Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2013) 21: 1035 – 1043

doi:10.3906/elk-1109-47

Wavelet multiscale analysis of a power system load variance

Samir AVDAKOVIC,[1,*] Amir NUHANOVIC,[2] Mirza KUSLJUGIC,[2]
Elvisa BECIROVIC,[1] Elma TURKOVIC[1]

[1]Department for Development, EPC Elektroprivreda B&H D.D. Sarajevo,
71000 Sarajevo, Bosnia and Herzegovina

[2]Department of Power Systems Analysis, Faculty of Electrical Engineering, University of Tuzla,
75000 Tuzla, Bosnia and Herzegovina

Received: 23.09.2011 • **Accepted:** 06.04.2012 • **Published Online:** 03.06.2013 • **Printed:** 24.06.2013

Abstract: Wavelet transform (WT) represents a very attractive mathematical area for just more than 15 years of its research in applications in electrical engineering. This is mainly due to its advantages over other processing techniques and signal analysis, which is reflected in the time-frequency analysis, and so it has an important application in the processing and analysis of time series. In this paper, for example, the analysis of the hourly load of a real power system over the past few years was performed by applying the continuous WT and using the Morlet wavelet function. The results show that this approach of data analysis can give a better insight into the basic characteristics of the consumption and identify the characteristic periods of the power system load variances over the past years, which can be very interesting for power system planners.

Key words: Wavelet transform, power system, time series, power system planning

1. Introduction

A power system is a complex dynamic system composed of a large number of elements, i.e. generation units, transmission and distribution lines, transformers, and loads, that are all interconnected and thus represent a specific group of elements. The basic function of a power system is to provide a reliable, secure, and economical supply of electricity to customers according to previously defined power quality standards. The planning and operation of a power system is quite an extensive and very complex area, where technology and economics are inextricably intertwined [1]. One step in power system planning is the electricity power balance, which is commonly connected to the planning of the incomes and outcomes of some physical, economical, or any other parameter in a certain time period (day, week, month, and year). The standard methodology of electricity power balance preparation on a monthly or yearly basis is based on the estimation of the approximated load duration curve according to predefined priorities on the available generation units [2]. One of the major shortcomings of such methodology is the objective lack of real dispatcher requests that arises from the daily load curves, hydrological occasions, dynamics on compensation reservoir usage, usage of pumped storage hydroelectricity, etc. A very important step in the power system planning and operation process is the total understanding of the load characteristic and demand. The consumers in power systems are numerous and varied with different load characteristics. Load diagrams represent the basic characteristics of the demand and the load duration curves can be defined and analyzed both for individual consumers or a complete system. Analysis of the daily, weekly,

*Correspondence: s.avdakovic@elektroprivreda.ba

monthly, and annual load profiles is common in the process of the planning, operation, and maintenance of the power system. The daily and weekly load profiles are often the input data in the processes of the short-term planning and short-term load forecasting of the power system, and since this is relatively small number of data, their changes over time can easily be seen. The monthly load curves mainly represent the inputs in the processes of the mid-term planning or mid-term load forecasting of the power system [3–5]. The annual curve of the load has a relatively large number of data and provides a good overview of the dynamic behavior of the power system load during the seasons. Further analysis of the processes of the long-term planning or long-term forecasting mainly involves the normalization of the annual load profile [6–8]. However, normalized annual load profiles do not provide the possibility of the time-frequency analysis of the observed time series. On the other hand, wavelet transform (WT) has attracted considerable attention in almost all areas of science in recent years. A large number of scientists from all fields of electrical engineering research confirm the remarkable possibilities of WT in analysis and signal processing in the fields of power quality, protection, processing and analysis, telecommunications, etc. In several papers, WT attracted considerable attention in the analysis of load profiles. In [9,10], different methods of power system load forecasting were presented, while in [11], the WT was used in the analysis of the weekly and monthly load diagram to identify the required amount of balancing capacity when observing the time-varying nature of the dominant frequencies contained in the power signals.

In this paper, by applying the continuous WT (CWT) and the Morlet wavelet function, we analyzed the hourly load variances of the real power system in Bosnia and Herzegovina over the past few years. The results show that this approach to data analysis can give a better insight into the basic characteristics of the consumption. Moreover, the time-frequency analyses of the observed time series are used to examine the characteristic periods of the power system load variances over the past several years, which can be very interesting for power system planners.

