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Multifractal detrended cross-correlation analysis on air pollutants of University of Hyderabad Campus, India

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HIGHLIGHTS

- We have studied the cross-correlation among nine air pollutants.
- The MF-X-DFA method was used to quantify the cross-correlation.
- Analysis of all bivariate time series shows the presence of anti-correlation behaviour.
- We found the existence of multifractal behaviour between all these time series.

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ABSTRACT

In this paper, we study the multifractal characteristics and cross-correlation behaviour of Air Pollution Index (API) time series data through multifractal detrended cross-correlation analysis method. We analyse the daily API records of nine air pollutants of the university of Hyderabad campus for a period of three years (2013–2016). The cross-correlation behaviour has been measured from the Hurst scaling exponents and the singularity spectrum quantitatively. From the results, it is found that the cross-correlation analysis shows anti-correlation behaviour for all possible 36 bivariate time series. We also observe the existence of multifractal nature in all the bivariate time series in which many of them show strong multifractal behaviour. In particular, the hazardous particulate matter $PM_{2.5}$ and inhalable particulate matter PM_{10} shows anti-correlated behaviour with all air pollutants.

1. Introduction

Air pollution is a series problem faced by the people globally, particularly in urban areas of developing countries, which experiences a rapid growth of population and industrialization accompanied by increased vehicular traffic. In developing countries, air pollution in cities is attributed to vehicular emission which contributes to 40–80% of total air pollution [1]. The urban population is mainly exposed to high levels of air pollution that includes toxic metals as well as fine and ultrafine particles from the vehicular traffic [2]. Sulphur dioxide, nitrogen oxide and suspended particulate matter are regarded as major air pollutants in India [3]. With growing energy consumption and rapid urbanization, an increase in ambient air pollution seemed inevitable.

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Air pollution is a major health hazard issue throughout the world, particularly in India. In recent days, Hyderabad city is facing severe air pollution problem due to the rapid increase of urban limits, population and industrial activity. Pollution levels in the city have risen enormously due to industrialization and excessive increase of automobiles usage. The levels of air pollution are observed from air pollution index, and higher the index severe the pollution. The main objective of the present study is to assess the ambient air quality with respect to carbon monoxide (CO), ozone (O_3), nitrous oxide (NO), nitrous oxide (NO_2), nitrogen oxide (NO_x), ammonia (NH_3), sulphur dioxide (SO_2), respiratory particular matter (PM2.5 and PM10) and understand the trends of air pollutants over a period of time. The temporal variation of air pollution system is highly complicated and complex. The air pollution data have been extensively analysed using statistical methods and also modelled for future predictions. In this work, we study the correlation behaviour, fractal characteristics and other statistical properties of air pollution indices time series.

As is known, fractals are ubiquitous in nature, they manifest in areas ranging from financial markets to biological, environmental and earth sciences [4–6]. Until now various methods have been developed and applied to characterize the correlation behaviour on many time series starting from R/S analysis [7,8], detrended fluctuation analysis (DFA) [9,10], detrended moving average method (DMA) [11,12], multifractal detrended fluctuation analysis (MFDFA) [13], wavelet based fluctuation analysis (WBFA) [14,15], average wavelet coefficient method (AWC) [16], wavelet transform modulus maxima (WTMM) [17], multifractal detrended moving average analysis [18,19] etc. These methods have found wide application in analysis of correlations and characterization of scaling behaviour of time-series data in physiology, finance, earth & space sciences, and natural sciences [20–27]. Most of these methods not only measure the correlation behaviour but also used to study the fractal characteristics of the time series using the Hurst scaling exponent ($0 < H < 1$). This scaling exponent measures the persistent ($H > 0.5$), uncorrelation ($H = 0.5$) and anti-persistent ($H < 0.5$) behaviour. Recently, some of the above mentioned methods were extended to study the cross-correlation behaviour between any two non-stationary data in 1D and higher dimensions. As an outcome, the methods such as detrended cross-correlation analysis (DCCA) [28,29], multifractal detrended cross-correlation analysis (MF-X-DFA) [30], multifractal detrending moving average cross-correlation analysis (MF-X-DMA) [31], including multifractal analysis methods such as MF-HXA [32], MF-X-PF [33–35], MF-CCA [36,37], MF-PX-DFA and MF-PX-DMA [38], MF-X-WT [39], MF-X-WL [40] etc. were developed. These approaches find applications ranging from finance, biology, atmospheric and earth science to technological data [41–52].

In this paper, we investigate the multifractal characteristics and cross-correlation behaviour using the recently developed multifractal detrended cross-correlation method on the above stated API time series data. For this purpose, we have analysed the API time series collected during the past 3 years from University of Hyderabad campus, India. The University campus is located very close to the Hyderabad–Bombay Highway in an area of about 2000 acres. The University houses more than 6000 people, including both floating and non-floating population every day. There are many software companies bordering the campus, where hundreds of thousands of personnel are employed. The vehicular traffic and construction activities are very high adjoining the campus area.

2. Methodology

We have assumed that there are two non-stationary time series $x(t)$ and $y(t)$, where $t = 1, 2, \ldots, N$ and N is the length of the time series. The procedure of the MF-X-DFA method is explained through following steps [30]. As a first step the profile of the time series was constructed from the cumulative sum of the time series after subtracting the mean from each data points (i.e.)

$$X(t) = \sum_{i=1}^{t} (x\,(i) - \bar{x}) \tag{1}$$

$$Y(t) = \sum_{i=1}^{t} (y\,(i) - \bar{y}) \tag{2}$$

Here $\bar{x}$ and $\bar{y}$ are the mean of the time series $x(t)$ and $y(t)$. Subsequently we have subdivided the time series profiles $x(t)$ and $y(t)$ into ($N_s = N/s$) non-overlapping segments of equal length 's'. It is obvious that the length of the measured or collected time series may not be multiples of length scale 's'. In such cases, a portion of time series is discarded for analysis and this may lead to biased results in the analysis. To avoid bias the above procedure is applied on the reverse profile of the time series. Thus, $2N_s$ non-overlapping segments are obtained altogether for further analysis.

In each segment v, the local polynomial trends on $X^v(t)$ and $Y^v(t)$ were removed by least square fitting on the data, then the detrended covariance is obtained, where $v = 1, 2, 3 \ldots\ldots N_s$.

$$F^s(s, v) = \frac{1}{s} \sum_{t=1}^{i} |X\,((v-1)\,s + t) - X^v\,(t)| \cdot |Y\,((v-1)\,s + t) - Y^v\,(t)| \tag{3}$$

Similarly, the local polynomial trends were removed on each segment v of the reverse profile, where $v = Ns + 1, Ns + 2, \ldots 2Ns$.

$$F^s(s, v) = \frac{1}{s} \sum_{t=1}^{i} |X\,(N - (v - N_s)\,s + t) - X^v\,(t)| \cdot |Y\,(N - (v - N_s)\,s + t) - Y^v\,(t)| \tag{4}$$