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Electricity Prices Neural Networks Forecast using the Hilbert-Huang Transform

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***Abstract*—The problem of forecasting of electicity prices is addressed in terms of joint approach employing the general regression artificial neural network and empirical mode decomposition approaches (EMD) which is part of Hilbert-Huang transform. The application of developed approach to day-ahead hourly time series has demonstrated the whole accuracy increase as well as peaks prediction.**

I. Introduction

Nowadays, one of the key conditions for a successful activity of electricity market participants in the free trade sector is consideration for the price situation in the market while preparing the bids for electricity purchase and/or sale. Fast creation of competitive electricity market in Russia has considerably complicated interrelations among the participants of the market that have to act under uncertainty. Total liberalization of the Russian electricity market is planned for 2011. The use of an efficient price forecasting system becomes a competitive advantage for the market participants.

A number mathematical models have been developed lately to address that challenge. They are based on statistical methods (Autoregressive Integrated Moving Average, ARIMA; Generalized Autoregressive Conditional Heteroscedasticity, GARCH), Fourier Spectral Analysis and on the artificial neural network (ANN) approaches (Radial basis function, RBF; Multilayer perceptron, MLP) [1] and on Support vector machine, SVM. The models from the family of ARIMA and GARCH were successfully tested on the Spanish and Norwegian electricity markets [2]. The models based on the ANNs heuristics were applied to the electricity markets in Brazil, Canada, Australia and Wales [3],[4].

Most of the works emphasize that the highest accuracy of the price forecast can be obtained on the basis of ANN models (Fig. 1). The readers may refer to [5],[6] for more details.

To increase the accuracy of electricity price forecasting the paper proposes the “intelligent[1]” approach which supposes the use of neural network technologies together with Hilbert-Huang Transform (HHT). The approach makes it possible to efficiently solve forecasting problems under rigid requirements of accuracy in such calculations and non-stationarity of the time series studied.

[1]“Intelligent” is taken to mean the approaches, methods, systems or complexes which employ artificial intelligence technologies

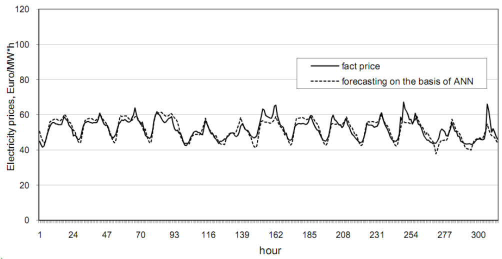

Fig. 1: The fourteen-ahead hourly electricity price forecasts for European price zone on the basis of ANN.

II. Empirical Mode Decomposition

A. EMD Alghoritm

It is to be noted that empirical mode decomposition is in the core of Hilbert-Hunag transform [7], but it can be employed as standalone algorithm of input signals decomposition into the set of special basis functions, called intristic mode functions (IMFs) and satisfying the two criteria:

- extreme numbers and zero-crossings on the entire interval are supposed to congruent;
- the median value of envelopes which are defined by local maxima and minima are supposed to be zeros for intrstic mode functions at any point.

In contrast to standard methods of time series processing, the method of IMF construction starts from the highest frequency component, and the last extracted function is usually monotone, or has one extreme. Let the original signal $x(t)$ be given, then algorithm of empirical mode decomposition can be presented as follows:

Step 1. Let $r_0(t) = x(t)$, $j = 1$.

Step 2. Search for j-th IMF using the sifting procedure:

1) Let $i = 1$ and $h_{i-1}(t) = r_{j-1}(t)$;
2) Find local minima and local maxima for $h_{i-1}(t)$. Form an lower $e_{min_{i-1}}(t)$ and upper envelope $e_{max_{i-1}}(t)$ by corresponding interpolation the local minima and maxima;
3) Compute the middle value $m_{i-1}(t) = \left(e_{min_{i-1}}(t) + e_{max_{i-1}}(t)\right)/2$ and find $h_i(t) = h_{i-1}(t) - m_{i-1}(t)$ such as

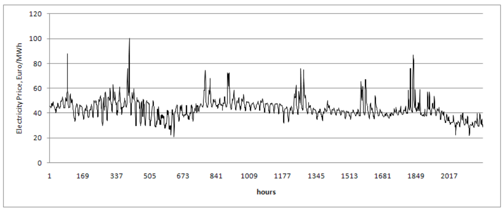

Fig. 2: Electricity prices for three months from 01.12.2007 till 01.02.2008

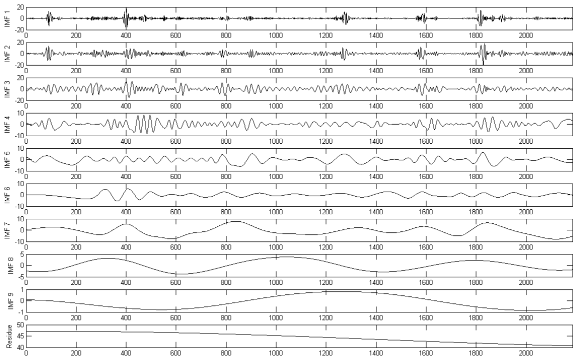

Fig. 3: Set of IMFs

$e_{min_{i-1}}(t) \leq h_i(t) \leq e_{max_{i-1}}(t)$, for all t. Let $i = i + 1$;

4) Repeat steps b) - d) until $h_i(t)$ satisfies a set of predetermined stopping criteria (following from properties of IMF). Let $c_j = h_i(t)$.

