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Wind Speed Simulation Using Wavelets

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Abstract: Most of the renewable energy sources have direct or indirect link with the sun. Wind is also a form of solar energy. It is initiated by uneven heating of the atmospheric air by the sun, affected from the topography and surface roughness of the earth's surface and rotation of the earth. The earth's terrain, water surfaces and vegetation cover modifies wind flow patterns. Wind energy or wind power terms describe the process by which the wind is used to generate mechanical energy or electricity. In view of this, there has been several studies of wind speed characteristics in different parts of the world using Weibull distribution and Fourier method of time series analysis. Wavelet methods invented in mid-eighties have attracted attention of Engineers, Physicists, Computer Scientists and Mathematicians alike for applications purposes in diverse fields. So much so that two prominent workers of this field Coifman and Daubechies have been given prestigious awards of U.S.A. in the year 2000 for their contribution in this field. In the present study we apply wavelet methods and related software to study wind speed data of certain places in Saudi Arabia.

Key words: Wind Speed, Simulation, Wavelets

INTRODUCTION

In the U.S.A. and in many other countries of the world, wind was a widespread source of energy on farms for the production of electricity for a long time in the last century. In the recent past wind energy is being examined as a possible source of electricity generation for individual houses and for integrated systems. In view of this pattern, wind speed characteristics has been studied by several researchers [1-5] and using Weibull distribution and Fourier method of time series analysis.

In the present study we apply wavelet methods and related software especially Wavelet tool box and FAWAV to study wind speed in Dhahran, Saudi Arabia. In 1982 Jean Morlet, French geophysical engineer introduced the concept of wavelet, meaning small wave and studied wavelet transform as a new tool for seismic signal and analysis. Immediately Alex Grossmann, a French theoretical physicist, studied inverse formula for the Wavelet transform. In 1984, the collaboration of Morlet and Grossmann yielded detailed mathematical study of the continuous wavelet transforms and their applications [6].

In the recent years wavelet methodology has been applied to study problems of atmospheric turbulence, ocean wind waves, sea floor bathymetry, seismic data, environmental biology, electrocardiogram data, temperature variation and global warming [7-13]. Wavelet methodology is capable of revealing aspects of data that other signal analysis techniques lack, aspects like trends, break down points, discontinuities in higher derivatives and self-similarity.

A wavelet is a waveform of effectively limited duration that has an average value of zero. As we know Fourier analysis consists of breaking up of a signal into line waves of various frequencies. Similarly, wavelet analysis is the breaking of a signal function, into shifted and scaled versions of the originator (or mother) wavelet. Just looking at pictures of wavelets and sine waves, one can say intuitively that signals with sharp changes might be better analyzed with an irregular wavelet with a smooth sinusoid.

MATERIALS AND METHODS

The meteorological data collection program in Saudi Arabia dates back to 1970. At present there are 20 locations in the Kingdom of Saudi Arabia where hourly mean values of meteorological parameters are measured and recorded. These measured parameters include mean, maximum and minimum values of wind speed, wind direction, dry bulb temperature, wet bulb temperature, relative humidity, rain, visibility and cloud type. This study utilizes hourly mean values of wind speed at Dhahran (Latitude = 26°06', Longitude = 50°10' and Altitude = 22 m), which is located on the east coast of Saudi Arabia. These meteorological stations are maintained by the government organization. The data collection program in Saudi Arabia was started in 1970.

