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Fine structure of the price-demand relationship in the electricity market: multi-scale correlation analysis☆

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Abstract

The price-demand relationship in the electricity market is a complicated phenomenon. In order to thoroughly investigate the peculiarities of this relationship, a multi-scale correlation analysis of electricity price and demand is carried out in this research. Using a modified method of so-called time-dependent intrinsic correlation (TDIC) (Chen et al., 2010), based on the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) (Torres et al., 2011), and bootstrapping, we investigate the problems of dynamic interconnection between electricity demand and prices over different time scales (i.e. its fine structure). We formulate and test three hypotheses on the type and strength of correlations between them in the short-, medium- and long-runs. In this research we analyze the data from two largest price zones of Russian wholesale electricity market: Europe-Ural and Siberia. These two zones differ from each other by the structures of electricity generation and consumption. It is shown that these two price zones significantly differ in internal price-demand correlation structure over the comparable time scales, and not each of the theoretically formulated hypotheses is true for each of the price zones. This allows us to conclude that the answer to the question whether it is necessary to take into account the influence of demand-side on electricity spot prices over different time scales, is significantly dependent on the structure of electricity generation and consumption on the corresponding market.

Keywords: electricity spot price, electricity demand, price-demand correlation, empirical mode decomposition, time-dependent intrinsic correlation, trend estimation

1. Introduction

It is well-known that competitive equilibrium price on most commodity markets is formed as the result of demand and supply interaction. Though, as compared to these commodity markets,

☆Matlab codes used in this article are available for download here: `http://dmafanasyev.ru/fine-structure-electricity-market/`. CEEMDAN implementation for Matlab is available here: `http://www.bioingenieria.edu.ar/grupos/ldnlys/`. If you use the codes from this paper in yours own researches, please do not forget to cite this article as well as Torres et al. (2011).

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electricity market has several peculiarities caused by physical properties of the subject being traded. Among these properties it is worth mentioning the following: (1) electricity cannot be stored in large amounts; (2) the moment of electricity production coincides with the moment of its consumption; (3) electricity producers often cannot refuse to deliver electricity even if the the price for it is insufficiently high; (4) the short term price elasticity of electricity demand is low; (5) there are daily, weekly, and annual seasonalities in electricity demand; (6) there are significant price peaks (both positive and negative); (7) the long term mean reverting of the price.

Most authors agree that demand structure and its fluctuations are fundamental factors in electricity price determination. In their seminal paper Skantze et al. (2000) use exponential price form of the following kind $P_t = exp(\alpha D_t + \beta C_t)$, where P_t is electricity price at time t, D_t is the corresponding demand volume (or load), C_t is the capacity (or supply). D_t and C_t are assumed to be stochastic and following the two-factor Ornstein-Uhlenbeck process (OU-process) with zero correlations.

Barlow (2002) studied electricity demand as a "non-linear OU-process" (NLOU). The price of electricity was related to its demand via a compound function comprising linear, power, and exponential forms (which are controlled by a special parameter).

Cartea and Villaplana (2008) used the observed data on the available generated power to calculate C_t as well as correlation between the demand and supply (the authors employed correlated OU-processes in the specification of their model).

Fuss et al. (2013) in their paper took into account the fact that both electricity demand and its volatility have seasonality and depend significantly on the time of the year. The authors used a time-dependent volatility function as it was proposed earlier in Geman and Nguyen (2005). In order to take into account demand seasonality, the authors introduced linear trend and a set of dummy variables (for months, weekends, and national holidays) into the specification of their model.

Coulon and Howison (2009) proposed parametric approach to approximation of bid stack B_t by using different probability distributions. In this case the price of electricity $P_t = B_t(x)$ is an x-quantile of the corresponding distribution. The value x can be represented both by the demand volume D_t itself, and a share of the available capacity D_t/C_t (see Coulon and Howison, 2009). More detailed review of approaches to electricity price modeling can be found, for example, in Carmon and Coulon (2014).

Although all the above-mentioned authors agree that electricity demand influences significantly electricity price, there are at least two issues to be mentioned that are typical for the studies in this domain.

First, it is implicitly assumed in these studies that the correlation between electricity price and demand is constant or at least doesn't change significantly over the period under investigation. This results in the parameters of the corresponding models being fixed over time. It is worth noting that some authors use Markov regime-switching models (see, for example, Zachmann, 2013), that allow parameter changes over time which lets partially abandon such a restrictive limitation. Still, over the time period corresponding to a specific regime (which in general can be quite long), both parameters and correlations remain constant. Moreover, as to our knowledge, in the papers employing Markov regime-switching models, the authors tend to analyze the question of price peaks identification (see, for example, De Jong, 2006; Janczura et al., 2013), to study cointegrated processes (see, for example, Haldrup et al., 2010) and market behavior forecasting (see, for example, Kosater and Mosler, 2006), but do not discuss the problems of dynamic influence of electricity demand on the price of electricity.

Second, to our knowledge, most of the studies on the subject matter explicitly or implicitly assume that removal of trend-seasonal component makes the corresponding time-series stationary that is tested using the classical unit-root tests (for example, ADF or KPSS). The obtained trend components are then used to study the long term dynamics of electricity price and demand, while the stochastic component is used to study short term fluctuations. At the same time, the fact that the tools used for deterministic components extraction, in most cases, cannot correctly handle neither non-stationary time-series (moving average over the given calibration period, exponentially weighted moving average, dummy variables regression, Fourier transformation), nor non-linear time-series (wavelet decomposition), is often simply ignored. The empirical trend extracted with these methods from substantially non-stationary and non-linear processes is very likely to differ from the original trend. Taking this into account it should be noted that the model parameters for such long term components are likely to incorrectly reflect the actual situation. The same is true for stochastic components since they are obtained by removing the incorrectly estimated time trend and are expected to have bias.

Third, a relatively small number of studies have focused on the quantitative assessment of correlations in the electricity markets. Uritskaya and Serletis (2008) using the detrended fluctuation analysis (DFA) showed that the dynamics of prices in the Alberta and Mid Columbia markets exhibit scale-dependent behavior. The fluctuations of prices differ significantly from Brownian motion and exhibit large-scale correlations. Alvarez-Ramirez and Escarela-Perez (2010) using DFA and the Allan factor method, conducted an analysis of the correlations, both in price and demand dynamics. They showed that takes place not only scale-dependent behavior, but also time-dependent with the annual cycle. At the same time, in these papers the correlation between price and demand has not been investigated.

In order to fill these gaps, the current research considers the questions of price-demand dynamic correlations in the electricity market over different time scales. Considering the results Uritskaya and Serletis (2008); Alvarez-Ramirez and Escarela-Perez (2010) we assume that price-demand correlation is time-dependent. Thus, in order to correctly take into account substantial non-stationarity and non-linearity of the studied processes, the analysis of this correlation should be carried out over different time scales which reflect their internal structure. Moreover, averaging this dynamic correlations we obtain a peculiar interconnection between electricity price and demand at each of these time scales. We call this approach a multi-scale correlation analysis or a fine-structure correlation analysis.

Using the terminology of Kydland and Prescott (1990), we will say that two time-series have procyclical, acyclical, or countercyclical correlation, if its value is positive, zero, or negative respectively. In order to characterize the strength of correlation we will use the following categories: zero correlation (0.00–0.13)[1], weak correlation (0.13–0.30), moderate correlation (0.30–0.70), and strong correlation (0.70–1.0).

In this research we formulate the following three hypotheses on the behavior of electricity price-demand correlation over different time scales.

H1. In the short term (up to 1 week) price-demand correlation is strongly procyclical. This reflects the two well-known facts. First, electricity prices are substantially influenced by the business cycle of consuming companies (week seasonality). Second, since the short term price elasticity of demand is extremely low, then sharply increasing electricity consumption within limited

[1]The lower bound equals 0.13 since this is the threshold value for rejection of the two-sided null hypothesis $\rho = 0$.

planned power generation leads to a substantial increase in electricity prices. In literature, this phenomenon is called "spike".

H2. In the medium term (from 2 weeks to 6 months) electricity price-demand correlation is acyclical or weakly procyclical since in that case demand fluctuations are smoothed by power generating companies who have time to adjust capacity to the demand over the corresponding time scales.

H3. In the long term (more than 6 months) electricity price-demand correlation is weakly countercyclical since a decrease in electricity demand over these time scales will lead to an increase of average total costs of power producers (which will be caused by an increase in average fixed costs) and therefore, to an increase in electricity price. In turn, a long term price growth will make the consumers optimize their electricity demand causing its reduction.

In order to test these hypotheses we employ a relatively new, but already having a good account technique – empirical mode decomposition (EMD). It was first proposed in Huang et al. (1998) and makes local and high-adaptive decomposition of a time-series into intrinsic mode functions (IMF) with different average time-scales: from low frequency to high frequency components.

The main advantage of EMD is its ability to handle non-stationary and nonlinear processes since this technique has no a priori assumptions regarding these properties of time-series under consideration. Still, each of the obtained IMFs reflects the dynamics of the time-series at a specific time scale which allow to study the fine structure of the time-series, which we mentioned above[2].