Step 3. Compute residue $r_j(t) = r_{j-1}(t) - c_j(t)$. Than let $j = j + 1$ and repeat step 2 until the number of extrema in residue $r_j(t)$ is less than 2. Thus, at the end of decomposition process, the original signal can be presented as follows:

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) =$$

$$\sum_{i=1}^{q} c_i(t) + \sum_{j=q+1}^{p} c_j(t) + \sum_{k=p+1}^{n} c_k(t) + r_n(t),$$

where $q < p < n$, $c_i(t)$ - are the high frequency noise components, $c_j(t)$ - are the components representing the physical properties of the series and $c_k(t)$, $r_n(t)$ - are trend non-sinusoidal components. It is to be noted that for the majority of analyzed realizations, the requested number of IMF are less then 10. For more detailed description of IMF alghoritm readers may refer to [8],[9].

The key objective of IMF in the problem of electricity prices prediction consists in preliminary processing of given non-stationary realization.

B. Example

Let us demonstrate our appoach in the Fig.2 time series, based on electricity prices of one of the European price zone.

Result of EMD application to the 1st realization is shown in Fig.3

TABLE I: A day-ahead hourly electricity price forecast for different types of samples

Type of learning sample	Initial time series	Sample 1	Sample 2
Average error for 4 days, %	7,35	6,60	7,36
Average error in region A, %	8.91	6.08	6.73

III. Calculations

In terms of forecasting the approach supposes exclusion of the first high-frequency IMFs from the initial time series. The experimental calculations were carried out for one of the European price zones. For this purpose three different types of hourly electricity price samples were taken over the period of 9 months. These are:

1) initial time series;
2) sample 1 – a transformed sample (with the 1st IMF excluded);
3) sample 2 – a transformed sample (with the 1st and 2nd IMFs excluded).

The samples were used for learning of artificial neural networks of General Regression Neural Network type to make a day-ahead price forecast. The GRNN employed had the following configuration: 24 – input neurons, 250 neurons of the 1-st hidden layer, 25 neurons of the second hidden layer and 24 output neurons.

The calculations presented in Fig.4 and TABLE I show that the best forecast was made by excluding only the first high-frequency IMF from the initial time series. Moreover, the forecast presented in Fig.4b is also more accurate for peak sections of the price curve (for example, region A), i.e. the neural network model learned by the sample with the 1st IMF excluded responds more adaptively to the occurrence of peaks.

IV. Conclusion

1) The intelligent approach was proposed to increase the accuracy of electricity price forecasting. The approach envisages the use of neural network technologies together with Hilbert-Huang Transform.
2) The experimental calculations have shown that the developed approach makes it possible to decrease the error of short-term electricity price forecast, first of all, on the peak sections of the price curve.

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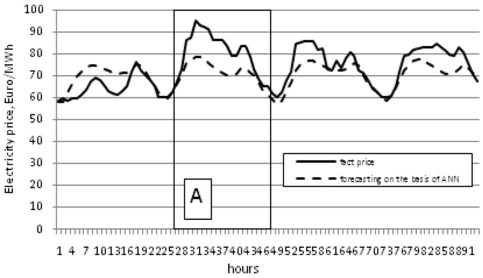
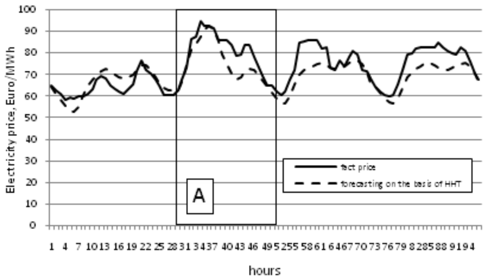
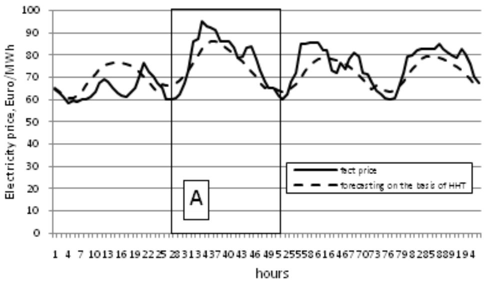


(a) initial time series



(b) sample 1 (the 1st IMF is excluded)



(c) sample 2 (the 1st and 2nd IMFs are excluded)

Fig. 4: A day-ahead hourly electricity price forecast

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