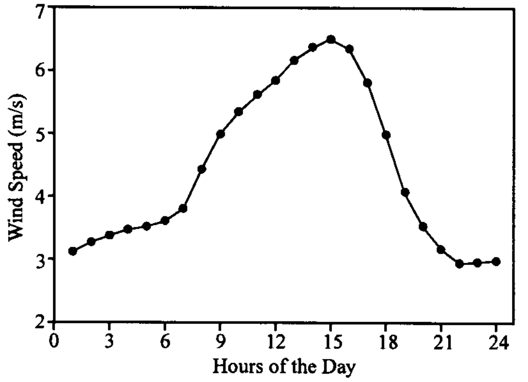

Fig. 1: Hourly Average Wind Speed Variation at Dhahran

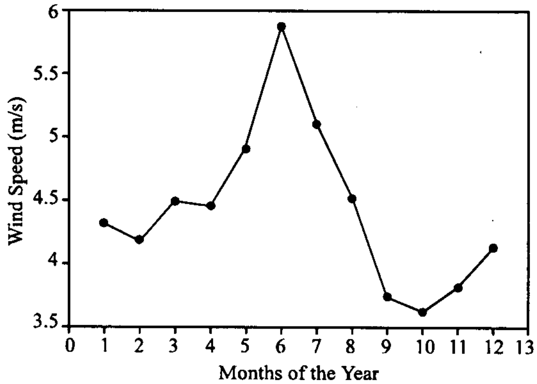

Fig. 2: Monthly Average Wind Speed Variation at Dhahran

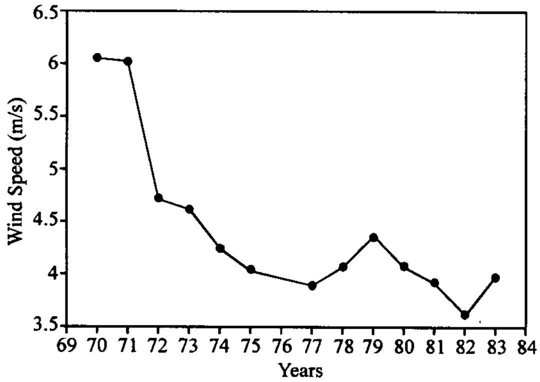

Fig. 3: Yearly Average Wind Speed Variation at Dhahran

The diurnal variation of hourly mean wind speed values at Dhahran is shown in Fig. 1. These hourly values are the average values calculated based on the data between 1970 and 1984. The mornings and the evenings are found to have smaller wind speed values compared to daytime. The month-to-month and year-to-year variation of mean values calculated over the period 1970 to 1984 is shown in Fig. 3 and 4, respectively. It is evident from Fig. 2 that the maximum mean wind speed is observed in the month of June while the minimum in October. So higher wind speeds are observed during summer months while smaller in winter months. Figure 3 shows the long-term variation of mean wind speed with year between 1970 and 1983. As seen from Fig. 3, the yearly mean values have decreased all the way from 1970 to 1983 with few exceptions between 1978 and 1981. This states a decreasing trend of wind speed values.

Any discussion of wavelets starts with Haar, the first and the simplest method. Haar is discontinuous and similar to a step function. It is the same as Daubechies wavelet 1 (db_1). Ingrid Daubechies, who has won several prestigious awards in the recent past, invented compactly supported orthonormal wavelets. The names of the Daubechies family wavelets are written db_N, where N is the order and db the surname of the wavelet. In this series, db_1 is the same as Haar. Properties of db_N, N=1, 2, 3, ... 10 can be obtained by typing waveinfo (db) from the MATLAB command line.

Coiflets were built by Ingrid Daubechies at the request of Renold Coifman. Coifman has received the U.S.A. president's award-2000 for his contribution in this field. Main properties of this class of wavelets can by obtained by typing waveinfo (coif) from the MATLAB command line. Other wavelets, like Morlet, Mexican Hat, Meyer and Symlets can be also obtained from MATLAB command line. The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled shifted versions of the wavelet function ψ:

$$C(scale, position) = \int_{-\infty}^{\infty} f(t)\psi(scale, position, t)dt$$

The results of the CWT are many wavelets coefficients C which are functions of scale and position. Scaling a wavelet simply means stretching or compressing it. Scale factor, usually, is denoted by a effects the shape of the wavelets. The smaller the scale factor, the more compressed the wavelets. Shifting a wavelet simply means delaying or hastening its onset. Mathematically, delaying a function f(t) by k is represented by f(t-k). In general a filter A is defined by: $Af_k = \sum_{m \in Z} a_{m-2k} f_m$

where, $f = (f_1, f_2, f_3, ..., f_m, ...)$.

