (13) and (14) are similar to their classical algorithm, that is, the movement rule keeps the inertia, memory and cooperation terms, which can be seen in Fig. 2.

The significant difference in EPSO is related to the weights w_{ik}^*, which undergo mutation, given as:

$$w_{ik}^* = w_{ik} + \tau N(0,1) \tag{15}$$

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

$$b_g^* = b_g + \tau' N(0,1) \tag{16}$$

In Equations (13–16), the parameters $\{X_i, V_i, b_i, k, \tau, \tau'\}$ represent the position X_i, velocity V_i, best point b_i found at generation k, the learning parameters τ and the mutated parameters τ'. EPSO usually presents much better convergence characteristics than PSO due to the fact that only the stronger particles survive in the evolutionary process [47].

2.4. Adaptive Neuro-Fuzzy Inference System

The NN and fuzzy systems are complementary tools that can be combined to create an adaptive architecture with fuzzy inference. The 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 representation [48]. The general ANFIS architecture is represented in Fig. 3, showing a five-layered feed forward network with the fuzzification, rules, normalization, defuzzification, and single summation layers, respectively.

In each layer, Ln_i is the output of the i_{th} node in layer n. In Layer 1 all nodes i are adaptive nodes with node function $L1_i$ given by:

$$L1_i = \mu A_i(x), \qquad i = 1, 2 \tag{17}$$

or

$$L1_i = \mu B_{i-2}(y), \qquad i = 3, 4 \tag{18}$$

where x or y is the input of the i_{th} node and A_i or B_{i-2} are the linguistic labels associated with these nodes.

The membership functions in A or B are typically described by a bell function where $\{p_i, q_i, r_i\}$ are the set parameters defined as:

$$\mu A_i(x) = \frac{1}{1 + \left|\frac{x - r_i}{p_i}\right|^{2q_i}} \tag{19}$$

A triangular membership function is considered in this paper as a node function due to being a continuous and piecewise differentiable function.

In Layer 2 all output nodes represent the firing strength of the rule w_i, where each node is represented by Π, that is, the output signals are multiplied by the previous inputs signals:

$$L2_i = w_i = \mu A_i(x)\mu B_i(y), \qquad i = 1, 2 \tag{20}$$

In Layer 3 every node N calculates the ratio of firing rules strength i_{th} with the sum of all firing strength rules:

$$L3_i = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \qquad i = 1,2 \tag{21}$$

In Layer 4 all nodes compute the contribution of the rule i_{th} to the global output, where $\{a_i, b_i, c_i\}$ is the parameter set and $\bar{w}_i$ is the layer output:

$$L4_i = \bar{w}_i z_i = \bar{w}_i(a_i x + b_i y + c_i), \qquad i = 1,2 \tag{22}$$

Layer 5 corresponds to the output node of the ANFIS tool where the summation Σ is made:

$$L5_i = \sum_i \bar{w}_i z_i = \frac{\sum_i w_i z_i}{\sum_i w_i} \tag{23}$$

The ANFIS used in this paper employs the least-squares and back-propagation gradient descent method. Furthermore, the EPSO assists the ANFIS in the tuning of their membership function parameters.

2.5. Hybrid Evolutionary-Adaptive Methodology

The HEA methodology will now be described in successive steps. Fig. 4 shows the structure of the HEA methodology in the form of a detailed flowchart. The information provided in the successive steps (given below) and Fig. 4 complement each other and provide all the necessary information.

- Step 1: Initialize the HEA methodology with an historical data matrix of electricity prices considering the previous six weeks/days. Each of the above six columns of the matrix represents the electricity price profile for one week or one day.
- Step 2: The matrix with the six previous weeks/days data will be normalized in *{0,1}* intervals, to find the set of historical electricity prices in the same scale, which will be later used by the MI in future candidate selections. This step is important to avoid the loss of relevant information.
- 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. The formation of these groups must be performed in a balanced way, thus avoiding compromising the ANFIS performance.
- Step 4: Compute the entropy and conditional entropy of each group by using (2) and (8) previously described, where $P(X_n)$ is given by a binomial distribution function.
- Step 5: Compute the MI, given by (10) previously described, of each group.
- Step 6: Compute the best group subset data. The best group found will be recombined in electricity data-sets. The selected sets are inputs for the WT.
- Step 7: Train the ANFIS with the previous constitutive sets. The optimization of the membership function

parameters is achieved by EPSO. Table 1 shows the parameters considered for MI, ANFIS and EPSO. These parameters result from the expertise acquired in the simulations, taking also into account previous publications. The approach developed in this paper uses A3 [17], along with D3 and D1, as inputs for the ANFIS. The inference rules of ANFIS are put into automatic mode to achieve the best performance. This is done due to the nature of the data, which requires a large number of inference rules to obtain the best results.

- Step 8: Until the best results or convergence are not reached, jump to Step 7. When the best results are found or convergence is reached, the inverse WT is applied and the output of the methodology is reached, that is, the electricity prices are forecasted for the next week/day.
- Step 9: Compute the price forecasting errors with different criteria to validate the methodology, comparing the results obtained with other results already available in the scientific literature.

3. Forecasting Accuracy Validation

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

$$MAPE = \frac{100}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \tag{24}$$

$$\bar{p} = \frac{1}{N}\sum_{h=1}^{N} p_h \tag{25}$$

where $\hat{p}_h$ is the electricity market price forecast at hour h, p_h is the actual electricity market price at hour h, $\bar{p}$ is the average electricity market price for the forecasting horizon, and N is the number of hours. 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 [17].

