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Spectral Analysis of Particulate Matter in the Atmosphere using Wavelet Transforms

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Abstract: Particulate matter contains solid or liquid particles that are transported and dispersed in the atmosphere. Study of particulate matter has attracted the great interest of scientists due to the effect on human health and its major role in climate change. Reduced lung function, development in respiratory diseases and premature death are the effect of long-term exposure to particle pollution. Wavelet transforms provide excellent analysis of non-stationary time series and extracts important information. Daubechies4 wavelet is orthogonal and compactly supportive and therefore, it is useful for multiresolution analysis of PM data. Skewness and Kurtosis parameter describes the lack of the symmetry of data and correlation coefficient between PM10 and PM2.5 describes the linear relationship between them.

Keywords: Particulate Matter; PM10; PM2.5; Wavelet; Wavelet; Wavelet Transforms.

I. INTRODUCTION

Particulate matter (PM), also called particle pollution, is used to describe solid or liquid particles that are airborne and transported and dispersed in the atmosphere. Particles vary in number, size, shape, surface area, chemical composition, and solubility. PM originates from a variety of natural or anthropogenic sources and possesses a range of morphological, physical, chemical, and thermodynamic properties [1]. The sources of PM10 and PM2.5 include a wide range of natural phenomena and human activities. Coarse particles mainly originate from sea salt, soil dust resuspension, construction & demolition activities, non-exhaust vehicle emissions, and industrial fugitives, whereas fine particles are mainly produced by combustion processes, forest fires, and transformation of gaseous species. The Primary sources of particulate matter are; Incomplete combustion, automobile emissions, dust, and cooking, while secondary sources are chemical reactions in the atmosphere. The current interest in PM is mainly due to its effect on human health [2] and its potential role in climate change [3]. Exposure to particle pollution is a public health hazard. When inhaled, particle pollution can travel deep into the lungs and cause or aggravate heart and lung diseases. Coughing, Shortness of breath, Tightness of the chest and irritation of eyes are the effect of short-term exposure. While reduced lung function, development in respiratory diseases and premature death are the effect of long-term exposure to particle pollution. Particle Pollution Affects the Heart Inhaled particles can pass from the lungs into the bloodstream and affect the cardiovascular system. National and International directives and legislations require lower and lower ambient near-surface PM concentrations.

The different behavior of PM10 and PM2.5 could be explained considering that the SD events have a lower importance on PM2.5 because the dust is mainly in the coarse size range. Thereby, the increase in the hot weather of this contribution is not able to compensate the decrease of anthropogenic emissions (traffic and domestic heating) in PM2.5 concentrations as it does in PM10 concentrations [4, 5]. It can be seen that concentrations of particulate matter have an obviously negative correlation with air temperature. As air temperature rises, the concentration of particulate matter is significantly decreased. The lower atmosphere is not very stable and turbulent strengthens, which is advantageous to the diffusion of pollutants. Therefore, the probability of atmospheric pollution decreased with the increase of air temperature in summer. While the temperature of the surface is low, the situation is contrary. Atmospheric pressure and concentrations of particulate matter are significantly positively correlated. It has shown that air temperature, precipitation, and other meteorological factors can preferably explain the relationship between concentrations of particulate matter and meteorological factors [6, 7]]. Atmospheric pressure and concentrations of particulate matter were significantly positively correlated, while other meteorological factors and concentrations of particulate matter have shown a negative correlation but the impact is different. The growing scientific interest in atmospheric aerosol particles is due to their high importance for environmental policy.

In fact, particulate matter constitutes one of the most challenging problems both for air quality and for climate change policies. The synthesis reveals many new processes and developments in the science underpinning climate–aerosol interactions and effects of PM on human health and the environment. However, while the airborne particulate matter is responsible for globally important influences on premature human mortality, we still do not know the relative importance of the different chemical components of PM for these effects. Likewise, the magnitude of the overall effects of PM on climate remains highly uncertain [8]. Fourier sine’s extracts only frequency information from a time signal, thus losing time information, while wavelet extracts both time evolution and frequency composition of a signal. Therefore Wavelet provides a new tool in the emerging field of data analysis for Physicists, Engineers, and environmentalists [9, 10]. It represents an efficient computational algorithm under the interest of a broad community.

