CO-MOVEMENT OF ACTIVE AND REACTIVE POWER CONSUMPTION

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In this paper, Wavelet Transform (WT) is applied for analysis active and reactive power consumption of the real power system of Bosnia and Herzegovina (B&H) for year 2011. Obtained results show that properties of active and reactive power consumption are significantly different and these two time series move together (in phase) throughout the year, which is especially expressed when it comes to daily and weekly periods (24 and 168 hours). Special attention is dedicated to changes in the power factor which is characterized by significant fluctuations during the summer period. Results based on the wavelet analyses clarify impact of changes in active and reactive power values (magnitudes) to the changes of power factor during observed time period.

Keywords: Active and reactive power consumption, wavelet transform, wavelet coherence, wavelet phase angle

1. Introduction

Fully understanding properties of the power consumption for the system operators can be helpful in the better distribution network operating and planning [1]. For many years, analysis of the power consumption is the subject of interest large number researchers applying different methodological approaches [2], [3], [4], [5]. In this paper, the Continuous WT (CWT) is applied to analyze an active and reactive power consumption of the real Bosnia and Herzegovina (B&H) power system using the data from 2011 obtained from the existing measurement system. Hourly values of the time series used in this study present the power consumption over 700.000 customers. The mathematical notation of the CWT of a function $x(t)$ is given by [6]:

$$W_{x,\psi}(\tau,s) = \int_{-\infty}^{\infty} x(t)\,\frac{1}{\sqrt{|s|}}\,\psi^{*}\left(\frac{t-\tau}{s}\right)dt \tag{1}$$

where are: ψ is wavelet function, τ corresponds to the time dimension and s refers to the scale dimension [6].

The wavelet power spectrum of time series $x(t)$ is defined as [6]:

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$\left|W_{x,\psi}(\tau,s)\right|^2$ and represents the local variance of time series, while global wavelet spectrum presents average variations of whole time series on every scale [2]. The Cross-WT (XWT) of active and reactive power consumption time series, noted as P and Q, will be [7]: $W_{PQ,\psi}(\tau,s) = W_{P,\psi}(\tau,s)W^*_{Q,\psi}(\tau,s)$. Also, XWT can be written as: $W_{PQ,\psi}(\tau,s) = \left|W_{PQ,\psi}(\tau,s)\right| e^{\phi_{PQ,\psi}(\tau,s)}$, whereas $\phi_{PQ,\psi}(\tau,s)$ corresponds to the wavelet phase angle [8]. The wavelet phase difference of P and Q time series now is defined as [9]:

$$\phi_{PQ,\psi}(\tau,s) = tan^{-1}\frac{Imag\left(W_{PQ,\psi}(\tau,s)\right)}{Real\left(W_{PQ,\psi}(\tau,s)\right)} \tag{2}$$

where $\phi_{PQ} \in [-\pi,\pi]$.

The Wavelet Coherence (WTC) is defined as the squared absolute value of the smoothed cross wavelet spectra normalized by the product of the smoothed individual wavelet power spectra of each series [6], [7], [8], [9] [10]:

$$R^2_{PQ,\psi}(\tau,s) = \frac{S\left(\left|W_{PQ,\psi}(\tau,s)\right|^2\right)}{S\left(\left|W_{P,\psi}(\tau,s)\right|^2\right)S\left(\left|W_{Q,\psi}(\tau,s)\right|^2\right)}, \tag{3}$$

where S is a smoothing operator.

WTC is often used approach for analyses of time series and present the local correlation between the time series in the time-frequency space. The WTC ranges from 0 to 1 and it can be interpreted as a correlation coefficient; the closer the value is to 1 the more correlated are the two series [1], [6], [7], [8], [9], [10], [11]. Also, in this paper the Morlet wavelet function is used and details about this function are available in [1], [6], [7], [8], [9], [10], [11]. Software's applied in this study were written by Torrence and Compo [7] and A. Grinsted [9]. Generally, the applied approaches, briefly described above, have been often used in different science areas [1], [6], [7], [8], [9], [10], [11], [12]. The author contributions in these area readers can find in [1], [2] and [12], where they studied the phenomena associated with the consumption of electricity. Different from [1], [2] and [12], this study has two primary objectives. First, determine the properties of the reactive power consumption at different time-frequency/period scales and visualize their co-movement with active power consumption. The second objective is analyses impact of the changes of active and reactive power consumption to the power factor variations during time. The rest of paper is organized as follows. The data from real B&H power system used in this study are presented in Section 2. Results and discussion are presented in Section 3, while Section 4 presents conclusion section.

