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On the multifractal analysis of air quality index time series before and during COVID-19 partial lockdown: A case study of Shanghai, China

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ABSTRACT
Due to the COVID-19 pandemic, human activities are largely restricted in Shanghai, China and it is a valuable experiment to testify the correlation of air quality and human activities. In consideration of the complexity of air pollution, this study aims to compare the multifractal characteristics of air quality index (AQI) time series before and during COVID-19 partial lockdown, and analyze the correlations between multifractal parameters of AQI time series and human activities in Shanghai, China. The hourly AQI series in Shanghai from November 27, 2019 to March 23, 2020 is used for this study. Firstly, using the MF-DFA method, the multifractal characteristics of the AQI series are explored. Secondly, the causes of the multifractality of the AQI series are determined. Finally, the correlations between multifractal parameters of AQI time series and human activities are investigated. The multifractal analysis results reveal that the AQI series during COVID-19 partial lockdown also has multifractal characteristics, and the slightly weaker multifractal characteristics and marginally smaller multifractal degree are obtained in comparison with the pre-lockdown phase. However, the contribution of the effective or intrinsic multifractality before and during COVID-19 partial lockdown are very close. The results via the sliding window procedure indicate that the multifractal parameters (ΔH, Δα, Δf) show the similar fluctuations along with the fluctuations of passenger volume in Shanghai Metro. Furthermore, it is found that ΔH, Δα, Δf and adjusted passenger volume in Shanghai Metro are positively correlated. The possible trend is that the higher adjusted passenger volume is, the larger the value of ΔH, Δα, Δf becomes, which means the stronger multifractal characteristics and larger multifractal degree of air quality system.

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1. Introduction

Since the first infection was diagnosed in Wuhan in December 2019, the novel coronavirus (COVID-19) has been spreading at a speed even beyond the expectation of medical experts. In response, the Chinese government mandated a quarantine of the Wuhan city on Jan 23, 2020. 31 provinces and municipalities, including Beijing and Shanghai, have also taken measures to prevent the spread of the outbreak.

Shanghai imposed its highest-level response mechanism for major public health emergencies on January 24, 2020, announcing the most strict prevention and control measures to contain the spread of infection, including health screenings conducted at all road entrances to Shanghai, temporarily suspension of all large public activities, the operation of
companies, elementary, middle and high schools, universities and other educational institutions. The public transportation started working with reduced hours. Based on the COVID-19 situation gradually being brought under control, Shanghai decided to lower the provincial public health emergency level from Level I to Level II since 0 am February 24, 2020. This period is a valuable experiment to testify the correlation of air quality and human activities.

Recently, researches start to study the air quality variations associated with social distancing measures, and consequent decrease of vehicle transit. Zambrano-Monserrate et al. [1] analyzed data of particulate matter (PM2.5) in China and observed approximately 20%–30% reduction in February 2020 (month average) when compared to monthly averages of February 2017, 2018 and 2019. P. Wang et al. [2] performed a simulation in China and showed that metrology played very important role in air pollution formation and severe air pollution was not avoided during the lockdown in January and February 2020.

In consideration of the complexity of air pollution, nonlinear methods to study the evolution of air pollutant have been adopted in the researches. Of these methods, the multifractal method provides a powerful tool for people to deal with complex objects. Detrended fluctuation analysis (DFA) [3] proposed by PENG et al. is suitable for the long-range power law correlation analysis of non-stationary time series. Based on DFA, Kantelhardt et al. [4] gave an improved version, The multifractal detrended fluctuation analysis (MF-DFA), which is capable of studying the multipoint correlation of the non-stationary series. This method can accurately quantify the long-range correlation of non-stationary time series, which is based on random walk theory and can avoid artificially induced time series instability. The MF-DFA has been successfully used in various fields, such as stock market [5], traffic flow [6], wind speed [7] etc.