In accordance with the MAPE criterion expressed in (24), the error variance criterion is given by:

$$\sigma_{e,t}^2 = \frac{1}{N}\sum_{h=1}^{N}\left(\frac{|\hat{p}_h - p_h|}{\bar{p}} - e_t\right)^2 \tag{26}$$

$$e_t = \frac{1}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \tag{27}$$

Both MAPE and error variance criterions are employed in this paper, where N corresponds to 24 or 168 hours. Note that the average price is used in Eq.(24) to elude the instability caused when the prices are near to zero [16].

4. Case Studies

4.1. Spanish Market

The HEA methodology is utilized first to predict electricity market prices for the next 24/168 hours (next day/week) for mainland Spain. The historical data of electricity prices are available in [49]. As mentioned in [17], this market is difficult to predict due to the changes in prices that occur as a result of the strategies of the dominant player.

The electricity price sets used for the Spanish market date back to the year 2002, to allow a clear and fair comparison with the results already obtained using other published methodologies, that is, the same four test weeks of the year 2002 were selected, each corresponding to a different season (winter, spring, summer, and fall). Moreover, for a clear and fair comparison with the results already obtained using other published methodologies, only historical data sets of electricity market prices were used, that is, no exogenous sets, such as load, oil prices, or others are taken into account. Otherwise a correct comparative study would not be possible. Moreover, demand data does not significantly improve predictions [50], The HEA methodology predicts the next 168 hours electricity market prices taking into account the previous 1008 hours (i.e. six weeks or 42 days for each season), which in turn will be the input sets. Very large training sets are not used to avoid over-training during the learning process. The output of the methodology corresponds directly to a set with 168 values, equal to the forecasting horizon. For day-ahead (24 hours) forecasts, the previous six days are considered. The results with the HEA methodology are initially provided in Figs. 5 to 8 for the four test weeks of 2002. Table 2 shows the MAPE criterion comparative results between HEA methodology and eighteen other methodologies.

The enhancements between HEA and the other methodologies are 58.0%, 55.1%, 53.1%, 48.5%, 48.1%, 44.4%, 43.7%, 40.0%, 38.1%, 37.1%, 36.3%, 27.2%, 21.4%, 19.9%, 18.7%, 18.5%, 17.6% and 15.6%,respectively. The MAPE criterion using HEA has an average value of only 4.18%, the lowest one of all, which is significant. Even if each week is analysed per se, the results are always better. Hence, although the proposed methodology is not specifically designed for price spike forecasting, which is the main goal of other papers [51-52], it behaves quite well in their presence with excellent overall results.

Table 3 shows the error variance criterion comparative results between the HEA methodology and fourteen other methodologies. The enhancements between HEA and the other methodologies 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. Results for the mixed-model, FNN, PSF and SRN are not available in their papers. The average value is only 0.0015, again the lowest one of all, indicating reduced uncertainty in the forecasts, which is another important feature.

More recent data (year 2006) for the Spanish market has also been considered. Moreover, the best and worst forecasts generated by PSF and HEA methodologies for year 2006 data have been compared. The best forecast for PSF occurred on June 23rd, 2006, in which the MAPE was 3.10%, while using the HEA methodology the MAPE decreases to 2.31%. The worst forecast for PSF occurred on May 8th, 2006, in which the MAPE was 9.39%, while using the HEA methodology (as illustrated in Fig. 10) the MAPE decreases to 4.37%. Hence, the forecasting trends for the year 2006 are in agreement with those previously observed for the year 2002: enhancements range from 25.5% to 53.5%, which is significant.

Furthermore, the HEA methodology requires a low computational burden: the average computation time for a 168-hours forecast is less than 40 sec. using MATLAB platform on a standard PC with a 1.8 GHz–based–processor and 1.5 GB RAM. Not only is the training time less, but also the accuracy is higher and the uncertainty is lower with the HEA methodology. This is the major added value the paper provides. More recently, the WT+CLSSVM+EGARCH methodology in [34] presented a lower MAPE but required a computation time of about 10 min. Hence, the proposed HEA methodology presents, indeed, the best trade-off between computation time and average MAPE, which is crucial for real-life and real-time applications.

Fig. 9 shows the daily error between the HEA methodology results and the results previously reported for the NN, NNWT, and WPA methodologies, for the four seasons of the year. It can be seen that, for most days, the HEA methodology presents better forecasting results, that is, lower errors, comparatively to the other three methodologies.

4.2. PJM Market

The HEA methodology is also utilized to predict electricity market prices for the next 24/168 hours (next day/week) for the PJM market. The historical data of electricity prices are available in [53]. Like in Spanish Market no exogenous data such as load, oil prices, and others sets are taken into account. The results with the HEA methodology for the PJM market are provided in Figs. 11 to 17 for five days and two weeks of the year 2006. The same test days/weeks of previous published papers have been considered to allow a clear and fair comparison with the results already obtained using other published methodologies. Otherwise a correct comparative study would not be possible. Table 4 and Table 5 show the MAPE and error variance results, respectively, for the HEA methodology and five other methodologies.

The MAPE enhancements between HEA and the other methodologies are 59.1%, 40.2%, 28.2%, 25.9% and 25.7%, respectively. The error variance enhancements between HEA and the other methodologies are 75.5%, 64.7%, 45.5%, 42.9% and 25.0%, respectively. The HEA methodology clearly outperforms, again, all other methodologies in every day/week analysed. Moreover, the electricity price forecast results for 168 hours are provided in about 40 seconds, while 24 hours forecasts require even less computation time. Hence, this second case study further and unequivocally demonstrates and validates the proficiency of the proposed methodology.