II. THEORETICAL BACKGROUND

Wavelet represents an efficient computational algorithm under the interest of a broad community. Wavelet is a special kind of the functions which exhibit oscillatory behaviour for a short time interval and then dies out. In wavelet, we use a single function and its dilation and translation to generate a set of orthonormal basis functions to represent a signal [11, 12]. A number of such functions are infinite and we choose one that suits to our application. The range of interval over which scaling function and wavelet function are defined is known as support of wavelet. Beyond this interval (support) the functions should be identically zero. There is an interesting relation between the length of support and number of coefficients in the refinement relation. For orthogonal wavelet system, the length of support is always less than no. of coefficients in the refinement relation. It is also very helpful to require that the mother function has a certain number of zero moments, according to:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0$$

The mother function can be used to generate a whole family of wavelets by translating and scaling the mother wavelet.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) = T_b D_a \psi$$

Here b is the translation parameter and a is the dilation or scaling parameter. Provided that $\psi(t)$ is real-valued, this collection of wavelets can be used as an orthonormal basis. A critical sampling of the continuous wavelet transform is

$$W_{a,b} = \int f(t) \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) dt$$

is obtained via $a = 2^{-j}$, where j and k are integers representing the set of discrete translations and discrete dilations. Upon this substitution, we can write discrete wavelet transform as;

$$W_{j,k} = \int f(t) 2^{j/2} \psi(2^j t - k) dt$$

Wavelet coefficients for every (a, b) combination whereas in discrete wavelet transform, we find wavelet coefficients only at very few points by the dots and the wavelets that follow these values are given by;

$$\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k)$$

This wavelet coefficient for all j and k produce an orthonormal basis. We call $\psi_{0,0}(t) = \psi(t)$ as mother wavelet. Other wavelets are produced by translation and dilation of mother wavelet. The wavelet transform of a signal captures the localized time frequency information of the signal. Suppose we are given a signal or sequences of data $S = \{S_n\}_{n \in \mathbb{Z}}$ sampled at regular time interval Δt . S is split into a “blurred” version a_1 at the coarser interval $\Delta t \square 2$ and “detail” d_1 at scale Δt . This process is repeated and gives a sequence $S_n, a_1, a_2, a_3, a_4, \dots$ of more and more blurred versions together with the details $d_1, d_2, d_3, d_4, \dots$ removed at every scale ($\Delta t = 2^m \tau$ in a_m and d_m). Here a_m s and d_m s are approximation and details of original signal. After N iteration the original signal S can be reconstructed as

$$S = a_N + d_1 + d_2 + d_3 + \dots \dots d_N$$

III. METHODOLOGY

The primary and most important work in the spectral analysis of any signal using wavelet transforms is the selection of suitable wavelet according to the signal. Suitable wavelet is selected on the basis of compatibility with signal characteristics. Accurate wavelet selection retains the original signal and also enhances the frequency spectrum of the denoised signal. Wavelet extracts both time evolution and frequency composition of a signal.

A multiresolution analysis for $L^2(\mathbb{R})$ consists of a Sequence $V_j, j \in \mathbb{Z}$ of closed subspaces of $L^2(\mathbb{R})$. Let $f(x)$ be a function in $L^2(\mathbb{R})$. We can write $f(x)$ in V_{j+1} space, i.e.,

$$f(x) = \sum c_{j+1,k} \phi_{j+1,k}(x)$$

Since

$$V_{j+1} = V_j \oplus W_j$$

where

$$V_{j+1} = \overline{\text{span}(\phi_{j+1,k}(x))}$$

$$V_j = \overline{\text{span}(\phi_{j,k}(x))}$$

$$W_j = \overline{\text{span}(\psi_{j,k}(x))}$$

Therefore

$$f(x) = \sum_k c_{j,k} \phi_{j,k}(x) + \sum_{j_0}^j \sum_k d_{j,k} \psi_{j,k}(x)$$