In recent years, more and more scholars have adopted this method to study environmental problems. C.-K. Lee et al. [8] find that there exist multifractal characteristics in the ozone concentration time series in Taipei. A. M. Diosdado et al. [9] provide evidence that the concentration time series of atmospheric pollutants have multifractal characteristics. Z. Liu et al. [10] prove the air pollution index (API), SO\(_2\), NO\(_2\) and PM\(_{10}\) time series in Shanghai, China have multifractal characteristics. Q. Dong et al. [11] show PM\(_{2.5}\) and PM\(_{10}\) time series in Shanghai, China have multifractal characteristics. C. Shen et al. [12] illustrate the air pollution index (API) time series in Nanjing, China has multifractal characteristics. Q. Wang [13] analyze the multifractal characteristics of polluted time series in Beijing, Zhengzhou, and Jinan.

The plan of this study is to investigate and compare the multifractal characteristics of AQI time series before and during COVID-19 partial lockdown in Shanghai, China. Furthermore, the correlation between multifractal parameters of AQI time series and human activities is to be analyzed.

This paper is structured as follows. The MF-DFA method and multifractal causes analysis method are introduced in Section 2. The data description and data preprocessing methods are described in Section 3. The correlations between multifractal parameters of AQI time series and passenger volume in Shanghai Metro are analyzed and illustrated in Section 4. Finally, Section 5 summarizes and concludes the study.

2. Methodology

2.1. MF-DFA method

Considering the time series \(x = \{x_1, x_2, \ldots, x_N\}\), MF-DFA method can be described as following five steps.

(1) Calculate the profile:
\[
y_i = \sum_{k=1}^{i} (x_k - \bar{x}), \quad i = 1, \ldots, N
\]
where \(\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i\).

(2) The profile is subdivided into \(N_s = \text{int}(N/s)\) non-overlapping windows of equal length \(s\). Since the length \(N\) of the series may not be an integer multiple of the window size \(s\), and a short part of the profile \(y_i\) at the end may be disregarded by the procedure. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end, obtaining a total of \(2N_s\) segments.

(3) Calculate the local trend for each of the \(2N_s\) segments by a least-square fit of the series. Then the variance can be determined as
\[
\text{Var}_v^\nu = \begin{cases} 
\frac{1}{s} \sum_{i=1}^{s} (y_{(v-1)s+i} - y_v^\nu)^2, & \text{if } v = 1, \ldots, N_s, \\
\frac{1}{s} \sum_{i=1}^{s} (y_{N-(v-N_s)s+i} - y_v^\nu)^2, & \text{if } v = N_s+1, \ldots, 2N_s 
\end{cases}
\]
where \(y_v^\nu\) is the fitting polynomial in segment \(v\).
Averaging over all segments to get qth order fluctuation function:

\[ F_q(s) = \begin{cases} \frac{1}{2N_s} \sum_{i=1}^{2N_s} (\text{Var}_i^{\text{ex}})^{q/2} & \text{if } q \neq 0, \\ \exp \left( \frac{1}{4N_s} \sum_{i=1}^{2N_s} \ln(\text{Var}_i^{\text{ex}}) \right) & \text{if } q = 0. \end{cases} \]  

Repeat step (2) to (4) with different time scales s, to see how different s affects the dependency of \( F_q(s) \) on q.

Analyze the log–log plots \( F_q(s) \) versus s for different q. If the series are long-range power-law correlated, for large values of s, the generalized Hurst exponent H(q) is defined by:

\[ F_q(s) \approx s^{H(q)}. \]

The generalized Hurst exponent defines the fractal structure of the time series by how fast \( F_q(s) \) of local fluctuations grows with increasing scale s. When the series is multifractal, e.g. the small and large fluctuations scale differently, a significant dependence of H(q) on q should be observed. If the series is monofractal, H(q) should be equal regardless of different q values. For stationary time series, H(2) is identical to the well-known Hurst exponent H. When H(2) > 0.5, the time series has a long-range correlation structure, an increase (decrease) is more likely followed by another increase (decrease). When H(2) < 0.5, the time series has an long-range anti-correlation structure, an increase (decrease) is more likely followed by another decrease (increase). The range of H(q), \( \Delta H = H(q_{\text{min}}) - H(q_{\text{max}}) \), indicates the extent to which the series is multifractal. Higher \( \Delta H \) means stronger multifractal characteristics. In addition, scaling exponent \( \tau(q) \) is defined by:

\[ \tau(q) = qH(q) - 1 \]

