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Wind Speed Data Analysis using Wavelet Transform

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Abstract**—**Renewable energy systems are becoming a topic of great interest and investment in the world. In recent years wind power generation has experienced a very fast development in the whole world. For planning and successful implementations of good wind power plant projects, wind potential measurements are required. In these projects, of great importance is the effective choice of the micro location for wind potential measurements, installation of the measurement station with the appropriate measuring equipment, its maintenance and analysis of the gained data on wind potential characteristics. In this paper, a wavelet transform has been applied to analyze the wind speed data in the context of insight in the characteristics of the wind and the selection of suitable locations that could be the subject of a wind farm construction. This approach shows that it can be a useful tool in investigation of wind potential.

Keywords**—**Wind potential, Wind speed data, Wavelet transform.

I. INTRODUCTION

THE accurate estimation of wind characteristics is difficult as these processes may not be stationary. Most traditional analysis tools are suited for stationary processes, which may not be always appropriate for the analysis of non-stationary data. Therefore, the performance evaluation of structures under transient conditions manifested by non-stationary has been rather elusive. In order to fully understand the wind characteristics and their effects on structures, there is clearly a need for analysis tools to analyze non-stationary data.

Wavelet Transforms (WT) have been recently developed as mathematical tools, based on a convolution operation between an original time series and an analyzing function, called wavelet or mother wavelet. The WT advantages over the conventional spectral transformations such as Fourier Transform (FT) and Short-Time Fourier Transform (STFT) in simultaneously time-frequency analysis with flexible resolutions. The WT becomes a powerful analyzing tool for stationary, non-stationary, intermittent time series, especially, to find out hidden short events inside the time series. Because of its advantages, the WT have been applied in the various fields such as digital signal processing, image coding and compressing, numerical analysis and digital simulation, system and flow identification and so on, and they still are increasingly evolving [1].

In the other hand, renewable energy systems are becoming a topic of great interest and investment in the world. In recent years wind power generation has experienced a very fast development in the whole world. For planning and successful implementations of good wind power plant projects, wind potential measurements are required. In these projects, of great importance is the effective choice of the micro location for wind potential measurements, installation of the measurement station with the appropriate measuring equipment, its maintenance and analysis of the gained data on wind potential characteristics.

When analyzing samples of collected data, a statistical approach to data processing is common. This approach does not provide an insight into time changes of signals, which is one of the limiting factors in data processing.

Recent applications of the WT for data analysis can be found in several studies which refer primarily to nonlinear spectral representation and multi-resolution analysis (MRA) of the (geomagnetic storms, solar wind, earthquake, meteorological, etc) data [2-10].

In this paper, a wavelet transform has been applied to analyze the wind speed data in the context of insight in the characteristics of the wind and the selection of suitable locations that could be the subject of a wind farm construction.

The paper is organized as follows. The methodology and materials used in this paper are presented in Section II. The wavelet analyses of wind speed data are given in Section III. Conclusions are given in Section IV.

II. METHODOLOGY AND MATERIALS

A. Basic Wavelet Theory

The wavelet transform (WT) introduces a useful representation of a function in the time-frequency domain [11-14]. Basically, a wavelet is a function $\psi \in L^2(R)$ with a zero average, i.e.:

$$\int_{-\infty}^{+\infty}\psi(t)dt = 0\,. \tag{1}$$

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The Continuous Wavelet Transformation (CWT) of a signal $x(t)$ is then defined as:

$$CWT_{\psi}x(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right)dt \qquad (2)$$

where $\psi(t)$ is called the mother wavelet, the asterisk denotes complex conjugate, while a and b $(a,b \in R)$ are scaling (dilation and translation) parameters, respectively. The scale parameter a determines the oscillatory frequency and the length of the wavelet, and the translation parameter b determines its shifting position.

The application of WT in engineering areas usually requires the discrete WT (DWT). The DWT is defined by using discrete values of the scaling parameter a and the translation parameter b. To do so, set $a = a_0^m$ and $b = nb_0 a_0^m$, then we get $\psi_{m,n}(t) = a_0^{-m/2}\psi\left(a_0^{-m}t - nb_0\right)$, where $m,n \in Z$, m is indicating frequency localization and n is indicating time localization. Generally, we can choose $a_0 = 2$ and $b_0 = 1$. This choice will define a dyadic-orthonormal WT and provide the basis for MRA. In MRA, any time series $x(t)$ can be completely decomposed in terms of approximations, provided by scaling functions $\phi_m(t)$ (also called father wavelet) and the details, provided by the wavelets $\psi_m(t)$. The scaling function is associated with the low-pass filters (LPF), and the wavelet function is associated with the high-pass filters (HPF). The decomposition procedure starts by passing a signal through these filters. The approximations are the low-frequency components of the time series and the details are the high-frequency components. The signal is passed through a HPF and a LPF. Then, the outputs from both filters are decimated by 2 to obtain the detail coefficients and the approximation coefficients at level 1 (A1 and D1). The approximation coefficients are then sent to the second stage to repeat the procedure. Finally, the signal is decomposed at the expected level.