Where

$$c_{j,k} = \langle f, \phi_{j,k} \rangle$$

$$= \int f(x) \phi_{j,k}(x) dx, \quad \forall k \in \mathbb{Z}$$

and

$$d_{j,k} = \langle f, \psi_{j,k} \rangle$$

$$= \int f(x) \psi_{j,k}(x) dx$$

are collectively known as an approximation and detailed coefficients. Thus given signal takes place a new version such as [10]

$$\begin{aligned} f(1) &= a_1 + d_1 \\ f(2) &= a_2 + d_2 + d_1 \\ f(3) &= a_3 + d_3 + d_2 + d_1 \\ f(4) &= a_4 + d_4 + d_3 + d_2 + d_1 \\ f(5) &= a_5 + d_5 + d_4 + d_3 + d_2 + d_1 \\ f(6) &= a_6 + d_6 + d_5 + d_4 + d_3 + d_2 + d_1 \\ f(7) &= a_7 + d_7 + d_6 + d_5 + d_4 + d_3 + d_2 + d_1 \\ f(8) &= a_8 + d_8 + d_7 + d_6 + d_5 + d_4 + d_3 + d_2 + d_1 \end{aligned}$$

Here $a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8$ are approximations of signal and $d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_8$ are details of signal at various scale or time frames. A signal f can be decomposed as in simplest form;

$$f = A + D$$

Where A and D are called Approximation and Details of the given signal f . Approximation is average of the signal and hence represents low frequency components, while Detail is the difference of the signal and hence represents high frequency components. Detail plays very important role and provides hidden information of any signal. The wavelet is a new analytical tool for chaotic data to the physics community. It allows detection and characterization of short-lived structures in data [13, 14].

IV. RESULTS AND DISCUSSION

Our study area is Anand Vihar, Delhi and we have used data observed by DPCC Anand Vihar. We have taken an average quantity of PM10 and PM2.5 for a day from 01-07-2016 to 13-03-2017.

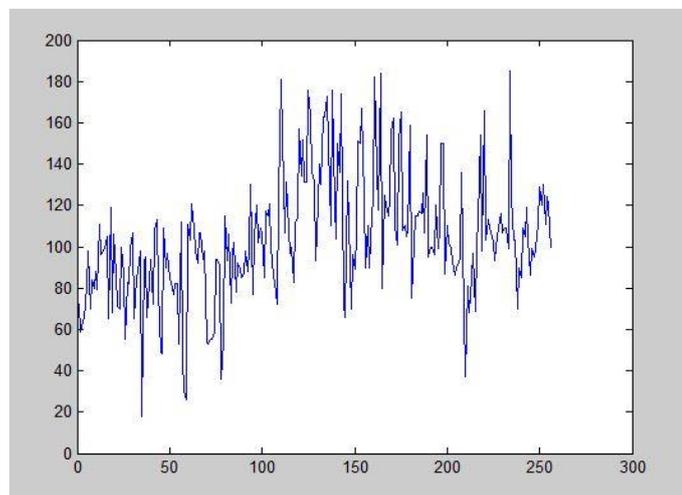


Figure 1: Average quantity of PM10 (in ppb)

