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Control Performance Monitoring with Temporal Features and Dissimilarity Analysis for Nonstationary Dynamic Processes

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Abstract: Recently, the combination of cointegration analysis (CA) and slow feature analysis (SFA), has been adopted for concurrent monitoring of operation condition and process dynamics for nonstationary dynamic processes subject to time variant conditions. By isolating long-term temporal equilibrium features and specific temporal slow features from steady-state information, the CA-SFA based monitoring scheme can well distinguish between the changes of operation conditions and real faults. Considering that the temporal variation can provide an indication of control performance changes, the CA-SFA algorithm is further exploited based on dissimilarity analysis of temporal distribution to explore its unique efficacy in control performance monitoring (CPM). Two attractive features of the proposed approach are noticed. First, it is compatible with various operation conditions simultaneously including multifarious steady states and dynamic switchings between different working points. Second, a new performance monitoring index is used to monitor the control performance by quantifying the distribution structure of temporal features against the benchmark from both fast and slow dynamics aspects. Case study on a chemical industrial scale multiphase flow experimental rig shows the feasibility of the new CPM method.

Keywords: Control performance monitoring, temporal features, dissimilarity analysis, nonstationary

1. INTRODUCTION

Data-driven methods (Zhao and Gao, 2014, Zhao and Gao, 2017, Zhao and Gao, 2016, Li et al., 2018) have been widely applied for process monitoring and fault diagnosis in industrial field. Owing to wide applications of automatic controllers, controller performance has become one of the key factors determining the productivity of a plant on industrial processes and its impacts are of increasing significance. Due to the labor cost of manual monitoring, the demand of online and automated controller performance monitoring has become increasingly necessary in practice. To this aim, the technique of control performance assessment (CPA) has drawn considerable attention with respect to both academia and industry aspects for the past two decades. The objective is to detect performance degradation by analyzing routine closed-loop operating data. In parallel, control performance monitoring (CPM) is to detect change of controller performance. The most common approach to controller performance monitoring is to compare the performance of the monitored loops with that of a benchmark. In general, the category of CPM benchmarks covers three types, i.e., theoretical optimal benchmarks, user-specified benchmarks and historical benchmarks. The performance benchmark can be the performance of either some optimal controller designed for certain objectives, or the monitored controller during its golden operation periods. Studies of CPA algorithms began to appear in the early 1990s after the work of Harris (Harris, 1989), in which Harris proposed the use of closed-loop data to evaluate and diagnose controller performance using minimum variance control (MVC) as a benchmark. Multivariable control performance assessment requires the knowledge of process time delay, the structure of which is represented by interactor matrix (Huang et al., 1997, Huang and Shah, 1998). In contrast, user-specified benchmarks are established using historical measurement data during which the concerned control system was operating at satisfactory statues. This approach can avoid ideal assumptions on processes and is becoming more practical(Yu and Qin, 2008a, Yu and Qin, 2008b, Li et al., 2015, Li et al., 2003, Schäfer and Cinar, 2004, Patwadhan, 2002, Huang et al., 2014). As a purely data-driven solution to CPA/CPM, it relieves users from cost of building physical models, and is thus applicable to both industrial single loops and more complicated MIMO processes. A covariance-based performance metric has been statistically defined (Schäfer and Cinar, 2004, Patwadhan, 2002), which makes use of only historical operation data in a period of time to form an index for CPM. An improved covariance-based index was put forward based on dissimilarity analysis (Huang et al., 2014). Although the DISSIM index can evaluate the changes of distribution structure and is thus more sensitive to control performance changes; it, however, only considers the unique static operation condition which thus may not work if the process has shifted to a new working point.