The singularity strength \( \alpha \) and the multifractal spectrum \( f(\alpha) \) can be calculated via Legendre transform, or be related with H(q) with the following equations:

\[ \alpha = \frac{d}{dq} qH(q) = H(q) + q\frac{dH(q)}{dq} \]

\[ f(\alpha) = qH(q) - \tau(q) = 1 + q[\alpha - H(q)] \]

Multifractal spectrum \( f(\alpha) \) describes the fractal dimension of the ensemble formed by all the points that share the same singularity exponent \( \alpha \). Fractal dimension \( f(\alpha) \sim \alpha \) is shaped like a single-peaked bell. The difference between maximum and minimum singularity exponent, \( \Delta \alpha = \alpha_{\text{max}} - \alpha_{\text{min}} \), is called the multifractal spectrum width, that represents the interval between the maximum probability and the minimum probability and measures the degree of the multifractality property. The type of the extreme fluctuation rate occurring with a higher probability can be qualified using \( \Delta f = f(\alpha_{\text{min}}) - f(\alpha_{\text{max}}) \) which is the difference between the fractal dimension of the maximum probability subset and that of the minimum probability subset. When \( \Delta f > 0 \), the maximal fluctuation rate occurs with a higher possibility than that of the minimal fluctuation rate and vice versa.

2.2. Causes of multifractality

It is usually argued that the sources of multifractality in time series are the fat tails and/or the long-range temporal correlations [4]. More recent studies think the multifractality in time series one observes may originate from long-range nonlinear autocorrelations, the presence of fat tails in probability distributions of data, or linear autocorrelations present in shorter (finite) time series [14]. However, many studies shows that empirical multifractal analysis of time series generated from monofractal models and mathematical models can produce spurious multifractality [15,16]. Possessing linear correlations or long memory in time series is not sufficient for the emergence of multifractality and a nonlinear process is required to have intrinsic multifractality [17]. The nonlinear correlations are the genuine source of the multifractality [18,19]. An even more critical question is to ask whether the empirical extracted multifractality is intrinsic or apparent. Understanding the origin of the measured multifractality in time series is an important problem which has attracted many researchers’ attention and interests [14,18–21].

In order to distinguish different sources of apparent multifractality, the simplest method is to shuffle or reshuffle the original time series and compare the multifractal characteristics of the original time series and the shuffled time series. The shuffling procedure destroys any linear or nonlinear long-range correlations while preserving the distribution of the values of the time series. Let \( F(q,s) \) and \( F^{\text{shuf}}(q,s) \) being the fluctuation functions for the original and the shuffled time series respectively, the differences between these two fluctuation functions indicate the presence of correlations in the original time series. The scaling behavior of the ratio is \( F(q,s)/F^{\text{shuf}}(q,s) \sim s^{H(q)-H^{\text{shuf}}(q)} \sim s^{H^{\text{corr}}(q)} \), where \( H(q) \) and \( H^{\text{shuf}}(q) \) are the generalized Hurst exponents of the original and the shuffled time series respectively, while \( H^{\text{corr}}(q) \) characterizes the scaling behavior of the correlations among small and large fluctuations in the original time series. That means the impact of the correlations is qualified by [4]

\[ H^{\text{corr}}(q) = H(q) - H^{\text{shuf}}(q) \]
the contribution of the broad probability distribution and probably the finite-size effect can be qualified by [4]

\[ \Delta a_{PDF} = \Delta a_{shuf}. \]  

(9)

The Fourier transform surrogate time series can contain the same linear correlations as the original data, while any nonlinear correlations are eliminated and the amplitude distribution becomes Gaussian [22]. The most commonly used methods for generating surrogates include the Fourier transform algorithm [23], the amplitude adjusted Fourier transform (AAFT) algorithm [23], and the iterative amplitude adjusted Fourier transform (IAAFT) algorithm [24].

The shuffling procedure and the Fourier transform surrogate procedure can be combined to understand the sources of the empirically estimated apparent multifractality.