Recently, a number of modifications of EMD was proposed to improve its characteristics and solve the problems concerned with the empirical nature of this technique. Wu and Huang (2009) introduced an ensemble empirical mode decomposition (EEMD) in order to obtain more accurate estimates of IMFs and to solve the problem of mode mixing. Torres et al. (2011) proposed to use complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), which does not generate excessive IMF by using adaptive white noise and is more computationally parsimonious than EEMD. To analyze correlation of IMFs over the corresponding time scales we will use time-dependent intrinsic correlation (TDIC) proposed in Chen et al. (2010).

EMD and its modifications, even taking into account their popularity in signal processing, are still quite rarely used in electricity markets analysis. Perhaps, we can mention only relatively limited number of such studies: Dong et al. (2011) (forecasting electricity price, EMD is used to remove high-frequency and seasonal components from the price time-series), Mhamdi et al. (2010) (comparison of EMD and Hodrick-Prescott filter while extracting trend component from peak load data), An et al. (2013) (electricity demand forecasting; EMD is used to clean the time-series from noise), Ismail (2013) (prediction of peak load via forecasting separate IMFs), Ghelardoni et al. (2013) (long term forecasting of electricity consumption).

As to our knowledge, multi-scale price-demand correlation analysis on the wholesale electricity market with application of CEEMDAN and TDIC has not been carried out earlier in other studies. [3]. Other distinguishing features of our study are as follows: 1) we run price-demand correlation

[2]As it was wittily mentioned in Crowley (2012), under EMD a time-series can be considered as the choir of singers with voices of different tone.

[3]It is worth noting that in Oladosu (2009) the author uses EMD and cross-correlation analysis to study the relation of the US economy and oil prices. To some extent, our idea is analogous to that study but we apply more effective technique of decomposition and a principally different approach to correlation calculation. Besides the technical aspects, our study lie completely in a different scientific domain.

analysis in the short, medium and long terms, i.e. we analyze intrinsic price determination mechanisms influenced by demand side; 2) we use a modified method of calculation of time-dependent intrinsic correlation, based on CEEMDAN and its averaging with bootstrap; 3) we propose two additional criteria (low frequency and statistical) to find IMFs that make trend; 4) we consider now comparatively less studied developing electricity markets of Russia in its two largest price zones: Europe-Ural and Siberia.

The rest of the paper is organized as follows. In section 2 we discuss the methodology of current research: EMD / EEMD / CEEMDAN, trend-cyclic component extraction and TDIC. In section 3 the data used are briefly described. Section 4 discusses the results. Section 5 concludes.

2. Methodology

2.1. Empirical mode decomposition

Empirical mode decomposition (Huang transformation) is a method that was first proposed in Huang et al. (1998) and allows to decompose an initial signal (i.e. time-series) into oscillating components in order to study a fine structure of that signal or time-series. EMD is actually a part of more general procedure known as Hilbert–Huang transformation (HHT) and by its nature resembles other well-known decompositions: Fourier decomposition and wavelet transformation. Although EMD does not suffer from the disadvantages that are attributed to these two decompositions. In order to obtain an adequate result while applying Fourier decomposition it is necessary that the initial signal be stationary, linear and defined over an infinite horizon. Wavelet decomposition using localized in time and quickly decaying basis functions (wavelets) partially loosens these limitations allowing the signal to be non-stationary and finitely defined. Still, this does not solve the problem of signal's possible nonlinear nature. Moreover, a common disadvantage of both methods is a priori defined decomposition basis which is either given by the type of transformation (in case of Fourier transformation) or is chosen from a given family of functions (in case of wavelet transformation).

It is obvious that no signal or process (including financial processes) is likely to be stationary or linear. And a priori choice of basis functions is often based on some speculative and rarely objective assumptions. This is why we can say that application of classical methods of decomposition may be not quite justified causing misleading results. By its nature, EMD can handle and overcome all these "unpleasant" properties of a time-series.

When applying EMD, an input signal is decomposed into a sum of IMFs that meet the following two conditions (see (Huang et al., 1998)): (1) the number of extrema and the number of zero crossings (the intersection of the time axis) must be equal or must differ by no more than 1; (2) at any time moment, the average value of the envelope built at the local maxima and the envelope built on local minima is equal to zero. In order to find IMF, an iterative algorithm of original signal sifting can be used, which was proposed in Huang et al. (1998). The original signal $x[t]_{t\in(1,T)}$ (a realization of stochastic process $\mathbf{X}$) can be reconstructed as a sum I of IMFs obtained (the empirical basis of decomposition) and the residual $r[t]$:

$$x[t] = \sum_{i=1}^{I} IMF_i[t] + r[t]. \tag{1}$$

EMD allows to decompose the input signal into components that reflect its intrinsic structure over different time scales. And each next IMF corresponds to a longer time scale. This allows to use EMD to study fine structures of financial processes.

The main disadvantage of classical EMD is the problem of mode mixing: components corresponding to different time scales sometimes appear to be mixed within one IMF or a component corresponding to a specific time scale appears to be included into different IMF. To overcome this disadvantage Wu and Huang (2009) proposed a modification of EMD - ensemble empirical modes decomposition (EEMD).

The main idea of EEMD is that EMD iterates quite a lot of times, and at each iteration the initial signal is added with different realizations of white noise $n_k[t] \sim N(0,1)$ with a limited amplitude α: $x_k[t] = x[t] + \alpha n_k[t]$. As a result, there is a number of $IMF_i^k[t]$, where $k = (1, \ldots, K)$ is the iteration number. More accurate estimate $\overline{IMF}_i$ is obtained by simple averaging of the IMFs.

EEMD allows to effectively solve the problem of mode mixing but creates two new problems: (1) the reconstructed signal $x[t]$ contains a residual noise which is introduced by the white noise added during the iterations; (2) different realizations of the noise can cause different number of IMFs. In order to solve these new problems Torres et al. (2011) proposed to use complete ensemble empirical modes decomposition with adaptive noise (CEEMDAN). The main difference of CEEMDAN from EEMD lies in the way the white noise is added. In case of EEMD each signal realization with noise is decomposed into modes independently thus the residuals for each realization are also independent introducing their individual input into the final residual of decomposition. CEEMDAN adds noise not to the original signal but to the residual obtained at the previous iteration. And it is not the noise itself that is used but its corresponding mode obtained by EMD. Thus, in CEEMDAN the noise is adaptive and does not create additional input to the original signal because its influence is being averaged at each iteration. Following Torres et al. (2011), let $E_i(\cdot)$ be the operator of taking i-th mode obtained by EMD (with $E_0(x[t]) = x[t]$), and $\widetilde{IMF}_i$ be the mode that is extracted by CEEMDAN. Setting $r_0[t] = x[t]$, $i = 1$, CEEMDAN consists of the following steps (Torres et al., 2011; Colominas et al., 2012):

1. Extract the first mode for K realizations of white noise $r_{i-1}[t] + \alpha_{i-1}E_{i-1}(n_k[t])$ and find the i-th mode of the original signal by averaging the obtained result:

$$\widetilde{IMF}_i[t] = \frac{1}{K}\sum_{k=1}^{K} E_1(r_{i-1}[t] + \alpha_{i-1}E_{i-1}(n_k[t])) \tag{2}$$

   It is worth noting that for $i = 1$ we get $\widetilde{IMF}_1[t] = \frac{1}{K}\sum_{k=1}^{K} E_1(x[t] + \alpha_0 n_k[t]) = \overline{IMF}_1[t]$, i.e. the first mode obtained by CEEMDAN coincides with the one obtained by EEMD.

2. Calculate the i-th residual as follows: $r_i[t] = r_{i-1}[t] - \widetilde{IMF}_i[t]$

3. If $r_i[t]$ has at least 2 extremum points then re-iterate for the next i.

The initial signal $x[t]$ can be reconstructed with the obtained modes $\widetilde{IMF}_i[t]$ using the formula analogous to (1) – this is why the decomposition proposed by Torres et al. (2011) is complete. As it is shown in Colominas et al. (2012), CEEMDAN, as compared to EEMD, has some robustness to changes in the amplitude of the noise being added. The reconstruction error does not depend significantly on the signal-noise ratio (SNR), while the global minimum of it is found at the amplitude equal to 0.2[4]. This is the specific value we use in this study. It is also worth noting that CEEMDAN is computationally more effective than EEMD since the former requires much less iterations for signal sifting. All this justifies the application of CEEMDAN for extracting intrinsic modes of electricity price and demand time-series being studied.

2.2. Time dependent intrinsic correlation

Correlation is a comparatively simple for calculation and interpretation statistic, which makes it widely used in econometrics. Still, when calculating the correlation coefficient for two processes, one implicitly assumes that these processes are stationary and linear. Not taking this into account often results in the situation when the correlation calculated for two non-stationary time-series may appear statistically significant while it is a priori known that there is no relation between the time-series over the whole sample or a subsample. This phenomenon is called "spurious" or "nonsense" correlation (Yule, 1926). This phenomenon is caused by the fact that non-stationary and nonlinear processes may have both time-variable frequency and non-stable phase with constant frequency.