As an alternative, Shang et al. (Shang et al., 2015) demonstrated that temporal behaviors of all types of variables including MV, CV and DV, can provide an indication of current control performance. Shang et al. (Shang et al., 2015) reported a data-driven monitoring and diagnosis of control performance based on process dynamic behaviors statistically described by slow feature analysis (SFA) (Wiskott and Sejnowski, 2002). The benefit of SFA-based monitoring method was revealed in CPM by new monitoring indices based on the temporal difference of slow features. The monitoring indices essentially allude to alterations in control performance to quantify how fast the process varies. However, the SFA-based monitoring method in CPM has not been analyzed for nonstationary processes subject to time variant conditions despite that it has claimed that the temporally differenced features are free from specific steady-states. In practical scenarios, changes of operation conditions can be frequent and common due to various reasons. For chemical processes with time variant conditions, the process status is often multimodal with not only multifarious steady states but also frequent dynamic switchings between different steady states. Besides, in their work, the SFA-based CPM method can only detect performance changes if the temporal variation increases based on the calculation of conventional monitoring statistics. It cannot indicate the change of temporal variations if the process varies more slowly. In fact, unusual process dynamics cover both increased and decreased temporal variations both of which may point to changes of control performance. Therefore, a proper CPM method needs to be developed to completely quantify the changes of temporal variations and indicate the changes of control performance for diversified operating conditions. In a very recent work, Zhao et al. (Zhao and Huang, 2017) provided a novel full-condition fault detection framework for nonstationary dynamic processes subject to time-variant conditions based on cointegration analysis (CA) (Engle and Granger, 1987) and SFA. That method can distinguish between the changes of operation conditions and real faults by checking deviations from equilibrium relation and deviations from the specific relation from both static and dynamic aspects. It is in particular powerful when the considered modeling data may not be representative enough to include all possible operation conditions. However, in (Zhao and Huang, 2017), potential benefits of the full-condition fault detection method for CPM of nonstationary processes, have not been fully considered and will be addressed in this article.

The orientation of this study is then towards a data-driven monitoring of control performance for nonstationary processes subject to time variant conditions on the basis of process temporal behaviors. The designed CPM strategy is applicable to a much broader scope and allows performance monitoring at different working points as well as the dynamic shifts between different steady statuses. It can work even if the process is undergoing some new normal operation conditions, resulting in new process statuses and shifts. Control performance indices are based on dissimilarity analysis of temporal distribution of both long-term equilibrium features and specific slow features to quantify how fast the process varies. They allow a real-time monitoring of control performance whenever a new observation is available. An important step is to elaborately quantify the changes of temporal variations from both fast and slow aspects, which furnishes useful information for further controller maintenance.

2. METHODOLOGY

2.1 Motivation

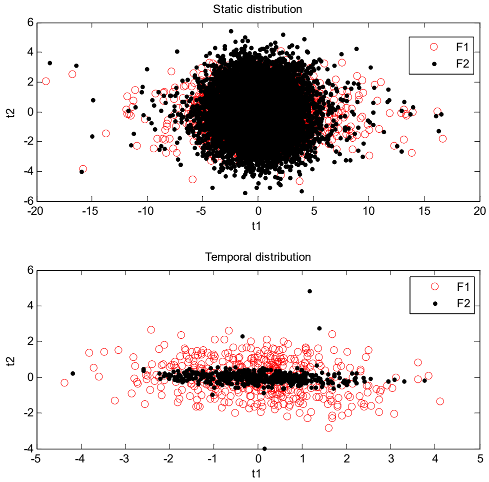


Fig. 1. Static and temporal distributions for two processes (t1 and t2 are two static/temporal features).

For time-variant processes, a frequent change of operating condition can be observed. It results in regulation of controllers and thus changes of control performance which necessitates the performance monitoring at different operation points. The proposed method is based on the following consideration. (1) Since the changes in system performance is reflected from changes in process dynamics, we can monitor control performance by evaluating the temporal distribution of process data. (2) Considering that the temporal distribution is free from specific steady-states, the analysis of temporal distribution allows performance monitoring at different working points which is separated from the static process distribution. (3) Both increased and decreased temporal variations point to changes of control performance and an elaborate analysis should embrace both types of variations for indication of control performance changes.

