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# Short-term electricity prices forecasting in a competitive market by a hybrid intelligent approach

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ABSTRACT

In this paper, a hybrid intelligent approach is proposed for short-term electricity prices forecasting in a competitive market. The proposed approach is based on the wavelet transform and a hybrid of neural networks and fuzzy logic. Results from a case study based on the electricity market of mainland Spain are presented. A thorough comparison is carried out, taking into account the results of previous publications. Conclusions are duly drawn.



## 1. Introduction

Deregulation processes during the last two decades across many developed economies have motivated the need for more accurate forecasting tools of electricity markets [1]. Short-term electricity prices forecasting is required by producers and consumers to derive their bidding strategies to the electricity market. Deregulation brings electricity prices uncertainty, placing higher requirements on forecasting [2]. Therefore, price forecasting tools are essential for all market participants for their survival under deregulated environment [3]. In most competitive electricity markets the series of prices presents the following features: high frequency, non-constant mean and variance, daily and weekly seasonality, calendar effect on weekend and public holidays, high volatility and high percentage of unusual prices [4].

Price forecast is a key issue in competitive electricity markets [5,6], and several techniques have been tried out in this task. In general, hard and soft computing techniques could be used to predict electricity prices.

The hard computing techniques include auto regressive integrated moving average (ARIMA) [7], wavelet-ARIMA [8], and mixed-model [9] approaches. Usually, an exact model of the system is required, and the solution is found using algorithms that consider the physical phenomena that govern the process. Although these approaches can be very accurate, they require a lot of information, and the computational cost is very high.

The soft computing techniques include neural networks (NN) [10–13], fuzzy neural networks (FNN) [14], weighted nearest neighbors (WNN) [15], adaptive wavelet neural network (AWNN) [16], and hybrid intelligent system (HIS) [17] approaches.

A combination of neural networks with wavelet transform (NNWT) has also been recently proposed [18]. Usually, an input–output mapping is learned from historical examples, thus there is no need to model the system. Hence, these approaches can be much more efficient computationally and as accurate as the first ones, if the correct inputs are considered [19].

In this paper, a hybrid intelligent approach is proposed for short-term electricity prices forecasting. The proposed approach is based on the wavelet transform and a hybrid of neural networks and fuzzy logic.

The proposed approach is examined on the electricity market of mainland Spain, commonly used as the test case in several price forecasting papers [7–9,13–18]. It has been concluded that the Spanish market has a hard non-linear behavior and time variant functional relationship [8,14]. So, this market is a real-world case study with sufficient complexity.

The proposed approach is compared with ARIMA, mixed-model, NN, wavelet-ARIMA, WNN, FNN, HIS, AWNN, and NNWT approaches, to demonstrate its effectiveness regarding forecasting accuracy and computation time.

This paper is organized as follows: Section 2 presents the proposed approach to forecast electricity prices. Section 3 provides the different criterions used to evaluate the forecasting accuracy.

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Section 4 provides the numerical results from a real-world case study. Finally, concluding remarks are given in Section 5.

## 2. Proposed approach

The proposed approach to forecast electricity prices is based on the wavelet transform (WT) and a hybrid of NN and fuzzy logic known as adaptive-network-based fuzzy inference system (ANFIS). The WT is used to decompose the usually ill-behaved price series into a set of better-behaved constitutive series. Then, the future values of these constitutive series are forecasted using ANFIS. In turn, the ANFIS forecasts allow, through the inverse WT, reconstructing the future behavior of the price series and therefore to forecast prices.

### 2.1. Wavelet transform

The WT convert a price series in a set of constitutive series. These constitutive series present a better behavior than the original price series, and therefore, they can be predicted more accurately. The reason for the better behavior of the constitutive series is the filtering effect of the WT [8].

A brief summary of WT is presented hereafter. For the sake of simplicity, one-dimensional wavelets are considered to illustrate the related concepts.

A wavelet is a waveform of effectively limited duration that has an average value of zero. Comparing wavelets with sine waves (which are the basis of Fourier analysis), sinusoids do not have limited duration (they extend from minus to plus infinity). Moreover, where sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric. Wavelet analysis is the breaking up of a signal into shifted and scaled versions of the mother wavelet. Signals with sharp changes might be better analyzed with an irregular wavelet than with a smooth sinusoid. Wavelet analysis does not use a time–frequency region (like the short-time Fourier transform), but rather a time-scale region.

Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, such as trends, breakdown points, discontinuities in higher derivatives and self-similarity. Furthermore, wavelet analysis can often compress or de-noise a signal without appreciable degradation [20]. These capabilities of WT can be useful in short-term electricity prices forecasting.WTs can be divided in two categories: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The CWT $W(a,b)$ of signal $f(x)$ with respect to a mother wavelet $\phi(x)$ is given by [20]:

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

where the scale parameter $a$ controls the spread of the wavelet and translation parameter $b$ determines its central position. The $W(a,b)$ coefficient represents how well the original signal $f(x)$ and the scaled/translated mother wavelet match. Thus, the set of all wavelet coefficients $W(a,b)$, associated to a particular signal, is the wavelet representation of the signal with respect to the mother wavelet. Since the CWT is achieved by continuously scaling and translating the mother wavelet, substantial redundant information is generated. Therefore, instead of doing that, the mother wavelet can be scaled and translated using certain scales and positions usually based on powers of two. This scheme is more efficient and just as accurate as the CWT [21]. It is known as the DWT and defined as:

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

where $T$ is the length of the signal $f(t)$. The scaling and translation parameters are functions of the integer variables $m$ and $n$ $(a = 2^m,\ b = n.2^m)$; $t$ is the discrete time index.

A fast DWT algorithm based on the four filters (decomposition low-pass, decomposition high-pass, reconstruction low-pass, and reconstruction high-pass filters), developed by Mallat [22], is considered in this paper. Multiresolution via Mallat's algorithm is a procedure to obtain "approximations" and "details" from a given signal. An approximation is a low-frequency representation of the original signal, whereas a detail is the difference between two successive approximations. An approximation holds the general trend of the original signal, whereas a detail depicts high-frequency components of it [21]. By successive decomposition of the approximations (Fig. 1), a multilevel decomposition process can be achieved where the original signal is broken down into lower resolution components.

A wavelet function of type Daubechies of order 4 (abbreviated as Db4) is used as the mother wavelet $\phi(t)$. This wavelet offers an appropriate trade-off between wave-length and smoothness, resulting in an appropriate behavior for short-term electricity prices forecasting.

Similar wavelets have been considered by previous researchers [8,20,21]. Also, three decomposition levels are considered, as shown in Fig. 1, since it describes the price series in a more thorough and meaningful way than the others [23].

### 2.2. Neuro-fuzzy approach

NN are simple, but powerful and flexible tools for forecasting, provided that there are enough data for training, an adequate selection of the input–output samples, an appropriated number of hidden units and enough computational resources available. Also, NN have the well-known advantages of being able to approximate any non-linear function and being able to solve problems where the input–output relationship is neither well defined nor easily computable, because NN are data-driven. Multi-layered feedforward NN are specially suited for forecasting, implementing non-linearities using sigmoid functions for the hidden layer and linear functions for the output layer [13].

Just like NN, a fuzzy logic system is a non-linear mapping of an input vector into a scalar output, but it can handle numerical values and linguistic knowledge. In general, a fuzzy logic system contains four components: fuzzifier, rules, inference engine, and defuzzifier. The fuzzifier converts a crisp input variable into a fuzzy representation, where membership functions give the degree of belonging of the variable to a given attribute. Fuzzy rules are of the type "if–then", and can be derived from numerical data or from expert linguistic. Mamdani and Sugeno inference engines are two of the main types of inference mechanisms. The Mamdani engine combines fuzzy rules into a mapping from fuzzy input sets to fuzzy output sets, while the Takagi–Sugeno type relates fuzzy inputs and

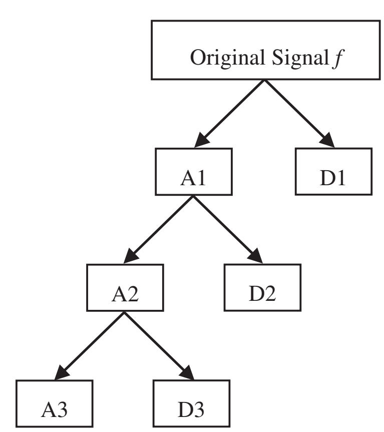


**Fig. 1.** Multilevel decomposition process.