2. The data

Hourly values of active and reactive power consumption for B&H power system and 2011 are presented in Fig. 1, and come from the period between 01.01.2011. up to 31.12.2011. The values of active and reactive power consumption (Fig. 1) present the total power distribution consumption (0.4 kV, 10 kV, 20 kV and 35 kV) of the Electric Public Company Elektroprivreda B&H d.d. Sarajevo in 2011, as one of the three public companies in B&H.

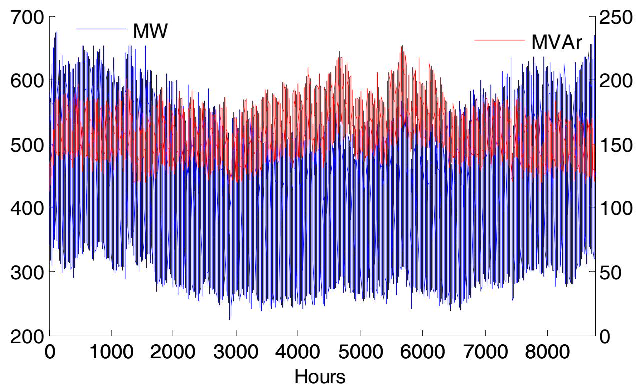

Fig. 1. Bosnian active and reactive power consumption for 2011

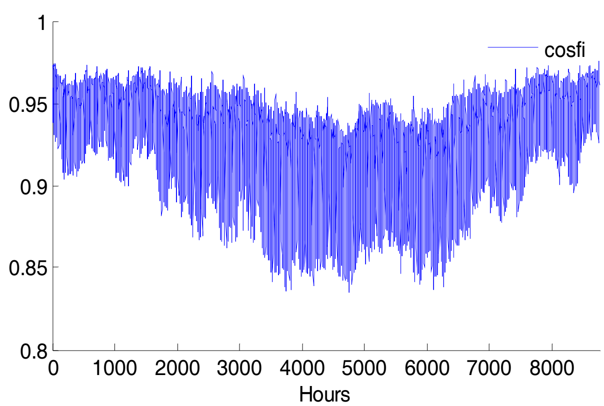

Fig 2. The power factor based on the data from Fig. 1

The data come from existing measurement system and 51 transformer substation 110/x kV. For system operators, special attention draws reactive power consumption and power factor. The calculated values of power factor ($cosfi = P/\sqrt{P^2 + Q^2}$; P [MW], Q [MVAr]) are shown in Fig. 2. Low values of power factor (less than 0.95) indicate the increasing of reactive power consumption which in addition to increase active power losses in distribution networks could results in the significant decreased of the voltage magnitudes. For the observed B&H power system, in 2011 the largest variations of the power factor were in the summer (Fig. 2). This is the results of decreasing of active power consumption and increasing of reactive power consumption, as a response to the high air temperatures during this period of year and intensive usage of air-conditions.

3. Results and discussions

The results of the research and discussions are presented in this section. The wavelet power spectrum and global wavelet spectrum of active and reactive power consumption for 2011 are presented in Figs. 3 and 4, respectively, where the colour code for power ranges are from blue (low power) to red (high power-significant regions) [1], [2], [9].

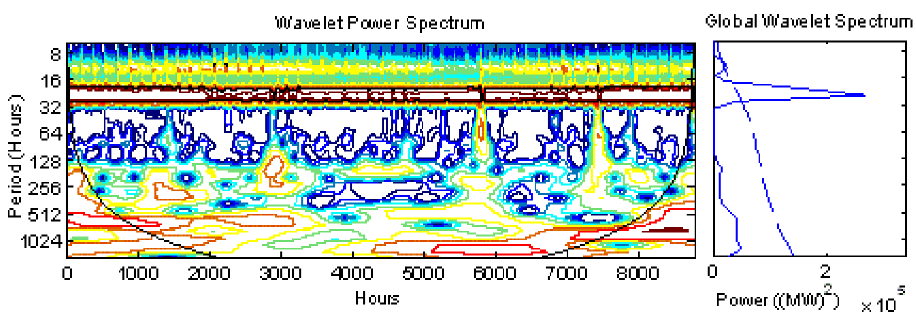

Fig. 3. The wavelet power spectrum and global wavelet spectrum of active power consumption (from Fig. 1)

