New Intelligent Approach in Short-Term Electricity Prices Prediction Towards Reducing Uncertainty

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Abstract—**In a deregulated profit-based environment, producers and consumers require short-term electricity price prediction to derive their bidding strategies to the electricity market. Hence, accurate forecasting tools with less uncertainty are required for producers to maximize their profits and for consumers to maximize their utilities. This paper presents a new intelligent approach based on a combination of wavelet transform (WT), evolutionary particle swarm optimization (EPSO) and adaptive-network-based inference system (ANFIS) for short-term electricity prices prediction. The accuracy attained with the proposed approach is evaluated, reporting its proficiency from a case study. Conclusions are duly drawn.**

Keywords-electricity prices; prediction; uncertainty; intelligent approach

I. INTRODUCTION

All over the world, the electricity market is converging toward a competitive framework and a market environment is replacing the traditional monopolistic scenery for the electricity industry. Hence, in a deregulated framework, producers and consumers require short-term electricity prices prediction to derive their bidding strategies to the market. Besides, accurate forecasting tools are required for producers to maximize their profits and for consumers to maximize their utilities [1].

In most liberalized electricity markets, price series presents several features, e.g., high frequency, non-constant mean and variance, calendar effect on weekend and public holidays, daily and weekly seasonality, and high volatility [2]. In the technical literature, several techniques have been reported [3], namely hard and soft computing techniques.

The hard computing techniques include, e.g., auto regressive integrated moving average (ARIMA) [4], wavelet-ARIMA [5], and mixed models [6] approaches. These methods require an exact model of the system, and the solution is found using algorithms that consider the physical phenomena that govern process. Besides, these approaches can be accurate, but require a lot of information and the computational cost is high.

The soft computing include, e.g., neural networks (NN) [7], fuzzy neural networks (FNN) [8], weighted nearest neighbors (WNN) [9], adaptive wavelet neural networks (AWNN) [10], hybrid intelligent system (HIS) [11], neural networks combined with wavelet transform [1], and cascaded neuro-evolutionary algorithms (CNEA) [12].

Usually, an input-output mapping is learned from historical examples, thus there is no need to model the system. Also, the previous approaches can be much more efficient and as accurate, if the correct inputs are considered [13].

This paper presents a successful application of combining wavelet transform (WT), evolutionary particle swarm optimization (EPSO) and adaptive-network-based fuzzy inference system (ANFIS), further referred as WEPA approach, for short-term electricity prices prediction.

This paper is structured as follows. In Section II, the proposed WEPA approach is described. Section III presents the results obtained on a case study, considering the electricity market of mainland Spain. Finally, Section IV outlines the conclusions.

II. PROPOSED APPROACH

The WEPA approach is based on the combination of WT, EPSO and ANFIS. The WT is used to decompose the electricity prices-data series into a set of constitutive series. After that, the future values of the constitutive series are predicted using ANFIS. Moreover, EPSO is used to improve the performance of ANFIS.

A. Wavelet Transform

The WT converts electricity prices-data series into a set of constitutive series. These series presents better behavior than the original series, due to the filtering effect of the WT. More details of WT can be found, for instance, in [14].

A Daubechies of order 4 is used as the mother wavelet. This wavelet gives a good trade-off between wave-length and smoothness. Besides, three decomposition levels are considered, as shown in Fig. 1.

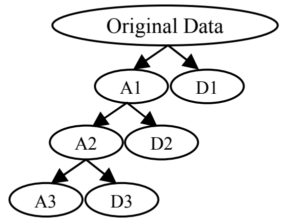

Figure 1. Multilevel decomposition model.

B. Evolutionary Particle Swarm Optimization

The EPSO incorporates a selection procedure to the original particle swarm optimization (PSO), and self-adapting properties for its parameters [15]. In short, EPSO uses the following [16]:

- Replication and Mutation: each particle is replicated r times but also has its weights mutated.
- Reproduction: each particle generates a new set of particles through the movement rule.
- Evaluation and Selection: each new particle has its fitness evaluated, and the best particles survive to create new particles.

