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The long-term trends on the electricity markets: Comparison of empirical mode and wavelet decompositions[☆]

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ABSTRACT

This paper proposes an improved approach to electricity prices trend-cyclical component filtering, which is based on the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN). A combined criterion for determining the modes to be included into the trend component is introduced. The performance of the proposed approach is compared with the ordinary empirical mode decomposition (EMD), as well as with the method of wavelet-decomposition well-known in the energy economics literature. We test it on four day-ahead electricity markets: the Europe-Ural and the Siberia price zones of the Russian ATS exchange, the PJM exchange of the USA and the APX exchange of the United Kingdom. Our results show that the proposed approach based on CEEMDAN and the combined criterion outperforms the standard EMD on all the four electricity markets, and on two of the studied markets (PJM, APX) it outperforms the wavelet-smoothing, while on the other two (ATS Europe-Ural and Siberia) it performs at least not worse than the wavelet-smoothing. At the same time, the proposed approach does not require a prior choice of the smoothing parameter, as in the case of the wavelet-decomposition, and demonstrates a certain degree of versatility on the studied markets.

1. Introduction

In many applied econometric studies concerned with financial time-series analysis, authors face the problem of separation of long-term dynamics and short-term fluctuations in the variables studied. Mathematically, this problem means the necessity of extraction of trend T_t and cyclical C_t components out of a time-series.[1] The residual of such decomposition can be considered as stochastic part S_t. Traditionally, their combination in an additive ($P_t = T_t + C_t + S_t = TC_t + S_t$) or a multiplicative ($P_t = T_t \times C_t \times S_t = TC_t \times S_t$) form is used for the original time-series reconstruction. It is worth noting that the second form for positive-valued time-series can be brought to the first one by the standard logarithmic transformation.

Despite apparent conceptual simplicity of this approach, there is a whole number of problems with its practical implementation. First of all, the absence of an unambiguous definition of "trend-cyclical component" term. It is intuitively clear that this term reflects the low-frequency oscillations in the time-series analyzed. Though, the exact quantitative criteria for its identification do not follow from this intuition. This results in the second problem: the absence of a generally accepted method for trend filtering. In a great strand of literature on this topic, there exist a lot of methods and procedures to solve the latter problem. But, even provided this diversity of methods, there is a third difficulty which is that most of these methods are not able to deal with either non-stationary or non-linear time-series, while in practice we usually meet such complicated financial processes.

☆ Software library ADAnalysis for Matlab used in this article is available for download here: http://dmafanasyev.ru/en/adanalysis-en/. EMD implementation is available here: http://perso.ens-lyon.fr/patrick.flandrin/emd.html, and CEEMDAN — here: http://www.bioingenieria.edu.ar/grupos/ldnlys/.

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[1] Though, in our study, traditionally for electricity market studies, we do not separate these components and consider an aggregate trend-cyclical or long-term seasonal component (LTSC) as trend $TC_t = T_t + C_t$.

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The specified problems are also directly related to the wholesale electricity market where the commodity price[2] shows intraday, weekly, and annual seasonality. In addition to specified above, electricity market has other peculiarities: impossibility to store the commodity on the market for long time; coincidence of production and consumption time-moments; presence of producers (generation technologies) that cannot cancel product delivery due to price decrease; low short-term price elasticity of demand; occurrence of substantial price outliers (positive—"spikes" and negative —"drops"); mean long-term price reversion. At the same time, the long-term component is an important part of price modeling since incorrect determination of this component may result in substantial risk underestimation, distorted expectations of both consumers and power generating companies, as well as financial losses. This is why in the current study we focus on trend component filtering, leaving the questions of short-term price fluctuations in the background.

Let us recall some most common approaches to trend component filtering that are typically used in electricity market studies:

- Polynomial regressions with different powers (though, linear regression is most frequently used) (De Jong, 2006; Weron et al., 2004).
- Linear regression on time-variable t given a sliding window or a so-called "loess-regression" (Bordignon et al., 2013; Veraart and Veraart, 2012).
- Moving average (including exponentially weighted moving average) or moving median given a sliding window (De Jong, 2006; Nowotarski et al., 2013; Trueck et al., 2007).
- Dummy variables regression (piecewise continuous functions) for each month in the year (Fanone et al., 2013; Haldrup et al., 2010; Lucia and Schwartz, 2002).
- Fourier transform, i.e. decomposition into a sum of sine functions (De Jong, 2006; Janczura et al., 2013).
- Wavelet-decomposition where different families of wavelets (localized in time, auto-modal functions with zero mean) are used as the basis of decomposition (Janczura et al., 2013; Trueck et al., 2007).
- Hodrick–Prescott (HP) filter (Hodrick and Prescott, 1997), which is based on the linear minimization problem being solved for a specified smoothing parameter.