According to Parseval's theorem, the energy of the distorted signal can be partitioned at different resolution levels. Mathematically this can be presented as $ED_i = \sum_{j=1}^{N}\left|D_{ij}\right|^2$, $i = 1,......,l$ and $EA_l = \sum_{j=1}^{N}\left|A_{lj}\right|^2$, where $i = 1,......,l$ is the wavelet decomposition level from level 1 to level l. N is the number of the coefficients of detail or approximate at each decomposition level. ED_i is the energy of the detail at decomposition level i and EA_l is the energy of the approximate at decomposition level l.

B. Wind Speed Data

The wind speed data used for analyses in this paper were taken from the available Electronic Wind Atlas for Bosnia and Herzegovina (B&H) (Atlas) [15]. Values in the Atlas are based on the meteorological model MM5 (Fifth-Generation NCAR/Penn State Mesoscale Model). MM5 is one of the leading meteorological models and is used in more than 50 countries worldwide. The Atlas accesses with 10 minute, hourly, monthly and annual average values of the wind speed, wind direction, annual average values of solar irradiation, temperature, and parameters (A and k) of Weibull's distribution, for the period from 01/01/1978 to 31/12/2007. Depending on the type of information, these values are available in form of maps, time lines and diagrams. In this paper, average hourly wind speed data signals for year 2007 from the Atlas for three locations in B&H were chosen. The choice of the locations was made according to their average wind speed for the available time period of 30 years, so that the first presents a location in the mountains, cca 1950 m a.s.l. (wind speed data 1), the second a highland area cca 1000 m a.s.l. (wind speed data 2) and the third a location in the plain area, cca 300 m a.s.l. (wind speed data 3). Fig. 1 shows the average hourly wind speed data signals for the chosen three locations which were used in this paper. Insight into these signals does not give much information about wind potential in the context of their usage for future wind farm constructions, and therefore requires additional data processing.

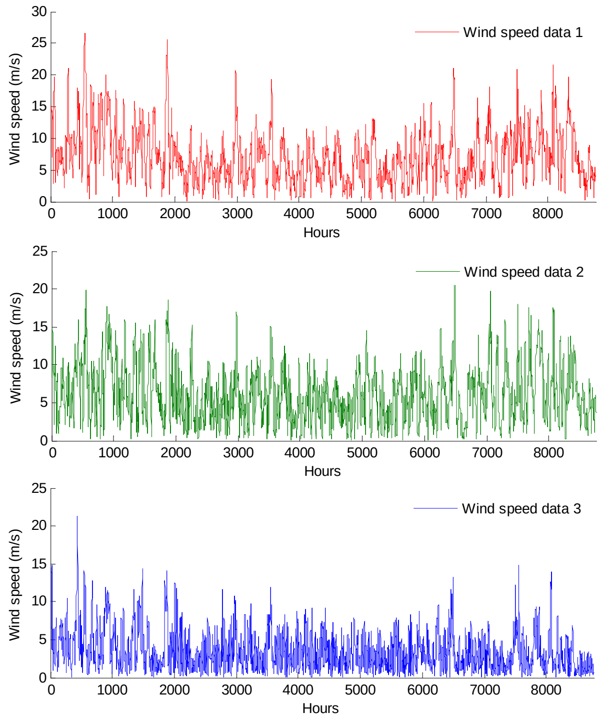

Fig. 1. Wind speed data

III. Wavelet Analyses of Wind Speed Data

A. Nonlinear Spectral Representation of the Data

Wavelet spectral analysis provides a natural basis to estimate the time-frequency-energy characteristics of the observed data. In the wavelet analysis of signals, the time

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series of signal level variation is mapped into a set of wavelets pertaining to different scales and time instants, using a Morlet function. Since the sampling interval for the present data is 1 hour, the smallest scale of wavelet is 2 hours. The details of approach used in this subsection may be found in [16].A wavelet analysis of the three signals of wind speed data from Fig. 1 is presented in Fig. 2 to demonstrate its temporal variability. The Wavelet Power Spectrum gives information on the relative power at a certain scale and a certain time. These figures show the actual oscillations of the individual wavelets, rather than just their magnitude. Observing these figures, the concentration of power can be easily identified in the frequency or time domain. We performed the Global Wavelet Spectrum (GWS) to study the dominant periods of the signals of wind speed data for the different conditions during the year. These GWS provide an unbiased and consistent estimation of the true power spectrum of the time series, and thus they are a simple and robust way to characterize the time series variability. For all signals, the results are shown in Fig. 2 - right.