$\{Af_k\} \in \ell_2 = \{\{a_k\} / |a_k|^2 < \infty\}$ that is, the filtering process consists of a discrete convolution of the filter sequence with the signal. The low pass filter is defined as:

$Hc_{j,k} = c_{j-1,k}, k$ fixed, where, $c_{j-1,k} = \sum_{m \in Z} a_{m-2k} c_{j,m}$. The high pass filter is defined as $Gc_{j,k} = d_{j-1}, k$ where, $d_{j-1}, k = \sum_{m \in Z} (-1)^m a_{-m+2k+1} c_{j,k}$. For Haar wavelet $a_0 = a_1 = \frac{1}{\sqrt{2}}$ and for $f = (f_1, f_2, f_3, ..., f_k, ...) = \{f_k\} \in \ell_2, Hf = f_k'$ where, $f_k' = \frac{1}{\sqrt{2}}(f_{2k} + f_{2k-1})$ and $Gf = f_k^*$, where, $f_k^* = \frac{1}{\sqrt{2}}(f_{2k} - f_{2k-1})$.

For many signals, the low frequency content is the most important part. In fact it is the characteristic of the signal and corresponds to the low pass filter H, often denoted by A also known as the approximation of the original, say S=f. The high frequency content imparts flavor or nuance and corresponds to the high pass filter, often denoted by D and known as the detail of the signal S=f. Thus the approximations are the low scale, high frequency components.

$c_{j,k} = \int_R f(t)\psi_{j,k}(2^j t - k)$ where, ψ is an arbitrary wavelet.

The detail coefficient cD (wavelet coefficients of D with respect to ψ, choose f(t) = D in the definition wavelet coefficients) consists mainly of the high frequency noise while the approximation coefficients cA contain much less noise than does the original signal. Using the MATLAB wavelet toolbox one can perform the following operations:

* Loading a signal
* A single level wavelet decomposition of a signal
* Construction of approximations and details from the coefficients
* Display of the approximations and details
* Regeneration of a signal by inverse wavelet transform
* A multilevel wavelet decomposition of a signal
* Extraction of approximation and detail coefficients
* Reconstruction of the level 3 approximation
* Reconstruction of the level 1, 2 and 3 details
* Display of the results of a multilevel decomposition
* Reconstruction of the original signal from the level 3 decomposition
* Removal of the noise from a signal
* Refinement of an analysis
* Compression of a signal
* Display of statistics and histograms of a signal

In the present study we performed the above operations on the hourly mean values of the wind speed data for Riyadh, Saudi Arabia. This wind speed data is treated just like a signal using the graphical interface tools. Using wavelet tools of the MATLAB and FAWAV software performs the wavelet analysis. In addition to the above listed operation, following problems were also addressed:

* Detection of discontinuities and breakdown points
* Detection of long term evolution
* Detection of self similarity
* Identification of pure frequencies

Detecting of Discontinuities: Wavelet analysis can detect the exact instant when a signal changes. The discontinuous signal consists of a slow sine wave abruptly followed by a medium sine wave. The first and second details D1 and D2 show the discontinuity most clearly because the rupture contains the high frequency part. It may be noted that if we are only interested in identifying the discontinuity, db1 would be a more useful wavelet than db5. The purpose of the analysis is to determine the site of the change (e.g. time or position), the type of change (a rupture of the signal, or an abrupt change in its first or second derivative) and the amplitude of the change. It may be observed that short wavelets are often more effective than the long ones in detecting a signal rupture. In the initial analysis scales, the support is small enough to allow fine analysis. The shapes of discontinuities that can be identified by the smaller wavelets are simpler than those that can be identified by the l ongest wavelets. The presence of noise, which is after all a fairly common situation in signal processing, makes identification of discontinuities more complicated. If the first level of decomposition can be used to eliminate a large part of the noise, the rupture is sometimes visible at deeper levels in the decomposition.

Detecting Long-Term Evolution: Wavelet analysis can detect the overall trend of a signal. We consider a signal which is a ramp obscured by colored (limited-spectrum) noise for example Fig. 4. There is so much noise in the original signal, s, that its overall shape is not apparent upon visual inspection. In this level-12 analysis, we note that the trend becomes more and more clear with each approximation, A1 to A12 (Fig. 4-6). The trend represents the slowest part of the signal. In wavelet analysis terms, this corresponds to the greatest scale value. As the scale increases, the resolution decreases, producing better estimate of the unknown trend. Wavelet analysis is useful in revealing signal trends, a goal that is complementary to the one revealing a signal hidden in noise. If the signal itself includes sharp changes then successive approximations look less and less similar to the original signal.