The generalized Hurst exponents can be utilized to measure the multifractality of the time series to analyze the sources of the multifractality. On one hand, the multifractality of broad probability distribution, will not be affected by shuffling the time series, and cannot be eliminated by the shuffling procedure. That is, if only the distribution multifractality exists in the time series, \( H(q) = H_{shuf}(q) \) depends on \( q \) and \( H^{corr}(q) = 0 \) holds, and \( H^{surr}(q) \) obtained by the surrogate method will be independent of \( q \). On the other hand, the multifractality of long-range temporal correlations, can be destroyed by the shuffling procedure, and the shuffled time series will exhibit simple random behavior. That is, if only the correlation multifractality exists in the time series, \( H^{corr}(q) \) is not zero and depends on \( q \), and \( H^{shuf}(q) = 0.5 \) and \( H^{surr}(q) = 0.5 + h^{corr}(q) \) hold.

The multifractality of the time series can also be characterized by the singularity spectrum, i.e. the width of the multifractal spectrum, with which the quantitative analysis of the origin of multifractality can be done. The width of the original series’ multifractal spectrum \( \Delta \alpha \) can be decomposed to the three main sources of multifractality, namely the nonlinear correlation \( \Delta \alpha_{NL} \), the linear correlation \( \Delta \alpha_{LM} \) and fat-tailed probability distribution \( \Delta \alpha_{PDF} \) and can be expressed as the following equation [21,25]:

\[ \Delta \alpha = \Delta \alpha_{NL} + \Delta \alpha_{LM} + \Delta \alpha_{PDF}. \]  

(10)

Because the AAFT algorithm can produce the same power spectrum only for time series with infinite length in the limit \( N \to \infty \) and does not usually result in the same sample power spectra [24]. To overcome this shortcoming, the IAAFT algorithm is introduced, which improves the AAFT algorithm [24]. It should be noted that in this study, a more practical and convenient way, which is directly introducing linear correlations into random time series generated from original time series, has been applied to construct the surrogate time series. By construction, the surrogate series have the same distribution and the same linear correlations as the raw time series, but do not possess any nonlinear correlations [24]. The width of multifractal spectrum of surrogate series can reflect the multifractality degree of the linear correlation part and the PDF part and can be expressed as follows [26]

\[ \Delta \alpha^{surr} = \Delta \alpha_{LM} + \Delta \alpha_{PDF}. \]  

(11)

According to Eqs. (10) (11), the nonlinear correlations part can be expressed as:

\[ \Delta \alpha_{NL} = \Delta \alpha - \Delta \alpha^{surr}. \]  

(12)

The intrinsic multifractal nature is characterized by the effective multifractality \( \Delta \alpha^{EFF} \) composing of the nonlinearity component \( \Delta \alpha_{NL} \) and the PDF component \( \Delta \alpha_{PDF} \) [21,25]

\[ \Delta \alpha^{EFF} = \Delta \alpha - \Delta \alpha_{LM} = \Delta \alpha_{NL} + \Delta \alpha_{PDF}. \]  

(13)

According to Eqs. (10) (11) (12), the effective multifractality can also be expressed as:

\[ \Delta \alpha^{EFF} = \Delta \alpha - \Delta \alpha^{surr} + \Delta \alpha_{PDF}. \]  

(14)

Based on the previous researches, the simulation procedure and multifractal causes analysis performed in this study are as follows:

**Step 1:** The original series is shuffled to remove any potential correlations. The multifractal analysis is conducted on the shuffled series and the multifractal characteristics \( H^{shuf}(q) \), \( \Delta \alpha^{shuf} \) is determined;

**Step 2:** The surrogate series are obtained by phase-randomizing the original series using the IAAFT algorithm. The multifractal analysis is carried out on the surrogate series and \( H^{surr}(q) \), \( \Delta \alpha^{surr} \) are calculated;

**Step 3:** The steps 1–2 are repeated until 20000 sets of \( \{H^{shuf}(q), H^{surr}(q), \Delta \alpha^{shuf}, \Delta \alpha^{surr}\} \) of the original series before and during COVID-19 partial lockdown are accumulated.

**Step 4:** Then the difference between \( H^{shuf}(q) \), \( H^{surr}(q) \), \( \Delta \alpha^{shuf} \), \( \Delta \alpha^{surr} \) are checked to determine the components of the multifractality and intrinsic multifractality of the original series before and during COVID-19 partial lockdown respectively.

