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Dynamical mechanism in aero-engine gas path system using minimum spanning tree and detrended cross-correlation analysis

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HIGHLIGHTS

- A new MSMF-DXA-based MST method is proposed.
- The method measures cross-correlation between two time series.
- The aero-engine dynamics verify the utility of the MSMF-DXA-based MST method.

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ABSTRACT

Identifying the mutual interaction in aero-engine gas path system is a crucial problem that facilitates the understanding of emerging structures in complex system. By employing the multiscale multifractal detrended cross-correlation analysis method to aero-engine gas path system, the cross-correlation characteristics between gas path system parameters are established. Further, we apply multiscale multifractal detrended cross-correlation distance matrix and minimum spanning tree to investigate the mutual interactions of gas path variables. The results can infer that the low-spool rotor speed (N1) and engine pressure ratio (EPR) are main gas path parameters. The application of proposed method contributes to promote our understanding of the internal mechanisms and structures of aero-engine dynamics.

1. Introduction

Aero-engine gas path system represents extremely complex system with a large number of interacting units. Recent studies have investigated large data-sets of aero-engine gas path system, and have analyzed the dynamic behaviors of this very complex system, suggesting that aero-engine dynamics exhibit long-term correlation, and cross-correlation properties between the gas path participants [1–4]. The presence of a high degree of cross-correlation between the synchronous time evolutions of a set of aero-engine gas path system is a well-known empirical fact. Despite the cross-correlation in the performance of gas path system are visible, it is difficult to obtain the exact nature of interactions between gas path participants. In this paper, we would try best to provide some precise quantitative indicator of interactions in gas path system. And then, the focus of gas path system research has been shifting from discovering cross-correlation regularities to uncovering the

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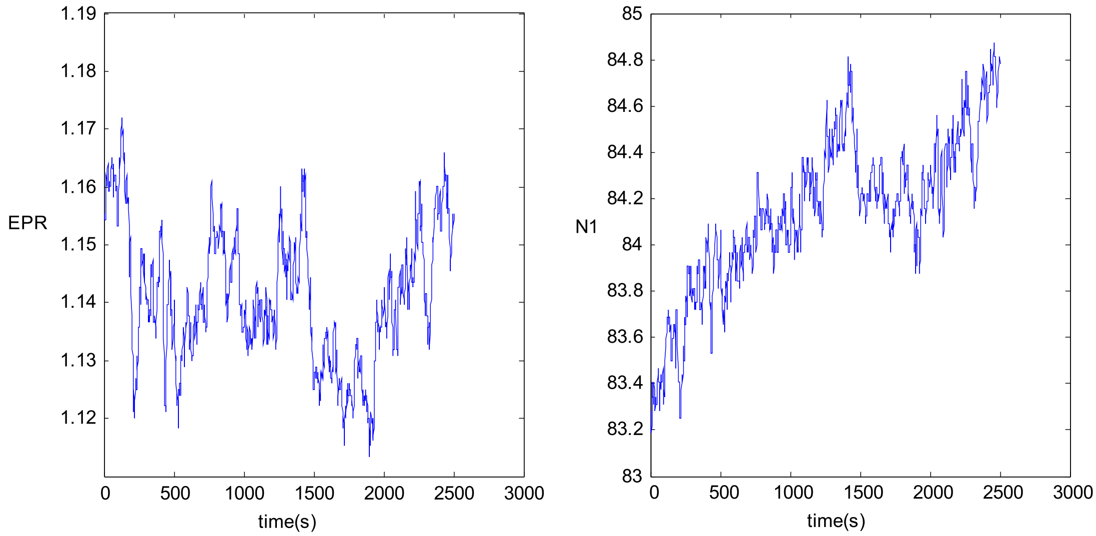

Fig. 1. The engine pressure ratio (EPR) and low-spool rotor speed (N1) time series.

role played by such elements as nodes, links and motifs in the structure and dynamics of the system. Conventional method to survey the importance of a node is to measure its degree [5,6]. Recent study argued that coreness is a better indicator of a node's influence on spreading dynamics than degree [7,8]. Here we discuss the extension of the multifractal detrended cross-correlation analysis (MF-DXA) method to quantify how important a node is to its network.