2. Background

Although it represents a relatively new mathematical area, a detailed description of wavelet theory can easily be found in a vast number of books and papers. In this section, a brief overview of the wavelet theory and the basic characteristics of the analyzed system data will be presented.

2.1. Wavelet theory

The WT historical development can be seen from the time of JBJ Fourier's work to the late 1980s. In 1988, Belgian mathematician Ingrid Daubechies presented her work to the scientific community, in which she created orthonormal wavelet bases of the space of square integrable functions, which consists of compactly supported functions with a prescribed degree of smoothness. Today, this is considered as the end of the first stage of the development of WT. WT is a natural continuation of the Fourier transform and its modified short-term Fourier transform. Over the years, it was developed independently in mathematics, quantum physics, and electrical engineering, as in other areas of science.

A wavelet is a function with the nature of wave functions with compact support. It is called "wave" because of the oscillatory nature of the small finite domain on which it is different from zero (compact support). The scaling and translation of basic wavelet $\psi(x)$ (mother wavelet) define the wavelet basis and represent the wave function of the limited duration for which it is valid:

$$\int_{-\infty}^{\infty} \psi(x)dx = 0. \tag{1}$$

The selection of the scaling and translation parameters provides a representation of the smaller fragments of a complicated form with a higher time resolution (zooming sharp and short-term peaks), while smooth segments can be represented at a smaller resolution, which is the wavelet's good characteristic (basis functions are time-limited). All of the details concerning the general theory of wavelets can be found in [12–17].

2.2. Test system and characteristic data

The Bosnia and Herzegovina (B&H) Electricity Power System is part of the European Network of Transmission System Operators for Electricity system and is integrated into the European power system. After the end of the war in the 1990s, the B&H power system was almost completely destroyed, as was most of the industrial sector in the country. Fifteen years after the signing of the Dayton Peace Agreement, the electricity consumption and the maximum load values have reached the values of those obtained in 1991 (approximately 2200 MW for the complete B&H power system). Today in B&H, there exist 1 common transmission company and 3 power companies for generation, distribution, and supply. The hourly load curves for EPC Elektroprivreda B&H consumption in 2008, 2009, and 2010 are presented in Figure 1. Geographically, EPC Elektroprivreda B&H supplies about 700,000 customers that are widespread over approximately a quarter of the total surface of the country. The hourly loads of EPC Elektroprivreda B&H over the past 3 years, without consideration of the electricity export to other countries, are presented in Figure 1.

It is obvious from Figure 1 that the yearly consumption is closely related to the temperature oscillations. Hence, in the autumn and winter periods, the consumption is evidently larger than in the spring and summer periods. Furthermore, it is obvious that the system load in 2009 was somewhat lower than expected, which is a consequence of the global economic crisis. However, the crisis was not reflected in the consumption of the voltage levels at 35 kV, 20 (10) kV, and 0.4 kV. The consumption has a continual annual growth trend of several percentages (2.2% in 2009 and 2.4% in 2010). A consumption decrease was reflected from the industrial consumers at a 110 kV voltage level, e.g. steel companies or the manufacturing industry. Along with the previously noted results of the evident load variance, it is obvious that temperature has the greatest impact on the shape of the load consumption curve. Thus, it is evident that in the summer, a minimum load is reported, while during the winter, a maximum peak value occurs. Otherwise, geographically, the temperature in B&H can vary from a very low temperature (–20 °C) in the winter to very high temperatures (+40 °C) in the summer.

3. Wavelet analysis results

WT is used for measuring the parity of the frequent function content and basic wavelet in the time-frequency domain. Based on the WT presented in [18], the CWT has been applied to analyze the data from Figure 1 by customizing a widely accessible software tool developed by Torrence and Compo (http://paos.colorado.edu/research/wavelets/). Similar analyses of the time series have been used for numerous studies in various science areas; see [18–32] for examples.