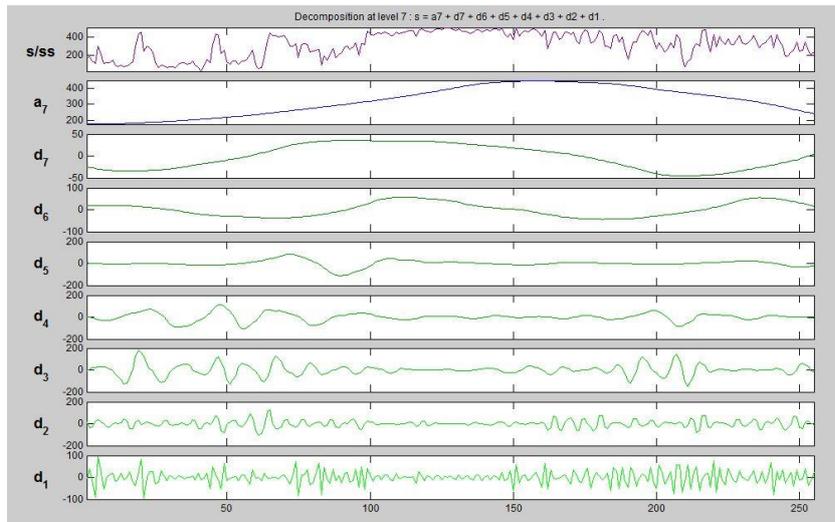


Figure 2: Wavelet decomposition of PM10

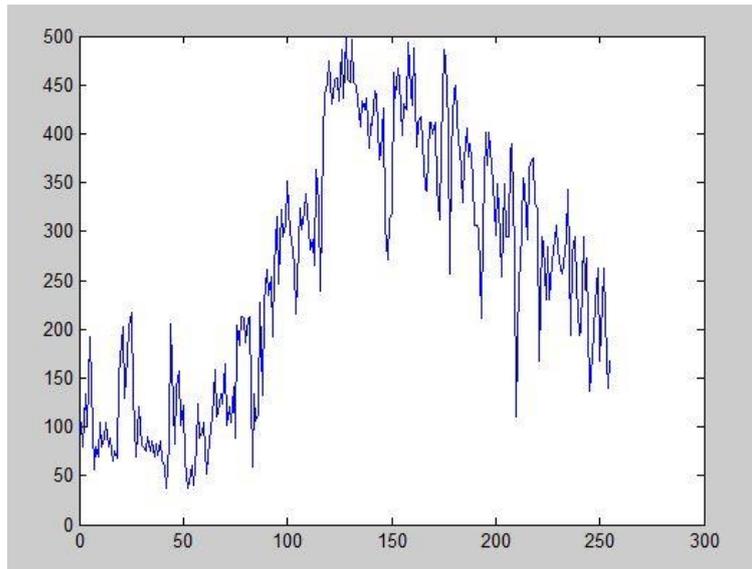


Figure 3: Average quantity of PM2.5

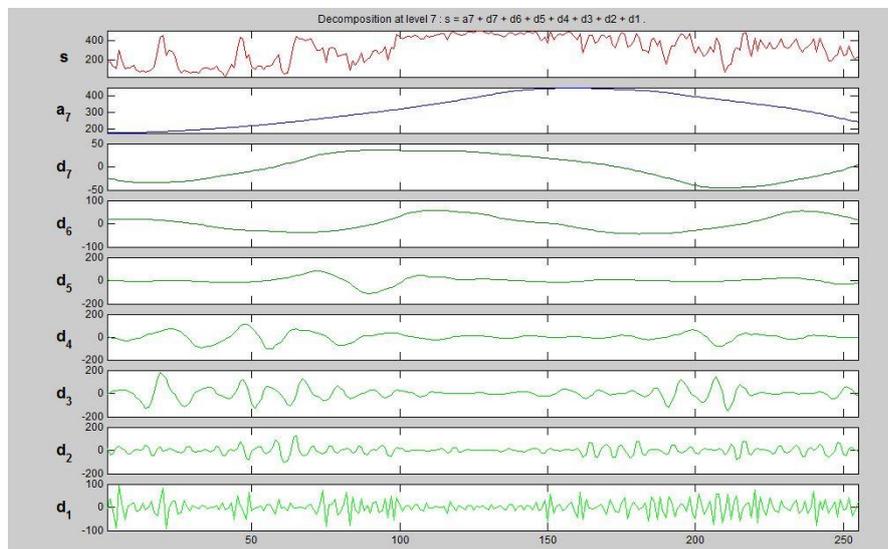


Figure 4: Wavelet decomposition of PM2.5

The original time series of PM10 and PM2.5 are shown in figure 1 & 3. A full decomposition of PM10 time series is shown in figure 2 and that of PM2.5 in Figure 4. In decomposition figures a1, a2, a3, a4, a5, a6, a7 and a8 are approximations and d1, d2, d3, d4, d5, d6, d7, and d8 are details of the of CO time series at different time modes. Original time series represents the average value of particulate matter taken as a one-day interval. Approximation a8 represents the behaviour of the signal S at level 8. While details d1 exhibits per day variation, d2 shows 2-days variation and d3 is 4-days variation in the value of CO also d4, d5, d6, d7 and d8 are variation in the value of the particulate matter in 8, 16, 32, 64, and 128 days mode, respectively. A peak in a detail shows rapid fall or rise in the value in that time mode.