**Step 5:** Furthermore, the comparisons between the above multifractality components are applied to determine the change of the multifractality of the original series before and during COVID-19 partial lockdown.
3. Data description and preprocessing method

The original hourly air quality index (AQI) data applied to the multifractal analysis is collected from RESSET Air Quality Monitoring Big Data Platform (http://res.resset.com/AQM, Accessed on 18 April 2020) which are obtained from the Ministry of Ecology and Environment of the People’s Republic of China (http://english.mee.gov.cn/). The original daily air quality index (AQI) data is collected from the Air Quality Publishing Platform of China (http://www.aqistudy.cn/historydata/index.php).

The time series in this study is selected from November 27, 2019 to March 23, 2020. Based on the period between Shanghai public health emergency level I, the data from January 25, 2020 to March 23, 2020 is chosen as the period of during COVID-19 partial lockdown in comparison with the data from November 27, 2019 to January 24, 2020 chosen as before COVID-19 partial lockdown. The number of entry/missing data is 1416/7(during COVID-19 partial lockdown) and 1416/57(before COVID-19 partial lockdown). Compared with the daily data in Air Quality Publishing Platform of China, 2 outlier data is found in the hourly data during COVID-19 partial lockdown. In this paper, arithmetic mean is adopted to handle the missing and outlier data.

The hourly air quality index (AQI) series before and during COVID-19 partial lockdown are illustrated in Fig. 1-A. The distribution of the hourly air quality index (AQI) series before and during COVID-19 partial lockdown and their probability density function are presented in Fig. 1-B and -C. The Descriptive statistics are listed in Table 1. It is clearly shown that there exist reductions in every metrics during COVID-19 partial lockdown in comparison with before COVID-19 partial lockdown.

The daily passenger volume in Shanghai Metro is collected from the official microblog of Shanghai Metro (https://weibo.com/shmetro).
4. Experiment results and analysis

4.1. Multifractal characteristics analysis

The generalized Hurst exponent of order $q$ and the multifractal spectrum of the hourly AQI series before and during COVID-19 partial lockdown are shown in Fig. 2.

In Fig. 2-A, it is shown that $H_{bl}(q) \in [1.0364, 1.8244]$ is not a constant but varies as $q$ changes, which means $H(q)$ is dependent on $q$, indicating that the hourly AQI series before COVID-19 partial lockdown has a multifractal structure. Moreover, $H_{bl}(q)$ decreases with the increase of order $q$, showing a downward trend on the interval $[-5, 5]$. When $q = 2$, $H_{bl}(2) = 1.1234 > 1$ shows the time series is nonstationary and long-range correlated, which means larger (smaller) values in the time series show up in succession with a high possibility.

In addition, in Fig. 2-B, the multifractal spectrum is of a bell shape. Therefore, it can be concluded that the hourly AQI series before COVID-19 partial lockdown has multifractal characteristics. Accordingly, it is not appropriate to describe the hourly AQI series before COVID-19 partial lockdown with a simple single fractal model.

The width of the multifractal spectrum of the hourly AQI series before COVID-19 partial lockdown $\Delta \alpha_{bl} = 1.09275$ and the difference of extreme fractal dimensions $\Delta f_{bl} = 0.4710$. The chance of maximization of the hourly AQI series before COVID-19 partial lockdown is greater than the chance of being at a minimum in that $\Delta f_{bl} > 0$.

For the hourly AQI series during COVID-19 partial lockdown, the similar conclusions from Fig. 2-C and D can be drawn.

In summary, the hourly AQI series in Shanghai both before and during COVID-19 partial lockdown have multifractal characteristics and both are long-range correlated. Moreover, $H_{dl}(2) < H_{bl}(2)$ and $\Delta \alpha_{dl} < \Delta \alpha_{bl}$ illustrate that the slightly weaker multifractal characteristics and marginally smaller multifractal degree are obtained during COVID-19 partial lockdown.

