Building and Environment 82 (2014) 580–587

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Detrended fluctuation analysis of particle number concentrations on roadsides in Hong Kong

Wei-Zhen Lu [a,*], Yu Xue [b,c], Hong-di He [a,d]

[a] Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong
[b] Institute of Physical Science and Engineering, Guangxi University, Nanning 53004, China
[c] Shanghai Institute of Applied Mathematics and Mechanics, Shanghai University, Shanghai 200072, China
[d] Logistics Research Center, Shanghai Maritime University, Shanghai 200135, China

ARTICLE INFO

Article history:
Received 2 July 2014
Received in revised form
17 September 2014
Accepted 19 September 2014
Available online 12 October 2014

Keywords:
Detrended fluctuation analysis
Particulate matter
Autocorrelation
Long-term correlations

ABSTRACT

Particulate matter at unban intersection is originated from a variety of sources and influenced by plenty of meteorological conditions. It frequently presents nonlinear patterns. To deep identify these nonlinear characteristic, statistical methods including power-law distribution, autocorrelation function and detrended fluctuation analysis are applied to investigate it. The experiment was carried out in various seasons in Hong Kong and the number concentrations of particles larger than 0.3 μm were collected. Based on the measurements database, autocorrelations were calculated for every particle size group and particles less than 5 μm show periodic variation. The obtained period is consistent with traffic signal period. Additionally, the power-law distribution for every particle size group is investigated and the results show that the concentration distributions for particle between 0.5 and 5 μm exhibit asymmetric forms while the concentration distributions for particle between 0.3 and 0.49 μm present symmetrical trend with the far tails. Furthermore, the detrended fluctuation analysis was applied to discover the long-term variation. The Hurst parameters for every particle size group were determinate by means of fractal analysis and these results provide fundamental insights into the nature of long-term correlations.

1. Introduction

Recently, vehicle emission has been regarded as the major sources of particulate matter in urban area and has attracted much attention, especially at urban traffic intersection [1–3]. At intersections, vehicles frequently stop with idling engines during the red-light period and speed up rapidly in the green-light period, which generally produce more pollutants than any other situations such as cruise. These pollutants continuously cumulate and release into air on roadsides. Meanwhile, the pedestrians are just exposed to high levels of particulate pollutants as they walk-by or cross the zebra areas. The inhaled particulates may affect the functions of hearts and lungs of human beings and cause adverse health effects [4–6]. Hence, it is significant and necessary to investigate the correlations of the particulate matter at the traffic intersection in street canyons.

To discover the correlation of particulate matter on roadside, many approaches have been developed to investigate it [7–11]. Chu et al. [7], applied computational fluid dynamics model to simulate the dynamical behaviors of particulate emission such as dilution, coagulation, and condensation. Romano [8], used the statistical distribution model to reveal the particular statistical properties. Gokhale and Khare [9] performed goodness-fit-test on pollutant level and found that most of the pollutants obey log-normal distribution. Eastwood [10] indicated different interaction patterns between particles and surrounding wind in terms of size levels. Although these traditional approaches could provide good result for understanding the characteristic of PM on roadside, the characteristics of long-term correlations for nonstationary data of PM level are seldom quantified.

Detrended fluctuation analysis (DFA) is a scaling analysis method providing a simple quantitative parameter (scaling exponent) which represents the correlation properties of a time series [12]. The advantages of DFA over many methods are that it permits the detection of long-term correlations embedded in seemingly nonstationary time series, and also avoids the spurious detection of apparent long-term correlations that are an artifact of nonstationarity [13–18]. Generally, Hurst parameter (H) is used to characterize the nature of correlations (memory). Processes that generate time series with such properties are said to have

* Corresponding author. Tel.: +852 27844316; fax: +852 27887612.
E-mail address: bcwzlu@cityu.edu.hk (W.-Z. Lu).

http://dx.doi.org/10.1016/j.buildenv.2014.09.015

antipersistent correlations if $0 < H < 1/2$, are memory less or have only short-range correlations if $H = 1/2$, and have persistent long-term correlations (long memory) if $1/2 < H < 1$. In the past few years, DFA has uncovered long-term power-law correlations in many research fields such as cardiac dynamics, bioinformatics, economics, etc and been regarded as a sophisticated tool in describing the long-terms correlations for nonlinear time series [17–21,25–28].

In this paper, we show what new insights are attainable by applying random fractal theory to the measured data of PM levels. Our goal is to try and go beyond the interpretations of trajectories of particle number concentrations by means of an accurate determination of scaling parameters. The paper is organized as follows: the methods are described in details in Section 2. In Section 3, the statistical methods such as power-law distribution and autocorrelation are applied reveal the characteristic of PM. Beside, DFA is adapted to discover the long-term cumulative variation of PM levels. Summaries are given in Section 4.

