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# A bat optimized neural network and wavelet transform approach for short-term price forecasting

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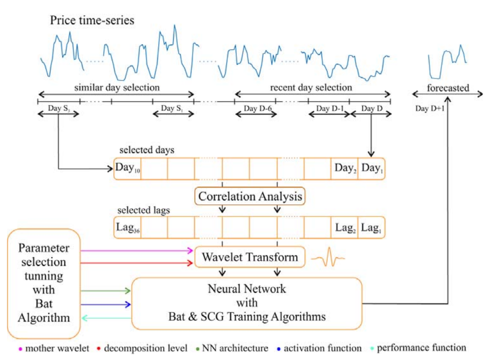
## HIGHLIGHTS

- We propose a new method for short-term price forecasting (STPF).
- The new method is based on Bat Algorithm, Wavelet Transform and Artificial Neural Networks.
- The method has the capability to auto-tune the best simulation parameters.
- We compare the proposed method in Spanish and Pennsylvania-New Jersey-Maryland (PJM) electricity markets.
- The proposed approach exhibits a better forecasting accuracy.

## GRAPHICAL ABSTRACT




## ARTICLE INFO

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## ABSTRACT

In the competitive power industry environment, electricity price forecasting is a fundamental task when market participants decide upon bidding strategies. This has led researchers in the last years to intensely search for accurate forecasting methods, contributing to better risk assessment, with significant financial repercussions. This paper presents a hybrid method that combines similar and recent day-based selection, correlation and wavelet analysis in a pre-processing stage. Afterwards a feedforward neural network is used alongside Bat and Scaled Conjugate Gradient Algorithms to improve the traditional neural network learning capability. Another feature is the method's capacity to fine-tune neural network architecture and wavelet decomposition, for which there is no optimal paradigm. Numerical testing was applied in a day-ahead framework to historical data pertaining to Spanish and Pennsylvania-New Jersey-Maryland (PJM) electricity markets, revealing positive forecasting results in comparison with other state-of-the-art methods.

## 1. Introduction

As a widely traded commodity, electricity is sold and bought by producers and consumers who submit their bids, under spot or derivative contracts in a pool-based market [1]. Bids are analyzed by the market operator who then determines the clearing price. But unlike other commodities, electricity cannot be queued and stored economically, with the exception of pumped-storage hydro plants in certain conditions [2].

Therefore, the power industry operates in a very competitive framework, largely due to deregulation and the search for competition policies with the clear intent to reduce marginal costs (and consequently obtain lower consumer electricity prices). In contrast with the previous monopolistic and government-controlled context [1], this deregulated environment creates an additional degree of uncertainty in electricity prices (price volatility). Therefore, the search for reliable and

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**Nomenclature**

| Label | Description (Unit) |
|---|---|
| $a_{j,k}(k)$ | wavelet decomposition approximation coefficients |
| $A_i^t$ | loudness parameter at iteration $t$ |
| $b_j$ | input signal (bias) for neuron $j$ |
| $d_{j,k}(k)$ | wavelet decomposition detailed coefficients |
| $\mathrm{E}(w_k)$ | error function |
| $f_i^t$ | frequency assigned to the $ith$ bat at iteration $t$ |
| $f_{\max}$ | bat frequency upper bound |
| $f_{\min}$ | bat frequency lower bound |
| $g_j$ | activation function value for neuron j |
| $m$ | number of neurons in a generic layer $k-1$ |
| $M$ | number of wavelet coefficients |
| $n$ | number of neurons in a generic layer $k$ |
| $N$ | signal length (number of samples) |
| $p_i$ | energy probability distribution for wavelet coefficient $i$ |
| $P_t$ | actual (real) price at time instant $t$ (€/MWh or $/MWh) |
| $\widehat{P}_t$ | forecasted price at time instant $t$ (€/MWh or $/MWh) |
| $P_{\mathrm{Week}}$ | average (mean) weekly price (€/MWh or $/MWh) |
| $q_k$ | search direction vector at iteration $k$ |
| $r_0$ | initial pulse emission parameter |
| $r_i^t$ | pulse emission parameter at iteration $t$ |
| $s_k$ | Hessian matrix approximation at iteration $k$ |
| $u_i$ | input signal for neuron $j$ |
| $v_i^t$ | velocity assigned to the $i^{th}$ bat at iteration $t$ |
| $w_k$ | weight vector at iteration $k$ |
| $wt_x(j,k)$ | discrete wavelet coefficients (DWT) |
| $\mathrm{WE}(s)$ | wavelet energy per scale |
| $\mathrm{WE}_{\mathrm{entropy}}(s)$ | wavelet entropy per scale |
| $x_i^t$ | position assigned to the $i^{th}$ bat at iteration $t$ |
| $x^*$ | current global best solution (bat) |
| $y_j$ | output signal for neuron $j$ in a generic layer $k$ |
| $z_i$ | target output response for training sample $i$ |
| $\alpha$ | loudness constant value |
| $\beta$ | random number from a uniform distribution |
| $\gamma$ | pulse rate constant value |
| $\lambda_k$, $\sigma_k$ | scaling factors (SCG) |
| $\upsilon(t)$ | price time-series |
| $\phi(t)$ | scale function (MRA) |
| $\psi(t)$ | mother (base) wavelet function |
| $\omega_{\mathrm{ij}}$ | weight of the synaptic connection between neurons $i$ and $j$ |