4.2. Multifractal causes analysis

After shuffling and phase-randomizing the original hourly AQI series before and during COVID-19 partial lockdown 10,000 times respectively, the multifractal analysis is conducted on these series and the multifractal characteristics, named $H_{bl}^{shuf}(q)$, $H_{bl}^{surr}(q)$, $H_{dl}^{shuf}(q)$, $H_{dl}^{surr}(q)$, $\Delta \alpha_{bl}^{shuf}$, $\Delta \alpha_{bl}^{surr}$, $\Delta \alpha_{dl}^{shuf}$, $\Delta \alpha_{dl}^{surr}$, $\Delta \alpha_{bl}^{surr}$, $\Delta \alpha_{dl}^{surr}$ are obtained.

The resulting generalized Hurst exponents $H(q)$ of the shuffled and the surrogate hourly AQI series before and during COVID-19 partial lockdown are illustrated in Fig. 3-A and -B. It is shown that after shuffling, $H_{bl}^{shuf}(q)$ and $H_{dl}^{shuf}(q)$ both are nearly a horizontal line of values around 0.5 with tiny fluctuations, rather than the exact value of 0.5, which means
The generalized Hurst exponent of the shuffled and surrogate hourly AQI series in Shanghai before and during COVID-19 partial lockdown. A: before COVID-19 partial lockdown. B: during COVID-19 partial lockdown. The error bars are the standard deviations for the 10,000 shuffled and surrogate series respectively.

Fig. 4. The multifractal spectra of the shuffled and surrogate hourly AQI series in Shanghai before and during COVID-19 partial lockdown. A: before COVID-19 partial lockdown. B: during COVID-19 partial lockdown. The error bars are the standard deviations for the 10,000 shuffled and surrogate series respectively.

$H_{\text{corr}}(q) > 0$, $H_{\text{surr}}(q) > 0$, and both $H_{\text{bl}}(q)$ and $H_{\text{dl}}(q)$ depend on $q$. For the surrogate time series, $H_{\text{bl}}(q)$, $H_{\text{dl}}(q)$ are dependent on $q$, and $H(q) > H_{\text{bl}}(q)$, $H(q) > H_{\text{dl}}(q)$ hold.

The multifractal spectra of the shuffled and the surrogate hourly AQI series before and during COVID-19 partial lockdown are shown in Fig. 4-A and -B and the numerical results are shown in Table 2.

Table 2 shows that the total multifractality of hourly AQI series before COVID-19 partial lockdown is $\Delta \alpha_{\text{bl}} = 1.09275$, and the multifractality contributed by the linear correlation part is $\Delta \alpha_{\text{LM}} = 0.37830 \pm 0.21655$. From the width of the shuffled series, the multifractality contributed by the PDF part is $\Delta \alpha_{\text{PDF}} = 0.18437 \pm 0.09748$, and the nonlinear correlation part’s multifractality degree is $\Delta \alpha_{\text{NL}} = 0.53008 \pm 0.19474$, and the effective multifractality $\Delta \alpha_{\text{EFF}} = 0.71444 \pm 0.21655$. Through the same steps, the values of the multifractal components of series during COVID-19 partial lockdown as well, and the detailed results are shown in Table 3.

Table 3 shows that the effective multifractality contributes to 65.38% $\pm$ 19.82% of the total multifractality before COVID-19 partial lockdown, and accounts for 65.64% $\pm$ 19.33% of the multifractality during COVID-19 partial lockdown. It is obvious that the effective multifractality, composed of the nonlinear correlation part and the PDF part, occupies a larger proportion of the total multifractality. Therefore, it can be concluded that the impact of multifractality generated from the nonlinear correlation part and the PDF part is greater than the linear correlation multifractality.

Furthermore, comparing the values of the multifractal components, it is shown that the value of $\Delta \alpha_{\text{LM}}$ and $\Delta \alpha_{\text{PDF}}$ slightly decrease during COVID-19 partial lockdown. While, the value of $\Delta \alpha_{\text{NL}}$ is a little larger during COVID-19 partial lockdown. However, the difference of $\Delta \alpha_{\text{EFF}}$ are very small in the two periods. Therefore, different from the slightly weaker
Table 2
Comparison of the width of multifractal spectra of original, shuffled and surrogate series of hourly AQI series before and during COVID-19 partial lockdown. The numbers in parentheses are the standard deviations.

