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Scale-specific importance of weather variables for explanation of variations of electricity consumption: The case of Prague, Czech Republic

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ABSTRACT

In this paper we explore the relative importance of the outside temperature and sunshine duration for the explanation of variations of electricity consumption in Prague, Czech Republic. An assessment of relative importance is made on various time scales ranging from the shortest ones associated with abrupt changes up to those associated with medium-run changes. Wavelet analysis is used to accomplish this task. We show that relative importance is scale-specific, i.e. depends on the analyzed time scale. Sunshine duration is generally the more important explanatory variable on the shortest time scales and the outside temperature dominates on higher time scales. The reason for the outside temperature being an inferior explanatory variable on the shortest time scales is a low variability of the outside temperature on these time scales and a dampened reaction of electricity consumption to abrupt changes in the outside temperature. Our results show that sunshine duration should be considered relevant when modeling electricity consumption.

1. Introduction

An effective electrical energy policy cannot be pursued without accurate modeling and predictions of electricity consumption since electricity cannot be stored effectively. There are two main groups of variables influencing electricity consumption – economic and weather variables. For economic variables see e.g. Payne (2010) who gives a survey of empirical literature dealing with the causal relationship between electricity consumption and economic growth. For literature dealing with the impact of weather variables onto electricity consumption see e.g. Akil and Miyauchi (2010), Beccali et al. (2008), Bessec and Fouquau (2008), Giannakopoulos and Psiloglou (2006), Lam et al. (2008), Manera and Marzullo (2005), Miller et al. (2008), Molnár (2011), Pardo et al. (2002), Pilli-Sihvola et al. (2010), Psiloglou et al. (2009), Wangpattarapong et al. (2008), and Włodarczyk and Zawada (2010).

Economic variables influencing electricity consumption change relatively slowly. Therefore, the use of yearly, quarterly or monthly time series is generally sufficient to adequately capture the relationship between economic variables and electricity consumption. For example, Mohamed and Bodger (2005) used annual time series to study the influence of GDP and electricity price on electricity consumption. Annual time series were also used by Egelioglu et al. (2001) or by Zachariadis and Pashourtidou (2007) to examine the relationship between electricity consumption and economic variables. Monthly time series were sufficient for Hondroyiannis (2004) to study the phenomenon. The object of modern research is to explore and understand the nature of the relationship between electricity consumption, prices and growth (expressed by GDP), employing panel data methods – see e.g. Ouedraogo (2013). Among economic variables, GDP is routinely employed for the explanation of variations in electricity consumption being usually calculated on annual and quarterly basis.

As it becomes obvious in further parts of the paper we are aiming to explain abrupt changes in electricity consumption. More specifically, the time scales of our interest range from one day to approximately two weeks. The previous paragraph suggests that economic variables which manifest themselves mainly on much longer time scales play a negligible role in our analysis. On the other hand, weather variables may be of substantial importance on these short time scales. The present paper is thus focused on the assessment of the relative importance of weather variables for explaining variations in electricity consumption.

For our analysis we use the time series of daily electricity consumption (in MWh) in the city of Prague, Czech Republic, in aggregate (i.e. including households, companies, industrial and public sites). In this very case, disaggregated data for particular sectors (households, companies, industrial and public sites) do not exist. Moreover, aggregate electricity

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consumption is crucial for electricity distributors since it is this very indicator which they attempt to forecast.

There are two weather variables used for explaining variations in electricity consumption in the paper – the outside temperature and sunshine duration, the latter being defined as the length of the day (in hours) during which the direct solar radiation exceeds a given threshold. In literature, the outside temperature is generally assumed to be the most important weather variable in explaining variations in electricity consumption. On the other hand, sunshine duration is often not taken into consideration at all. However, its relevance is obvious since all the sectors may react to an increase in sunshine duration by switching off lights, and companies, public sites and households also by turning down the heating in cold seasons of the year. As for households, longer sunshine duration may motivate people to spend more time doing outdoor activities and thus consuming less electrical energy. For similar arguments see Molnár (2011), who used annual changes in daylight duration to get less biased estimates of the impact of temperature changes onto electricity consumption over the year. Moreover, Summer Time (Daylight Saving Time) – as a reaction to changes in sunshine duration, which influence the behavior of people and their consumption of electricity in all the sectors – has been in operation in the European Union in order to save electrical energy.

It is also to be noted that so called heating degree days (HDD) and cooling degree days (CDD) are sometimes used for studying the impact of the temperature on electricity consumption. The use of HDD and CDD takes the non-linear relationship between electricity consumption and outside temperature into account. However, as documented e.g. in Hinman and Hickey (2009) and references therein, there are other possibilities how to deal with these non-linearities. In our paper, we have decided to apply an approach inspired by the climatological literature (see e.g. Blandford et al., 2008; Karl et al., 1993; Ware and Thomson, 2000), consisting of analyzing the data separately for four different seasons of the year. By resorting to such an approach, we may approximate any non-linearities by linear relationships within each season individually. As shown in the diagnostics part of the paper this approach provides a viable approximation of reality.