Detecting Self-Similarity: A repeating pattern in the wavelet coefficients plot is characteristic of a signal that looks similar on many scales. From an intuitive point of view, the wavelet decomposition consists of calculating a resemblance index between the signal and the wavelet. If the index is large, the resemblance is strong otherwise it is weak. The indices are the wavelet coefficients. If a signal is similar to itself at different scales then the resemblance index or the wavelet coefficients will also be similar at different scales. In the coefficients plot, which shows scale on the vertical axis, this self-similarity generates a characteristic pattern. It may also be observed that the authoritative studies suggest that wavelet decomposition is very well adapted to the study of the practical properties of signals and images.

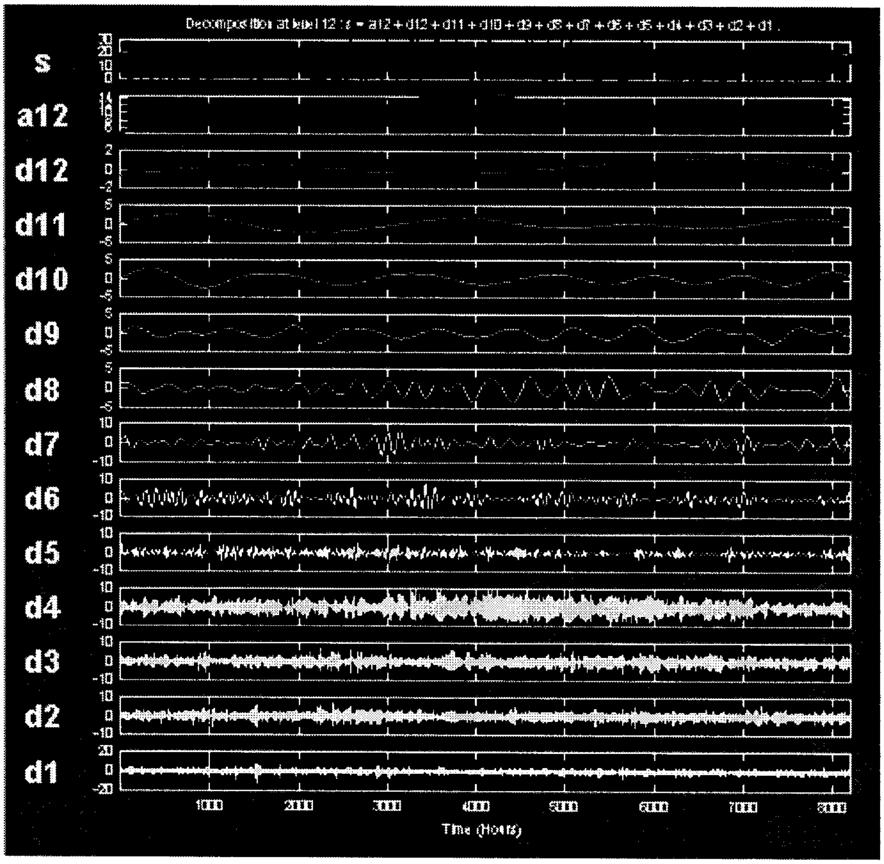

Fig. 4: Decomposition of Hourly Mean Wind Speed Data Using db10 with 12 Levels