5. Conclusion

A new hybrid evolutionary–adaptive methodology, called HEA, was proposed in this paper for short-term electricity market price forecasting. The HEA methodology results from the valuable and innovative joint characteristics of WT (bringing a filtering effect), EPSO (bringing evolutionary optimization) and ANFIS (bringing an adaptive architecture), considering also MI in the selection of the best input data. For a fair and clear comparison, identical test days/weeks used by other methods were considered, but without exogenous variables. The application of the proposed HEA methodology was revealed to be accurate and effective, helping to reduce the uncertainty associated with market prices. The results for the Spanish and PJM markets demonstrated the superiority of the HEA methodology, regarding both average MAPE and error variance criterions. Even if each day/week is analysed per se the results are always better. The low computational burden is also demonstrated, providing 168 hours electricity price forecast results in less than 40 seconds. Hence, it can be concluded that the proposed methodology is proficient taking into account previously reported results in the specialized literature, with the best trade-off between computation time and average MAPE.

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Figure captions

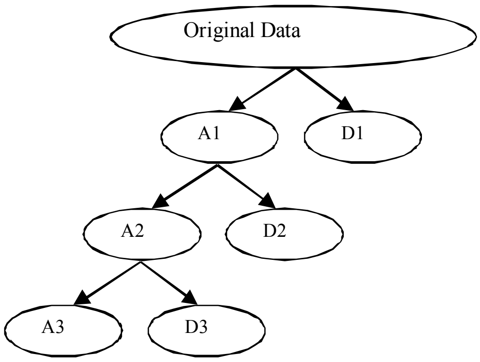


Fig. 1. Three-level decomposition model of WT.

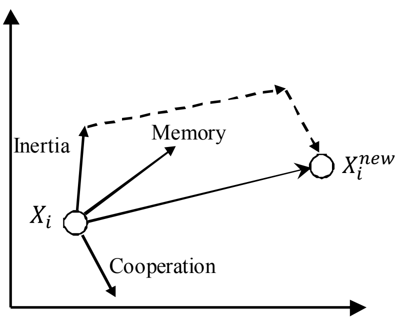


Fig. 2. Movement rule of a particle.

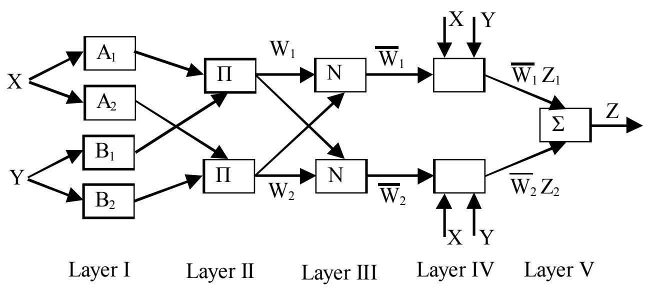
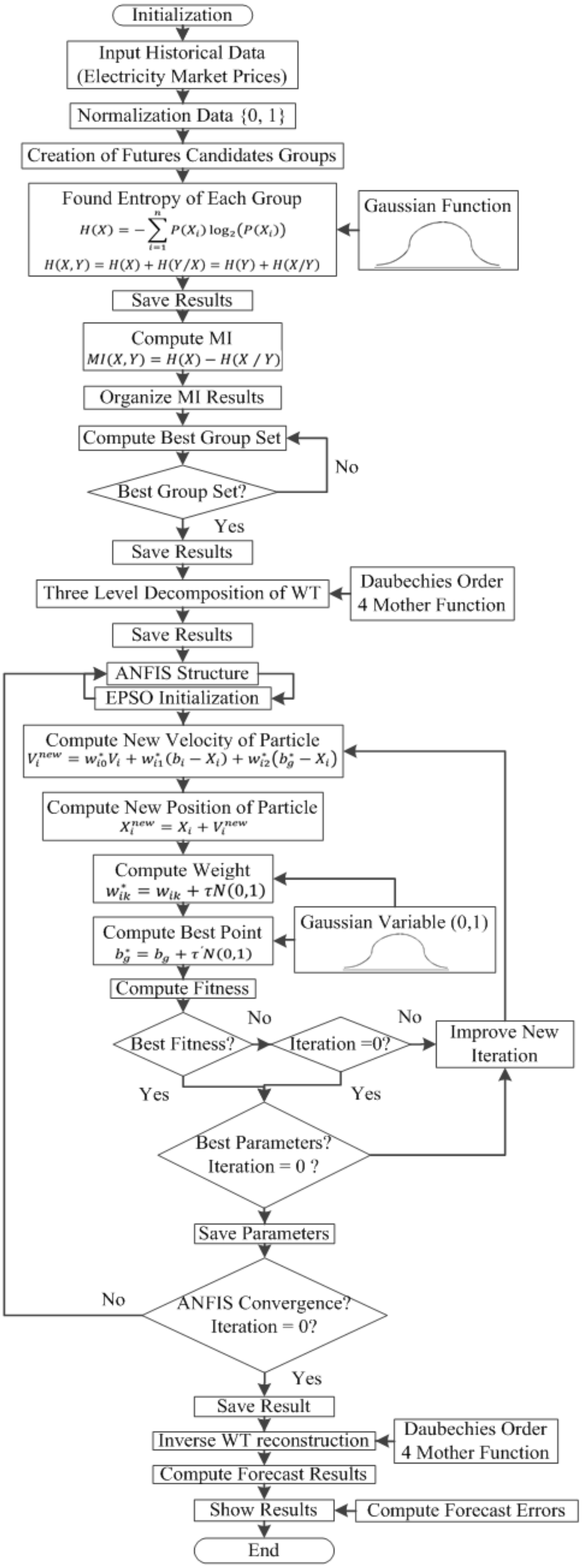


Fig. 3. ANFIS architecture.