Based on the above considerations, hence, the control performance change can be determined by investigating the temporal distribution of process data. The proposed method takes into account of changes among the hyper-ellipsoids defined by different temporal covariance matrices based on extraction of temporal features from nonstationary processes. Dissimilarity analysis is conducted to quantify the difference of temporal distribution by considering not only the volume of the hyper-ellipsoid defined by the temporal features, but also the direction of the hyper-ellipsoid. Besides, both the increased and decreased temporal variations are evaluated. For clarity, a simple illustration is shown in Fig. 1 to show distribution difference for static and temporal features (t1 and t2) respectively which are extracted from the process data using SFA. Comparing the two processes (F1 and F2), they share similar static distribution. In contrast, they have different temporal distribution. The temporal variations of F2 are obviously smaller than those of F1 as indicated by the smaller ellipsoids, revealing that F1 is changing slower than F2. It means that the control performance may be different between the two processes. If the conventional monitoring statistics, such as T^2 and SPE, are used for monitoring, the results will show that F2 lies in the normal region defined based on F1, which can not reveal the difference of temporal distribution. The critical problem is how to quantify the speed that the process varies including both faster and slower temporal changes.

2.2 CA-SFA temporal feature extraction

Assume that J process variables are measured online over N time instances subject to time variant conditions. It forms the regular data analysis unit, denoted as $\mathbf{X}(N\times J)$, where J is the number of variables (i.e., time series), the subscript j denotes the variable index, and N is the number of samples. The variables are normalized to have zero mean. They prepare the normalized data set $\mathbf{X}$. Here for simplicity, the centered data sets are denoted by the same symbols.

First, apply the Augmented Dickey-Fuller (ADF) test for stationarity test to separate all nonstationary variables $\mathbf{X}_1(N\times J_1)$ from those stationary variables $\mathbf{X}_2(N\times J_2)$, where $J=J_1+J_2$. For simplicity, only integrated variables of order 1 will be discussed in the paper.

Second, CA algorithm is applied on the identified nonstationary variables $\mathbf{X}_1$. The cointegration model and the temporal equilibrium features are calculated,

$$\begin{aligned}\mathbf{E} &= \Delta\mathbf{X}_{1,p} - \Delta\mathbf{X}_1^p\mathbf{\Theta}\\ \mathbf{T}_e &= \mathbf{E}\mathbf{B}_e\end{aligned} \tag{1}$$

where, $\Delta\mathbf{X}_{1,p}\left((N-p)\times J\right)=\begin{bmatrix}\Delta\mathbf{x}_{1,p+1}{}^T\\ \Delta\mathbf{x}_{1,p+2}{}^T\\ \vdots\\ \Delta\mathbf{x}_{1,N}{}^T\end{bmatrix}$ and $\Delta\mathbf{x}_{1,p+1}(J\times 1)=\mathbf{x}_{1,p+1}-\mathbf{x}_{1,p}$, which denotes the temporal difference between two neighboring observations in $\mathbf{X}_1$; $\Delta\mathbf{X}_1^p\left((N-p)\times Jp\right)$ is constructed by augmenting each temporal difference vector with the previous p vectors so that $\Delta\mathbf{X}_1^p=\begin{bmatrix}\Delta\mathbf{x}_{1,1}{}^T,\Delta\mathbf{x}_{1,2}{}^T,\ldots,\Delta\mathbf{x}_{1,p}{}^T\\ \Delta\mathbf{x}_{1,2}{}^T,\Delta\mathbf{x}_{1,3}{}^T,\ldots,\Delta\mathbf{x}_{1,p+1}{}^T\\ \vdots\\ \Delta\mathbf{x}_{1,N-p}{}^T,\Delta\mathbf{x}_{1,N-p-1}{}^T,\ldots,\Delta\mathbf{x}_{1,N-1}{}^T\end{bmatrix}$. The subscript p denotes the number of past vectors (i.e., the number of past lags) included into the regressor matrix and the optimal value can be determined by the Akaike information criterion (AIC). $\mathbf{X}_{1,p}\left((N-p)\times J\right)$ denotes the observation matrix, $\mathbf{X}_{1,p}=\begin{bmatrix}\mathbf{x}_{1,p}{}^T,\\ \mathbf{x}_{1,p+1}{}^T\\ \vdots\\ \mathbf{x}_{1,N-1}{}^T\end{bmatrix}$. $\mathbf{B}_e$ are the weight matrix for $\mathbf{E}$ calculated by performing canonical correlation anlaysis between $\mathbf{E}$ and $\mathbf{F}$ (Engle and Granger, 1987). The temporal equilibrium features ($\mathbf{T}_e$) are computed for the error matrices, $\mathbf{E}$. Note that $\forall i\neq j$, $\langle t_{e,i},t_{e,j}\rangle=0$. Besides, they have unit length for each temporal feature. Choose R_c most stationary static sequences to determine the dominate temporal equilibrium features.