In order to overcome these problems, Papadimitriou et al. (2006) proposed to use local (or time-dependent) correlation which is calculated using the traditional formula but over some "window" t_ω that "moves" over the whole time period. Still, first, this approach does not make it clear how to choose the size of window t_ω, and, second, does not allow to find correlations in the case when the input signal consists of several modes corresponding to different time scales (frequencies). These two problems are solved by EMD-based time-dependent intrinsic correlation (TDIC) introduced in Chen et al. (2010).

Chen et al. (2010) proposed to use EMD to decompose the input signal into IMF corresponding to different time scales and to calculate pair-wise local correlation between the IMFs. In order to find the size of window t_ω it is proposed to use instantaneous periods obtained by Hilbert transformation of IMFs[5]. Instantaneous period $T[t]$ is a highly local characteristic of a signal since it is calculated as a result of singular Hilbert transformation and taking a derivative of instantaneous phase θ with respect to time. The algorithm of TDIC calculation has the following steps (Chen et al., 2010):

1. With EMD the initial signals $x_j[t]$, $j = 1, 2$ are decomposed into I intrinsic modes IMF_i^j, $i = 1, \ldots, I$.

2. For each IMF, Hilbert transformation is applied, instantaneous phases $\theta[t]$ are found, and instantaneous periods $T_i^j[t] = 1/\dot{\theta}_i^j[t]$ are calculated at each time moment, where $\cdot$ denotes the derivative with respect to time.

3. Find the size of window for each time moment t as $t_\omega^n[t] = [t - nt_i^h[t]/2 : t + nt_i^h[t]/2]$, where $t_i^h[t] = \max(T_i^1[t], T_i^2[t])$ is the maximum instantaneous period for two IMFs, and $n \geqslant 1$ is the number of times these periods fall into the window. For the purposes of current study $n = 1$.

[4] In general, noise amplitude α_{i-1} in CEEMDAN may differ for each of the IMF_i. Still, following the idea of Colominas et al. (2012), in this paper we assume that the amplitude is the same for each i.

[5] The idea of using Hilbert transformation to analyze the spectrum of IMFs was given in Huang et al. (1998), and, as it was said above, along with EMD is called Hilbert-Huang transformation (HHT). We are not going to dwell on the mathematical details of Hilbert transformation since it is quite well described in many papers and the inclined reader can study it him/herself.

4. For each pair of IMFs TDIC is calculated at each moment of time as follows:

$$\rho_i^n[t] = corr(IMF_i^1[t_\omega^n], IMF_i^2[t_\omega^n]) \tag{3}$$

In this research we apply this relatively new approach to study the fine structure of electricity price-demand correlation. We have extended and modified this approach. First, instead of EMD we use more robust method (CEEMDAN) which allows us to avoid the problem of mode mixing and always obtain the same number of empirical modes during decompositions. Second, we calculate TDIC not for each pair of IMFs, but only for those IMFs whose frequencies do not differ significantly. This is justified by the consideration that such modes correspond to comparable time scales of studied processes, over which correlation may have some economic sense and not be a formal statistic. The average period of an IMF can be estimated by the number of local extrema and zero crossings (Rilling et al., 2003). Third, in order to reveal the most typical (averaged) characteristic of IMF relation, we also propose to analyze median $\rho_i^n[t]$. To obtain more accurate estimates of median and its confidence interval we use bootstrapping (Efron, 1979), while to test its statistical significance we apply classical t-test on bootstrapped sample. Fourth, since several last IMF in decomposition represent the components of trend then, in our opinion, their correlation should be analyzed separately from other pair-wise IMF correlations.

In the next section we discuss how EMD can be used to extract trend from non-stationary time-series.

2.3. Trend estimation

The problem of trend-cyclic component extraction from electricity prices was studied earlier in several papers (see, for example, Trück et al., 2007; Janczura et al., 2013). Still, there is no single method to apply to this problem, and the authors use quite different approaches. Several of them can be mentioned here: regression with time trend, regression with dummy variables, moving average or median for given calibration window, exponentially weighted moving average, Fourier decomposition, Hodrick-Prescott filter, as well as wavelet decomposition.

Besides the absence of a single interpretation of the term "trend" and a common view on the best method of its estimation, there is yet another problem. As it was shown in Janczura et al. (2013), there is a significant influence on the extraction of deterministic components in electricity price time-series with the above mentioned methods from the part of extreme outliers ("spikes") as we discussed above. The questions of effective time-series filtering of such "spikes" are discussed in several papers (see, for example, Fanone et al., 2013; Janczura et al., 2013). In this paper we use CEEMDAN for extraction of trend-cyclic component in electricity price and demand time-series. This allows to, first, get this component without any additional a priori assumptions about the properties of these timed-series (stationarity, linearity) or the parameters of the methods used (the size of calibration window, the family of basis functions, smoothing parameter, etc.), and, second, without worrying about the spikes.

It is quite obvious that when decomposing the original signal into a set of IMFs the trend component is represented as a sum of several low frequency modes and the residual of decomposition. The main question here is how to find the number i^* after which to start composing the modes into trend. Flandrin et al. (2004) were the first to show that it is potentially possible to use EMD to extract the trend component connecting it to statistical properties of IMFs. According to them, i^* corresponds to the number of IMF after which normalized average of partially reconstructed signal

$\widehat{x}[t] = \sum_{i=1}^{i^*} IMF_i[t]$ is statistically different from zero. Although, this rule is not quite accurate, and in order to make it more accurate the authors studied the statistical properties of the IMFs of fractional Gaussian noise (fGn) for different values of Hurst exponent H (Hurst, 1951). The authors proposed the following formula for finding confidence interval of C_i^H of i-th mode energy G_i:

$$\log_2(\log_2(C_i^H/\widehat{W}_i^H)) = a_H i + b_H, \tag{4}$$

where $\widehat{W}_i^H = (\widehat{W}_1^H/\beta_H)\rho_H^{-2(1-H)i}$ is the estimated value of i-th mode energy ($i \geqslant 2, \rho_H \approx 2$) of the fractional Gaussian noise (the first mode of the original signal is assumed to be equivalent to noise, i.e. $\widehat{W}_1^H = G_1$). If $G_i > C_i^H$ then i-th IMF of the original signal is considered statistically significant, and, according to Flandrin et al. (2004), is included into trend component. The values of parameters β_H, a_H, b_H for different confidence levels γ can be found in Flandrin et al. (2004).

Moghtader et al. (2011) proposed two approaches to finding i^*: energy and zero-crossing ratio, as well as the efficiency of their combined application is proven. According to the energy approach, i^* corresponds to the minimum of the indexes $i \geqslant 2$ for which $G_i > G_{i-1}$, i.e. the energy of current mode is higher than the energy of previous mode. This follow from the fact (shown in Flandrin et al. (2004)) that if the process under study is a generalized broadband signal then the energy of its modes decreases when index i increases. Thus, the energy rises for some i then this index is a candidate to be i^*.

Another approach proposed in Moghtader et al. (2011) assumes analyzing the ratio of zero-crossing numbers (RZCN) $R_i = Z_{i-1}/Z_i$, where Z_i is the number of points in which the i-th IMF crosses the horizontal axis. The authors showed that if the studied process is a generalized broadband signal then $R_i \approx 2$. Thus, for i^* should be taken the minimum of the indexes i such that R_i "is significantly different from 2". In order to specify the size of that difference the authors ran a number of simulations and obtained the empirical distribution of R_i. For the standard levels of significance α they found the left and the right borders of the corresponding confidence intervals. The values outside these borders denote significant difference from 2.

Since the two approaches are independent, their simultaneous application allows to increase the precision of i^* determination, as it is shown in Moghtader et al. (2011). Thus the smallest of the indexes i ($2 \leqslant i \leqslant I$) such that $G_i > G_{i-1}$ and R_i is significantly different 2, is recognized the i^*, and the trend is calculated as sum of the residual and all of the IMFs with $i \geqslant i^*$.

In this paper we have modified this approach to some extent. First, as potential trend components we propose to consider only those IMFs with indexes i such that $I/2 + 1 \leqslant i \leqslant I$ (we call it *low-frequency criterion*). In our opinion, it can be motivated by the fact that only IMFs with high enough indexes (low-frequency modes) should be considered. Although this criterion is quite simple and even obvious, it allows to avoid incorrect determination of index i as we show further. Second, in addition to the above-mentioned methods of i^* determination, we propose to take into account only those IMFs that are statistically different from the white noise with given Hurst exponent H (we call it *statistical criterion*). For such IMFs the condition $G_i > C_i^H$ should hold, where C_i^H is the confidence interval which is found from (4). As it will be shown further, the application of these two additional criteria allows to more precisely estimate the trend component in the electricity prices as compared to taking into account only the energy criterion and the ratio of zero-crossing numbers.

Table 1: The technological structure of total electricity generation in Russia in 2012 and its distribution by the types of power plants in Europe-Ural and Siberia price zones.