| Period                  | Original series | Shuffled series | Surrogate series |
|-------------------------|-----------------|-----------------|------------------|
| Before COVID-19 partial lockdown | 1.09275         | 0.18437         | 0.56267          |
|                         | (0.09748)       | (0.19474)       |
| During COVID-19 partial lockdown | 1.0877          | 0.17728         | 0.55097          |
|                         | (0.09488)       | (0.18826)       |

Table 3
Comparison of the components of the width of multifractal spectra of original, shuffled and surrogate series of hourly AQI series before and during COVID-19 partial lockdown. The numbers in parentheses are the standard deviations.

| Period                  | $\Delta \alpha$ | $\Delta \alpha^{LM}$ | $\Delta \alpha^{NL}$ | $\Delta \alpha^{PDF}$ | $\Delta \alpha^{EFF}$ | $\Delta \alpha^{EFF}$ |
|-------------------------|-----------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Before COVID-19 partial lockdown | 1.09275         | 0.37830               | 0.53008               | 0.18437               | 0.71444               | 65.38%                |
|                         | (0.21655)       | (0.19474)             | (0.09748)             | (0.21655)             | (19.82%)              |                       |
| During COVID-19 partial lockdown | 1.0877          | 0.37369               | 0.53673               | 0.17728               | 0.71401               | 65.64%                |
|                         | (0.21031)       | (0.18826)             | (0.09488)             | (0.21031)             | (19.33%)              |                       |

Table 4
The correlation coefficients, standard errors and t-test on the correlations between the multifractal parameters $\Delta H$, $\Delta \alpha$, $\Delta f$ and the adjusted passenger volume in Shanghai Metro during COVID-19 partial lockdown. $\rho$ is the correlation coefficient.

| $\Delta H$ and passenger volume | $\rho$ | Standard error | t statistics | p   |
|---------------------------------|--------|----------------|--------------|-----|
|                                 | 0.5540 | 0.1103         | 5.0244       | 2.655e−06 |

| $\Delta \alpha$ and passenger volume | $\rho$ | Standard error | t statistics | p   |
|--------------------------------------|--------|----------------|--------------|-----|
|                                      | 0.4726 | 0.1167         | 4.0492       | 7.847e−05 |

| $\Delta f$ and passenger volume      | $\rho$ | Standard error | t statistics | p   |
|--------------------------------------|--------|----------------|--------------|-----|
|                                      | 0.7126 | 0.0929         | 7.6691       | 1.22e−10  |

4.3. Impact of human activities on multifractality

In this section, a sliding (moving) window procedure is utilized to investigate the dynamics of the multifractal parameters ($\Delta H$, $\Delta \alpha$, $\Delta f$) of hourly AQI series in Shanghai and relation with human activities during COVID-19 partial lockdown.

A sliding window of 2808 hourly AQI data in 117 days (from November 28, 2019 to March 23, 2020) is chosen, a large enough set to engage in multifractal analysis; each window includes 1416 hourly AQI data, the shift between two successive windows is set to 24 hourly data in two successive days, so that 59 time windows (from January 25, 2020 to March 23, 2020) are obtained.

The passenger volume in Shanghai Metro is chosen to represent the extent of human activities in Shanghai during COVID-19 partial lockdown. It is shown that passenger volume decreased sharply and the recovered slowly, the fluctuations during recovering are big due to the large difference of volume on weekdays and weekends. To smooth the fluctuations, the 5-day simple moving average method is introduced to obtain adjusted passenger volume. Considering the time series of passenger volume, 5-day simple moving average method would average out the closing volume for the first 5 days as the first data point.

The resulting multifractal parameters $\Delta H$, $\Delta \alpha$ and $\Delta f$ time series, the original and adjusted passenger volume series in Shanghai Metro during COVID-19 partial lockdown are shown in Fig. 5. The graphical evidence indicates that the multifractal parameters $\Delta H$, $\Delta \alpha$ and $\Delta f$ show the similar fluctuations along with the fluctuations of adjusted passenger volume in Shanghai Metro. With the rapid reduction of adjusted passenger volume, $\Delta H$, $\Delta \alpha$ and $\Delta f$ descend. Then along with the progressive recovery of adjusted passenger volume, $\Delta H$, $\Delta \alpha$ and $\Delta f$ ascend.