Third, a new analysis unit ($\breve{\mathbf{X}}(N\times J)$) is constructed by putting the stationary variables $\mathbf{X}_2$ that were separated before and the remaining data $\tilde{\mathbf{X}}_1$ together, $\breve{\mathbf{X}}=\left[\tilde{\mathbf{X}}_1,\mathbf{X}_2\right]$. $\tilde{\mathbf{X}}_1$ is calculated by performing an orthogonal decomposition to the data space of $\mathbf{X}_1$ as $\tilde{\mathbf{X}}_1=\mathbf{X}_1\mathbf{B}_f{}^{\perp}$ where, $\mathbf{B}_f{}^{\perp}$ denotes the space orthogonal to columns of $\mathbf{B}_f$ calculated as $\mathbf{B}_f{}^{\perp}=\mathbf{I}-\mathbf{B}_f\left(\mathbf{B}_f{}^T\mathbf{B}_f\right)^{-1}\mathbf{B}_f{}^T$ and $\mathbf{I}$ is a J_1 -dimensional identity matrix.

Fourth, apply SFA algorithm on $\breve{\mathbf{X}}$ to get the temporal slow features

$$\dot{\mathbf{S}}=\dot{\breve{\mathbf{X}}}\mathbf{V} \tag{2}$$

where, the derived slow features $\mathbf{S}$ and the temporal slow features $\dot{\mathbf{S}}$ are directly calculated from the combined data set $\breve{\mathbf{X}}$. The SFA model $\mathbf{V}$ can carry out dimension reduction and denoising simultaneously. All slow features (denoted as R_s) are retained here except those with zero variances.

Based on the low-dimensional CA model and SFA model given in the preceding subsection, temporal features are extracted with reference to two different types of temporal distribution. For temporal equilibrium features($\mathbf{T}_e$), they can reveal one equilibrium relation that extends beyond the current time. For temporal slow features ($\dot{\mathbf{S}}$), they can reveal the other dynamic relation that stays invariant under different normal operating conditions. Control performance indices are based on temporal distribution of both long-term equilibrium features and specific slow features to quantify how fast the process varies.

2.3 Dissimilarity analysis for temporal features

According to Fig. 1, it can be seen that different hyper-ellipsoids correspond to different temporal distribution. Meanwhile, the change in the shape of hyper-ellipsoids indicates a change in temporal distribution and thus a change in control performance, i.e., the process varies either faster or slower. Hence, the performance change can be determined by analyzing the dissimilarity among the hyper-ellipsoids defined by different temporal covariance matrices. Based on the extraction of temporal features, dissimilarity analysis is conducted on them to quantify the changes of temporal distribution for CPM.

