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Wavelet Analysis of Air Pollution due to Carbon Monoxide

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Abstract: Carbon monoxide is the most abundant of the criteria pollutants. High concentration of Carbon monoxide generally occurs in areas with heavy traffic congestion. There are adverse effects on Human health due to the high concentration of CO in the atmosphere. The metropolitan cities are facing such type of problems a lot. In a given signal (data of average CO per day, observed by DPCC Anand Vihar, Delhi), the trend is the most important part and also slowest part of a signal. In wavelet analysis terms this corresponds to the greatest scale value. Symlet wavelet is orthogonal and compactly supportive and therefore, it is useful for multiresolution analysis of a CO data. Approximation and Detailed coefficients have been determined using Sym4 wavelet transforms.

Keywords: Carbon Monoxide, Pollution, Wavelet, Symlet, Wavelet Transforms.

I. INTRODUCTION

Carbon monoxide (CO) is a colorless, odorless gas formed when carbon in fuels is not burned completely. It is a product of motor vehicle exhaust, which contributes the most CO emissions nationwide. High concentrations of CO generally occur in areas with heavy traffic congestion. Other sources of CO emissions include industrial processes such as carbon black manufacturing, fuel combustion, and natural sources such as wildfires. Peak CO concentrations in the ambient air typically occur during the colder months of the year when CO concentrations in automotive emissions are greater and nighttime inversion conditions are more frequent. CO, in the presence of solar radiation, reacts with other chemical compounds to form ground-level ozone. As a result of current and foreseen emission reduction measures for road traffic, a downward trend in concentrations is observed at many locations, and this trend is expected to continue. The fact that industrial levels are hardly reported suggests that levels near industrial CO sources are not of major concern. CO readily reacts with hemoglobin in the human blood and as a result, the oxygen-carrying capacity of the blood is reduced. In order to protect non-smoking, middle-aged, and elderly population groups with documented or latent coronary artery disease from acute ischemic heart attacks, and to protect foetuses of non-smoking pregnant mothers from untoward hypoxic effects, the World Health Organisation (WHO) recommends that a carboxy- hemoglobin level of 2.5% should not be exceeded. For the ambient air quality, the 15- and 30-minutes guidelines give no additional protection compared to the 1- and 8-hour guidelines. A few situations have been observed where the 1- hour guideline was exceeded and the 8-hour guideline was not, but the 8-hour guideline is found to be in practice more protective than the 1-hour guideline. It is proposed to set a limit value for CO and base it on the 8-hour guideline. From a practical point of view, it is generally preferable to allow a limited number of exceedances per year. However, in the special case of CO, the levels are expected to decrease far enough to achieve full protection against exceedance of the WHO guideline [1].

CO is brought into the atmosphere by two different mechanisms: emission of CO and chemical formation from other pollutants. The chemical formation of CO is due to the oxidation of hydrocarbons, and it adds 600 - 1600 Mtonnes to the atmosphere. Two-thirds of it stems from methane. It is a slow process and does not give rise. However, being a source of the same magnitude of the direct emission, CO formation contributes considerably to the global background level. It is estimated that about one-third of CO results from natural sources, including that derived from hydrocarbon oxidation. CO reacts readily with hemoglobin in the human blood to form carboxyhaemoglobin (COHb). The affinity of haemoglobin for CO is 200-250 times that for oxygen, and as a result, this binding reduces the oxygen-carrying capacity of the blood and impairs the release of oxygen to extravascular tissues. The most important variables determining the COHb level are CO in inhaled air, duration of exposure and lung ventilation. During an exposure to a fixed concentration of CO, the COHb concentration increases rapidly at the onset of exposure, starts to level off after 3 hours, and reaches a steady-state after 6-8 hours of exposure. Physical exercise accelerates the CO uptake process. The formation of COHb is a reversible process, but because of the tight binding of CO to haemoglobin, the elimination half-life while breathing room air is 2-6.5 hours depending on the initial COHb level. The elimination half-life of COHb is much longer in the fetus than in the pregnant mother.