The type of power plant	Russia (total), %	Price zones of DAM, %	
		Europe-Ural	Siberia
Thermal PP	66.0	69.0	60.0
Hydroelectric PP	16.3	7.0	40.0
Nuclear PP	17.7	24.0	0.0

Note: according to the data of the Ministry of Energy of the Russian Federation (http://minenergo.gov.ru) and OJSC "ATS" (http://atsenergo.ru); PP stands for "power plant".

3. Data

In this research we consider functioning of Russian wholesale electricity market during the period from the 10th of February, 2011, to the 31st of December, 2013, in the two price zones: Europe-Ural (the first price zone) and Siberia (the second price zone). The functioning of a competitive electricity day-ahead market (DAM) was organized in these zones in 2006. Since 2011, about 80% of all the power generated in the country has been traded on this market. The expansion of this free market was gradual, hopping 2 times a year. We study the period from 2011 since it is at this time that the electricity day-ahead market's share in the total amount of power traded in the country becomes the most substantial is the whole history of Russian wholesale electricity market (and holds this position up to now). The sample starts with the 10th of February, 2011. This is justified by the fact that from the 1st of January to the 9th of February, 2011, there was yet another electricity market expansion, and the market mechanisms were definitely distorted during this time.

The electricity DAM in Russia is a mechanism of competitive selection (auction) of price claims of electricity suppliers and buyers one day ahead of the electricity delivery with determination of prices and supply volumes for each hour of the day. The selection is organized by a commercial operator (open joint stock company "ATS").

It should be noticed that there exists margin pricing on Russian electricity DAM. This means that electricity price is determined via equalizing electricity demand and supply, which is fair for each market participant. As an auction result, there appears a single equilibrium electricity price which is the highest of the prices at which producers are willing to meet the demand. The price indexes and the volumes traded at the DAM are published daily on the website of OJSC "ATS" (http://www.atsenergo.ru).

The technological structure of Russian energy industry includes 3 types of power plants: thermal (TPP), hydro (HPP) and nuclear power plants (NPP). Table 1 shows the distribution of annual power generation by types of power plants in 2012. It can be seen that TPPs generate about 2/3 of all energy in the country. The share of HPPs and NPPs are approximately the same. At the same time the distributions of generated power within the two price zones differ by all power plant types. For example, in Europe-Ural price zone the share of HPPs is 7% while their share in Siberia price zone is 40%. The share of NPPs in the first price zone is 24%, but in the second price zone their share falls dramatically down to zero. The data clearly show that TPPs play the leading role in both price zones. Still, in Siberia price zone HPPs are also of particular importance due to significant hydro energy potential of the region's water basin.

It is worth noting that the structures of energy consumption in the price zones are also different. For example, in Siberia price zone a considerable part of energy consumption is due to the

Table 2: Descriptive statistics of electricity demand and prices for the period 10.02.2011 – 31.12.2013 in price zones Europe-Ural and Siberia.

Statistics	Price, rubles/MWh		Demand, mln MWh	
	Europe-Ural	Siberia	Europe-Ural	Siberia
Mean	1001.6 (6.90)	650.4 (6.47)	1.66	0.46
Median	988.1 (6.90)	661.4 (6.45)	1.63	0.45
Standard deviation	115.4 (0.11)	97.1 (0.15)	0.22	0.06
Kurtosis	2.97 (2.73)	2.32 (2.47)	3.03	3.04
Skewness	0.52 (0.24)	-0.08 (-0.38)	0.72	0.80
Correlation	-0.23	0.40	–	–

Note: Descriptive statistics for logarithm of electricity price are given in parentheses. The correlations between the logarithm of price and demand are calculated on the whole sample and are statistically significant at 1% level.

manufacturing industry, and specifically due to aluminum production which reached the level of 3,436 thousand tons in 2013 (or 89% of total aluminum production in Russia). This is why that region shows the highest level of electricity usage in industrial production and GRP formation, which is twice as higher as the average electricity usage level in Russia (the share of energy costs in the cost of aluminum production is 25% to 40% depending on the specific technological process).

In general, the two price zones of Russian electricity DAM can be considered as two independent markets, which is caused both by a significant difference in their technological structure and consumption patterns, and minor amounts of electricity flows between the zones (hence, the low level of cointegration of pricing processes). Taking all this into account, we expect to obtain considerably different results of price-demand correlation analysis for these two markets.

Following Skantze et al. (2000), we assume that price-demand dependency is exponential. This is why here we take the logarithms of electricity prices. Descriptive statistics of the data are given in Table 2. The linear correlation between the logarithm of electricity price and demand in Europe-Ural price zone is -0.23, which reflects a weak countercyclical relation between the indicators. For Siberia price zone the correlation is 0.40, which shows a moderate procyclical correlation. Still, as it will be shown further, these linear correlation coefficients are unable to completely reflect the complex structure of price-demand interaction on the electricity market.

As to the control parameters for empirical calculations, it should be noted that for the multiscale correlation analysis used here there is a comparatively small number of such parameters: the amplitude of Gaussian noise α for CEEMDAN and Hurst exponent H for statistically significant IMFs determination. As it was said above, in Colominas et al. (2012) it was shown that the minimum error of initial signal reconstruction is achieved at $\alpha = 0.2$. We use the same value in our calculations. When choosing H we took into account the following considerations. It is well-known (Peters, 1991) that the process with $0 \leqslant H < 0.5$ is antipersistent, i.e. mean reverting. Such behavior is quite typical for stochastic component of electricity prices (Cartea and Figueroa, 2005) because in reality one can often observe price spikes (outliers from the trend) being rather quickly replaced by the average price values. This is why we take $H = 0.2$ for electricity prices. The choice of this exact value is dictated by the availability (Flandrin et al., 2004) of empirical coefficients for IMFs statistical significance determination. For the processes with $H = 0.5$ there are no prominent trends in their dynamics at all. Keeping in mind that we have no evidence to suggest that electricity demand is mean reverting or vice versa, in this study we use $H = 0.5$ to describe the behavior of electricity demand.

Table 3: Fine structure of electricity price-demand correlation in Europe-Ural and Siberia price zones during the period 10.02.2011 – 31.12.2013.

#	$\overline{T}_P$, days	$\overline{T}_D$, days	r	Conf. Int. r	$\overline{\rho}$	Conf. Int. $\overline{\rho}$	Type	Strength
Europe-Ural price zone								
1	3.1	3.4	-	-	-	-	-	-
2	4.8	5.3	-	-	-	-	-	-
3	6.8	7.0	0.71^{***}	[0.68; 0.74]	0.88^{***}	[0.86; 0.89]	P	S
4	12.8	9.5	0.30^{***}	[0.25; 0.36]	0.46^{***}	[0.43; 0.49]	P	M
5	25.9	21.7	0.38^{***}	[0.33; 0.43]	0.60^{***}	[0.57; 0.62]	P	M
6	52.1	52.1	0.32^{***}	[0.27; 0.38]	0.42^{***}	[0.38; 0.53]	P	M
7	114.2	108.3	0.04^{**}	[-0.02; 0.10]	0.08^{***}	[0.04; 0.11]	A	U
8	**192.0**	**324.9**						
9	**469.3**	**469.3**	-0.40^{***}	[-0.45; -0.34]	-0.40^{***}	[-0.40; -0.40]	N	M
10	**2112.0**	**2112.0**						
Siberia price zone								
1	3.1	3.3	-	-	-	-	-	-
2	4.9	5.1	-	-	-	-	-	-
3	7.0	6.8	0.03	[-0.03; 0.09]	0.10^{***}	[0.02; 0.15]	A	U
4	12.8	10.9	-0.04	[-0.1; 0.02]	0.07^{***}	[0.01; 0.14]	A	U
5	25.4	22.1	-0.01	[-0.07; 0.05]	0.12^{***}	[0.08; 0.15]	A	U
6	46.4	46.9	-0.07^{**}	[-0.13; -0.01]	0.04^{***}	[-0.01; 0.09]	A	U
7	105.6	98.2	-0.19^{***}	[-0.25; -0.13]	-0.19^{***}	[-0.20; -0.18]	N	W
8	201.1	**324.9**						
9	**704.0**	**603.4**	0.49^{***}	[0.44; 0.53]	0.49^{***}	[0.49; 0.49]	P	M
10	**2112.0**	**2112.0**						
11	∞	-						

Note: $\overline{T}_P$ – the estimate of oscillation period of electricity price IMF, $\overline{T}_D$ – the estimate of oscillation period of electricity demand IMF, r – coefficient of linear correlation, $\overline{\rho}$ – the median of TDIC, Conf. Int. – confidence interval. The periods of IMFs corresponding to trend components are given in bold. The significance of coefficient is determined on the basis of t-test with the following levels of significance: *** – 1% level, ** – 5% level, * – 10% level. The types of correlation: P - procyclical, A - acyclical, N - countercyclical. The levels of correlation strength: U - zero, W - weak, M - moderate, S - strong.