The analysis focuses on the temporal features extracted from two data sets, which share the same number of features but may have different number of samples. One data set is referred as the reference. The other is the current data set. The difference of distributions between the two data sets is evaluated for modeling. The details of DISSIM algorithm can refer to the work by Zhao et al. (Zhao and Gao, 2017). The distribution difference between two data sets which can be evaluated by defining the following index D,

$$\begin{aligned} D_c &= diss\left(\mathbf{T}_{e,r}, \mathbf{T}_{e,c}\right) = \frac{4}{R_c}\sum_{j=1}^{R_c}\left(\lambda_c^j - 0.5\right)^2 \\ D_s &= diss\left(\dot{\mathbf{S}}_r, \dot{\mathbf{S}}_c\right) = \frac{4}{R_s}\sum_{j=1}^{R_s}\left(\lambda_s^j - 0.5\right)^2 \end{aligned} \tag{3}$$

where, λ_c^j and λ_s^j denote the eigenvalues of the covariance matrices of the transformed data matrices from two different types of temporal features ($\mathbf{T}_e$ and $\dot{\mathbf{S}}$) respectively. D_c and D_s represent the dissimilarity values for $\mathbf{T}_e$ and $\dot{\mathbf{S}}$ respectively. The subscript r and c denote the reference data and the current one.

When the two sets share similar temporal distribution, they should present similar eigenvalues along the same eigenvectors. That is, the eigenvalues must be near 0.5 from Eq. (3) along the same directions, and then D should be near zero. On the other hand, when data sets temporally distribute quite differently from each other, D should be near one. Therefore, the index D quantifies the temporal distribution dissimilarity between two data sets which covers both increased and decreased process dynamics.

2.4 The outline of the performance monitoring strategy

Based on the above mentioned temporal feature extraction and dissimilarity analysis, the offline modeling and online monitoring are depicted as below.

For offline modeling, two types of temporal features are extracted for the training samples. Then use time-window to generate multiple temporal data sets from the data, each composing of L samples. Then, a reference temporal feature set is chosen from the time-windows as the benchmark for $\mathbf{T}_e$ and $\dot{\mathbf{S}}$, respectively. Calculate the index D to evaluate the distribution difference between the moving windows and the reference one, and determine the control limit.

For on-line process monitoring, first, the new sample $\mathbf{x}_{new}$ is normalized using the mean information obtained from training data. Then, the nonstationary variables $\mathbf{x}_{new,1}$ are picked up and the temporal equilibrium feature is calculated similarly as shown in Eq. (1),

$$\begin{aligned} \mathbf{e}_{new}{}^T &= \Delta\mathbf{x}_{new,1,p}{}^T - \Delta\mathbf{x}^p_{new,1}{}^T\mathbf{\Theta} \\ \mathbf{t}_{new,e}{}^T &= \mathbf{e}_{new}{}^T\mathbf{B}_e \end{aligned} \tag{4}$$

The remaining information is calculated and then combined with the original stationary variables, $\mathbf{x}_{new,2}$,

$$\begin{aligned} \tilde{\mathbf{x}}_{new,1}{}^T &= \mathbf{x}_{new,1}{}^T\mathbf{B}_f{}^{\perp} \\ \breve{\mathbf{x}}_{new}{}^T &= \left[\tilde{\mathbf{x}}_{new,1}{}^T, \mathbf{x}_{new,2}{}^T\right] \end{aligned} \tag{5}$$

Then temporal slow features are extracted from $\breve{\mathbf{x}}_{new}$,

$$\dot{\mathbf{s}}_{new}{}^T = \dot{\breve{\mathbf{x}}}_{new}{}^T\mathbf{V} \tag{6}$$

With the new temporal features available, the current moving window representing the actual operating status is then updated continuously by moving the time-window forward step-wise. The dissimilarity index D is calculated for the two temporal features respectively to evaluate the temporal distribution difference between the actual and the reference data sets. Compare the values of two monitoring statistics calculated at each time with the predefined control limits respectively. If both monitoring statistics stay well within the predefined normal regions, the current sample can be deemed to be operating according to the reference temporal distribution. In contrast, if any of the two indices is consistently outside the control limit, the current temporal covariance structure is judged to be different from the reference one, revealing that the controlled dynamics may have changed, resulting in different control performance.