Briefly, the analysis presented in this paper uses the Morlet wavelet function $\psi_0(\eta)$, defined as [18]:

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\eta^2/2}, \tag{2}$$

where ω_0 is the dimensionless frequency and η is the dimensionless time [18]. The dimensionless time parameter is defined as $\eta = t/s$, where t is the time parameter and s is the scale. The dimensionless frequency parameter is defined as $\omega_0 = s\omega$ where ω is the frequency parameter [31]. Selecting $\omega_0 = 6$ for the Morlet wavelet provides

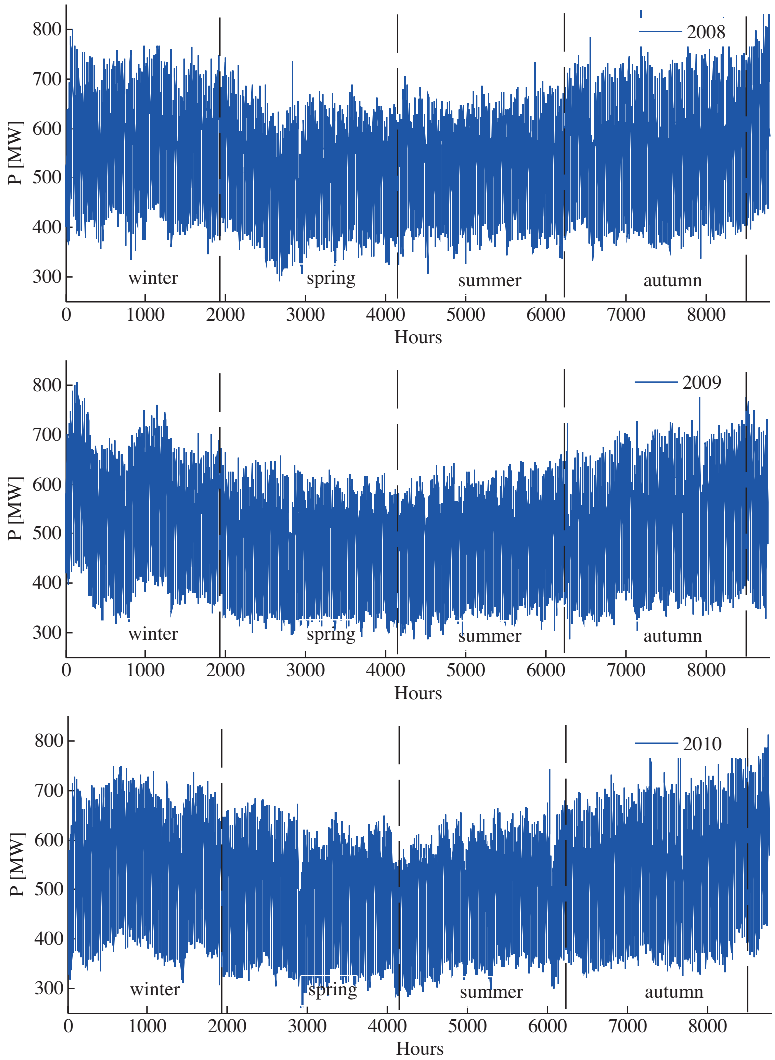

Figure 1. Hourly load for EPC Elektroprivreda B&H for 2008, 2009, and 2010.

a great balance between the time and frequency localization, and for this central frequency, the Fourier frequency period is almost equal to the scale [32].

The continuous WT of the time series $P = \{P_n, n = 0, \ldots, N-1\}$, which has equal time intervals δ_t (a time interval of 1 h), with defined wavelet function $\psi_0(\eta)$ will be calculated as [32]:

$$W_m(s) = \frac{\delta_t}{\sqrt{s}} \sum_{n=0}^{N-1} P_n \psi * \left[\frac{(n-m)\,\delta_t}{s} \right], m = 0, 1, \ldots, N-1, \tag{3}$$

where * represents the conjugate complex value, N is the number of points in the time series, and $\psi(t)$ is the wavelet function at scale s and is translated in time by m. The previous equation describes the convolution of P_n with a scaled and translated version of the wavelet function.

The local wavelet power spectrum is defined as $|W_m(s)|^2$ and represents the squared absolute value of the wavelet transform coefficients (or squared amplitude) [18,29,32]. Concerning the fact that the wavelet power spectrum gives more information in one picture, it is often practical to show the information as the averaged value of the result in the range of scale or time. Torrence and Compo showed the average variations of the whole time series on every scale, called the global wavelet spectrum (GWS) (time-averaged wavelet spectrum), which is defined as [29]:

$$\overline{W}^2(s) = \frac{1}{N}\sum_{n=0}^{N} |W_m(s)|^2 . \tag{4}$$

The scales are a series of fractional powers of 2 and are defined as [18]:

$$s_j = s_0 2^{k\delta_j}, k = 0, 1, \ldots, J, \tag{5}$$

where s_0 is the smallest resolvable scale and J determines the largest scale [18]. In this study, the value $s_0 = 6h$ is used. Moreover, the scale $\delta_j = 0.25$ is used, which will do 4 suboctaves per octave. The smaller values of δ_j give a finer resolution [18].