The MF-DXA method, which is a combination of the multifractal detrended fluctuation analysis (MF-DFA) and detrended cross-correlation analysis (DCCA) method [9–11]. The performance of detrended method was systematically tested for the effect of non-stationarities [9–14]. One advantage of the detrended method is that it allows the detection of cross-correlations between noisy signals with non-stationarities that can mask the true cross-correlations in the fluctuations of signals. Since MF-DXA, DCCA and DFA method were introduced to analyze non-stationary time series, they have been widely applied to research fields such as economics [15–20], geophysics [21,22], transportation [23,24], and aero-engine dynamics [2–4,25]. The DCCA coefficient and detrending moving-average cross-correlation (DMCA) coefficient method were proposed in order to provide a single scaling parameter representing the cross-correlation between two non-stationary time series [26–29]. However, many records do not exhibit a simple monofractal scaling behavior, which can be accounted for by a single scaling parameter. Therefore, the MF-DXA method may also help to identify different states of the same system with different scaling behavior. Similar arguments were introduced by Lin et al. [30].

To understand the intrinsic dynamics of a complex system, the multiscale multifractal detrended fluctuation analysis (MSMF-DFA) and multiscale multifractal detrended cross-correlation analysis (MSMF-DXA), were introduced to solve the complex, multiscale and multifractal structures [30–35]. Here, we attempt to obtain a new look on the idea of interaction by quantifying the cross-correlation properties of the gas path system using the MSMF-DXA. Furthermore, the multiscale multifractal detrended cross-correlation distance matrix and minimum spanning tree (MSMF-DXA-based MST) method is proposed to learn about the coreness of interactions in the gas path system. The results indicate that the low-spool rotor speed (N1), and the engine pressure ratio (EPR) may be the coreness of gas path elements. The possible main variables are in accord with that of previous document [3,36,37]. Therefore, the MSMF-DXA-based MST method is a promising method to explore internal structures and influential interactions of gas path system.

The organization of this paper is as follows. In Section 2, we simply present the MF-DXA, MSMF-DXA and MSMF-DXA-based MST method. We show the main empirical results and discussion in Section 3. Finally, we draw some conclusions in Section 4.

2. Data and methodology

2.1. The dataset

The aero-engine gas path parameters are civil aviation flight data from on-board flight data recorders. These recorders are part of the Aircraft Condition Monitoring System (ACMS) such as Smart ACMS Recorder (SAR) and Quick Access Recorder (QAR) [38,39]. Here, the QAR data, offered by Aircraft Maintenance and Engineering Corporation, are employed because of the extensive list of flight parameters recorded at specific sampling intervals which are set by the manufacturer [see Fig. 1].

2.2. MF-DXA method and MSMF-DXA method

MF-DXA method is an extension of detrended cross-correlation analysis (DCCA) and multifractal detrended fluctuation analysis (MF-DFA) method. For two non-stationary time series $\{x_i\}$ and $\{y_i\}$, where $i = 1, 2, \ldots, T$ and T is the length of data, the MF-DXA method is given as follows.

Step 1: Describe the profiles of time series $\{x_i\}$ and $\{y_i\}$ by Eq. (1).

$$\begin{cases} X_i = \sum_{k=1}^{i} (x_k - \langle x \rangle) \\ Y_i = \sum_{k=1}^{i} (y_k - \langle y \rangle), \end{cases} \tag{1}$$

where $\langle x \rangle = \frac{1}{k} x_j$ and $\langle y \rangle = \frac{1}{k} \sum_{j=1}^{k} y_j$ are the average values. Step 2: Cut the profiles X and Y into $T_s = [T/s]$ non-overlapping segments of equal length s, respectively. In each segment v, we calculate the local trend by a least-square fit of the data and obtain the difference between the profiles and the local trend. Considering the time series length T is often not a multiple of the time scale length s, the same procedure is repeated starting from the end of profiles.