Obtained results from Fig. 3 show that active power consumption is a dominant daily time series. This is expected, given the results presented in [2] where they also analyzed hourly values of active power consumption for the same power system for the Years 2008-2010. Also, in [2] were identified and significant changes in power consumption during the observed periods as a consequence of certain events that have an impact on power consumption, such as national and religious holidays, the suspension of gas supplies, etc. However, for the time series of reactive power consumption cannot be said that is a dominant daily time series (Fig. 4). Looking at global wavelet spectrum graph in Fig. 4, it is possible to discern three local maximums (24, 168 and about 700 hours). The local maximum in the period of 24 hours present a daily reactive power consumption variations that are not very pronounced as daily variations of the active power consumption. (Fig. 1).

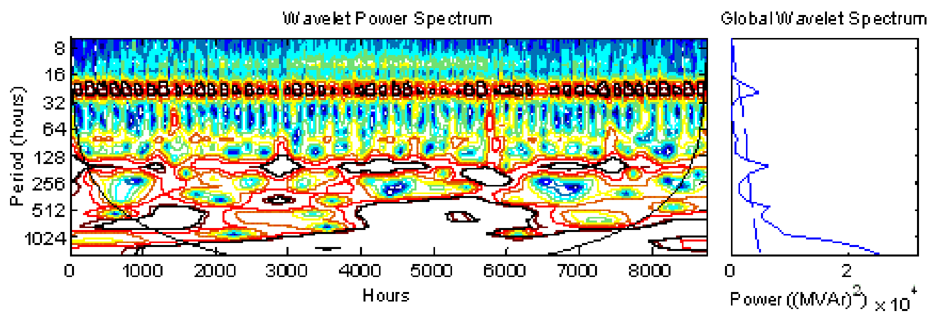

Fig. 4. The wavelet power spectrum and global wavelet spectrum of reactive power consumption (from Fig. 1)

A daily changes in the time series are evident throughout the year, as confirmed by the wavelet power spectrum (Fig. 4). The higher value of the local maximum for this time series has been identified for the period of 168 hours. This is the consequence of reducing of the reactive power consumption during non-working days (weekend) which can be identified from careful observation in Fig. 1. This can be interpreted as reduced industrial consumption during non-working days, which determines one properties of this time series. Finally, the third local maximum is identified for period about 700 hours which gives the properties of monthly time series. This is due to air temperature variations which are especially expressed in the summer months (Fig. 1).

WTC and wavelet phase angle analyses of active and reactive power consumption from Fig. 1 is presented in Fig. 5. All identified significant regions show in-phase behavior of this two time series (Fig. 5). This is particularly true for the periods of 16-32, 64-256 and 300-600 hour bands. In other words, daily active and reactive power changes are in-phase, i.e. the increase of the active power consumption growth is accompanied by reactive power consumption (and vice versa) for 16-32 hour bands. This is evident from the position of the arrow (Fig. 5). An arrow pointing to the right demonstrates that for certain frequency/period range time series of active and reactive power consumption are in phase, while the position of an arrow to the left talks about the out of phase behaviour of two time series. Same (in-phase) characteristics of these two time series show for weekly changes (64-256 hour bands) during the all observed time interval and monthly (300-600 hour bands) changes during the summer (4000-6000 hours of the observed time interval) (Fig. 5).

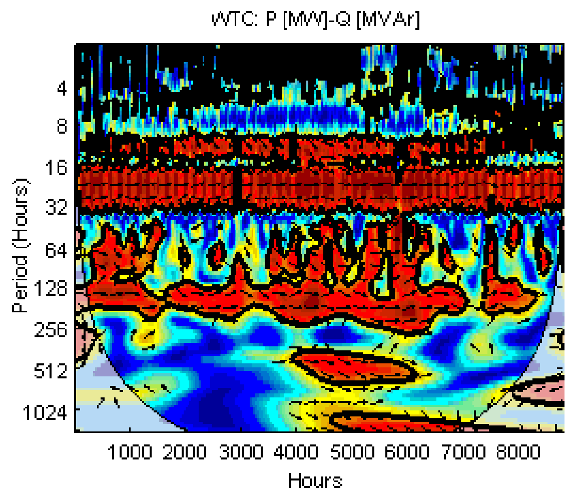

Fig. 5. WTC and wavelet phase angle of active and reactive power consumption time series (from Fig. 1)