4. Results

Turning to the analysis of fine structure of electricity price-demand correlation, it can be stated that for Europe-Ural price zone we found that both time-series (electricity price and demand) contain 10 IMFs each, and the residuals of decomposition are zero at almost each of the time moments. The estimated values of price and demand IMFs periods ($\overline{T}_P$ and $\overline{T}_D$ correspondingly) are given in Table 3 (upper panel). The first two components correspond to the periods of 3.1 and 4.8 days (for the price time-series), and 3.4 and 5.3 days (for the demand time-series). Taking into account both that such high-frequency fluctuations cannot be explained economically and that according to the energy criterion these IMFs are statistically insignificant (see upper-middle graphs in Fig. 3 and Fig. 4), we conclude that these two components are noise and thus are excluded from analysis.

The IMFs with indexes 3–7 for Europe-Ural price zone have almost equal average oscillation

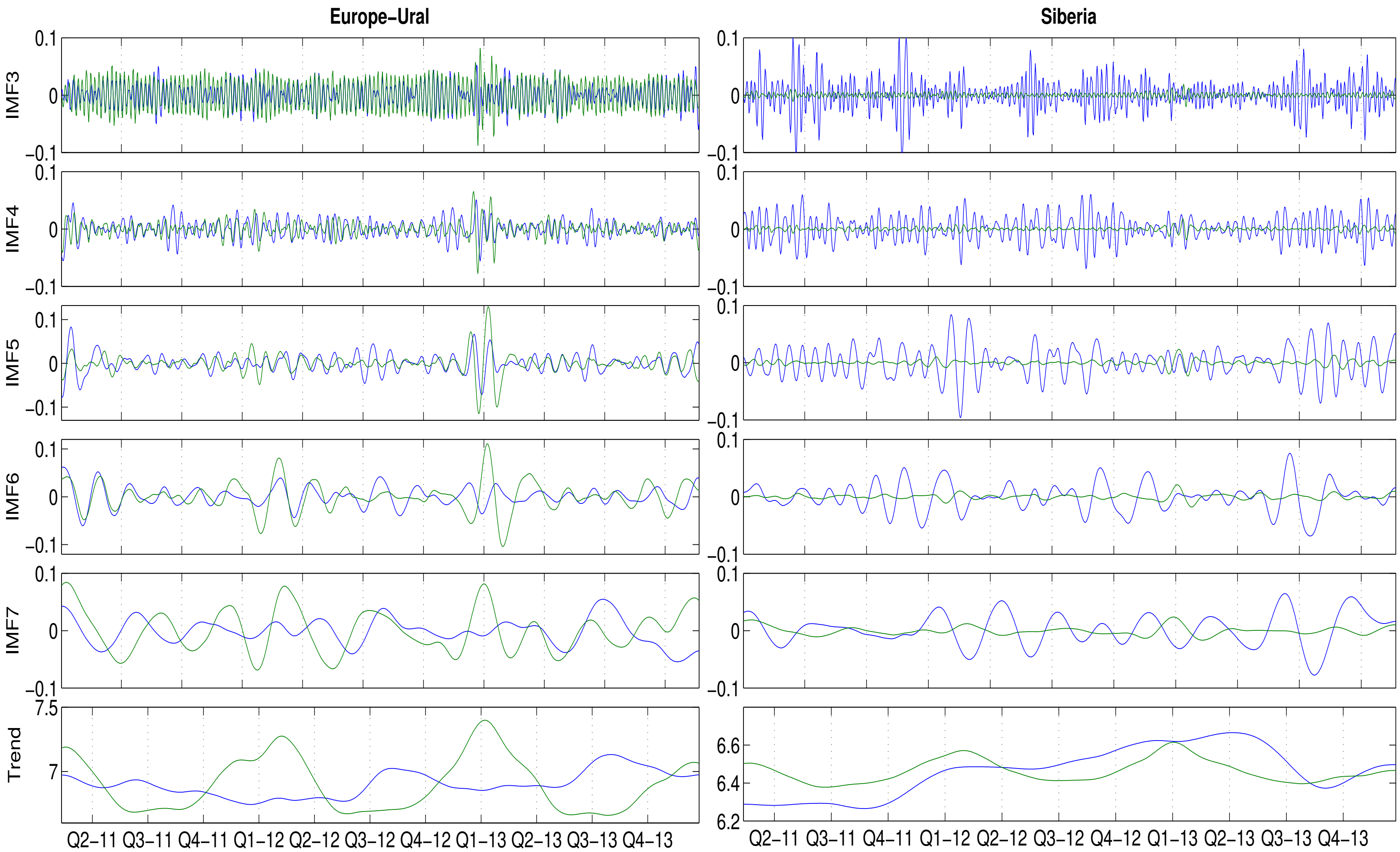

Figure 1: IMFs of the logarithm of electricity price and demand in Europe-Ural and Siberia price zones with indexex 3–7, and their trend components. For clarity, the demand trend has been adjusted so that its mean value coincides with the mean value of the price trend. The blue line denotes the logarithm of electricity price, the green line - the electricity demand.

periods and are represented in Fig. 1 (left panel). TDICs of these IMFs are shown in Fig. 2 (left panel). IMF_3 corresponds to short term weekly fluctuations ($\overline{T}^3_{P,D} \approx 7$) and demonstrates a well-known stylized fact: consuming organizations tend to buy less power over weekends and more power on weekdays. The coefficient of linear correlation r_3 and the median of TDIC $\overline{\rho}_3$ are equal to 0.70 and 0.88 correspondingly and are statistically significant at 1% level. The upper-left graphs in Fig. 2 clearly shows that $\overline{\rho}_3$ most of the time stays in the range from 0.85 to 1.00 with comparatively few outliers in negative area. This allows us to conclude the in Europe-Ural price zone there is a strong procyclical price-demand correlation at the time scale of one week.

IMFs 4–6 correspond to two-week, month and two-month fluctuations and demonstrate moderate procyclical correlations. This can be seen from the analysis of both TDIC median and linear correlation coefficients. It is worth noting that at monthly time scale there is a comparatively higher price-demand correlation ($\overline{\rho}_5 = 0.60$) than at the other two time scales ($\overline{\rho}_4 = 0.46$, $\overline{\rho}_6 = 0.41$). In our opinion this can be explained by the presence of a monthly pattern in the functioning of power consuming organizations. This pattern is caused by the ongoing planning of their production activities. The period of IMF_7 is about 3.5 months (114.2 days and 108.3 days $\approx$ 3.5 months), while the correlation at this time scale is zero. This gives us a reason to state that on the average during these 3.5 months power generating companies have enough time to adjust power generation to any significant changes in electricity demand and the influence of electricity demand on the price becomes insignificant. In general, it can be concluded that at the medium term time-scales in Europe-Ural price zone there is a moderate procyclical price-demand correlation which at the period of 3.5 months becomes acyclical.

Fig. 3 provides the results of electricity price trend estimation in Europe-Ural price zone. The upper-left graph demonstrates the evolution of standardized mean of the signal reconstructed by a consecutive summing of IMFs. Following the simple criterion of Flandrin et al. (2004) (the mean is statistically different from zero), IMF_{10} should be considered as a trend estimate. The upper-middle graph shows the logarithm (to the base 2) of energy $\widehat{W}_i^H$ of the modes of fractional Gaussian noise model with $H = 0.2$, the empirical 95% confidence interval C_i^H and the energy G_i of IMFs. The smallest of the indexes i which meets the energy criterion is $i = 3$. The upper-right graph demonstrates the values of the ratios of zero-crossing numbers R_i and the empirical 95% confidence interval for each of the indexes i. In the case, when $Z_i = 0$ ($RZCN_i = Z_{i-1}/0 = \infty$), we set $RZCN_i$ equal to the upper bound of the confidence interval. It can be seen from Fig. 3 that the smallest of the IMF indexes, which meets the RZCN criterion, is $i = 2$.

The obtained results show that the smallest common index which meets both criteria (proposed in Torres et al. (2011)) is $i = 3$. Still, it is quite obvious that such high-frequency changes cannot reflect the common tendency in electricity price changes. Taking into account the additionally introduced criterion for low-frequency modes ($i \geqslant I/2 + 1$), we get the required index $i^* = 8$. As to the criterion of mode significance, all the IMFs with $i \geqslant 3$ satisfy this criterion, and in this case the criterion does not play any important role. Still, our empirical trials with different values of Hurst exponent H showed that if we considered price changes as a persistent process with $0.5 < H = 0.8 \leqslant 1.0$, then this criterion would allow us to discard the IMFs with $i \leqslant 4$.