The 3 time series analyzed in this paper start with the first hour on 1 January 2008 and end with 0000 hours on 31 November 2010. The wavelet power spectrum and the GWS for the 3 time series are shown in Figure 2, where the color codes for the power ranges are from blue (low power) to red (high power), and the significant regions are the ones associated with red, orange, and yellow. From Figure 2 it is possible to identify a few very interesting pieces of information about the analyzed time series, which describes the dynamical behavior of the EPC Elektroprivreda B&H consumption.

It is obvious that the GWSs for the 3 analyzed time series are very similar, which is logical considering that the data from the same system are analyzed. As can be seen in the GWS graph, a few local maximums are identified, where the largest is that in a 24-h period for all 3 of the analyzed time series. It is clear that there is a higher concentration of power about the 24-h period, which shows that these time series have strong daily signals [30].

The maximums of 3 analyzed time series are at intervals of 12 and 24 h, between the 64- and 168-h bands, and between the 500- and 1000-h bands. The local maximum period of 12 h physically represents the daily consumption variation (day–night), and it is clear that the intensity depends on the temperature conditions, i.e. the season. The intensity of the daily active power consumption changes has a higher intensity in the spring and autumn periods, which is obvious from Figure 2.

This is a consequence of the considerable temperature fluctuations during these periods of the year compared to the temperature fluctuations during the periods of winter and summer. This conclusion would be a difficult one to come up with from Figure 1 without a detailed analysis of the daily load profiles throughout the year. The largest of the GWS maximums is identified at 24-h periods for all 3 of the analyzed time series. It is obvious from Figure 2 that the wavelet coefficient values for the analyzed case vary in a 24-h period depending on the season. They are more intensive during the winter periods, while their intensity is a bit lower during the summer months. This is also obvious from Figure 1. Furthermore, the maximum in the 168-h period corresponds with the characteristic weekly consumption. It is obvious for all 3 of the analyzed time series that the first characteristic weeks occur in the second half of April and the first days of May, i.e. during the observed times of 2500 h up to 3000 h. These increases in the wavelet coefficients identified in Figure 2 are consequences of the ending of the winter (heating) season in that period with the public holidays occurring during this period.