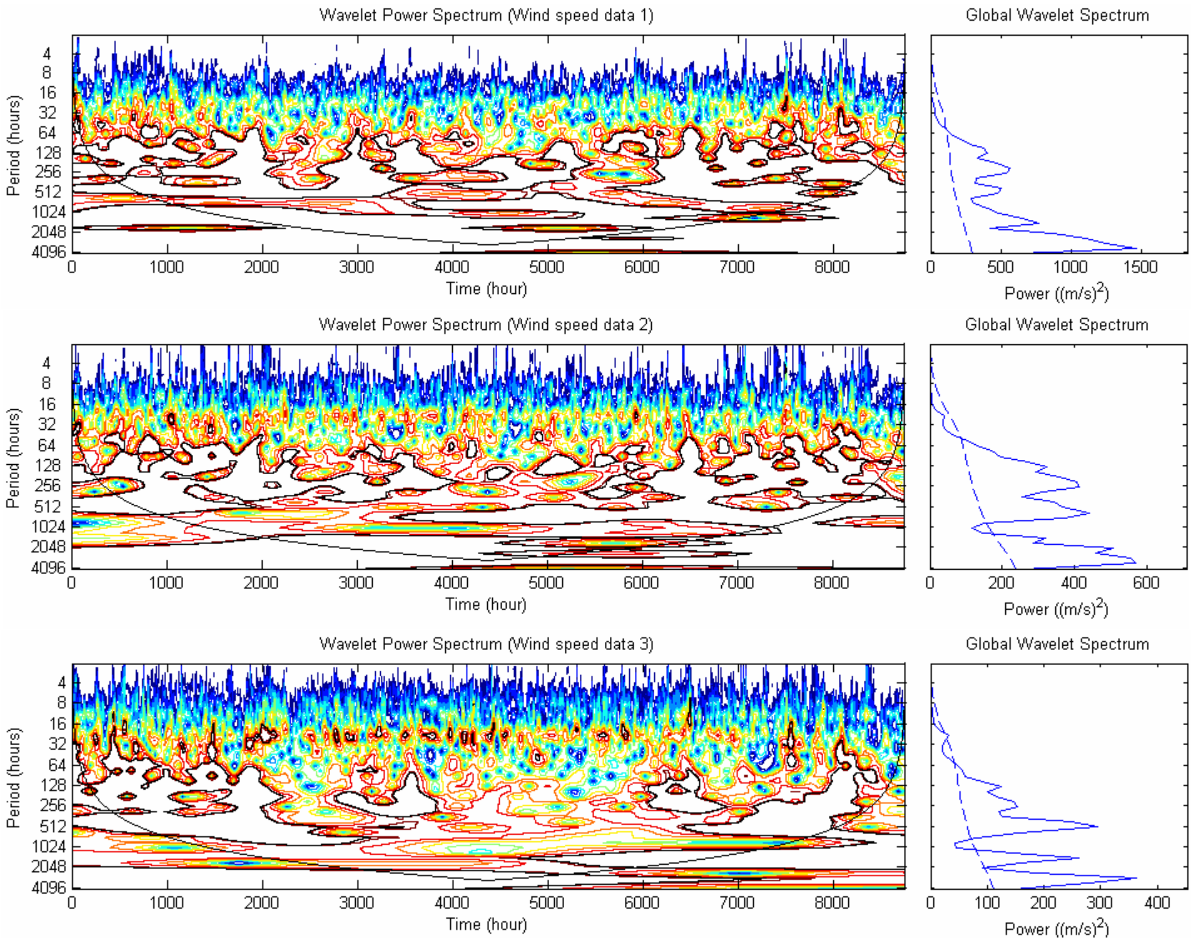

Fig. 2 Wavelet Power Spectrum and GWS of the time series of wind speed data 1, wind speed data 2 and wind speed data 3

For signal of wind speed data 1 we observe in Fig. 2, five relative maximum in cross-wavelet (120, 256, 500, 2000 and 4000 hours). It is interesting to note that the relative maximum of 4000 hours may be associated with the summer period of signal, while the relative maximum of 4000 hours may be associated with the winter and summer period of signal. Similarly, for signal of wind speed data 2, we observe seven relative maximum in cross-wavelet: 20, 120, 200, 500, 2000, 2050 and 4000 hours. The relative maximum of 2000, 2050 and 4000 hours associated with the summer period of signal. For signal of wind speed data 3, we observe six relative maximum in cross-wavelet: 20, 120, 200, 500, 2000 and 4000 hours. The relative maximum of 2000 and 4000 hours associated with the autumn period of signal.