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429 **Fig. 4.** Detailed flowchart of the proposed methodology.

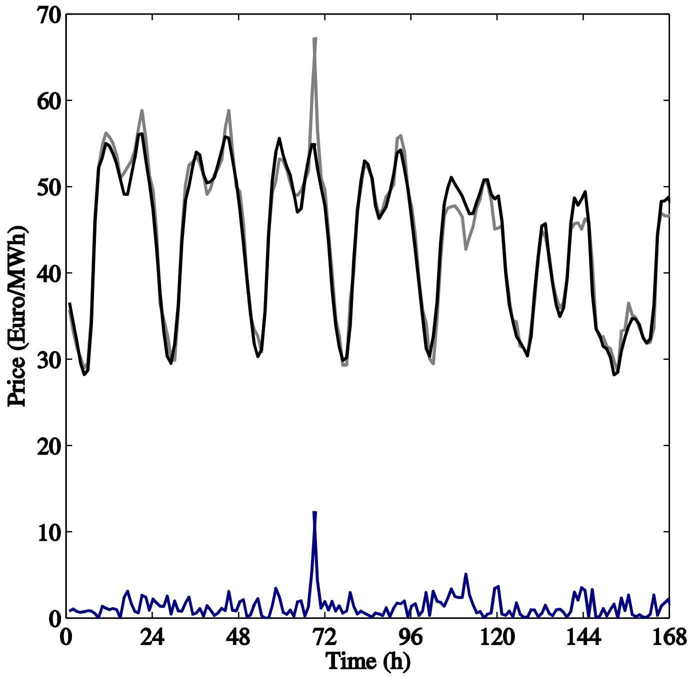

Fig. 5. Winter week 2002 results for the Spanish market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

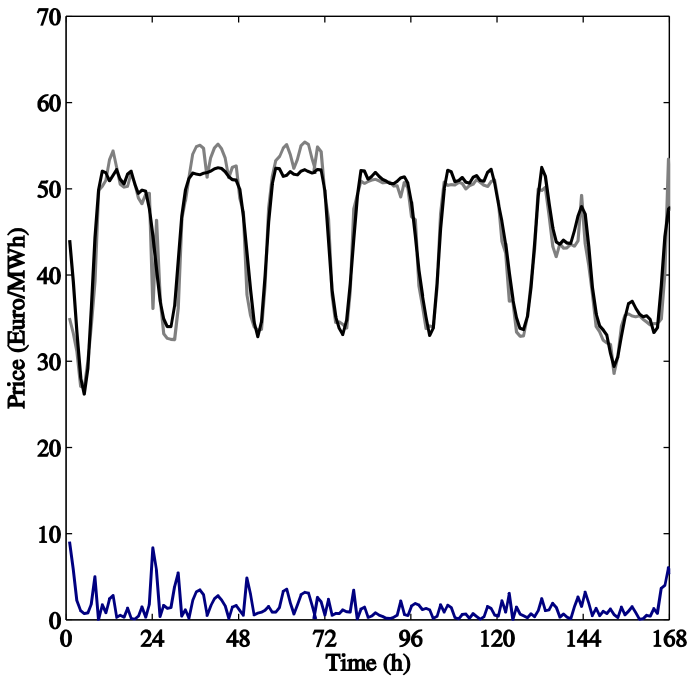

Fig. 6. Spring week 2002 results for the Spanish market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

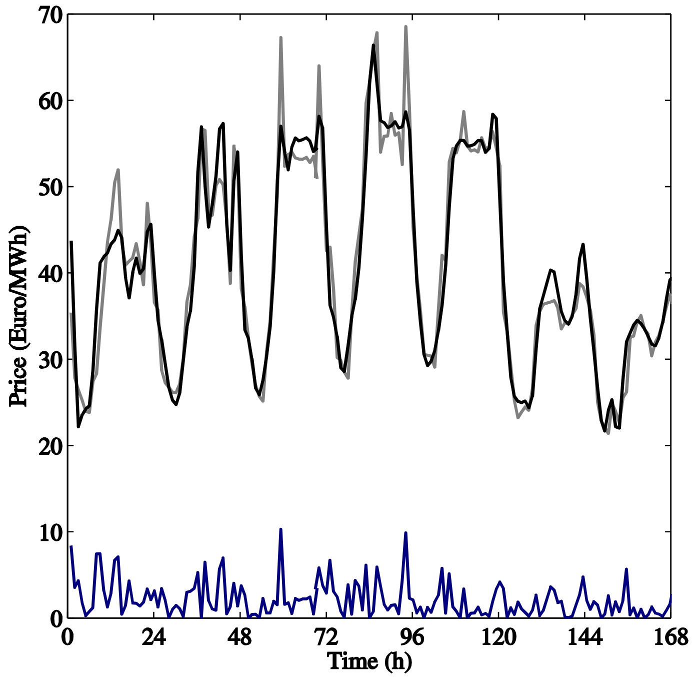

Fig. 7. Summer week 2002 results for the Spanish market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