We have calculated the value of skewness parameter for PM10 -0.42901 and Kurtosis parameter -1.12602, while skewness parameter for PM2.5 0.001437 and kurtosis parameter -1.22797. A positive value of skewness indicates that data are skewed right while a negative value shows that data are skewed left. The behaviour of skewness parameter tells about the intermittency phenomenon. Correlation describes the degree of linear relationship between two functions (or signals). The value of correlation coefficient for PM10 and PM2.5 is 0.822449. A positive value means that PM10 and PM2.5 are linearly related and high value means that PM10 and PM2.5 in the atmosphere are strongly correlated.

CONCLUSION

The wavelet method allows the decomposition of the signal according to different frequency levels which characterize the intensity of natural and man-made disturbances. According to the behaviour studied, it is possible to conjecture that the difference between all-time series can be directly associated with a large number of anthropogenic activity. Taking into account these results we have shown, the wavelet analytical approach provides a simple and accurate framework for modeling the statistical behaviour of particulate matter variation. The behaviour of skewness parameter tells about the intermittency phenomenon of PM10 and PM2.5. The positive and high value of correlation coefficient represents directly and strongly correlation between PM10 and PM2.5 in the atmosphere.

REFERENCES

- [1]. J. Flemming, R. Stern, and R. J. Yamartino, "A new air quality regime classification scheme for O3, NO2, SO2 and PM10 observations sites", *Atmos. Environ.*, Vol. 39, pp. 6121–6129, 2005.
- [2] A. J. COHEN, "Outdoor air pollution and lung cancer", *Environmental health perspectives*, Vol. 108, pp. 743–750, 2000.
- [3] A. Bunde, S. Havlin, E. Koscielny-Bunde, and H. J. Schellnhuber, "Long-term persistence in the atmosphere: Global laws and tests of climate models", *Physica A, Stat. Mech. Apps* Vol. 302, pp. 255-267, 2001.
- [4] R. J. Charlson, S. E. Schwartz, J. M. Hales, D. Cess, J. A. Coakley, and J. E. Hansen, "Climate forcing by anthropogenic aerosols", *Science*, 1992, Vol. 255, pp. 423–430, 1992.
- [5] S. Beirle, U. Platt, M. Wenig, and T. Wagner, "Weekly cycle of NO2 by GOME measurements: A signature of anthropogenic sources", *Atmos. Chem. Phys.*, Vol. 3, pp. 2225–2232, 2003.
- [6] J. J. Lin, "Characterization of water-soluble ion species in urban ambient particles" *Environ. Int.* Vol. 28, 55–61, 2002.
- [7] C. Y. Mu, Y. Q. Tu and Y. Feng, "Effect analysis of meteorological factors on the inhalable particle matter concentration of atmosphere in Hami", *Meteorol. Environ. Sci.*, Vol. 34, pp. 75–79, 2011.
- [8] S. G. Dobrovolski, *Stochastic Climate Theory, Models, and Applications*, Nerlin-Heidelberg, Springer, 2009.
- [9] C. K. Chui, *An Introduction to Wavelets*, Academic Press, New York, 1992.
- [10] J. P. Antoine, "Wavelet analysis: A new tool in Physics", *Wavelets in Physics*, Van Der Berg, J. C., ed., 2004, 9-21.
- [11] S. G. Mallat, *A wavelet tour of Signal Processing*, Academic Press, New York, 1998.
- [12] I. Daubechies, "Ten lectures on wavelets", *CBS-NSF, Regional Conference in Applied Mathematics*, SIAM Philadelphia, Vol. 61, 1992, pp. 278-285,
- [13] M. Farge, "Wavelet transforms and their applications to turbulence", *Annu. Rev. Fluid Mech.*, Vol. 24, pp. 395–457, 1992.
- [14] A. Grinsted, J. C. Moore and S. Jevrejeva, "Application of the cross wavelet transform and wavelet coherence to geophysical time series", *Nonl. Proc. Geophy.*, Vol. 11, pp. 561-566, 2004.
- [15] B. B. S. Kumar and P. S. Satyanarayana, "Image Analysis Using Biorthogonal Wavelet", *International Journal of Innovative Research And Development*, Vol. 2 (6), pp. 543-565, 2013.