The particle movement is defined as:

$$X_i^{(k+1)} = X_i^{(k)} + V_i^{(k+1)} \tag{1}$$

$$V_i^{(k+1)} = w_{i1}^* V_i^{(k)} + w_{i2}^*(b_i - X_i) + w_{i3}^* P(b_g^* - X_i) \tag{2}$$

where $X_i^{(k)}$ is the location of particle i at generation k, $V_i^{(k)}$ is the velocity of particle i at generation k, b_i is the best point found by particle i in its past life up to the current generation, b_g^* is the best overall point found by the swarm of particles in their past life up to the current generation, w_{i1} is the weight conditioning the *inertia* term (a new particle is created in the same direction as its previous couple of ancestors), w_{i2} is the weight conditioning the *memory* term (the new particle is attracted to the best position occupied by its ancestors), w_{i3} is the weight conditioning the *cooperation* term (the new particle is attracted to the overall best-so-far found by the swarm), and P is the communication factor, a diagonal matrix containing value 1 with probability p and value 0 with probability $(1-p)$. The weights undergo evolution under a mutation process w_{ik}^*, and the global best position b_g^* is:

$$w_{ik}^* = w_{ik} + \tau N(0,1) \tag{3}$$

$$b_g^* = b_g + \tau' N(0,1) \tag{4}$$

where $N(0,1)$ is a random number following a normalized Gaussian distribution with zero mean and unit variance; the parameters τ and τ' are learning parameters that can be either fixed or treated as strategic parameters and therefore subject to mutation. With the considerations and hints used in [16] the algorithm is profitable in the right direction: - first, the Darwinistic process of selection and the particle movement rule, and second, it is natural to expect that it may display advantageous convergence properties. As shown in Fig. 2, the movement rule of each particle depends of inertia, memory and cooperation.

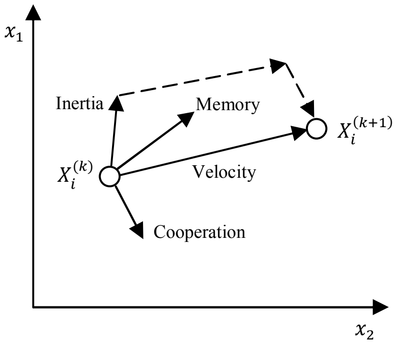

Figure 2. Movement rule of each particle.

C. Adaptive Neuro-Fuzzy Inference System

ANFIS is a class of adaptive multi-layer feed forward 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 [17]. Thus, an adaptive network is functionally equivalent to a Sugeno-type fuzzy inference system as in [18]. Moreover, ANFIS employs EPSO method to adjust the parameters of the membership functions, and the membership functions considered are triangular-shaped. Each layer contains several nodes described by the node function, Fig. 3. Let O_i^j denote the output of the i_{th} node in layer j.

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

$$O_i^1 = \mu A_i(x), \qquad i = 1, 2 \tag{5}$$

or

$$O_i^1 = \mu B_{i-2}(y), \qquad i = 3, 4 \tag{6}$$

where x or y is the input to the i_{th} 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.:

$$\mu A_i(x) = \frac{1}{1 + \left|\frac{x - r_i}{p_i}\right|^{2q_i}} \tag{7}$$

where $\{p_i,\ q_i,\ r_i\}$ is the parameter set.

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

$$O_i^2 = w_i = \mu A_i(x) \mu B_i(y), \qquad i = 1, 2 \tag{8}$$

In layer 3, each node N computes the ratio of the i_{th} rules's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \qquad i = 1,2 \tag{9}$$

In layer 4, each node computes the contribution of the i_{th} rule to the overall output:

$$O_i^4 = \overline{w}_i z_i = \overline{w}_i (a_i x + b_i y + c_i), \qquad i = 1, 2 \tag{10}$$

where $\overline{w}_i$ is the output of layer 3 and $\overline{w}_i$ 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:

$$O_i^5 = \sum_i \overline{w}_i z_i = \frac{\sum_i w_i z_i}{\sum_i W_i} \tag{11}$$

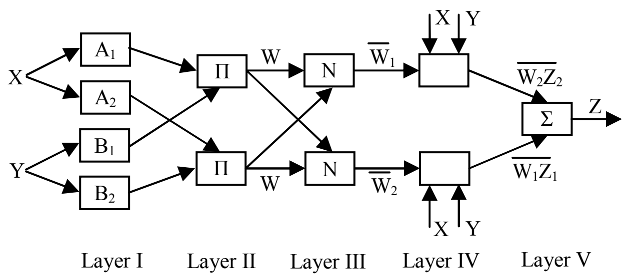

Figure 3. ANFIS architecture.

