Mitigating the Influence of Crossover Phenomena on Wind Resources Scaling Analysis Based on Season Division

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ABSTRACT: As a natural signal, the wind is affected by many other natural factors and shows features of seasonal alternation. Considering the crossover phenomena (CP) of wind speed time series (WSTS) occurs at seasonal time scaling and WSTS shows different features among seasons, the seasonal scaling analysis of WSTS is carried out in this study. The original WSTS (also called chronological order WSTS) is firstly divided into several seasonal WSTS and then the scaling analysis is done based on the seasonal WSTS. A multi-index method is proposed to divide original WSTS into seasonal WSTS by including parameters such as temperature, wind speed. Besides the proposed method, the solar terms method and the gregorian calendar method are also used to obtain the seasonal WSTS. The results of a case study in southwestern China show that the CP is mitigated by dividing the chronological order WSTS into several seasonal WSTS, and this mitigation is more obvious when the seasonal WSTS is obtained by the multi-index method proposed in this paper. This study does not only illustrate the effect of season division but also denote the existence of different scaling features among seasons.

1. INTRODUCTION
The uncertainty and variability of wind energy is the main barrier to its promotion and application. Scaling analysis could be used to identify and predict the variety of wind energy parameters, thereby enhancing its utilization. The accuracy of the wind speed time series (WSTS) scaling analysis is influenced by crossover phenomena (CP) [1]. Discussing the generation mechanisms and natural features of wind energy, together with the analysis of WSTS for different time periods, should make it possible to recognize and mitigate the influence of CP.

Scaling analysis of WSTS [1-7] has shown that WSTS is characterized by the positive long-range power-law correlations, which means the increases in wind speed are likely to be followed by further increases, while the decreases are likely to be followed by decreases. However, due to the influence of CP, the scaling exponents cannot objectively manifest the scaling features of WSTS. The role of CP in WSTS scaling analysis was first demonstrated by Kavasseri [1], but no in-depth analysis of the influence of CP on WSTS has been carried out as yet. Despite the fact that most recent researches
examining WSTS mention the existence of CP [1-3], no conclusion has been reached in terms of significant parameters such as time node (i.e., the abscissa time value when the CP is shown in the log-log curve of scaling analysis) and scaling behavior (i.e., the linear fitting slope of the log-log curve before/after the CP). The occurrence of CP at seasonal time nodes was pointed out but no further discussion was undertaken [3]. To the best of our knowledge, in more recent studies, WSTS are always treated as entire chronological order series. Although wind typically has a strong seasonal nature, as yet no seasonal WSTS scaling analysis has been carried out. In light of this fact, we here attempt to conduct an in-depth study of CP at seasonal time nodes and analyze seasonal WSTS scaling behavior.

2. CROSSOVER PHENOMENA OF WSTS

The scaling exponent, $\alpha$, is the key index employed to illustrate scaling behavior and correlation in time series, with its value being the slope of the log-log curve of the linear regression in a scaling analysis. Values of $\alpha$ ranging from 0 to 0.5 indicate an anti-correlation (i.e., large fluctuations are likely to be followed by small fluctuations, and vice versa); values of $\alpha$ equal to 0.5 indicate no correlation; and values of $\alpha$ ranging from 0.5 to 1 point to a persistent long-range correlations (i.e., large fluctuations likely to be followed by large ones, and vice versa) [2].

CP refers to the crossover of the linear fitting of the log-log curve at a certain time node. Due to the impact of CP, the scaling exponent calculated via regression analysis does not accurately reflect the scaling features of the WSTS [1]. Peng C K et al. [9,12] were among the first to illustrate the presence of CP in scaling analysis, while Kavasseri[1] firstly pointed out the existence of CP specifically in WSTS scaling. In the literature, although most papers mention the CP in WSTS scaling analysis, the time nodes and scaling behaviors of CP vary. Here we refer to the time node as the time value of the CP abscissa in the log-log curve. Kocak [2] defined scaling exponent $\alpha$ as the slope of the entire curve, with local scaling exponents $\alpha_1$ and $\alpha_2$ the slopes of the curve sections before and after the time node, respectively. These definitions are also applicable to this study.