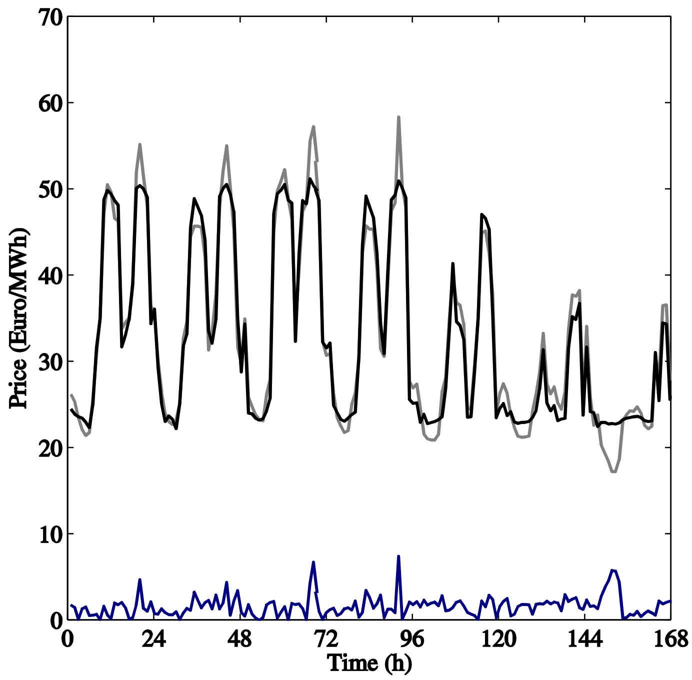

Fig. 8. Fall week 2002 results for the Spanish market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

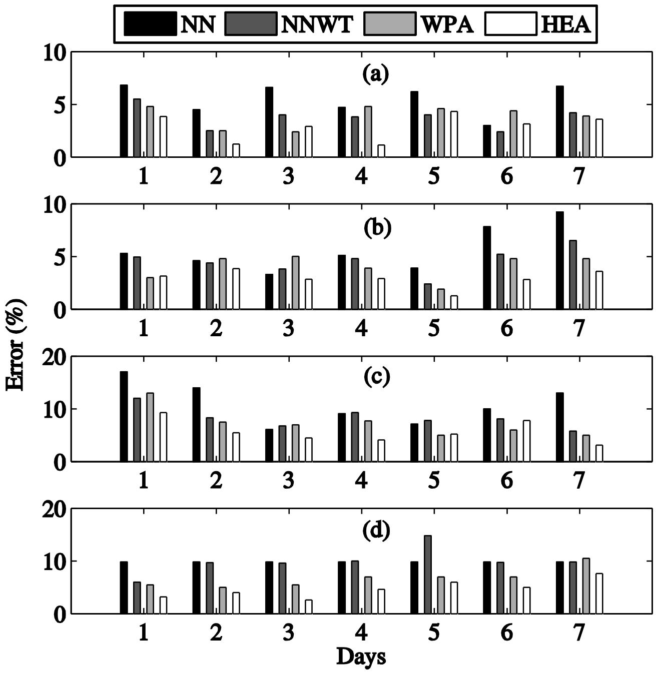

Fig. 9. Daily error comparative results between NN, NNWT, WPA and HEA methodologies, regarding the four seasons of year 2002for the Spanish market: (a) winter; (b) spring; (c) summer; (d) fall.

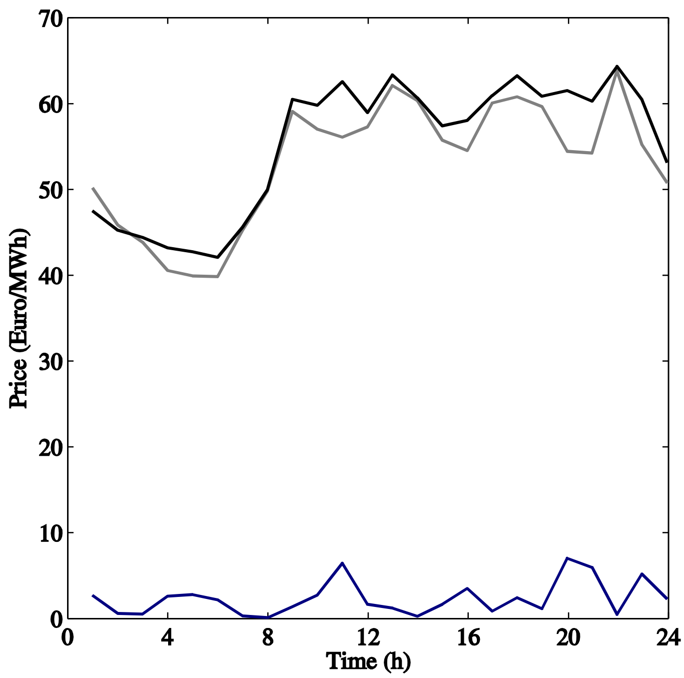

Fig. 10. May 8, 2006, results for the Spanish market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