Furthermore, the correlations between multifractal parameters of AQI series and human activities are investigated and the resulting are shown in Fig. 6. It is found that $\Delta H$, $\Delta \alpha$, $\Delta f$ of AQI series and adjusted passenger volume series in Shanghai Metro are positively correlated. The correlation coefficients, standard errors and t-test on the correlations between $\Delta H$, $\Delta \alpha$, $\Delta f$ and adjusted passenger volume are illustrated in Table 4. The null hypothesis of t-test is $H_0$: $\rho \leq 0$ and the alternative hypothesis is $H_1$: $\rho > 0$.

From Table 4, it can be shown that at the significant level of 1%, the null hypothesis can be rejected for all correlations between $\Delta H$, $\Delta \alpha$, $\Delta f$ and adjusted passenger volume. The alternative hypothesis can be accepted, indicating that
Fig. 5. Time evolution of the multifractal parameters $\Delta H$, $\Delta \alpha$, $\Delta f$ and the original and adjusted passenger volume in Shanghai Metro during COVID-19 partial lockdown, multifractal parameter 1 is $\Delta H$, multifractal parameter 2 is $\Delta \alpha$, multifractal parameter 3 is $\Delta f$.

Fig. 6. The correlations between the multifractal parameters $\Delta H$, $\Delta \alpha$, $\Delta f$ and the adjusted passenger volume in Shanghai Metro during COVID-19 partial lockdown (unit of volume is million people).

three multifractal parameters $\Delta H$, $\Delta \alpha$, $\Delta f$ and the adjusted passenger volume are positively correlated. The possible trend is that the higher adjusted passenger volume is, the larger the value of $\Delta H$, $\Delta \alpha$, $\Delta f$ becomes, which means the stronger multifractal characteristics and larger multifractal degree of air quality system. It is observed that the correlation coefficient between $\Delta f$ and adjusted passenger volume is the largest, which illustrates the $\Delta f$ is also a useful indicator of multifractality of AQI series.

5. Conclusions

Due to the COVID-19 pandemic, human activities are largely restricted in Shanghai, China and it is a valuable experiment to testify the correlation of air quality and human activities. In consideration of the complexity of air pollution,
the multifractal characteristics of the AQI series are investigated with the application of the multifract detrended fluctuation analysis (MF-DFA) method. Furthermore, the correlations between multifractal parameters of AQI time series and human activities are analyzed. The conclusions can be summarized as follows:

(1) The hourly AQI series in Shanghai both before and during COVID-19 partial lockdown have multifractal characteristics and both are long-range correlated. Moreover, the slightly weaker multifractal characteristics and marginally smaller multifractal degree are obtained during COVID-19 partial lockdown.

(2) The impact of multifractality generated from the nonlinear correlation part and the PDF part is greater than the linear correlation multifractality. Different from the slightly weaker apparent multifractality in hourly AQI series, the contribution of the effective or intrinsic multifractality before and during COVID-19 partial lockdown are very close.

(3) The results utilized the moving window procedure indicate that the multifractal parameters($\Delta H$, $\Delta \alpha$, $\Delta f$) show the similar fluctuations along with the fluctuations of passenger volume in Shanghai Metro. With the rapid reduction of adjusted passenger volume, $\Delta H$, $\Delta \alpha$ and $\Delta f$ descend. Then along with the progressive recovery of adjusted passenger volume, $\Delta H$, $\Delta \alpha$ and $\Delta f$ ascend.

(4) Furthermore, it is found that $\Delta H$, $\Delta \alpha$ and $\Delta f$ and adjusted passenger volume in Shanghai Metro are positively correlated. The possible trend is that the higher adjusted passenger volume is, the larger the value of $\Delta H$, $\Delta \alpha$, $\Delta f$ becomes, which means the stronger multifractal characteristics and larger multifractal degree of air quality system.

Therefore, the multifractal analysis of AQI series in Shanghai before and during COVID-19 partial lockdown and correlation analysis between multifractal characteristic and human activities provide new insights into the evolution of urban air quality, which can obtain a better understanding of the complex structure of environmental condition. This study is helpful in providing objective guidance and credible decision making support in environmental condition forecasting and regulation.

CRediT authorship contribution statement

Xing Li: Compete the whole work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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