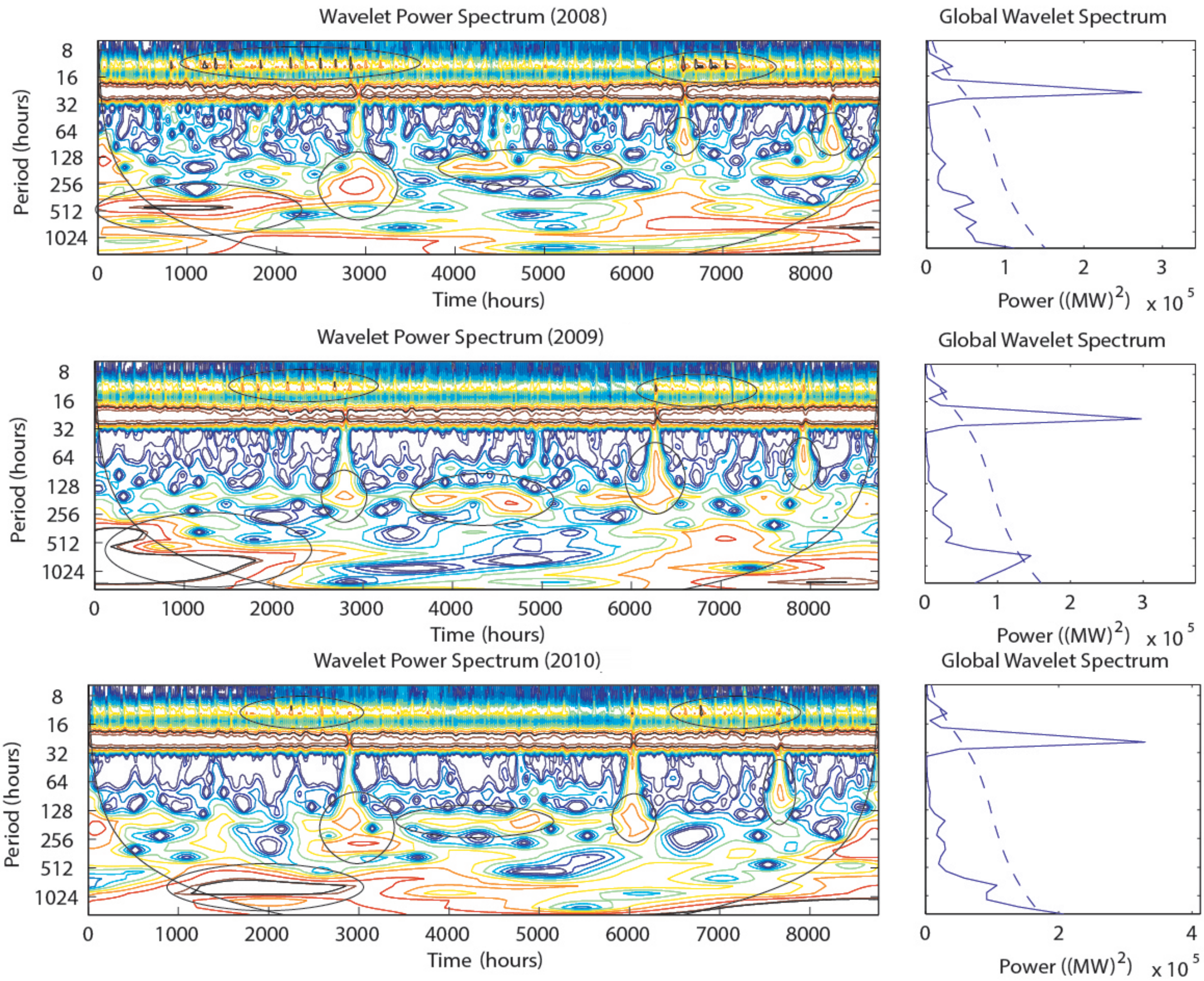

Figure 2. The wavelet power spectrum and the GWSs for the hourly consumption of the B&H power system for 2008, 2009, and 2010.

Furthermore, observing Figure 2, 2 interesting weeks in the summer period are identified. In relation to 2009 and 2010, in which these weeks are the same, the 2 characteristic weeks for the summer of 2008 year were moved for 1 week, which is obvious from Figure 2. This can be interpreted as very hot weeks and the intensive use of air conditioners.

Very interesting results have been identified for the period between the 64- and 168-h bands in the second half of the year for all 3 of the analyzed time series. Two typical weeks (or a few days) can be identified and are moved for 10 days for each next year analyzed. This is the result of religious holidays, when a somewhat significant change of electricity is evident, but this is very difficult to observe from Figure 1.

Finally, the significant maximums for all 3 of the analyzed series are evident in the period between the 500- and 1000-h bands. This is the result of extremely low winter temperatures. Additionally, in 2009, during this period, a complete suspension of the gas supply to B&H occurred, which additionally had a significant increase in the consumer's consumption. For this reason, the maximum GWS during this period for 2009 was slightly higher than in the other 2 years.

From the previous analysis, it is evident that the main impact on the consumption is the temperature oscillations. However, all of the other factors are not negligible, such as natural gas consumption and some social events. All of this gives a more complete understanding of the consumptions and indicates the specific consumption periods during the year, which can be very interesting for power system planners.

4. Conclusions

In this paper, by applying CWT, the time series of real power system consumption demand were analyzed. With spectral wavelet analysis, the time-frequency power characteristics of the analyzed data were estimated, thus providing an exceptional insight into the dynamic behavior of the observed system load over time.

For all 3 of the analyzed time series, several local maximums were identified in the GWS graphs, where the largest is that in a 24-h period, which shows that these time series have strong daily signals. It was shown that the daily fluctuations in consumption are slightly higher during the periods of spring and autumn as a result of significant temperature fluctuations during these periods of the year. Moreover, it was shown that some typical weeks do not appear at the same time intervals during the year, which may provide useful information for power system planners. For the analyzed power system, it is obvious that the consumption is in close dependence on the temperature oscillations.

As it was presented in this paper, this approach in power system consumption analysis enables a different insight into the consumption behavior and also the identification of characteristic time periods during the year that occur due to certain reasons (temperature changes, social events, etc.), which have a significant impact on power system consumption.

Acknowledgment

We hereby express our gratitude to our colleagues from EPC Elektroprivreda B&H, Department of Operation, for putting at our disposal all system data. The data were used during the writing of the study of long-term energy and power demand forecasting at EPC Elektroprivreda B&H - Sarajevo [33].

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