D. Hybrid Approach

This section describes the WEPA approach for electricity prices prediction. The flowchart is given in Fig. 4.

Step One: Form a matrix with a set of historical data, arranged in C columns of the same matrix. Select a number of random columns of the previous matrix. These columns represent the input data. Step Two: Decompose the input data using WT. The signal is divided into three levels, i.e., a level of approximation A and details D. Step Three: Train the ANFIS structure with data of the previous step. The ANFIS structure uses a combination of the least-squares method and back-propagation gradient descent method. The EPSO structure is used to improve the parameters associated with the membership functions of fuzzy inference system. Create a vector D, where D equals the number of membership function and is optimized by the EPSO algorithm. Step Four: Define the parameter associated with EPSO algorithm. These parameters are provided in Table I. Extract the output data of the ANFIS. Step Five: Use inverse of WT to reconstruct the electricity prices-data forecast given by ANFIS, corresponding to the output of the WEPA approach.

E. Prediction Accuracy Evaluation

To evaluate the accuracy in electricity prices prediction, the mean absolute percentage error (MAPE) is considered. The MAPE criterion is defined as follows:

$$MAPE = \frac{100}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \tag{12}$$

$$\bar{p} = \frac{1}{N}\sum_{h=1}^{N} p_h \tag{13}$$

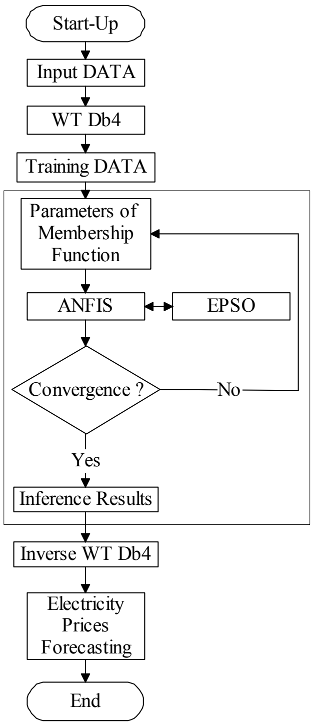

Figure 4. Flowchart of WEPA approach.

TABLE I. Parameters of ANFIS and EPSO.

	Parameters	Type or Size
ANFIS	Initial Membership Functions	4
	Necessary Iterations	5-25
	Type of Membership Functions	Triangular-shaped
EPSO	Fitness Acceleration	2
	Sharing Acceleration	2
	Initial Inertia Weight of Population	0.9
	Final Inertia Weight of Population	0.4
	Population Size	168
	Maximum Generation	320
	Number of New Particles	168
	Generation for Each New Particle	2
	Necessary Iterations	320
	Minimum Value of New Position	30
	Maximum Value of New Position	60

In (12) and (13), $\hat{p}_h$ is the forecasted values and p_h is the actual values at period h, $\bar{p}$ is the average values of the prediction period, and N is the number of forecasted periods, i.e., the weakly MAPE is N=*168.*

The average price is used in (12) to avoid the adverse effects of prices close to zero [19].

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, as in [5].

Consistent with definition (12), weekly error variance can be estimated as:

$$\sigma_{e,day}^2 = \frac{1}{N}\sum_{h=1}^{N}\left(\frac{|\hat{p}_h - p_h|}{\bar{p}} - \left(e_{day}\right)^2\right) \tag{14}$$

$$e_{day} = \frac{1}{N}\sum_{h=1}^{N}\frac{|\hat{p}_h - p_h|}{\bar{p}} \tag{15}$$

III. CASE STUDY

The WEPA approach has been applied to forecast next-week (168 hours) prices in the electricity market of mainland Spain. Price prediction is computed using historical data of year 2002 for the Spanish market, available at [20].

For the sake of simplicity and clear comparison, no exogenous variables are considered and the same test weeks as in [10]-[12], [14], [21] and [22] are selected, which correspond to the four seasons of year 2002.