The toxic effects of CO become evident in organs and tissues with high oxygen consumption such as the brain, the heart, the exercising skeletal muscle, and the developing fetus. The effects of CO exposure at very high concentrations (well above ambient levels) are lethal. High concentrations may cause both reversible, short-lasting neurological deficits and severe, often delayed neurological damage. At COHb levels as low as 5.1-8.2% impaired coordination, tracking, driving ability, vigilance and cognitive performance have been observed. In healthy subjects, the endogenous production of CO During pregnancy, elevated maternal COHb levels of 0.7-2.5% have been reported, which is mainly due to increased endogenous production. The COHb levels in non-smoking general populations are usually 0.5-1.5% due to endogenous production and environmental exposures. Non-smoking people in certain occupations (car drivers, policemen, traffic wardens, garage and tunnel workers, firemen etc.) can have long-term COHb levels up to 5%, and heavy cigarette smokers have COHb levels up to 10%. Well-trained subjects engaging in a heavy exercise in polluted indoor environments can increase their COHb levels quickly up to 10- 20% [2]. In indoor ice arenas, there have been recently reported epidemic CO Poisonings. As a precursor of carbon dioxide and ozone, CO indirectly contributes to global warming and to direct effects by ozone to vegetation and materials.

Wavelet is a new development in the emerging field of data analysis for Physicists, Engineers, and Environmentalists [3], [4], [5]. It represents an efficient computational algorithm under the interest of a broad community. 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. 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. A number of such functions is 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. 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.

II. THEORETICAL BACKGROUND

It is also very helpful to require that the mother function has a certain number of zero moments, according to:

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

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 ψ(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 mothere 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 □t □□□. S is split into a "blurred" version a1 at the coarser interval □t □□2□□and "detail" d1 at scale □t □□□. This process is repeated and gives a sequence S_n , a_1, a_2, a_3, a_4,…..of more and more blurred versions together with the details d_1, d_2, d_3, d_4, …….removed at every scale ($\Delta t = 2^m\tau$ in a_m and d_m). Here a_ms and d_ms are approximation and details of original signal. After N iteration the original signal S can be reconstructed as

$$S = a_N + d_1 + d_2 + d_3 + \cdots \ldots\ldots d_N$$

A. Skewness and Kurtosis parameter: A fundamental task in many statistical analyses is to characterize the location and variability of a data set. A further characterization of the data includes skewness and kurtosis [6], [7]. Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point. Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. For univariate data $Y_1, Y_2, \ldots, Y_N$, the formula for skewness is:

$$\text{Skewness parameter } (S) = \frac{\sum_{i=1}^{N}(Y_i-\bar{Y})^3}{(N-1)s^3}$$

where $\bar{Y}$ is the mean, s is the standard deviation, and N is the number of data points. The skewness for a normal distribution is zero, and any symmetric data should have a skewness near zero. Some measurements have a lower bound and are skewed right. For example, in reliability studies, failure times cannot be negative. For univariate data $Y_1, Y_2, \ldots, Y_N$, the formula for kurtosis is:

$$\text{Kurtosis parameter}(K) = \frac{\sum_{i=1}^{N}(Y_i-\bar{Y})^4}{(N-1)s^4}$$

where $\bar{Y}$ is the mean, s is the standard deviation, and N is the number of data points.

III. METHODOLOGY

The primary and most important work in the spectral analysis of any signal (data) 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 $L^2(\mathbb{R})$ introduced by Mallat [8], [9] and extended by other researchers [10], [11], [12], consists of a Sequence $V_j, j\epsilon\mathbb{Z}$ 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,

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

Since

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

where

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

$$V_j = span\ \overline{\left(\phi_{J,k}(x)\right)}$$

$$W_j = span\ \overline{\left(\psi_{J,k}(x)\right)}$$

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;

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

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. Since maximum 8 level are possible therefore, f(8) will be combined into a zero frequency component a_8 as well as 8 frequency components $d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_8$.

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 [13], [14], [15].