The graph in the bottom panel of Fig. 3 demonstrates the raw data on the electricity prices and the trend which is obtained by summing all the IMFs with $i \geqslant i^* = 8$. It can be clearly seen that during the time period under study the trend several times changes both its direction and its slope. During 2011 there is a slight downward trend which is followed by the period of almost no trend in early 2012. In the 2nd quarter of 2012 there appears a quite steep upcoming trend but it

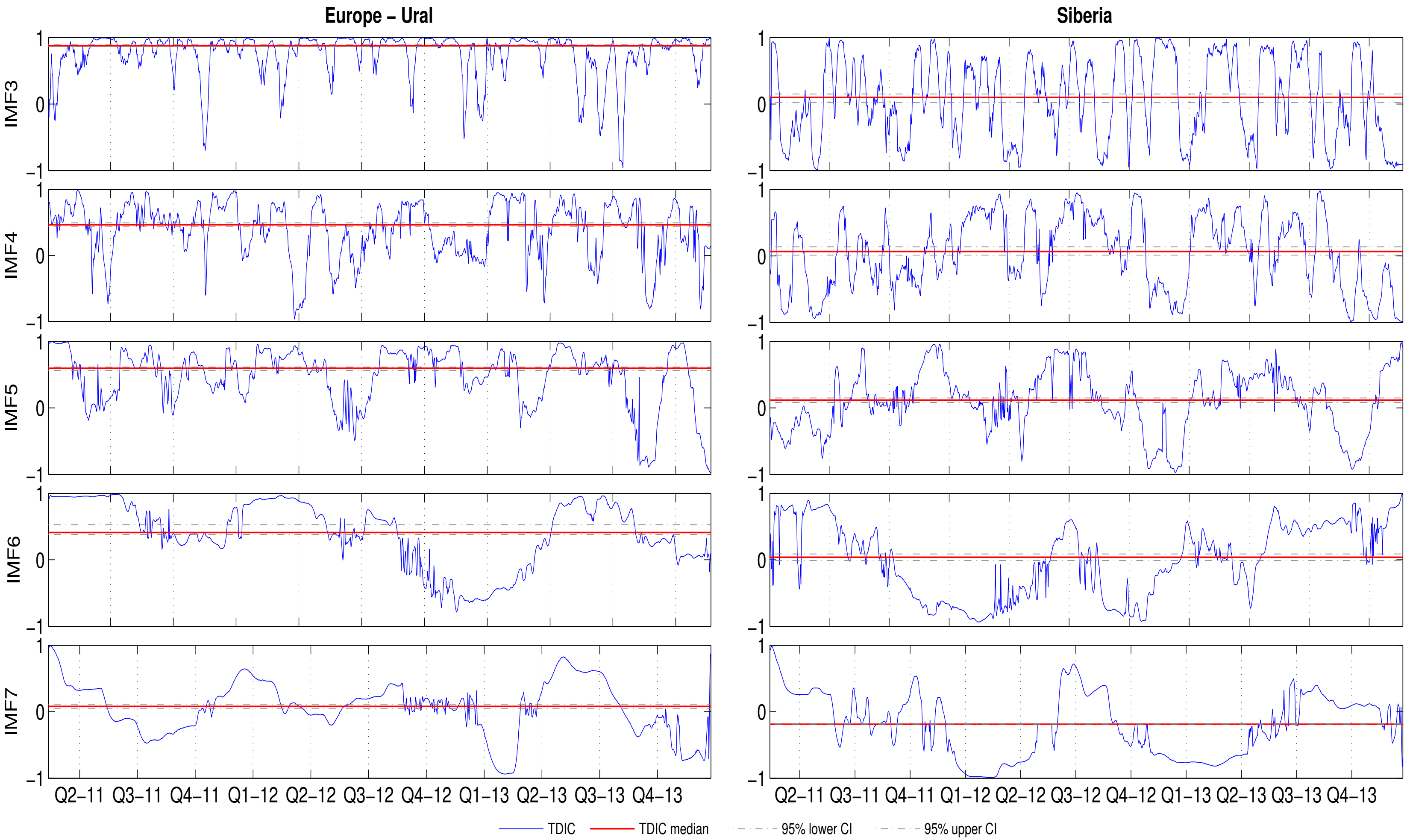

Figure 2: TDIC of electricity price and demand ($\rho[t]$) in Europe-Ural and Siberia price zones for IMFs 3–7. The solid horizontal line reflects the median of TDIC; the dashed lines correspond to upper and lower bounds of the 95% confidence interval.

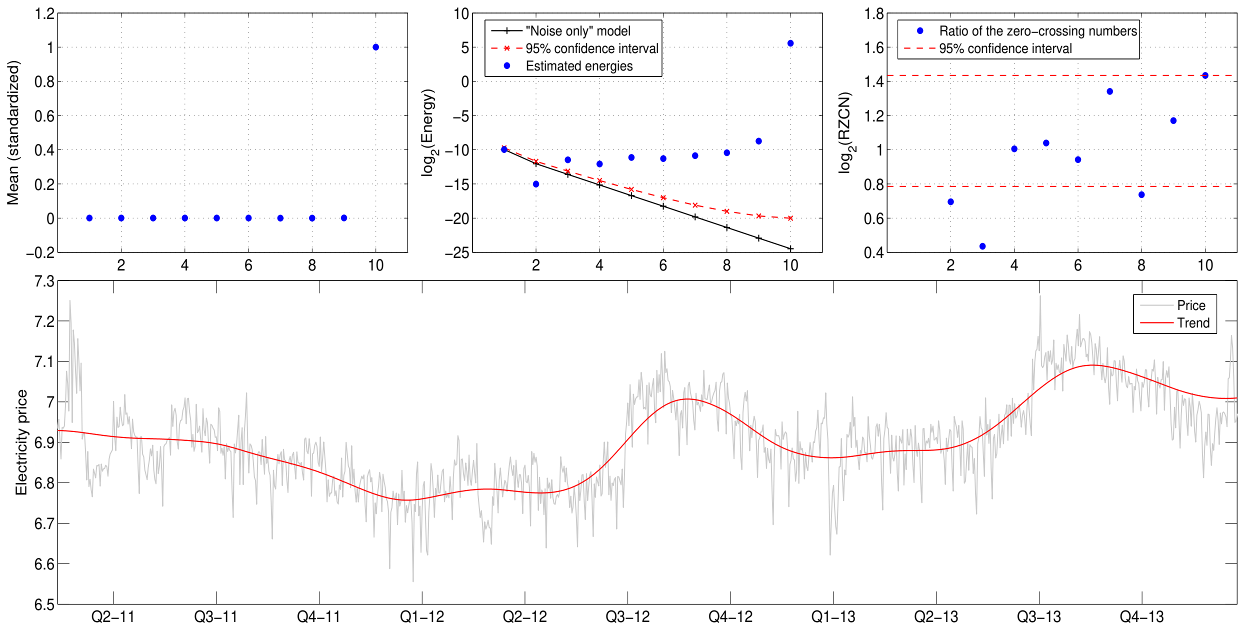

Figure 3: Electricity price trend in Europe-Ural price zone. The top panel: the left graph shows the evolution of standardized mean depending on the number of IMFs being summed; the middle graph shows the energy of modes $\widehat{W}_i^H$ of fractional Gaussian noise with $H = 0.2$ (solid line with markers $+$), the 95% confidence interval C_i^H (dashed line with markers *) and the energy G_i of price IMF (dots); the right graph shows the ratio of zero crossing numbers R_i (dots) and the 95% confidence interval (dashed lines). The bottom panel: the graph reflects electricity price dynamics and its trend for $i^* = 8$.

is in the 3rd quarter of 2012 that this trend changes its direction and becomes downward, although the fall stops at a higher price level than it was in the 1st quarter of 2012. The situation in 2013 is approximately similar to the previous year. Thus, we can see that the expected effect of electricity price reduction after a yet another expansion of the wholesale electricity market took place only in 2011, while in 2012–2013 a certain pattern of behavior is observed: a relatively constant average price dynamics in the winter months and sharply increasing trends in spring and summer.

Fig. 4 presents the results of trend extraction in electricity demand time-series in Europe-Ural price zone. The look of the graphs in this figure is similar to Fig. 3. The smallest index, satisfying all criteria, is $i^* = 8$. The extracted trend is given on the bottom panel. It can be seen that electricity demand demonstrates a pronounced seasonality in its behavior.

Recall that in Table 3 the IMFs, comprising trends, are given in bold (see upper panel for Europe-Ural price zone). It can be seen that the estimates of periods for IMFs 9–10 coincide both for price and demand. IMF_9 corresponds to the time scale of 1 year and 3 months, while IMF_{10} corresponds to the time scale of 5 years and 6 months. At the same time, for IMF_8 the estimates fo periods differ substantially: the period for demand is 1.7 times longer that the period for price. The time scale of IMF_8 for price is about half-year while for demand it is about 11 months.