A variety of time node lengths have been investigated, from several days[1-2]through to seasons[3]. WSTS with a length of nearly 12 years were analyzed [3]. The results revealed the seasonal time node of the CP to be about $10^{3.5}$ h, with the local scaling exponent $\alpha_2$ relatively small. It was pointed out that the CP may be linked to meteo-climatic phenomena. The authors argued that the presence of crossover may reflect the fact that on short time scales (tens of hours), fluctuations in wind speed may be dominated by atmospheric phenomena governed by the “local or regional” weather system, whereas on longer time scales (extending from several days to months) the fluctuations may be influenced by more general “global” weather patterns [1]. It was pointed out that the CP of WSTS is also influenced by the alternation of dry and wet climates, a pattern similar to that observed in rainfall and runoff time series[17].

Based on recent researches, most conclusions regarding CP refer to meteorology, climate and weather patterns. As a natural signal, wind cannot avoid the impact of the natural laws which govern and are reflected in these patterns. Influenced by the Earth’s rotation, climate and weather alternate between seasons. During these different seasons, wind speeds also exhibit a range of different features, which can be measured statistically as mean values, variation, and other stochastic parameters. However, in the existing literature, WSTS in different seasons are typically combined into a single whole chronological order series, without considering the seasonal diversity that might result in CP at a seasonal time node. In this paper, we attempt to compare chronological order and seasonal WSTS in order to explore the causes of seasonal CP, as well as analyze scaling behavior for different seasons.

3. METHODS

3.1 Season Division Methods

Influenced by the Earth’s physical laws, temperature evolution and rainfall periodicity, methods used to divide seasons in China include the solar terms method, the gregorian calendar method and the pentad average of temperature [18-20]. As the present study focuses on wind speed, the technique
proposed here (i.e., the multi-index method) combines the gregorian calendar method with temperature and wind speed indices. The following sections also include a comparison of the solar terms, gregorian calendar, and multi-index methods.

The solar terms method involves establishing seasons according to the location of the Earth in its revolutionary orbit [20]. Spring begins at the spring equinox (21st March) and ends at the summer solstice (22nd June) when summer starts. Summer then extends to the beginning of autumn at the autumnal equinox (23rd September), with winter commencing at the winter solstice (22nd December). According to the gregorian calendar method, spring lasts from March to May; summer lasts from June to August, autumn lasts from September to November and winter lasts from December to February. The multi-index method is based on this division but also takes temperature and wind speed indices (i.e., average monthly wind speed and its standard deviation) into consideration. The months showing similar values of these indices are classified to in the one season.

3.2 Scaling Analysis Methods

Among the many scaling analysis methods, such as R/S analysis and wavelet analysis [8], detrended fluctuation analysis (DFA) has its own advantages and has been successfully applied in many fields [1-7,9-17].

First developed by Peng et al. [9], DFA was extended in 2002 by Kantelhardt et al. with the introduction of multi-fractal detrended fluctuation analysis (MF-DFA) [10]. DFA and MF-DFA are hereafter together referred to as ‘DFA methods’ in the present paper. DFA methods have been widely applied in a range of fields, including DNA sequencing [11], pathology [12], economics [13], physics [14], geography [15], meteorology [16] and hydrology [17]. DFA methods have also been employed as part of WSTS scaling analysis [1-7].

DFA methods involve several steps, such as accumulated deviation calculation, segment partition, segment detrending, fluctuation function and scaling exponent computation. Detailed descriptions can be found in the Ref. Bin S and Haitao Y [6].

DFA methods employ the following major parameters: series length \( N \), segment length \( s \), fitting polynomial order \( k \), fluctuation function order \( q \) and scaling exponent \( \alpha \). When \( q=2 \), MF-DFA is simplified to DFA. The range of \( s \) can be generally represented as \( \frac{2}{4} \leq s \leq \frac{2}{4}N \).

4. CASE STUDY

4.1 Wind data

In this study, the time series length refers to the actual length of time between the beginning and end of a time series, and the time series resolution specifically refers to the measurement interval employed within a time series. The WSTS studied here was downloaded using Modern-era Retrospective Analysis for Research and Applications (MERRA, https://gmao.gsfc.nasa.gov/research/merra/), an application developed by NASA. This series covers the Jinning region in southwestern China (N24° 30', E102° 40.13'), with a length of 30 years (from 1st March 1984 to 28th February 2014) and a resolution of 1 h (as displayed in Appendix).