IV. STUDY AREA AND RESULTS

Our study area is Anand Vihar, Delhi and we have used data (online) observed by DPCC Anand Vihar. We have taken an average quantity of CO per day from 01-07-2016 to 13-03-2017.

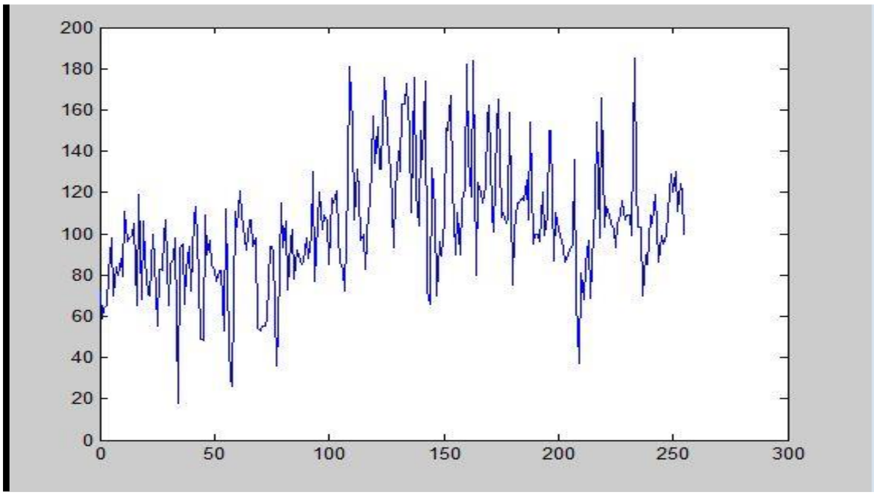

Figure 1: Average quantity of CO per day (in ppm)

In order to perform a more detailed investigation, we decompose the time series of CO at different scale by using discrete wavelet transform (Symlet4). The original time series of CO is shown in figure 1. A full decomposition of CO time series is shown in figure 2. In decomposition figures a8 is the approximation at level 6 and d1, d2, d3, d4, d5, d6, d7, and d8 are details of the of CO time series at a different time mode.