For the WEPA approach, 168 hours ahead predictions are computed, taking into account the hourly historical price data of 42 days previous to the week whose prices are to be forecasted. Thus, the WEPA output directly provides a vector of dimension equal to the length of the forecasting horizon, i.e., 168 hours ahead.

Numerical results with WEPA approach are shown in Figs. 5 to 8 respectively for the winter, spring, summer and fall weeks.

Table II shows a comparison between WEPA approach with other six approaches (HIS, AWNN, NNWT, CNEA, EPA and WPA), regarding MAPE. The WEPA approach presents better forecasting accuracy: the average value of MAPE is 4.42%. Improvement in the average MAPE of the proposed approach with respect to the six other approaches is 36.59%, 34.52%, 33.53%, 16.92%, 13.67% and 12.82%, respectively.

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

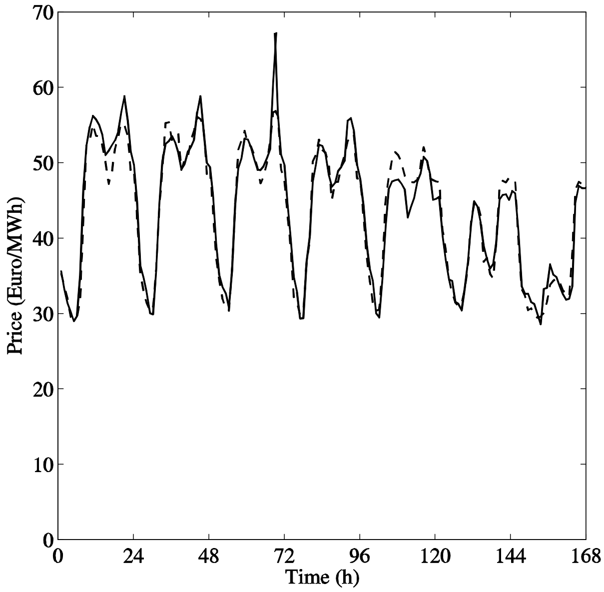

Figure 5. Winter week: actual electricity prices, solid line, together with the forecasted electricity prices, dashed line.

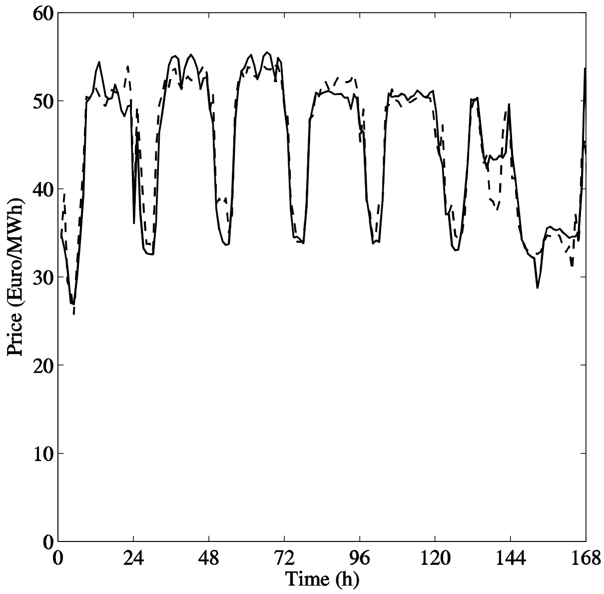

Figure 6. Spring week: actual electricity prices, solid line, together with the forecasted electricity prices, dashed line.

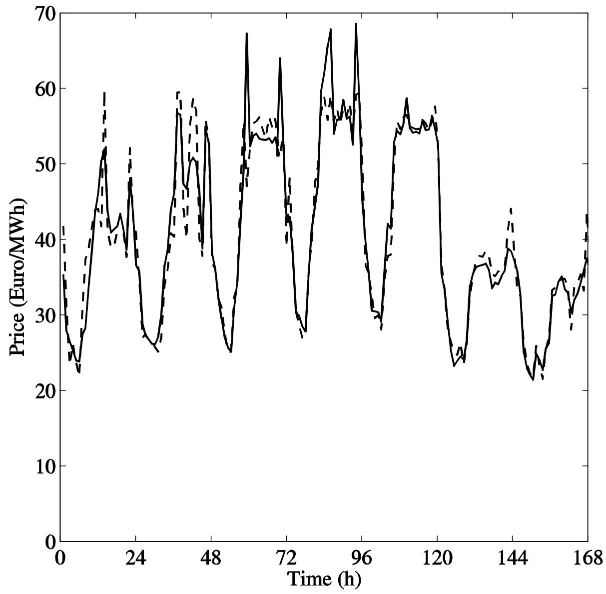

Figure 7. Summer week: actual electricity prices, solid line, together with the forecasted electricity prices, dashed line.