The importance of weather variables for explaining variations in electricity consumption is analyzed as a function of time scale. While standard methods do not facilitate this scale-specific aspect of analysis, our approach reveals some new insights into the role of weather variables. We clearly show that (for Prague, Czech Republic) the relative importance of outside temperature and sunshine duration for explaining variations in electricity consumption is scale-specific, i.e. dependent on the time scale considered. One of the research outcomes is a strong suggestion that sunshine duration is a more important variable on the shortest time scales in comparison with the importance of the outside temperature.

When examining the scale-specific importance of weather variables for explaining electricity consumption we adhere to the wavelet analysis. Models similar to that we propose in our paper have appeared in the literature. These literature models, however, are related to other fields than the analysis of electricity consumption; Ramsey and Lampart (1998a,b) or Ramsey (1999) serve as examples in the sphere of economy, Keitt and Urban (2005) in that of ecology. The methodology we employed to study the scale-specific importance of weather variables for explaining electricity consumption variability seems rather unique, wavelets having appeared in electricity consumption research papers in a slightly different context. For example, Lai et al. (2008) used wavelet artificial neural networks to identify key variables that affect monthly electricity consumption, Nguyen and Nabney (2010) combined wavelet transform and adaptive models to forecast electricity demand one day ahead. A fair number of research projects using wavelets aims at different electricity-related variables; e.g. Kim et al. (2002) proposed a wavelet transform based technique for the prediction of the system marginal price (SMP) of electricity.

Our paper is organized as follows. A brief introduction to the wavelet analysis is given in Section 2. In Section 3, the dataset used in our paper is introduced. In Section 4, weather-unrelated variables influencing electricity consumption are mentioned and the way how to adjust for them is given. In Section 5, a parametric model is defined, enabling us to study relative importance on different time scales. Measures of relative importance are provided in Section 6. The analysis results are presented in Section 7, Section 8 is bringing conclusions.

During the analysis the R statistical software was used (R Development Core Team, 2011) with several contributed packages (see e.g. Constantine and Percival, 2011; Fox, 2005; Grömping, 2006; Harrell with contributions, 2012; James and Hornik, 2011; Zeileis and Hothorn, 2002).

2. The wavelet analysis

An extensive body of literature exists on rigorous introductions to wavelet analysis (see e.g. Percival and Walden (2002), Vidakovic (1999) or Gençay et al. (2001)). An overview – not a comprehensive manual – of wavelet analysis is given below, defining necessary formulas and concepts (used henceforth).

The way we introduce wavelets may be found too technical and abstract. We, therefore, start the wavelet analysis introduction by explaining intuitively its role in the paper (see Section 2.1). After that (from Section 2.2) the so called maximal overlap discrete wavelet transform (MODWT) is summarized more formally. This summary is based on Percival and Walden (2002) which encompasses details and proofs of the statements given below. (There are further resources – e.g. Vidakovic (1999) – giving a more technical and abstract introduction to wavelets.)

2.1. Intuitive understanding of the role of wavelet analysis in our paper

The variability of a specific time series can be decomposed into time scales. Abrupt and fast movements are associated with the variability at short time scales and very slow and long-run movements with that at long time scales. Below (Section 2.4) we will introduce the time series of MODWT wavelet coefficients which may be obtained from an input time series by filtering it with a special linear filter. The resultant time series of MODWT wavelet coefficients has a specific time scale associated with it and captures the temporal information on this specific time scale's contribution to the variability of the input time series. For one input time series we can construct a *set* of time series of MODWT wavelet coefficients, each time series in the set being associated with a *different* time scale.

One of standard approaches to exploring relationships between several time series is to construct regression models in which some time series (explanatory ones) are used to explain the variability of another time series. MODWT wavelet coefficients can be also used within these regression models. More specifically, it is possible to construct a regression model in which several time series of MODWT wavelet coefficients – each associated with a *different* input time series but with *the same* time scale – are used to explain the variability of the time series of MODWT wavelet coefficients of another input time series but associated again with exactly the same time scale. In this way, we can explain abrupt movements (i.e. those associated with short time scales) in the time series of electricity consumption by abrupt movements in both the time series of outside temperature and that of sunshine duration. Similarly, we can explain the long-run movements (i.e. those associated with long time scales) in the time series of electricity consumption by long-run movements in both the time series of outside temperature and that of sunshine duration. Several such models could be constructed, each associated with a specific time scale. That is a rough intuitive idea of the role of wavelet analysis in this paper. In the following sections, rigorous formal definitions and formulas are provided, building up on the above idea.