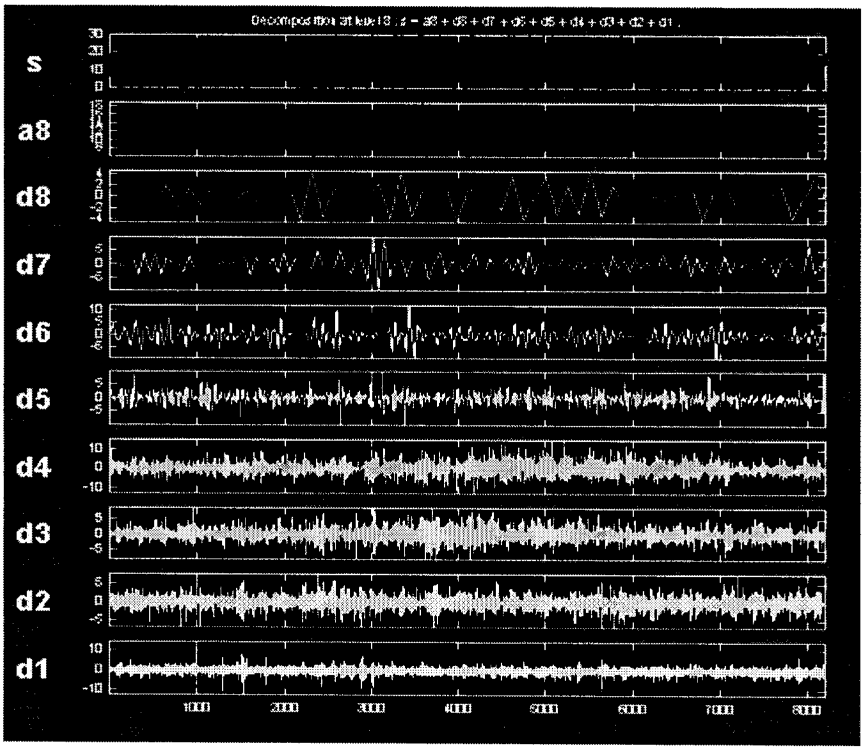

Fig. 5: Decomposition of Hourly Wind Speed Data Using db3 with 8 Levels

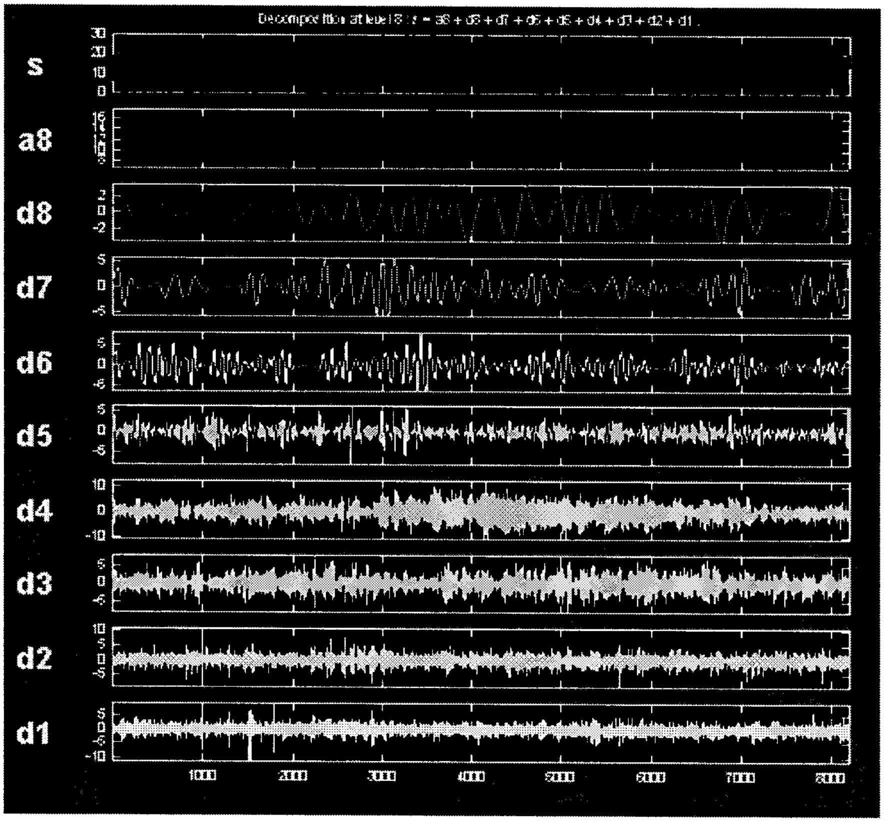

Fig. 6: Decomposition of Hourly Wind Speed Data Using db6 with 8 Levels

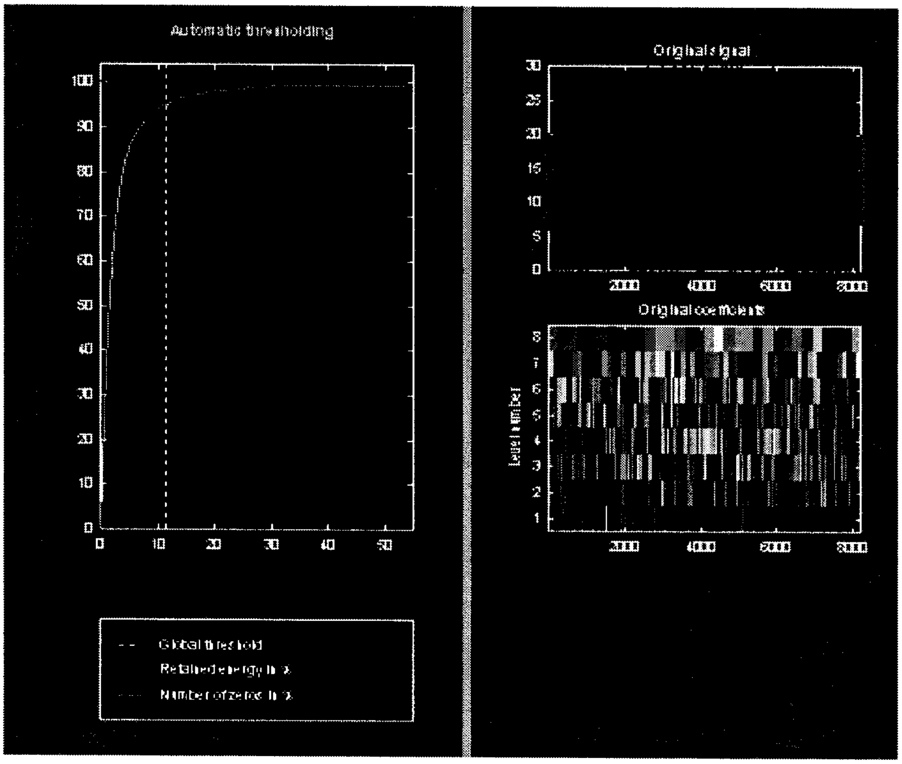

Fig. 7: Compression of Hourly Wind Speed Data Using db6 with Levels 8

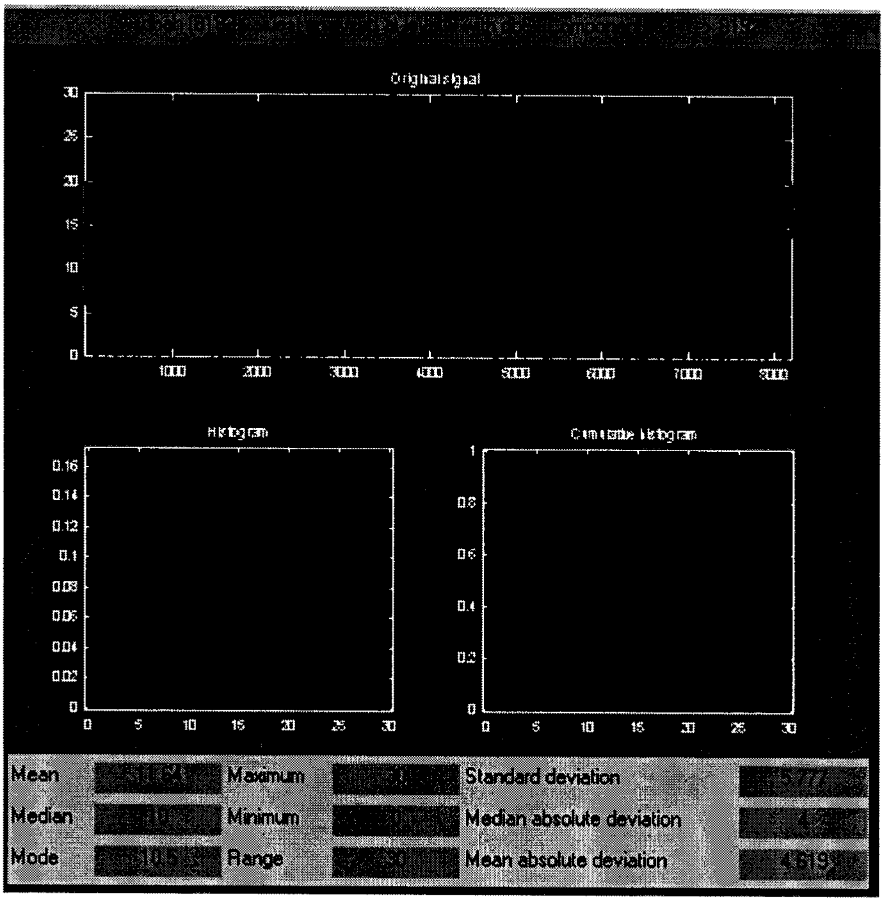

Fig. 8: Statistics of the Original Hourly Wind Speed Data with db6 and Levels 8