The trends of electricity price and demand for Europe-Ural price zone are given on a single graph in the bottom left pane of Fig. 1. Even visual analysis allows to conclude that they move in different directions. The linear correlation coefficient r_{tr} and the median of TDIC $\overline{\rho}_{tr}$ are both equal to -0.40 and significant at 1% level. The coincidence of these values is caused by the fact that the instantaneous periods at each point of the trend are quite long and the window for correlation

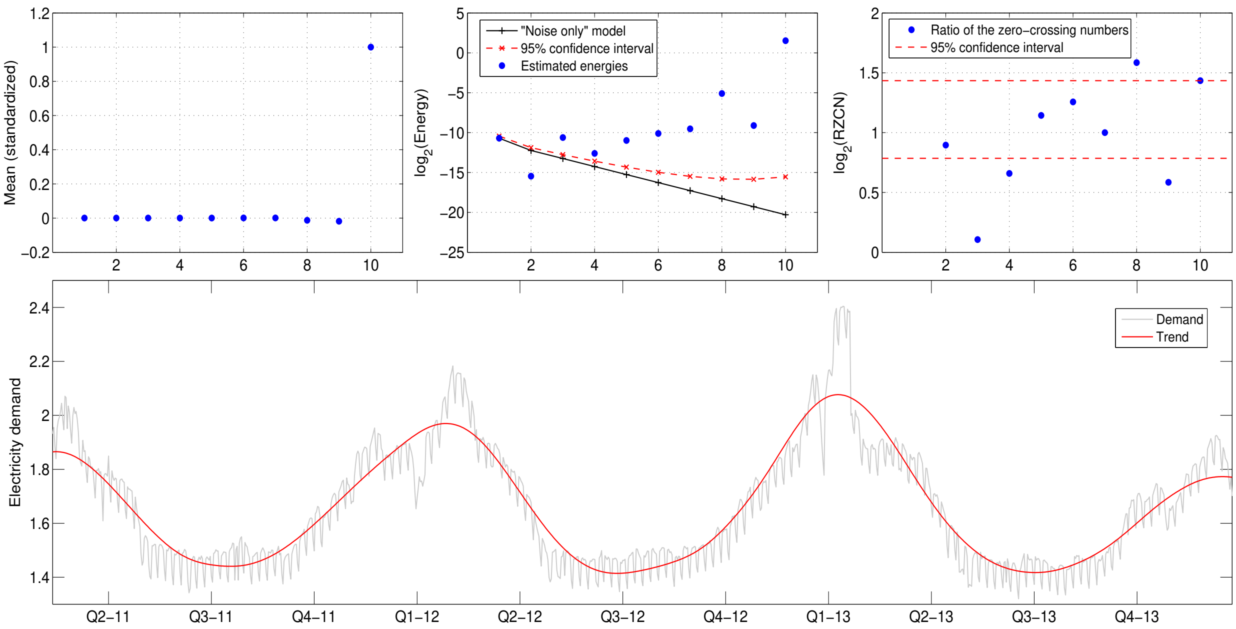

Figure 4: Electricity demand trend in Europe-Ural price zone. The top panel: the left graph shows the evolution of standardized mean depending on the number of IMFs being summed; the middle graph shows the energy of modes $\widehat{W}_i^H$ of fractional Gaussian noise with $H = 0.5$ (solid line with markers +), the 95% confidence interval C_i^H (dashed lines with markers *) and the energy G_i of demand IMF (dots); the right graph presents the ratio of zero crossing numbers R_i (dots) and the 95% confidence interval (dashed lines). The bottom panel: the graph reflects the electricity demand dynamics and its trend for $i^* = 8$.

calculation almost always covered the time interval under study[6]. This also explains the coincidence of the upper and lower bounds of the confidence interval $\overline{\rho}_{tr}$, which we calculated using bootstrap procedure. In general, it can be concluded that in the long term time scales there is a moderate countercyclical electricity price-demand correlation in Europe-Ural price zone. Thus, a decrease in electricity price level can cause an increase in electricity consumption in that zone in the long term.

Now we turn to Siberia price zone. We found that the price time-series here consists of 11 IMFs, while the demand time-series consists of 10 IMFs. The residuals of decomposition for both time-series are zero at almost every time moment. The estimates of periods $\overline{T}_P$ and $\overline{T}_D$ are given in Table 3 (lower panel). IMFs 1–2 are also statistically noise and are excluded from the further analysis (see upper-middle graphs in Fig. 5 and Fig. 6). IMFs 3–7 for Siberia price zone (as well as for Europe-Ural price zone earlier) demonstrate approximately equal average periods and are given in Fig. 1 (right panel). TDICs of these IMFs are given in Fig. 2 (right panel).

As compared to Europe-Ural price zone, the IMF_3 of price and demand, which correspond to weekly fluctuations, show very low correlation: the linear correlation coefficient r_3 is statistically insignificant, while the median $\overline{\rho}_3$ is significant at 10% level with a quite wide confidence interval [0.02; 0.15]. It can clearly be seen from the upper-right graph in Fig. 2 that correlation $\overline{\rho}_3$ changes all the time − from significantly negative to significantly positive. It is worth noting that after mid-2012 there are 4 quite long time periods (about a month long each), during which $\overline{\rho}_3$ is high.

[6]This is why we do not show $\rho_{tr}[t]$ in Fig. 2, since this becomes a horizontal line and is not informative.

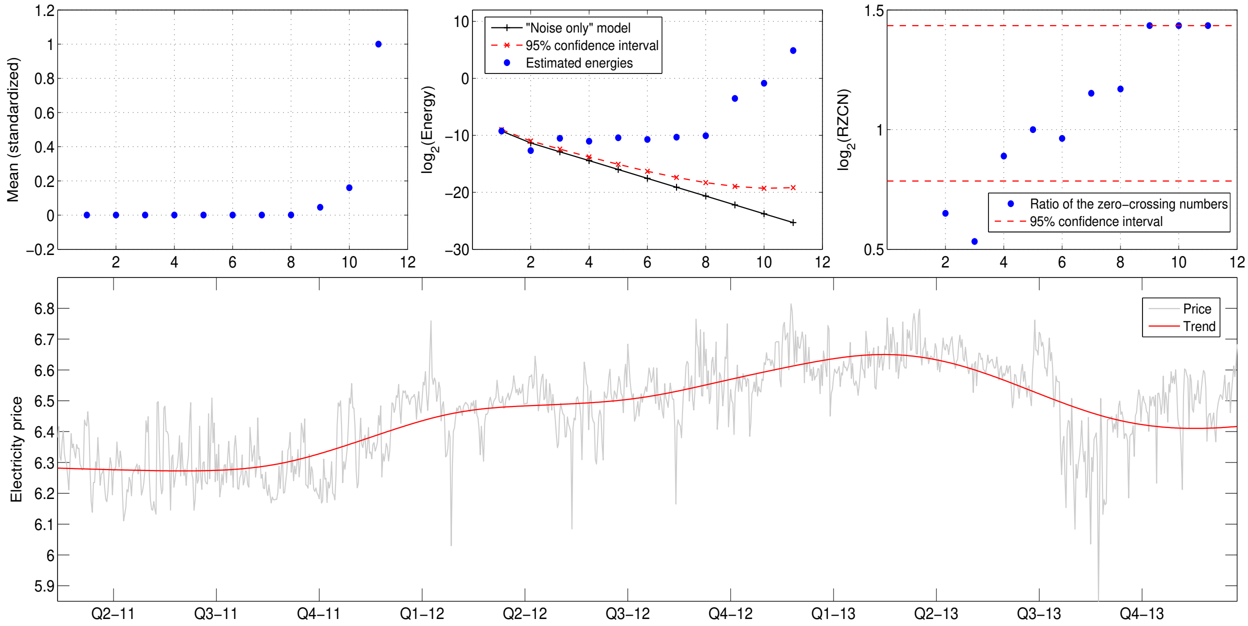

Figure 5: Electricity price trend in Siberia price zone. The top panel: the left graph shows the evolution of standardized mean depending on the number of IMFs being summed; the middle graph shows the mode energy $\widehat{W}_i^H$ of fractional Gaussian noise with $H = 0.2$ (solid line with markers +), the 95% confidence interval C_i^H (dashed lines with *) and the energy G_i of price IMF (dots); the right graph shows the ratio of zero crossing numbers R_i (dots) and the 95% confidence interval (dashed lines). The bottom panel: the graph reflects the dynamics of electricity price and its trend for $i^* = 9$.

But on the average the correlation is acyclical, i.e. for Siberia price zone the influence of week demand seasonality on the price is unsubstantial. This surprising result allows us to conclude that the need of taking this influence into account strongly depends on the structure of electricity consumption. Indeed, as it was noted above, in Siberia price zone a considerable share of electricity consumption is attributed to aluminum production. Moreover, the technological processes in most processing plants are continuous, and there is no significant decline in electricity consumption during weekends. This leads to the fact that electricity price in Siberia price zone does not change significantly during the weekends, and price-demand correlation is acyclical at weekly time scale.

IMFs 4–6 demonstrate almost zero correlation. The linear correlation coefficient for IMFs 4–5 is statistically insignificant, while the median of TDIC, though significant, is acyclical. For IMF_5, which corresponds to monthly period, there exists unsubstantial increase of $\overline{\rho}_5$ as compared to its neighbors. However, we do not tend to associate this fact with the same reasons (the ongoing planning of production activities by electricity consuming enterprises) as for Europe-Ural price zone, because this increase in negligible. For IMF_7 the correlation is weakly countercyclical, which, economically speaking, is quite strange for the period of 3.5 month and definitely requires further studying. In general, it can be stated that electricity price-demand correlation is acyclical in Siberia price zone at medium term time scales.