Step 3: Compute the covariance of the residuals in each segment:

$$F^2(s, v) = \frac{1}{s} \sum_{i=1}^{s} (X_{(v-1)s+i} - \tilde{X}_{i,v})(Y_{(v-1)s+i} - \tilde{Y}_{i,v}), \tag{2}$$

for $v = 1, 2, \ldots, T_s$ and

$$F^2(s, v) = \frac{1}{s} \sum_{i=1}^{s} (X_{T-(v-T_s)s+i} - \tilde{X}_{i,v})(Y_{T-(v-T_s)s+i} - \tilde{Y}_{i,v}), \tag{3}$$

for $v = T_s + 1, T_s + 2, \ldots, 2T_s$, where $\tilde{X}_{i,v}$ and $\tilde{Y}_{i,v}$ are the local trends in vth segment.

Step 4: Average over all segments to obtain the qth fluctuation function:

$$F_q(s) = \left[\frac{1}{2T_s} \sum_{v=1}^{2T_s} \left[F^2(s, v) \right]^{\frac{q}{2}} \right]^{\frac{1}{q}}, \tag{4}$$

for $q \neq 0$ and

$$F_0(s) = \exp \left[\frac{1}{4T_s} \sum_{v=1}^{2T_s} \ln \left[F^2(s, v) \right] \right], \tag{5}$$

for $q = 0$.

Step 5: For two non-stationary cross-correlated time series $\{x_i\}$ and $\{y_i\}$, the power-law relationship exists as

$$F_q(s) \sim s^{h_{xy}(q)}, \tag{6}$$

where the MF-DXA scaling exponent $h_{xy}(q)$ represents the degrees of the cross-correlation between the two time series $\{x_i\}$ and $\{y_i\}$. For time series $x_i = y_i$, the MF-DXA fluctuate function reduces to MF-DFA fluctuate function. For $q = 2$, the standard DCCA scaling exponent h_{xy} is retrieved. The case of $h_{xy} = \frac{h_x + h_y}{2}$ is a natural limiting case for various processes with the non-zero squared coherency [40,41].

In order to obtain the MSMF-DXA method, we use the moving fitting window in Step 2, sweeping through all ranges of the scale s along the fluctuation function $F_q(s)$, and then the Hurst surface $h_{xy}(q, s)$ is acquired [42].

2.3. The MSMF-DXA-based MST method

As mentioned in Section 2.2, the Hurst surface $h_{xy}(q, s)$ is a function of the different time scale s and order q of data, which allows us to survey the local variations of the multifractal cross-correlation of signals.

And then, based on the Hurst surface $h_{xy}(q, s)$, we simply describe the construction of the gas path parameter network using the minimum spanning tree (MST) method. To construct the MST network, we concentrate on the differences of $h_{xx}(q, s)$ and $h_{yy}(q, s)$, by using the Hurst surface distance $d_{x,y}$ between parameter x and y. Inspiring from Ref. [30], we define the Hurst surface distance as follows,

$$d_{x,y} = \frac{\left[\left\langle \left[h_{xx}(q, s) - h_{yy}(q, s) \right]^2 \right\rangle \right]^{\frac{1}{2}}}{h_{xy}(q, s)}, \tag{7}$$