4.2 Analysis schemes

To compare the influence of CP in schemes employing different seasonal division methods, a standard chronological order WSTS was first analyzed, followed by the extraction of corresponding seasonal WSTS based on the seasonal division periods derived by the solar terms and gregorian calendar methods. Temperature, wind speeds and standard deviations were then calculated via the above-mentioned multi-index method. The results of these procedures are shown in Fig. 1.
As can be seen from Fig. 1, in May the average monthly wind speed (5.6 m/s) is less than that during March and April (6.9 m/s), while the temperature (19.3°C > 16.2°C) is higher. The difference between these two periods in terms of both parameters (6.9-5.6 = 1.3 m/s, 19.3-16.2 = 3.1°C) is greater than that between May and the mean for June, July and August (5.6-4.6 = 1 m/s, 20.1-19.3 = 0.8°C). Furthermore, whereas values of wind speed standard deviation from May to August are all lower than 2.0 m/s, values in March and April are larger than 2.0 m/s. Therefore, May can be reclassified as a month in summer. In December, wind speed and its standard deviation are obviously close to values of the period from September to November. Even though the temperature in December is close to that during January and February, due to the wind speed indices are the main characteristics of WSTS the December is adjusted to a month in autumn. Index values for the remaining months are similar for those belonging to the same gregorian season and thus these months are not adjusted. In summary, four different schemes were obtained: the chronological order WSTS and three seasonal WSTS divided according to the different seasonal division methods. Details of these schemes are shown in Table 1.

### 5. RESULTS AND DISCUSSION

In the present study, DFA was applied during scaling analysis. The main DFA parameters, the fitting polynomial of order $k$ and fluctuation function of order $q$, were both selected as equal to 2.
Figure 2. Log-log curve of WSTS scheme 1.

Analysis of the log-log curve for scheme 1 (shown in Fig. 2) reveals the presence of two CP. The abscissa of the left-hand CP is 1.38, which means the value of $w$ is $10^{0.38 \times 1h = 24h}$ given a logarithmic base of 10. Similarly, the $w$ value of the right-hand CP is $10^{3.510 \times 1h = 3162h = 132d} \approx$. The left-hand CP in Fig. 2 is close to that found elsewhere [13], with all occurring at a daily time node. However, considering that the WSTS analyzed here had a resolution of 1h, the precision of daily wind speed variation measurement at such a short time scale is low. In this paper, the left-hand section of the log-log curve covering a time scale of several days will not be discussed further. The right-hand CP in Fig. 2 is almost the same as that found in Reference by Telesca L et al. [15], i.e. both occurring at the seasonal time node scale. Given that a WSTS length of 30 years was employed in the present study, wind speed variation on such a long time scale can be depicted precisely. There thus follows a discussion regarding the WSTS CP occurring on a seasonal scale.

The $s$ value represents the length of a segment during scaling analysis. The WSTS analyzed in scheme 1 is a standard chronological order series in which all four seasons are combined. When $s$ is larger than season length, the segment will contain periods belonging to different seasons. Considering that wind speed varies between different seasons, such segments might result in different scaling behavior compared with segments whose length is shorter than one season. In order to test this theory, we analyzed schemes 2 to 4, whose WSTS does not contain different seasons by employing three distinct methods of series seasonal division.

Analysis of the log-log curve for scheme 2, shown in Fig. 3, reveals that the CP associated with the spring and winter WSTS (Fig. 3.a) are more obvious than those for summer and autumn (Fig. 3.b). Indeed, in comparison to those in scheme 1, the summer and especially autumn CP in scheme 2 are almost negligible, suggesting that the use of seasonal division in WSTS could mitigate the effects of CP. Local scaling exponents $\alpha_1$ and $\alpha_2$ are respectively the slope of the log-log curve section before and after the time node ($10^{3.510 \times 1h = 3162h = 132d}$ in the present paper) of the CP, with scaling exponent $\alpha$ being the slope of the entire curve[13]. In order to quantitatively describe the effect of CP mitigation, the standard deviation (SD) of $\alpha_1$, $\alpha_2$ and $\alpha$ values should be calculated, with the lower the SD value, the more effective the scheme. The CP parameters for scheme 2 are shown in Table 2. As this table shows, the SD value for the autumn WSTS is rather low, which means that isolating autumn using the solar terms method could potentially mitigate CP to some extent. Compared with scheme 1, for which CP is particularly evident, the obvious difference in scheme 2 demonstrates the existence of different scaling features among the different seasons and thus it is not appropriate to combine them during scaling analysis. However, analysis of Fig. 4 reveals the continued presence of CP for the remaining three seasons (spring, summer, and winter) in scheme 2, indicating that the solar terms method alone is not sufficiently effective and that other methods must be developed.
Figure 3. Log-log curve of WSTS scheme 2.