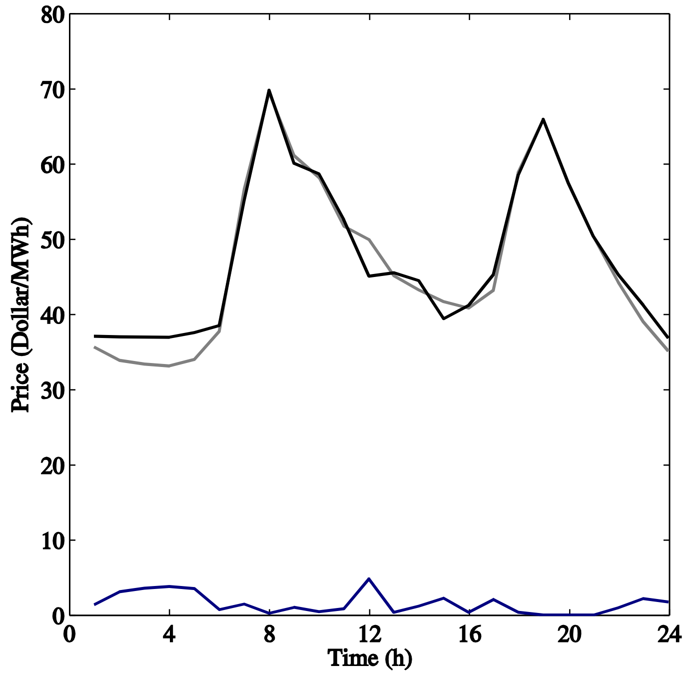

Fig. 11. January 20, 2006, results for the PJM market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

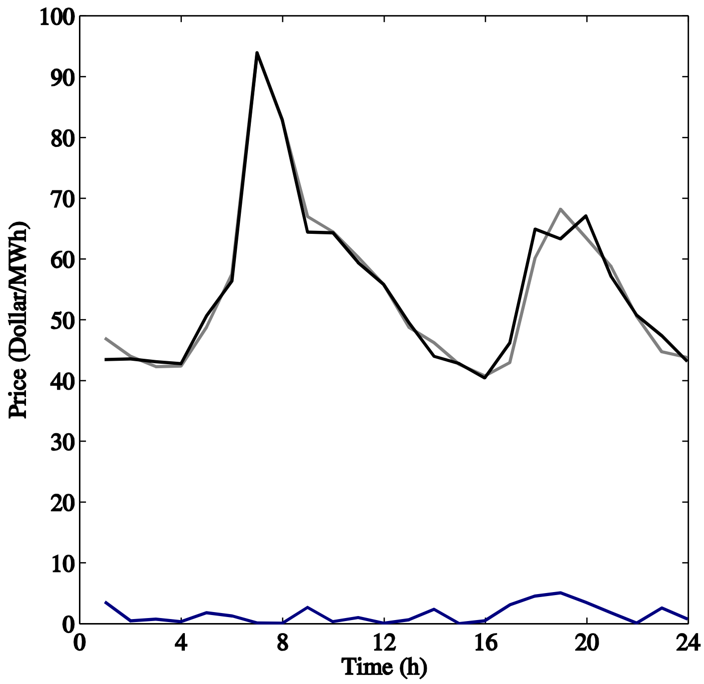

Fig. 12. February 10, 2006, results for the PJM market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

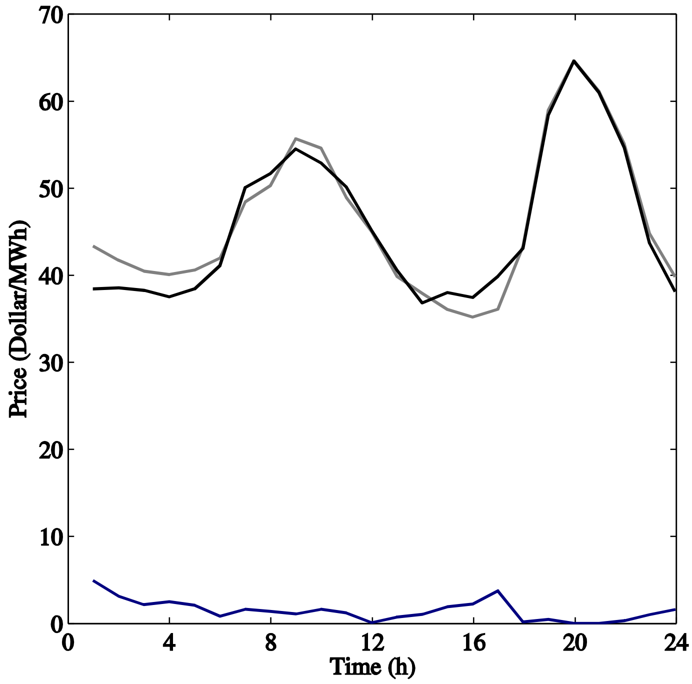

Fig. 13. March5, 2006, results for the PJM market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

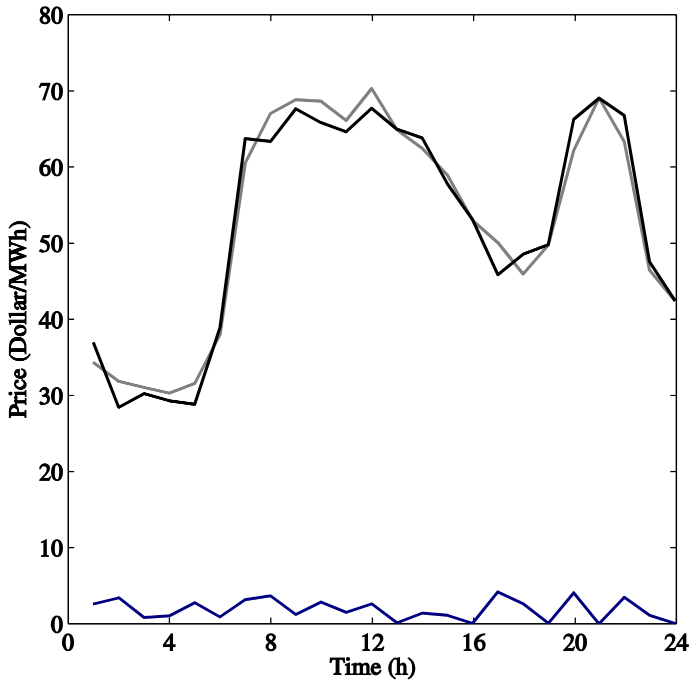

Fig. 14. April7, 2006, results for the PJM market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