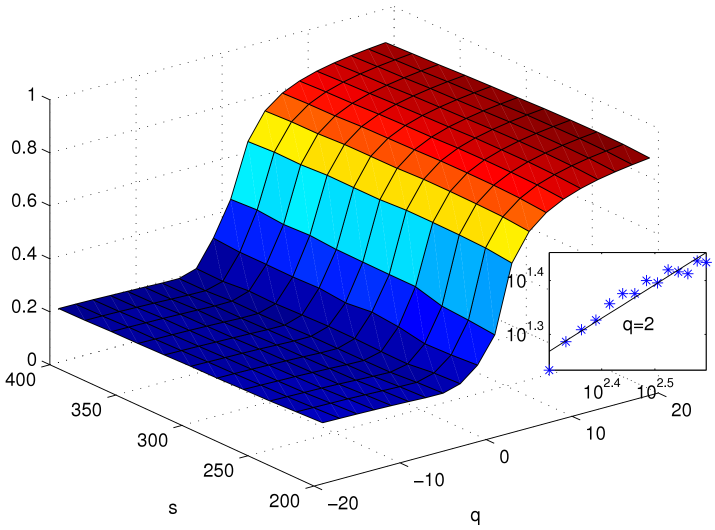

Fig. 2. The Hurst surface $h_{xy}(q, s)$ of N1 versus EPR.

which represents the degrees of the cross-correlation. The smaller Hurst surface distance $d_{x,y}$ denotes the stronger cross-correlation between parameter x and y.

Based on the Hurst surface distance $d_{x,y}$, the matrix of N parameters in gas path system consisting of elements $d_{x,y}$ is known as generalized Hurst distance matrix D. We then construct the MST G proposed by Mantegna for N parameters in the gas path system [42]. The MST network of the gas path system connects the N parameters (nodes) with $N - 1$ stronger links such that no loops are produced, i.e., the gas path system is structured with the strongest cross-correlations of each parameter.

3. Empirical results and analysis

3.1. MSMF-DXA results

This section investigates the existence of cross-correlation in aero-engine gas path system applying the MSMF-DXA method. Fig. 2 displays the Hurst surface $h_{xy}(q, s)$ for low-spool rotor speed (N1) and engine pressure ratio (EPR). The multiscale DCCA curve exhibits obvious power-law behavior with the Hurst exponent $h_{xy}(q, s) = 0.62$ for $q = 2$ [see the right lower in Fig. 2], implying power-law cross-correlations between in N1 and EPR.

In order to amplify the study of cross-correlation between aero-engine gas path variables, we here measure the Hurst surface $h_{xy}(q, s)$ for more variables such as EGT, EPR, N1, N1 tracked vibration channel A (N1TRKCHNA), N1 tracked vibration channel B (N1TRKCHNB), N2, N2 tracked vibration channel A (N2TRKCHNA), N2 tracked vibration channel B (N2TRKCHNB), inlet air pressure (P2), other pressure (P2.5, P5), WF, and wind speed (WIND SPEED).

To better understand the complex behavior, we investigate the Hurst surface $h_{xy}(q, s)$ for gas path variables. In Fig. 3, the Hurst surface of EPR versus N2, EGT, WF, wind speed is illustrated. We interestingly find tiny difference in the multiscale DCCA curve, which exhibits obvious power-law behavior of $F_q(s) \sim s^{h_{xy}(q)}$ when q is a fixed value specified. To capture the degree of variability of cross-correlation for more variables, the Hurst surface $h_{xy}(q, s)$ of N1 versus N1TA, N1TB, P2, P2.5, P5, and WF is shown in Fig. 4. The similar fluctuations exhibited by the $h_{xy}(q, s)$ provide evidence that the cross-correlation characterizes exist in gas path system.

3.2. The MSMF-DXA-based MST results

Based on the MSMF-DXA analysis, we observe the cross-correlation behaviors among gas path participants. But no obvious difference is shown among the $h_{xy}(q, s)$ of gas path parameters. In order to clarify the results more directly, the Hurst surface distance matrix which describes the cross-correlations between multiple variables is constructed by Eq. (7). In Fig. 5 the distance matrix of 13 parameters in gas path system is demonstrated. The minor distances among gas path parameters confirm the cross-correlation behaviors above mentioned. The distances between N1 and other variables, except for N1TA, N1TB and WS, are no larger than 0.3, which indicate the strong cross-correlation between N1 and other variables.