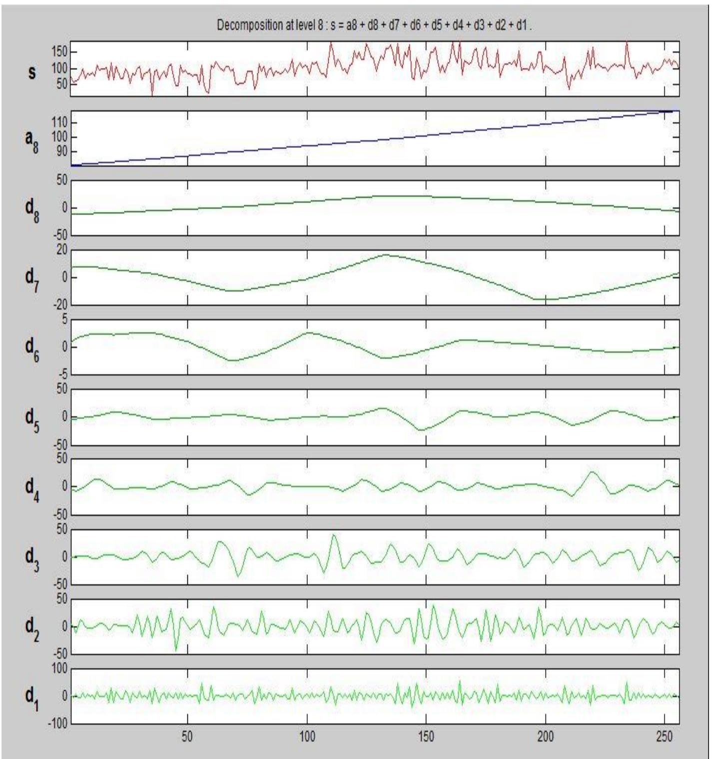

Figure 2: Wavelet decomposition of CO time series

Original time series, i. e., the average value of CO is taken as one-day interval. Approximation a1 represents the two days behaviour of the signal S, a2 represents four days behaviour of the signal, a3 is 8-days mode behaviour, a4 is the behaviour of the signal in 16-days mode and so on. Likewise, 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 CO in 8, 16, 32, 64, and 128 days mode, respectively. A peak in a detail shows rapid fall or rise in the value of CO in that time mode. The measurement of CO depends on anthropogenic driving forces. Fluctuation in quantity of CO over time may be as a result of the effluent load. In signal analysis, the low-frequency content of the signal is an important part, because it gives the identity of the signal. The trend is the slowest part of the signal means lowest frequency part of the signal. In wavelet analysis terms, this corresponds to the greatest scale value. In figure 2, it corresponds to a8. As the scale increases, the resolution decreases, producing a better estimate of the unknown trend. A trend of the CO signal is exhibited in figure 3.

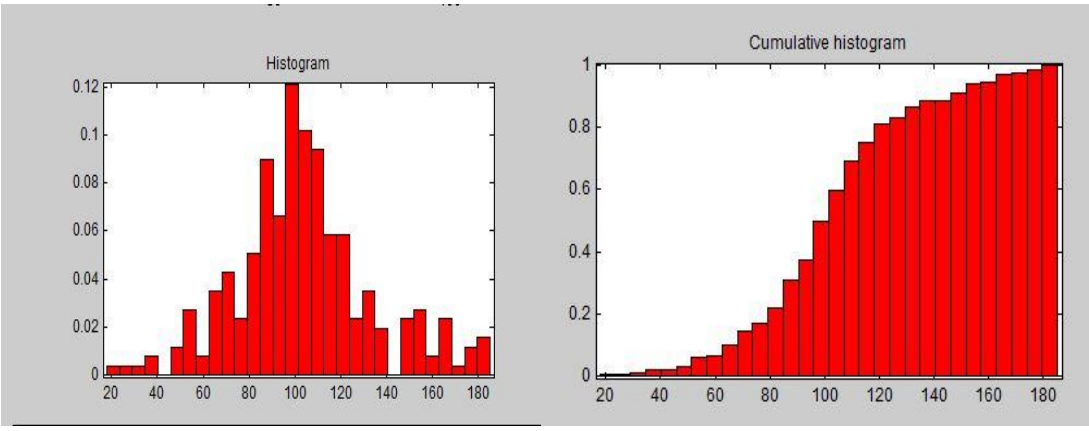

Figure 3: Histogram & Cumulative histogram

Histograms depict the trends of the average value of CO for Approximations. A cumulative histogram is a mapping that counts the cumulative number of observations in all of the bins up to the specified bin. The histogram provides important information about the shape of a distribution. A variance in the value of CO during a time interval (01-07-2016 to 13-03-2017) in individual sampling spot is clearly depicted in approximation a8 of the decomposition. It is clear that the CO level is minimum in Sampling spots August & January and maximum in November. We have calculated the value of skewness parameter for ground level CO 0.32539 and Kurtosis parameter 0.6685. A positive value of skewness indicates that data are skewed right. The behaviour of skewness parameter tells about the intermittency phenomenon.

CONCLUSION

Signal analysis CO a stressor indicator by Symlet wavelet (Sym 4 level 8) makes it possible to quantify the variations on a particular time frame and variations and interrelationships existing between natural and anthropogenic interferences of CO quality indicators. The wavelet method allows the decomposition of the signal according to different frequency levels which characterize the intensity of natural and man-made disturbances. A histogram is a graphical representation showing a visual impression of the distribution of data. 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. The behaviour of skewness parameter tells about the intermittency phenomenon. The histogram is an effective graphical technique for showing both the skewness and kurtosis of data set. Taking into account these results we have shown, the wavelet analytical approach provides a simple and accurate framework for modeling the statistical behaviour of CO variation. Our purpose of the study is to support air quality management and to make information available to the public.

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