The results of trend estimation for electricity price time-series in Siberia price zone are given in Fig. 5. Again, the structure of these graphs is similar to the previous ones. The smallest index, meeting all the criteria, is $i^* = 9$. The obtained trend, given in the bottom panel of the figure, has a flat segment, corresponding to the first three quarters of 2011, that is followed by a slightly

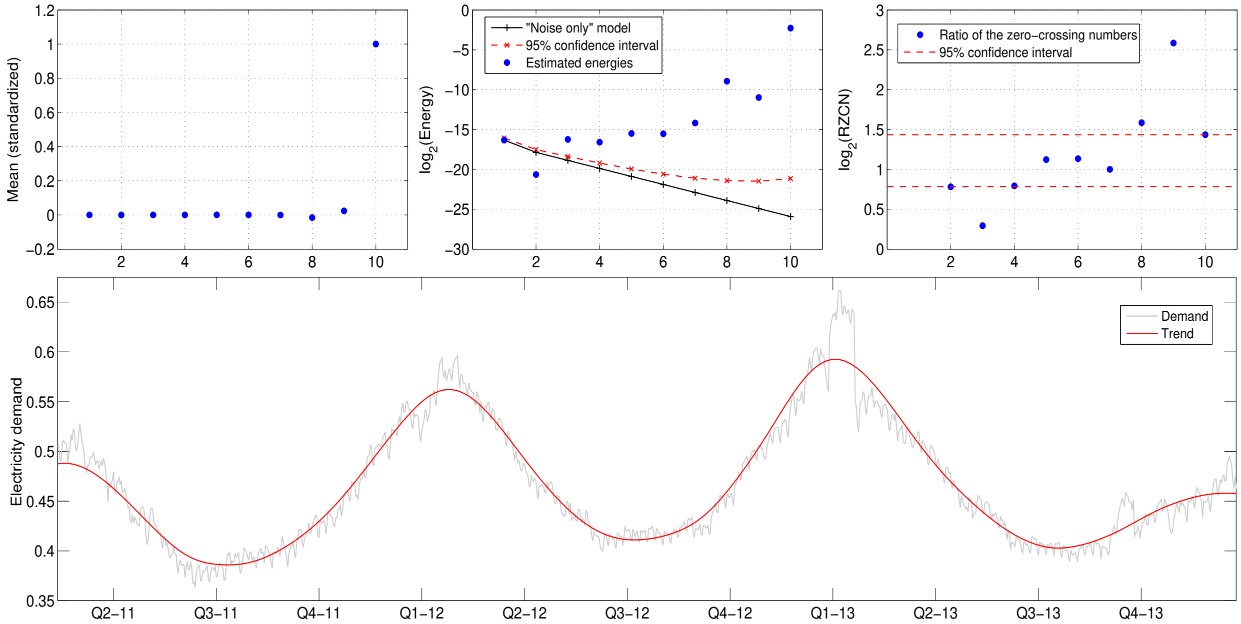

Figure 6: Electricity demand trend in Siberia price zone. The top panel: the left graph shows the evolution of standardized mean depending on the number of IMFs being summed; the middle graph shows the mode energy $\widehat{W}_i^H$ of fractional Gaussian noise with $H = 0.5$ (solid line with markers +), the 95% confidence interval C_i^H (dashed lines with markers *) and the energy G_i of demand IMF (dots); the right graph shows the ratio of zero crossing numbers R_i (dots) and the 95% confidence interval (dashed lines). The bottom panel: the graph demonstrates the electricity demand time-series and its trend for $i^* = 8$.

increasing segment (up to the 1st quarter of 2013), after which there is a downward tendency till the end of 2013. Unlike Europe-Ural price zone, the electricity prices in Siberia price zone do not show any pronounced behavioral pattern. In general, the sample time period under study is characterized by a quite slow increase of average electricity price. IMF_8 of the price is not included in the trend component and reflects the time period that does not correspond to any of demand IMFs. This is why IMF_8 of electricity price is excluded from the further analysis (since it is impossible to put it in correspondence to any of the time scales which would be common for price and demand time-series simultaneously).

Fig. 6 shows the results of trend extraction in electricity demand time-series in Siberia price zone. The structure of the graphs in this figure is similar to the previous graphs. The smallest index that meets all the criteria is $i^* = 8$. The obtained trend is given on the graph (see the bottom panel) and demonstrates the behavioral pattern analogous to the one found in demand time-series in Europe-Ural price zone.

Recall again that in Table 3 the IMFs, comprising trends, are given in bold (see lower panel for Siberia price zone). The estimates of periods for these IMFs coincide only for the 10th index and correspond approximately to 5 years and 6 months. Average periods of fluctuations for IMF_9 of electricity price and demand are, correspondingly, 2 years and 1 year and 9 months. The price and demand trends are given on the same graph in the bottom-right panel of Fig. 1. It is obvious that this trends are positively correlated. The linear correlation coefficient ρ_{tr} and the median $\overline{\rho}_{tr}$ of the trends both are equal to 0.49 and statistically significant at 1% level.

Unlike Europe-Ural price zone, for Siberia price zone it can be concluded that there is a moderate procyclical electricity price-demand correlation at the long term time scales. In our opinion, this as well can be explained by the structural peculiarities of electricity consumption in the Siberian region. During the sample time period under study, there was a constant growth in aluminum production, which was accompanied by the growth of the amount of electricity consumed. The high energy intensity of aluminum production and the increasing of planned production volumes did not allow the processing organizations to decrease their electricity consumption, despite the long-term growth of electricity prices. This in turn lead to a procyclical correlation in Siberia price zone.

5. Conclusion

Linear electricity wholesale price-demand correlation in Europe-Ural price zone is $r_{EU} = -0.23$ which shows a weak countercyclical correlation between the two indicators. At the same time, when analyzing the IMFs obtained by Huang decomposition, the median of TDIC $\overline{\rho}_i$ changes substantially from positive values at short term time scales to negative values at long term time scales. In Siberia price zone the linear correlation is moderately procyclical with $r_S = 0.40$. When considering the median $\overline{\rho}_i$ of IMFs, the correlation (the median of TDIC at each time scale) changes from zero at the short term time scales to moderately positive at the long term time scales. Thus, it is obvious that Europe-Ural and Siberia price zones have quite different fine structures of price-demand correlation. Certainly, the classical correlation coefficient r does not allow to obtain such a detailed internal mechanisms description for these economic indicators relationship. Thus, it clearly follows from this that the use of the proposed multi-scale correlation analysis on the basis of TDIC and CEEMDAN allows to understand more deeply the relationship of demand and price in the electricity market, and in particular the mechanisms of price formation under the influence of demand.

Comparing our results with the findings of Uritskaya and Serletis (2008); Alvarez-Ramirez and Escarela-Perez (2010) we can conclude that we were also able to show a complex multi-scale behavior of the correlation in the electricity market, as well as its dependence on time. However, unlike previous studies, we considered a correlation between price and demand, rather than the independent dynamics of these indicators.

Turning back to the hypotheses of this research (see subsection 1), we can state the following. Hypothesis 1 (about the existence of a strong procyclical price-demand correlation in the short term (up to 1 week)) was confirmed for Europe-Ural price zone ($\overline{\rho}_3 = 0.88$) and was rejected for Siberia price zone ($\overline{\rho}_3 = 0.10$). This seems to be quite an interesting result and speaks in favor of almost complete absence of influence of the demand weekly seasonality on the electricity price in Siberia price zone. In our opinion, this is caused by the fact that in the Siberian part of Russia a substantial share of electricity consumption is attributed to electricity intensive aluminum production with continuous technological process. This, in turn, causes negligible electricity price changes under the demand changes at weekly time scale.

Hypothesis 2 about zero or weak procyclical correlation in the middle term (from 2 week to 6 months) was confirmed for Siberian price zone and was only partially rejected for Europe-Ural price zone. While in Siberia price zone price-demand interaction is zero already at the two-week time scale, in Europe-Ural price zone the correlation stays moderately procyclical up to the 3.5 month time scale after which it becomes zero.

Hypothesis 3 about the moderate countercyclical price-demand correlation in the long term (six months or more) was confirmed for Europe-Ural price zone ($\overline{\rho}_{tr} = -0.40$) and was rejected for

Siberia price zone ($\overline{\rho}_{tr} = 0.49$) in which the correlation at such time scales is moderately procyclical. This also seem to be quite an unusual result and allows to conclude that the long term growth of electricity price level in Siberia price zone does not cause the proportionate demand decrease (unlike in Europe-Ural price zone). In our opinion, it, again, is caused by the substantial share of aluminum production in the structure of Siberian electricity consumption. The long term growth of aluminum production and high electricity intensity of the technological process do not allow the processing enterprises to adequately respond to increases in electricity price level by lowering the demand for electricity. This can also be explained by the fact that in Europe-Ural price zone all the levers of manipulation are in the hands of suppliers whose number on the market is quite substantial and thus the actual possibilities for manipulation are limited on this free market. In Siberia price zone the main levers of manipulation are in the hands of major electricity consumers whose number on the market is quite small and the influence is substantial thus leading to a significant distortion of market mechanisms.

It is especially worth noting that the obtained significantly different results for Europe-Ural and Siberia price zones show that the need and the way of taking into account the influence on electricity price from the part of different demand seasonality types depend to large extent on the structure of electricity consumption on the corresponding electricity market. The presence of energy intensive enterprises among the electricity consumers on the market leads to violation of such well-known stylized fact as, for example, the influence of weekly seasonality on the prices.

6. Acknowledgements

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