accurate price forecasting techniques, which allow market players to best derive their pool bidding strategies and to optimally schedule energy resources [2,3], can be a differentiating factor between competitors, allowing producers to maximize their profits and consumers to maximize their utilities [4]. As a result, forecasting electricity demand and prices has emerged as one of the major fields of research in electrical engineering [5,6].

A set of details about the price time-series makes the task of forecasting prices far from trivial [7], including high frequency, non-constant mean and variance, multiple seasonality, calendar effect, high level of volatility, and high percentage of unusual price movements [5]. Another set of aspects affecting forecasting accuracy is the uncertainty related with fuel prices, future additions of generation and transmission capacity, regulatory structure and rules, future demand growth, plant operations, and climate changes [2,8].

Presently, some markets with strong penetration of renewable energy sources, particularly wind power (as the Iberian market), have special regulatory regimes (feed-in-tariff scheme) imposing new challenges, mainly due to the fluctuating feed-in of wind power. For example, a day with prices close to zero can be followed by a day of maximum prices, which together with transmission congestion, contributes to price volatility.

A variety of methods have been developed for electricity price forecasting [1] and can also be used for load forecasting [5]. The majority of them, including the present method, focus on lead times ranging from one hour to week-ahead forecasting, with a particular emphasis on day-ahead forecasting, the time horizon corresponding to short-term price forecasting (STPF).

Most methods are based on time-series models, focusing on the past behaviour of price time-series, and can be complemented with some exogenous variables. The first major approach are Parsimonious stochastic methods, for example autoregressive integrated moving average (ARIMA) [9,10] and generalized autoregressive conditional heteroskedastic (GARCH) [11,12] models. A recent approach, proposed in [13], combined ARIMA models and stochastic programming with good results. Other time-series models based on regression are presented in [14,15]. A disadvantage of these methods is their high computational cost [2].

The wavelet transform (WT) is another commonly used feature to better deal with a non-constant mean and variance and a significant number of outliers (also known as spikes). The transformed time-series presents typically a better behaviour (more stable variance and less outliers) than the original price series, thus resulting in a better performance [4,16]. A forecasting model integrating DWT and back-propagation neural networks for financial time-series revealed that the low-frequency components coupled with high-frequency components resulted in higher accuracy performance [17]. For instance in [4,18] the authors combine WT with the classical ARIMA and GARCH models.

Given the limitations presented by the first set of methods, authors focused their efforts on artificial intelligence (AI) methods, based on data-driven structures where input–output mapping is learned from historical samples [19], which constitute the second major group of methods. These are better suited to deal with hard non-linear relationships typical of price time-series, and are thus computationally more efficient [2]. A large portion of these AI methods are centered on Artificial Neural Networks (ANNs). While authors in [2,16,20] used feed forward, radial basis and Elman networks in classical approaches, in [21] authors propose an improved training process for the ANN.

In order to conjugate synergies from different features, the current approaches focus on hybrid methods (combining classical and intelligent computing methods). For example, the use of WT and a fused version of neural networks and fuzzy logic [22]. In [23] the authors used a cascaded neural network (CNN) combined with the Chemical reaction optimization (CRO) algorithm to properly train the CNN. Furthermore an hybrid approach, followed in [24], combined fuzzy ARTMAP, wavelet transform and the firefly algorithm to perform the STPF. A hybrid approach based on the MIMO- LSSVM model, complemented with GMI input selection and WT, and optimized by Quasi-Oppositional Artificial Bee Colony (QOABC) was proposed in [19].

This paper introduces an enhanced method to accurately forecast prices with 24 h lead times, combining synergies from different techniques, in brief: (i) a data selection process, enabling a higher predictive performance, combining both similar and recent days to form the training set, then extracting the most relevant lags using correlation analysis; (ii) a pre-processing phase, using wavelet decomposition, whereby a quantitative method is used to select the best mother wavelet candidates; (iii) an ANN training task, blending the bat algorithm and scaled conjugate gradient algorithm, thus improving neural network learning accuracy; (iv) an optimization strategy to determine parameters involving the ANN architecture and wavelet decomposition.

This paper is organized in the following manner: Section 2 provides a succinct theoretical review of artificial neural networks, scaled

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