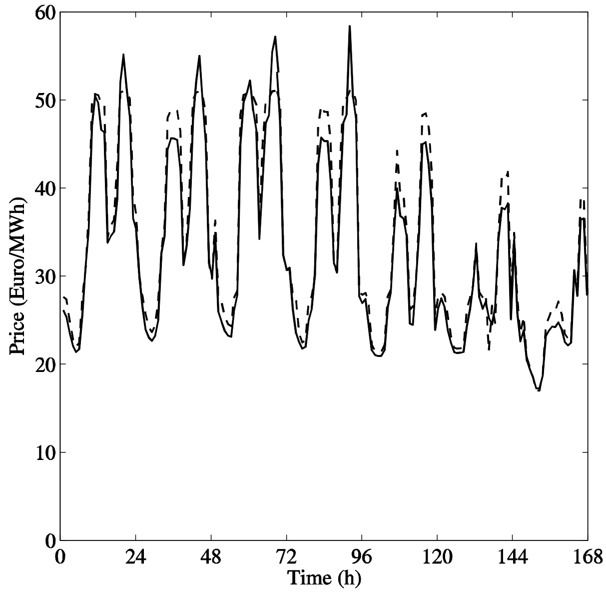

Figure 8. Fall week: actual electricity prices, solid line, together with the forecasted electricity prices, dashed line.

Table III shows a comparison between the WEPA approach and the six previous approaches, regarding weekly error variance. The average weekly error variance is smaller for the WEPA approach, indicating less uncertainty in the predictions. Improvement in the average weekly error variance of the proposed approach with respect to the six other approaches is, 44.44%, 58.33%, 45.95%, 44.44%, 25.93% and 25.93%, respectively.

All the cases have been run on a PC with 1.5 GB of RAM and a 1.8-GHz-based processor. The average computation is less than 1 minute. Hence, the WEPA approach presents not only better forecasting accuracy and less uncertainty, but also an acceptable computation time.

TABLE II. Comparative MAPE results.

	Winter	Spring	Summer	Fall	Average
HIS [11]	6.06	7.07	7.47	7.30	6.97
AWNN [10]	3.43	4.67	9.64	9.29	6.75
NNWT [14]	3.61	4.22	9.50	9.28	6.65
CNEA [12]	4.88	4.65	5.79	5.96	5.32
EPA [22]	3.59	4.10	6.39	6.40	5.12
WPA [21]	3.37	3.91	6.50	6.51	5.07
WEPA	3.24	3.78	5.49	5.17	4.42

TABLE III. Weekly forecasting error variance.

	Winter	Spring	Summer	Fall	Average
HIS [11]	0.0034	0.0049	0.0029	0.0031	0.0036
AWNN [10]	0.0012	0.0031	0.0074	0.0075	0.0048
NNWT [14]	0.0009	0.0017	0.0074	0.0049	0.0037
CNEA [12]	0.0036	0.0027	0.0043	0.0039	0.0036
EPA [22]	0.0012	0.0016	0.0048	0.0032	0.0027
WPA [21]	0.0008	0.0013	0.0056	0.0033	0.0027
WEPA	0.0008	0.0013	0.0042	0.0016	0.0020

IV. CONCLUSIONS

This paper proposed an intelligent approach based on combining WT, EPSO and ANFIS for short-term electricity prices prediction. The MAPE for the proposed WEPA approach has an average value of 4.42%, while the average computation time is less than 1 minute. The average error variance is also smaller, indicating less uncertainty in the predictions. Hence, the proposed WEPA approach presents an excellent trade-off between forecasting accuracy, uncertainty reduction and computation time, taking into account results previously reported in the technical literature.

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