Moreover, in addition to considering the distance matrix, we are also interested in discussing the interaction structure of the gas path system. For this purpose, we construct MST of the gas path system as shown in Fig. 6. The MST gives us a more intuitive picture about the cross-correlation among the gas path system parameters. There is an observably cluster phenomenon that arouses interest in us. The result of Fig. 6 demonstrates that the 13gas path variables center on the

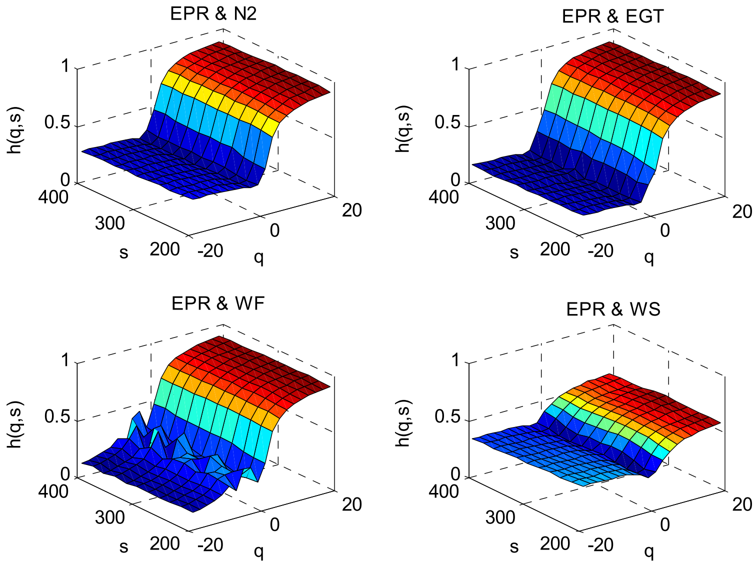

Fig. 3. The Hurst surface $h_{xy}(q, s)$ of EPR versus gas path variables.

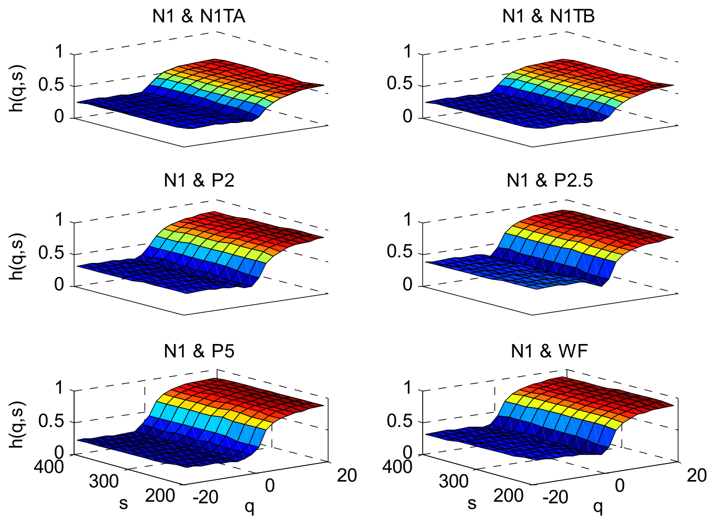

Fig. 4. The Hurst surface $h_{xy}(q, s)$ of N1 versus gas path variables.

parameters N1 and EPR, which suggest that N1 and EPR may be the main gas path elements. The possible main variables are in accord with that of Refs. [3,36,37], where some variables, such as N1and EPR are considered as the main gas path elements.

Aero-engine behavior can be described by major aero-engine gas path parameters and by their temporal and qualitative relationships. The parameters EPR and N1 are chosen for indicating the thrust by Pratt & Whitney, GE and Rolls-Royce, which indicate EPR and N1 are the most important gas path variables. The results of MST show that the N1 and EPR are major parameters which contribute significantly to explore the dynamics of aero-engine.

4. Conclusion

In the paper, we consider multiscale multifractal detrended cross-correlation analysis method to understand the cross-correlation characteristics in aero-engine gas path system firstly. The technique has been implemented on the low-spool rotor speed and engine pressure ratio time series. For the low-spool rotor speed and engine pressure ratio time series, the Hurst surface exhibits obvious power-law behavior which provides evidence that cross-correlation characteristic exist here. And then, by applying the multiscale multifractal detrended cross-correlation analysis method to 13 parameters of gas path system, we obtain the similar fluctuations exhibited by the $h_{xy}(q, s)$ implying the existence of cross-correlation in gas path system.