Generally, three signals which are analyzed are very similar. The multiple peaks in the global spectra indicate that the signal is composed of oscillations with different time periods and with different magnitudes. As stated in Chapter II, an insight into selected signals does not give much information about wind potential. Using this approach, we get a different insight into the characteristics of wind and the magnitude of the GWS indicates the available potential for the

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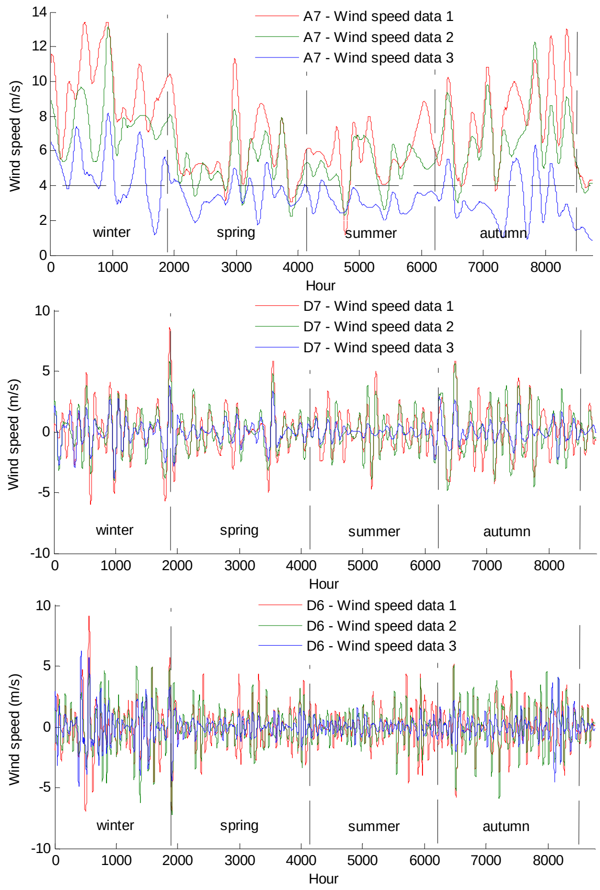
analyzed signal. From Figure 2, it is obvious that the Wind Speed Data 1 has the best characteristics.

B. MRA of Wind Speed Data

Implementation of the DWT can be realized by considering MRA. The algorithm uses digital HPF and LPF, which when combined in a structure, constitute a filter bank able to decompose the signal equally into high and low frequency components. After filtering, the two components contain redundancies and it is valid to down-sample each of the components by a factor of two, without losing any information.

An example of a seven level decomposition of the wind speed data signals from Fig. 1 is shown in Fig. 3. This approach provides several information [5]: detection discontinuous and breakdown points (usually using high frequency components D1 and D2), detection of self-similarity, identifications of pure frequencies and detection of long term evolutions (usually using low frequency component of signal).