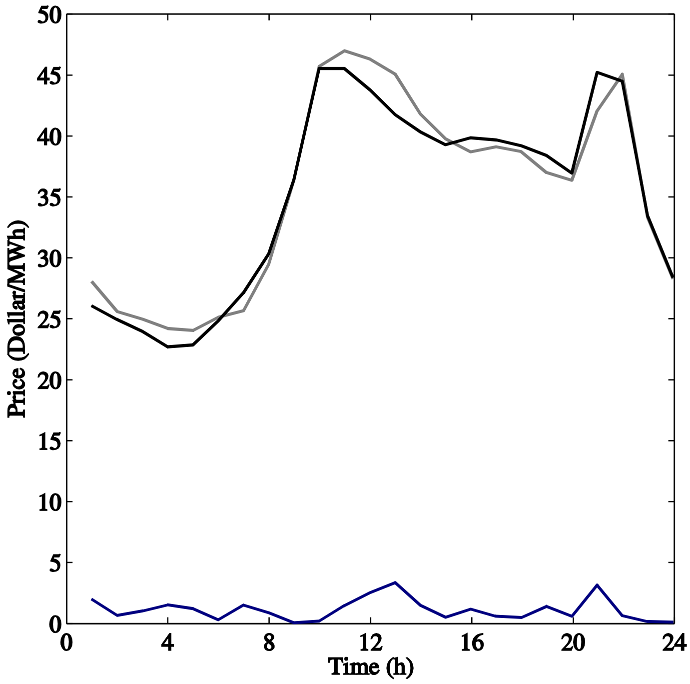

Fig. 15. May13, 2006, results for the PJM market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

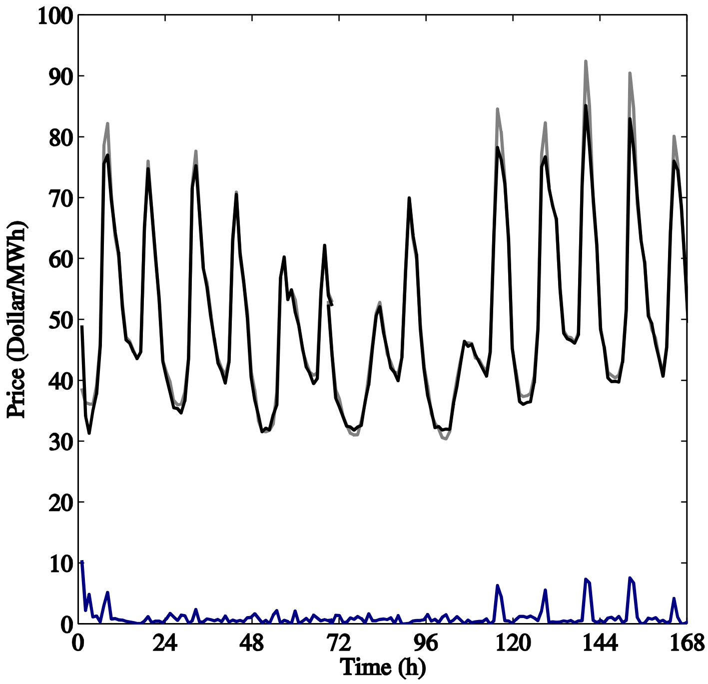

Fig. 16. February 1-7, 2006, results for the PJM mar8ket: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

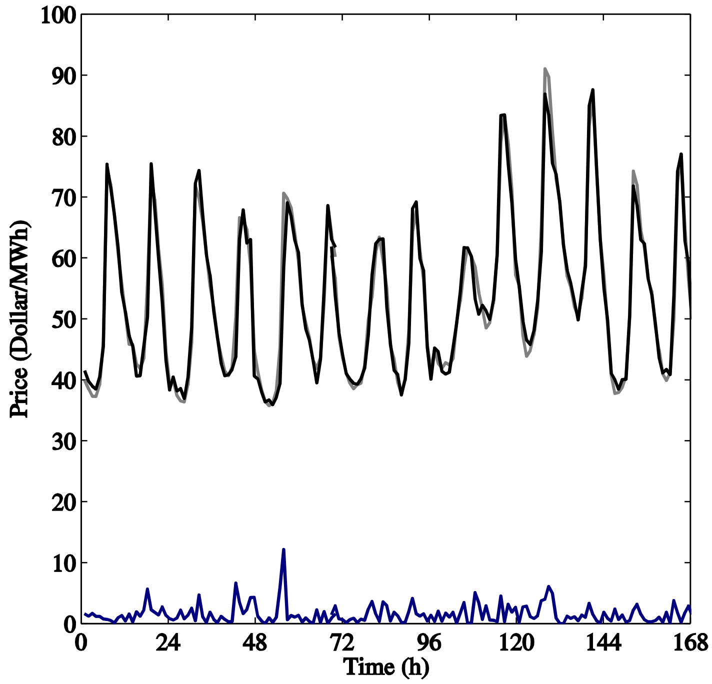

Fig. 17. February 22-28, 2006, results for the PJM market: The gray and black lines represent the actual and forecasted prices, respectively, while the dark-blue line at the bottom represents the errors in absolute value.