2. Data collection

The measurement of pollutant levels were performed for 90 min duration in afternoon rush hours at a selected traffic intersection in Mong Kok along Nathan Road, a major commercial and transport line in Kowloon Peninsula, which is surrounded by high-rise buildings, with high traffic volume, and a typical street canyon in Hong Kong territory. The measurement equipment is located 20 cm above the ground on the roadside of the selected location, which is very close to a bus station. Such settings provide the best chance for the equipment to capture the vehicle exhaust timely before further dilution. The particles were measured by the Fluke 983 Particle Counter, which counts the particle number every second by using the laser diffraction technique for size differentiation from submicron to millimeter (0.3–0.49 μm, 0.5–0.99 μm, 1–1.99 μm, 2–4.99 μm, 5–9.99 μm, and >10 μm). A digital camera was also dismounted to record both traffic counts and signals. All equipment operations were adjusted to synchronize to the same pace of traffic signal cycles on site, under which the equipment can react instantly and capture, as possible as, the particle number concentrations from vehicular emission.

3. Methodology

3.1. Power-law distribution

In recent years, the power-law (PL) correlation is popular and widely used in handling physical and biological systems as growing evidence indicating that these systems have no characteristic length scale and exhibit long-term, power-law correlations. Traditional power-law approaches such as the power-spectrum and correlation analysis are suitable to quantify correlations in stationary signals [22,23]. In this study, the PL method will provide the correlations between the data measured and the resultant particle concentration number distributions at interested site.

3.2. Autocorrelation

In sequence, the superposition of cyclic variations with different amplitudes and random fluctuations constructs a time series. These cyclic variations in the time domain can be identified by the correlation analysis. Concerning the long-term correlated particle concentration series $x(i)$ ($i = 1, \ldots, N$), the autocorrelation at lag τ is given by [23]:

$$C(\tau) = \frac{<x(i) - <x>> <x(i-\tau) - <x>>}{\sigma^2} = \frac{\frac{1}{N}\sum_i (x(i) - mx)(x(i-\tau) - mx)}{\frac{1}{N}\sum_i (x(i) - mx)^2} \quad (1)$$

Eq. (1) reflects the decay of particle concentration levels with increasing τ in terms of the power-law $C(\tau)$–$\tau^{-\gamma}$. Here, γ is the autocorrelation exponent for which its typical values range between $0.4 < \gamma < 0.8$ and are case dependent often. In Eq. (1), the angular brackets $<\ldots>_n$ indicate the average over time and N means the total number of measurements in the time series. The variance of the time series is denoted by σ^2 and mx are the means of the corresponding series. If values $x(i)$ versus the corresponding values a fixed lag τ earlier $x(i-\tau)$ is plotted, the autocorrelation $C(\tau)$ values quantify the distribution of these points. If these points tend to crowd along the diagonal line of $x(i) = x(i-\tau)$, then $C(\tau) > 0$. Or else they spread out evenly over the plane, and then $C(\tau) = 0$. If a time series is periodic in time, then the autocorrelation function is also periodic in terms of the lag τ. The occurrence of the relative maximum of $C(\tau)$ indicates the cyclic variations with period τ, whereas the value of $C(\tau)$ yields the correlation coefficient for the lag τ.

3.3. Detrended fluctuation analysis

The DFA method is firstly proposed by Peng et al. for analyzing the long-term correlation in DNA sequence in 1994 [12]. Currently, it is a major approach to reliably detect the long-term (or long-range) correlations in data sequence [12,15]. The DFA method systematically eliminates the polynomial trends of different orders and produces a new insight into the trend of time series concerned. To date, DFA is intensively used to diagnose the complex heartbeat time series, the scaling phenomenon of flow in complex networks, the extreme atmospheric events, the effect of stochastic probability of acceleration and delay in traffic flow, and the fluctuation of stock market [24,25]. The original DFA algorithm contains the following five steps [12].

Step 1. Considering a time series $x(t)$, $t = 1, 2, \ldots, N$, firstly construct the cumulative sum as below:

$$u(t) = \sum_{i=1}^{t} x(i), \quad t = 1, 2, \ldots, N \quad (2)$$

Step 2. The new series $u(t)$ is partitioned into N_s disjoint segments of the same size s, where $Ns = [N/s]$. Each segment can be denoted by u_v such that $u_v(i) = u(l + i)$ for $1 \le i \le s$, where $l = (v - 1)s$.

Step 3. In each segment u_v, one should determine the local trend $\tilde{u}_v$ with the method of polynomial fitting. When a polynomial of order l is adopted in this step, the DFA method is called DFA-l (DFA-1 if $l = 1$, DFA-2 if $l = 2$, DFA-3 if $l = 3$, and so on). One can then obtain the residual sequence as:

$$e_v(i) = u_v(i) - \tilde{u}_v(i), \quad 1 \le i \le s \quad (4)$$

Step 4. The detrended fluctuation function $F(v, s)$ of the segment u_v is defined as the root of mean squares of the sample residuals $e_v(i)$ as:

$$[F(v,s)]^2 = \frac{1}{s}\sum_{i=1}^{s} [e_v(i)]^2 \quad (5)$$

The overall detrended fluctuation is calculated by averaging over all segments, that is.