These approaches can be used both independently and as a combination (for instance, linear trend with a sum of sine functions; Fourier transform with exponentially weighted moving average; etc.). The main problems occurring while applying these methods are: (1) the necessity to "a priori" set the value for some unknown parameters; (2) the inability of these methods to deal both with non-stationary and non-linear processes. This allows to conclude that it is necessary to use a new approach to electricity market studying, which will effectively overcome these problems. We propose to consider the empirical mode decomposition (EMD) (Huang et al., 1998) as such an approach.

The central idea of EMD is a local and data-driven decomposition of a time-series into intrinsic mode functions (IMF) with different average periods: from low-frequency to high-frequency components, plus residual. The main advantage of EMD is its intrinsic ability to deal with non-stationary and non-linear processes since there are no "a priori" assumptions on these properties. Also, this approach does not require an a priori specification of any parameters (unlike, for example, in wavelet-decomposition or HP filter application).

Nevertheless, empirical mode decomposition (Huang et al., 1998) in its classical form has several flaws that we consider further. In order to get rid of them, Wu and Huang (2009) proposed to use ensemble empirical mode decomposition (EEMD). But, at the same time, EEMD both introduces additional noise into the results of decomposition and does not produce a stable number of IMFs after applying to the same time-series. Complete ensemble empirical mode decomposition with adaptive noise, proposed in Torres et al. (2011), solves these problems, being at the same time quite parsimonious to computing resources.

There are not so many studies of the electricity market which employ EMD (An et al., 2013; Ghelardoni et al., 2013; Ismail, 2013; Kurbatsky and Tomin, 2010). Its application is limited to filtering noise components out of time-series. There are even fewer studies that address the issues of comparing EMD with other popular methods of trend filtering. Mhamdi et al. (2010) compared EMD and the HP filter on the data on peak electricity loads and showed that EMD provides quite adequate results while not requiring selection of an optimal value of the smoothing parameter which is required for the HP filter. The authors considered the monotonic residual of the empirical decomposition as a trend. Moghtader et al. (2011) proposed a more advanced approach which, based on certain criteria, allows to include low-frequency IMFs into trend. This in turn makes it possible to take into account changes in the direction of the trend which results in a more exact trend-cyclical component estimation (non-monotonic trend). Moghtader et al. (2011) compared their approach to the HP filter on simulated data and concluded that the proposed approach is quite effective.

As of now, as far as we know, there are no studies that thoroughly compare the approach of Moghtader et al. (2011) with another popular method —the wavelet-decomposition. This may be especially topical since relatively recently in Nowotarski et al. (2013) it was shown that using wavelet-decomposition for trend filtering (in order to forecast electricity prices) shows much better performance than the Fourier transform and dummy variables regression. Moreover, as of our best knowledge, using CEEMDAN in combination with Moghtader et al. (2011) approach for trend filtering was not proposed in previous studies. In order to fill this gap, in our study we empirically compare the wavelet-decomposition, EMD and CEEMDAN in the context of electricity price trend-filtering.

The rest of the paper is organized as follows. In Section 2 we consider the methodology of the research: CEEMDAN, criteria for trend-cyclical component filtering, and simulation experiment design. In Section 3 the dataset used for calculations is described. Section 4 contains the discussion of the results obtained. Section 5 concludes.

2. Research methodology

2.1. Empirical mode decomposition

Empirical mode decomposition was first proposed in Huang et al. (1998) and is itself a data-driven method allowing to obtain the original signal (time-series) decomposition into oscillatory components. Using EMD, the original signal is decomposed into a sum of intrinsic mode functions (IMFs) that meet two conditions (see Huang et al., 1998): (1) the number of extrema and the number of transitions through zero (intersection of the time axis) are either equal or differ by no more than one; (2) at any time, the average value of the envelope constructed on the local maxima and the envelope constructed on the local minima is equal to zero. In order to extract the IMFs, an iterative sifting algorithm proposed in Huang et al. (1998) is used. An example of a time-series and its decomposition into empirical modes is shown in Fig. 1. The original signal $x[t]_{t\in(1,T)}$ may be reconstructed as a sum I of the obtained IMFs and the residual $r[t]$ (the empirical basis of decomposition).

But the classical EMD has several flaws, specifically (1) a substantial influence of boundary effects on the decomposition components

[2] Hereafter, when speaking about electricity price, we assume the logarithm of that price, which is commonly accepted in econometric studies.