Tables

Table 1

Parameters used in MI, ANFIS and EPSO techniques

	Parameters	Type or Size
MI	Best Lower Bound of Set	0.15
	Best Upper Bound of Set	0.65
ANFIS	Membership Functions	2-7
	Necessary Iterations	3-50
	Type of Membership Function	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	24-168
	Maximum Generation	48-326
	Number of New Particles	24-168
	Generation for Each New Particle	2
	Necessary Iterations	48-326
	Minimum Value of New Position	20
	Maximum Value of New Position	70-120

Table 2

MAPE Criterion: Comparative results for Spanish market

	Winter	Spring	Summer	Fall	Average
ARIMA [16], 2003	6.32	6.36	13.39	13.78	9.96
Mixed–model [39], 2007	6.15	4.46	14.90	11.68	9.30
NN [19], 2007	5.23	5.36	11.40	13.65	8.91
Wavelet–ARIMA [17], 2005	4.78	5.69	10.70	11.27	8.11
WNN [22], 2007	5.15	4.34	10.89	11.83	8.05
FNN [21], 2006	4.62	5.30	9.84	10.32	7.52
PSF [23], 2011	5.98	4.51	9.11	10.07	7.42
HIS [24], 2009	6.06	7.07	7.47	7.30	6.97
AWNN [6], 2008	3.43	4.67	9.64	9.29	6.75
NNWT [25], 2010	3.61	4.22	9.50	9.28	6.65
SRN [26], 2013	4.11	4.37	9.09	8.66	6.56
RBFN [15], 2011	4.27	4.58	6.76	7.35	5.74
CNEA [27], 2009	4.88	4.65	5.79	5.96	5.32
CNN [28], 2009	4.21	4.76	6.01	5.88	5.22
HNES [29], 2010	4.28	4.39	6.53	5.37	5.14
MI+CNN [33], 2012	4.51	4.28	6.47	5.27	5.13
WPA [12], 2011	3.37	3.91	6.50	6.51	5.07
MI–MI+CNN [33], 2012	4.29	4.20	6.31	5.01	4.95
HEA, 2013	3.04	3.33	5.38	4.97	4.18

Table 3

Weakly Error Variance Criterion: Comparative results for Spanish market

	Winter	Spring	Summer	Fall	Average
ARIMA [16], 2003	0.0034	0.0020	0.0158	0.0157	0.0092
NN [19], 2007	0.0017	0.0018	0.0109	0.0136	0.0070
Wavelet-ARIMA [17], 2005	0.0019	0.0025	0.0108	0.0103	0.0064
FNN [21], 2006	0.0018	0.0019	0.0092	0.0088	0.0054
AWNN [6], 2008	0.0012	0.0031	0.0074	0.0075	0.0048
NNWT [25], 2010	0.0009	0.0017	0.0074	0.0049	0.0037
HIS [24], 2009	0.0034	0.0049	0.0029	0.0031	0.0036
CNEA [27], 2009	0.0036	0.0027	0.0043	0.0039	0.0036
CNN [28], 2009	0.0014	0.0033	0.0045	0.0048	0.0035
RBFN [15], 2011	0.0015	0.0019	0.0047	0.0049	0.0033
WPA [12], 2011	0.0008	0.0013	0.0056	0.0033	0.0027
MI+CNN [33], 2012	0.0014	0.0014	0.0033	0.0022	0.0021
HNES [29], 2010	0.0013	0.0015	0.0033	0.0022	0.0021
MI–MI+CNN [33], 2012	0.0014	0.0014	0.0032	0.0023	0.0021
HEA, 2013	0.0008	0.0011	0.0026	0.0014	0.0015

Table 4

MAPE Criterion: Comparative results for PJM market

	SDNN [20], 2007	WT+FF+FA [36], 2013	HNES [29], 2010	Hybrid [30], 2010	CNEA [27], 2009	HEA, 2013
Jan. 20	6.93	5.04	4.98	3.71	4.73	3.29
Feb. 10	7.96	5.43	4.10	2.85	4.50	2.80
Mar. 5	7.88	4.82	4.45	5.48	4.92	3.32
Apr. 7	9.02	6.24	4.67	4.17	4.22	3.55
May 13	6.91	4.11	4.05	4.06	3.96	3.43
Feb. 1-7	7.66	6.07	4.62	5.27	4.02	3.11
Feb. 22-28	8.88	6.12	4.66	5.01	4.13	3.08
Average	7.89	5.40	4.50	4.36	4.35	3.23

Table 5

Error Variance Criterion: Comparative results for PJM market

	SDNN [20], 2007	CNEA [27], 2009	WT+FF+FA [36], 2013	Hybrid [30], 2010	HNES [29], 2010	HEA, 2013
Jan. 20	0.0034	0.0031	0.0016	0.0010	0.0020	0.0010
Feb. 10	0.0050	0.0036	0.0021	0.0015	0.0012	0.0009
Mar. 5	0.0061	0.0042	0.0032	0.0033	0.0015	0.0011
Apr. 7	0.0038	0.0022	0.0019	0.0013	0.0018	0.0011
May 13	0.0049	0.0027	0.0016	0.0015	0.0013	0.0012
Feb. 1-7	0.0066	0.0044	0.0023	0.0037	0.0016	0.0012
Feb. 22-28	0.0047	0.0035	0.0024	0.0025	0.0017	0.0017
Average	0.0049	0.0034	0.0022	0.0021	0.0016	0.0012