3. RESULT AND DISCUSSION

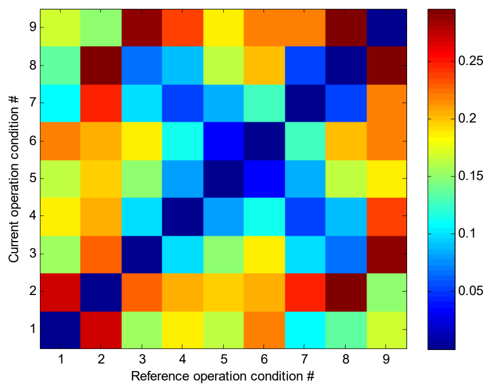
3.1 Three-phase flow facility description

The Three-phase Flow Facility, which is widely used in petrochemical industry, has been designed by Cranfield University to provide a controlled and measured flow rate of water, oil and air to a pressurized system(Ruiz-Cárcel, 2015). For simplicity, the specific description of process mechanism is not presented here. Readers can refer to (Ruiz-Cárcel, 2015) for more details.

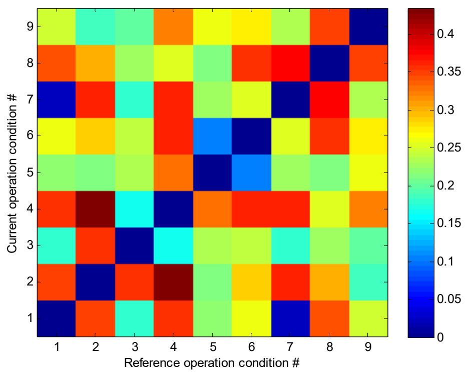
This process has typical nonstationary characteristics subject to time variant conditions by deliberately varying the set points of two process inputs including air and water flow rate. Three data sets (T1, T2 and T3) are obtained representing normal working status under time variant operation conditions. In each one of them, the flow conditions were changed in order to obtain a good variety of fast and slow process changes happening at different operation conditions. This provides a good platform to verify our method for full-condition CPM for nonstationary processes subject to time variant conditions. In the present work, 23 measured variables which cover CVs and MVs from five control loops are used for control performance analysis and monitoring purpose.

3.2 Results and discussions

First, CA-SFA is used to extract two types of temporal features from the first normal data (T1). For temporal equilibrium features ($\mathbf{T}_e$) and temporal slow features ($\dot{\mathbf{S}}$) respectively, DISSIM index is calculated to quantify the difference of process dynamics between any two steady operation conditions. The temporal features are selected for each steady operation condition based on the indication of trajectories of air flow rate and water flow rate. The time regions in which the trajectories are stable are chosen to represent steady operation status. From the first normal data set (T1), we can choose nine steady operation statuses. Then DISSIM index is evaluated to quantify whether the process is varying similarly as shown in Fig. 2 using different temporal features respectively. Clearly, some steady statuses are changing with a similar speed while others are more different. Besides, it is clear that the temporal equilibrium features are more similar between different operation conditions, revealing that this part of dynamics is more similar. In contrast, the temporal slow features are more different between different operation conditions, revealing that this part of dynamics is quite different from each other. Therefore, the temporal slow features more focus on revealing the difference of process dynamics after the extraction of temporal equilibrium features.



(a)



(b)

Fig. 2. DISSIM index between any two operation conditions for (a) temporal equilibrium features and (b) temporal slow features.