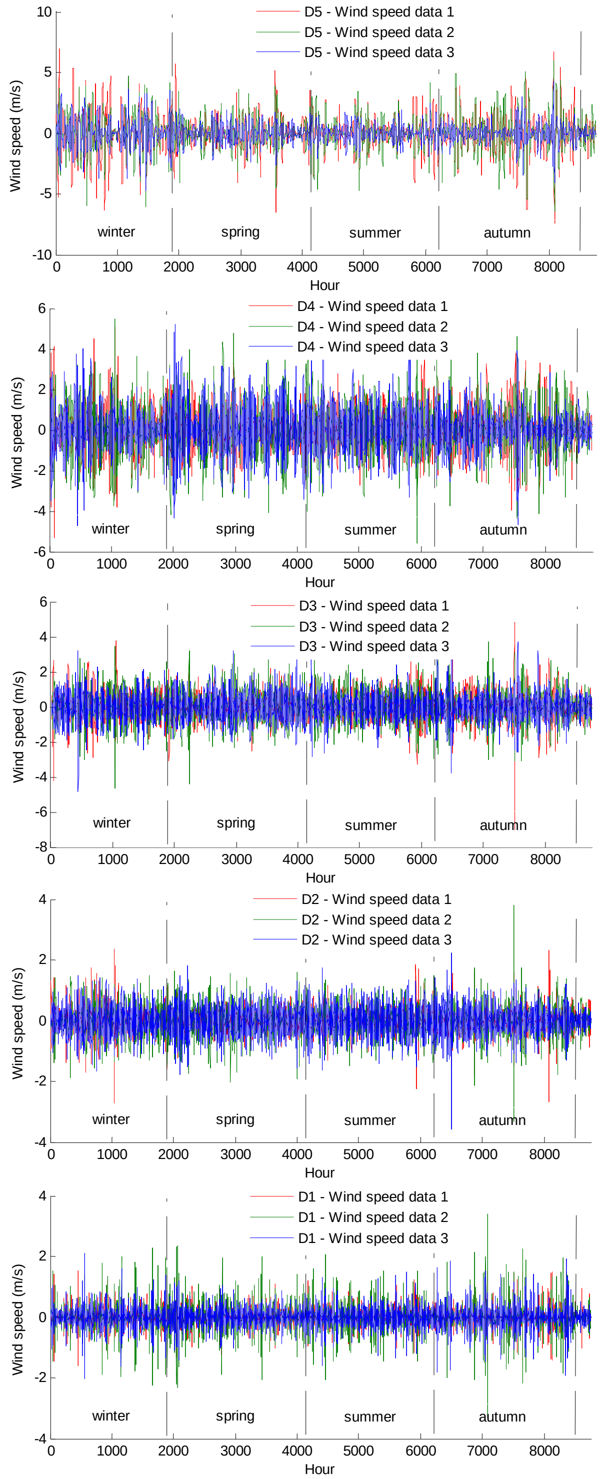


Fig. 3 Components of the wind speed data and their activity

For many signals, low frequency content is the most important part. In fact it is a characteristic of the signal and corresponds to the low pass filter. The high frequency content imparts flavour or nuance and corresponds to the high pass filter. Fig. 3 show components of the three selected signals of the wind speed data and their activity. In order to gain a better view of the wind potential at selected locations, the data are shown in a period of seasons. The signals for each location contain the seasonal variations. For low frequency component signals (A7) of three seasonal variations are evident. Somewhat lower values of wind speed are obvious to the seasons of spring and summer, while the wind speed is a lot more intense in autumn and winter time. Given that wind turbines operate with a minimum wind speed of around 4 m/s to approximately 25 m/s as the maximal wind speed value, it is obvious that the location with wind speed data 3 is not good for the potential construction of a wind farm. It is obvious that the other two locations are very interesting for potential construction of a wind farm.

From the top seven series D1, D2, D3, D4, D5, D6 and D7, we find some interesting features which can help us to analyse the data. The MRA of the signals indicate that there are some types of seasonal dependency in the variance of the details series. Magnitude of components D5, D6 and D7 were slightly higher during autumn and winter, while the smaller amplitude is present during spring and summer. Magnitude of components D1, D2, D3 and D4 are quite similar and constant throughout the year. Calculating energy at different decomposition levels, it is possible to compare the intensity of the signal components during the year. Table I shows results of calculated energy of the wind speed data at decomposition levels.

TABLE I
ENERGY OF THE WIND SPEED DATA AT DECOMPOSITION LEVELS

	WIND SPEED DATA 1	WIND SPEED DATA 2	WIND SPEED DATA 3
		$(m/s)^2$	
D1	321.74	636.61	414.66
D2	782.50	1156.63	1121.41
D3	3681.84	4135.78	3220.88
D4	7964.69	11080.93	8138.84
D5	19117.69	14865.61	5634.18
D6	23408.43	20541.95	7830.74
D7	29927.70	22600.76	6390.61
A7	521860.30	368307.30	130695.80
TOTAL	607065.00	443326.00	163447.00

The DWT's coefficients represent amplitude of wavelet decompositions associated with the time-frequency information at certain spectral bands. Energy of wavelet decompositions, however, plays more significant role than the amplitude themselves, because the energy of wavelet decompositions relates to the energy contribution of coefficients on total energy of original time series.

Values of energy in D1, D2, D3 and D4 component of signal wind speed data 2 is higher during the year than the other two. This is primarily due to the influence of local factors, since the location that corresponds to wind speed data 2 lies on the border between continental and Mediterranean climate.

IV. CONCLUSION

A good analysis of wind speed data is a key factor in the selection of potential locations for future wind farm constructions. In this paper, a wavelet transform has been applied to analyze the wind speed data in the context of insight into characteristics of the wind potential and the selection of suitable locations that could be the subject of a wind farm construction. It has been shown that this approach provides a good insight into the characteristics of the wind potential at the analyzed locations. For the presentation of the methodology used in this paper, three locations were selected and their average hourly wind speed data were analyzed. In the same way, this approach allows the analysis of data for a time period of several years, for data available in electronic wind atlases, which are generally available.

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