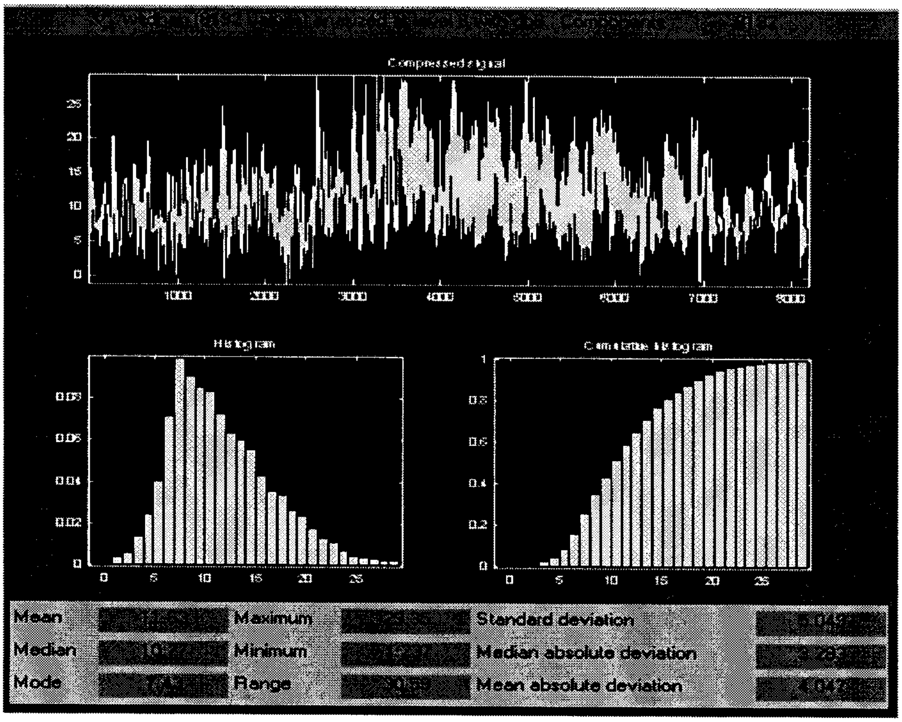

Fig. 9: Statistics of Compressed Hourly wind Speed Data with db6 and Level 8

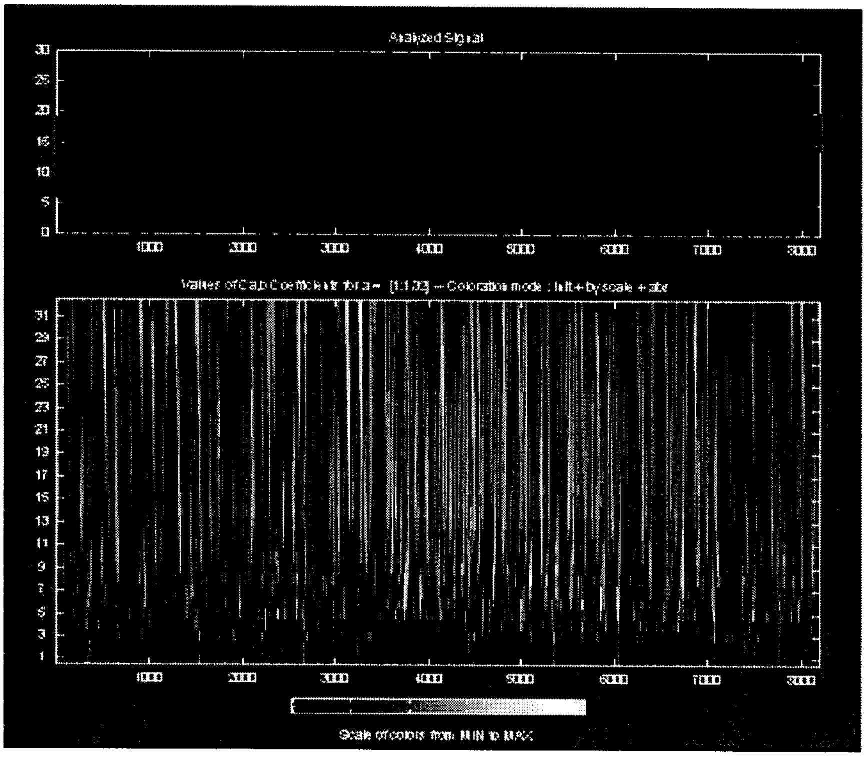

Fig. 10: Detection of Self-similarity of Hourly Wind Speed Data with db6

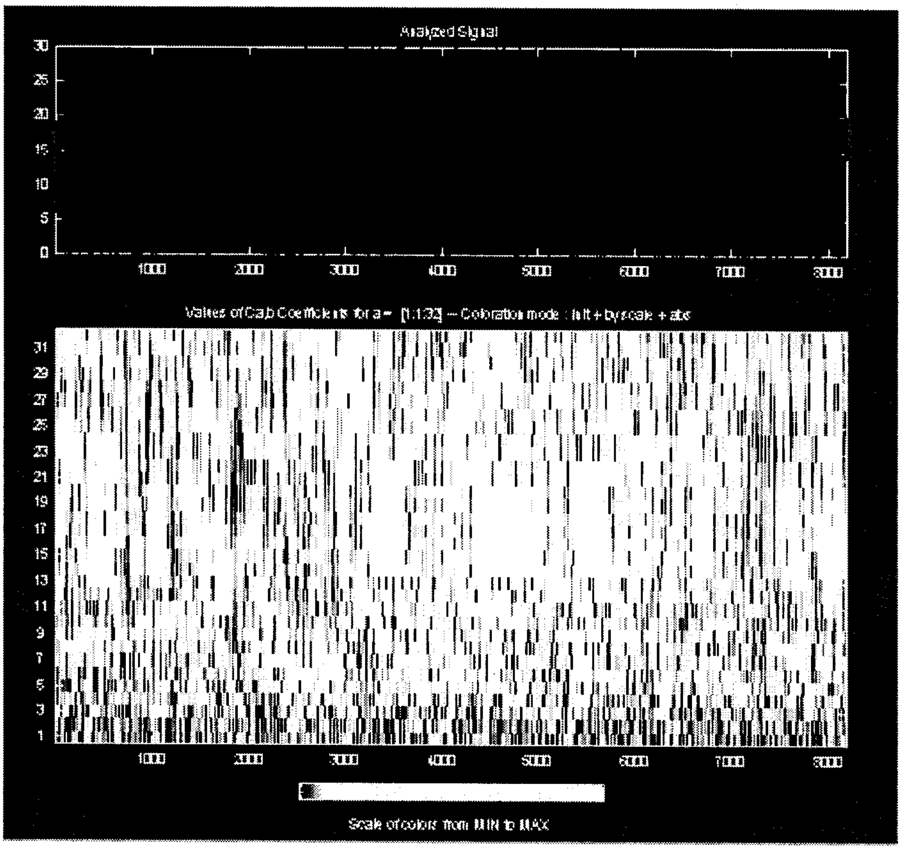

Fig. 11: Detection of Self-similarity of Hourly Wind Speed Data with db6

RESULTS

Decomposition of hourly wind speed data using db10 at level 12, db3 at level 8, db6 at level 8 can be seen, respectively in Fig. 4-6. It is an easy and authentic way to visual changes in the wind speed data at different levels. Compression of this data using db6 at level 8 is given in Fig. 7. Statistics of original data and compressed data using db6 at level 8 can be seen, respectively in Fig. 8 and 9. Figures 10 and 11 present self-similarity in the data under considered.

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