Table 2. Parameters of scheme 2.

| Scaling exponent | spring | summer | autumn | winter |
|------------------|--------|--------|--------|--------|
| α1               | 0.94   | 0.89   | 0.79   | 0.89   |
| α2               | 0.27   | 0.50   | 0.69   | 0.46   |
| α                | 0.90   | 0.84   | 0.78   | 0.86   |
| SD               | 0.31   | 0.18   | 0.05   | 0.20   |

*SD means the standard deviation of α1, α2, and α.

The log-log curve for scheme 3 is shown in Fig. 4, with its parameters listed in Table 3. Analysis of these figures reveals that the results for scheme 3 are similar to those for scheme 2, suggesting that although the solar terms and gregorian calendar methods both alleviate CP to some extent, a different approach is required.
Figure 4. Log-log curve of WSTS scheme 3.

Table 3. Parameters of scheme 3.

| Scaling exponent | spring | summer | autumn | winter |
|------------------|--------|--------|--------|--------|
| $\alpha_1$       | 0.92   | 0.91   | 0.81   | 0.91   |
| $\alpha_2$       | 0.29   | 0.39   | 0.55   | 0.41   |
| $\alpha$         | 0.87   | 0.85   | 0.77   | 0.88   |
| SD               | 0.28   | 0.23   | 0.11   | 0.23   |

The results for scheme 4 (the multi-index method) are shown in Fig. 5 and Table 4. Compared with those for schemes 2 and 3, scheme 4 CP from spring to winter is not as obvious. SD values produced via the different seasonal division methods are displayed in Table 6. With the exception of autumn, whose SD is slightly increased, values for the other 3 seasons all decrease considerably under scheme 4, especially that of spring, which falls from around 0.35/0.34 (scheme 2/scheme 3) to 0.10 (scheme 4). These figures demonstrate that with the proper seasonal division in place, the impact of WSTS CP could be mitigated and potentially even eliminated altogether. However, the indices used in the present paper for seasonal division comprised only temperature, wind speed, and the latter’s SD. These parameters are not exhaustive and the effect of CP can still be observed. In particular, the intra-comparison of seasons for scheme 4 reveals that winter CP is more remarkable than those of other seasons. A greater number of indices, including precipitation and sunshine hours, should therefore be considered in order to develop a more effective seasonal division method. Nevertheless, the multi-index method proposed here has been shown to mitigate CP to a certain extent, with the presented technique valid for the acquisition of an objective WSTS scaling exponent.

Figure 5. Log-log curve of WSTS scheme 4.
Table 4. Parameters of scheme 4.

| Scaling exponent | spring | summer | autumn | winter |
|------------------|--------|--------|--------|--------|
| $\alpha_1$       | 0.84   | 0.93   | 0.81   | 0.85   |
| $\alpha_2$       | 0.75   | 0.50   | 0.85   | 0.47   |
| $\alpha$         | 0.79   | 0.89   | 0.79   | 0.81   |
| SD               | 0.04   | 0.19   | 0.03   | 0.17   |

6. CONCLUSIONS
Wind speed is a natural signal and is thus affected by many other natural factors, including sunshine, the Earth’s rotation, rainfall, temperature, and topography. These factors may lead to the occurrence of CP in WSTS, which in turn influences scaling exponent accuracy. In this study, we attempted to analyze WSTS by taking into consideration the abovementioned partial factors. A new technique is proposed involving the use of a seasonal division method aimed at mitigating CP in wind speed scaling analysis. In view of the research status of CP and considering the resolution and length of the available WSTS, seasonal time scale CP were investigated. Due to the features of wind speed, a multi-index including parameters such as temperature, wind speed and the latter’s standard deviation is suggested, based on the gregorian calendar. Three different seasonal division methods were applied during the scaling analysis of WSTS for Jinning, southwestern China. Compared with the results obtained when not dividing the series into seasons, the CP observed in the seasonal WSTS were mitigated to some extent, especially by the multi-index method. These findings demonstrate the existence of different scaling features among the seasons and thus it suggested that it is inappropriate to combine seasons during scaling analysis. Comparative analysis revealed the multi-index method to be more effective in both demarcating the seasons and mitigating CP. This study has potentially demonstrated a new and improved method with which to carry out the WSTS scaling analysis.

Future work will consider more parameters, which also influence seasonal wind speed features, such as precipitation and sunshine hours to improve the method.

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APPENDIX
Fig. A1 WSTS form 1st March 1984 to 28th February 2014.

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