Finally, to determine impact of active and reactive power variations to the power factor over year the WTC and wavelet phase angle analysis was performed (Fig. 6 and Fig. 7). Since the power factor present the calculated value of active and reactive power, it is clear that there will be significant correlation between them (P and cosfi and Q and cosfi). However, from Figs. 1 and 2 is very difficult (almost impossible) to determine how active and reactive magnitudes changes affect to the values of the power factor. This is possible clearly identify in Figs. 6 and 7. It is evident that the changes of active power consumption has a significant impact to the daily variations of power factor and co-move together for a period of 8-32 hour bands (Fig. 6). Also, for the same period (16-32 hour bands), the reactive power and power factor time series co-move together (Fig. 7). For a period of 4-8 hour bands and spring and summer seasons, the changes of power factor are consequence from changes of active power consumption. For the 256-1024 hour bands and autumn-winter seasons, unlike the time series of reactive power (Fig. 7), time series of active power consumption co-move together with time series of power factor (Fig. 6). The reactive power and power factor time series are out of phase for all periods greater than 32 hours. In other words, for weekly, monthly or seasonal changes of the power factor, the increase or decrease of reactive power consumption mean decrease or increase values of power factor, which is especially pronounced for the spring and summer seasons. It can be concluded that the main properties of analyzed time series (presented in Figs. 3 and 4) for different frequency/period bands will determine the power factor variations during year.

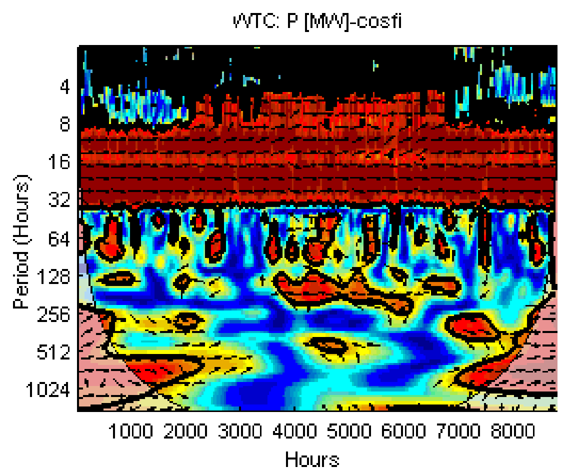

Fig. 6. WTC and wavelet phase angle of active power consumption and power factor time series

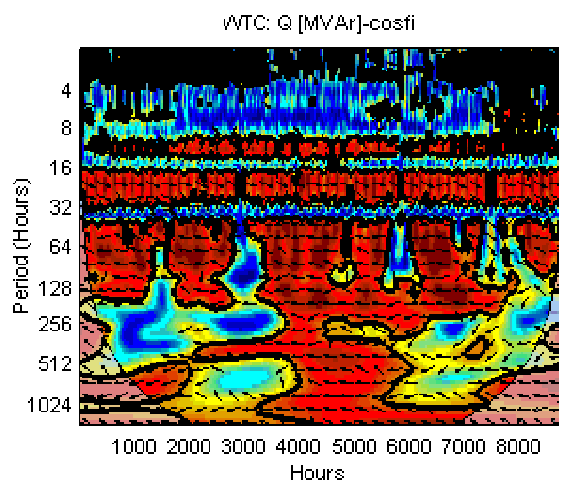

Fig. 7. WTC and wavelet phase angle of reactive power consumption and power factor time series

For example, the active power consumption is the dominant daily time series and its impact to the changes of power factor is evident in this period, while the time series of reactive power consumption has properties of a weekly and monthly time series and change the power factor for these periods are evident.

4. Conclusions

In this paper, the wavelet power spectrum, global wavelet power, WTC and wavelet phase angle approaches are applied for analyses of real data of active and reactive power consumption of B&H power system for year 2011. The main properties of these time series are presented and special attention is focused for the better understanding of the power factor variations during the year, which is a very important parameter for distribution systems operators. It is shown that applied approaches may help in better understanding dynamic behaviors of active and reactive power consumption.

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