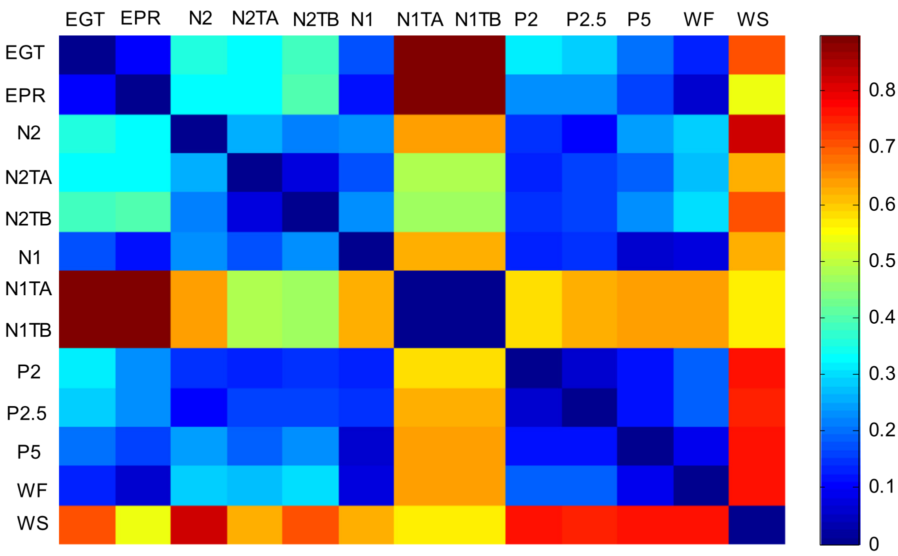

Fig. 5. The distance matrix of gas path system variables.

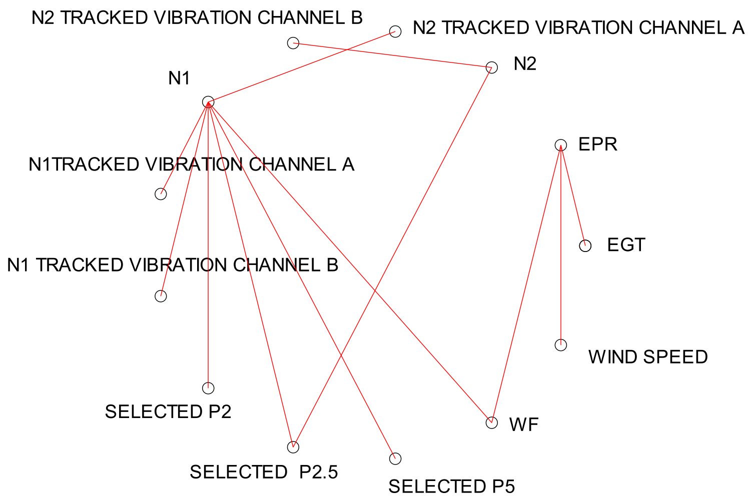

Fig. 6. The MST of gas path system variables.

To capture the degree of variability of cross-correlation in detail, we construct minimum spanning tree based on the multiscale multifractal detrended cross-correlation distance matrix to research the cross-correlation between aero-engine gas path participants. The results can infer that the variables low-spool rotor speed and engine pressure ratio time series are main gas path parameters.

We present two possible applications of the proposed MSMF-DXA-based MST method. First, we analyze the cross-correlation relationship of aero-engine gas path dynamics and show one gas path parameter can be influenced by different parameters. Second, we give the main gas path parameters as the primary nodes. Therefore, we do believe that our method and results may provide some help to promote our understanding of the internal mechanisms and structures of aero-engine dynamics.

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