Besides the offline control performance comparison, online performance monitoring is conducted based on the two types of temporal features. Using the eighth operation condition as the reference one, DISSIM monitoring model is developed based on two types of temporal features in which the length of moving window is set to be 50 and different moving windows are available with the new samples updated along the time. Then the monitoring model is used for online monitoring. The DISSIM monitoring results are calculated and shown in Fig. 3 for two types of temporal features extracted from T1 data set. It is clear that the temporal equilibrium features are more stable among different operation conditions than temporal slow features. For temporal equilibrium features, the results indicate that the process dynamics do not change significantly since all DISSIM monitoring values stay well within the normal region. For temporal slow features, the process dynamics are more different along time among different operation conditions, in particular for the switchings between different operation conditions.

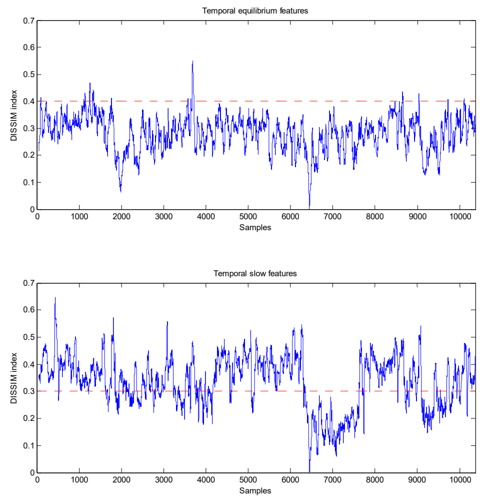


Fig. 3. Online CPM for training data (T1) based on two types of temporal features.

Then the designed CA-SFA model is used to extract temporal features for testing data. For T2 data set, after the extraction of two types of temporal features, the DISSIM index is online calculated by comparing the current moving window with the benchmark. As shown in Fig. 4, the temporal equilibrium features indicate that the control performance has changed more or less before 3500^{th} sample. For the temporal slow features, the process dynamics have changed significantly with DISSIM index out of control throughout the process. Therefore, even for normal process with multifarious steady states and dynamic switchings, the control performance may change owing to the regulation of controller. For the third normal data set (T3), the similar phenomenon is observed which is not shown here for brevity.

Then one fault case is chosen to present how the control performance changes after the disturbances happen. For Fault #1 (Case #1), the operation conditions are time variant for both water and air flow rates and the fault starts from the 1566th sample. Using the proposed method, the temporal variations are significantly disturbed as shown in Fig. 5. Both the dynamic equilibrium relation and the dynamic slow relation are broken. In particular, the DISSIM index shows a gradual increase and goes out of control after the 3000th sample. It may result from the effects of some controllers which are working to bring the process back to normal. In contrast, using the conventional monitoring statistics, like T2 and SPE, the temporal variations did not indicate significant changes as shown in our previous work (Zhao and Huang, 2017). It may result from the fact that only the increased variations were counted for monitoring. Using DISSIM index for temporal features, the inherent temporal information can be elaborated considering both fast and slow temporal changes which indicate that the controllers begin to work, resulting in changes of control performance.

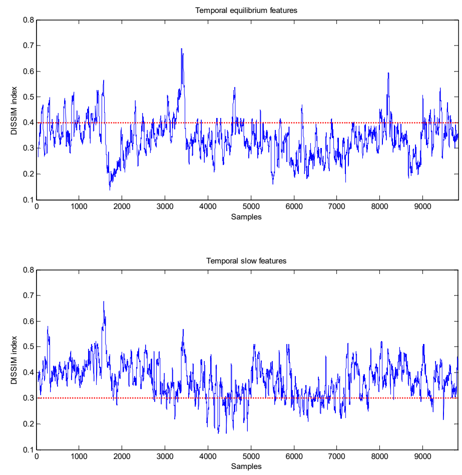


Fig. 4. Online CPM for testing data (T2) based on two types of temporal features.

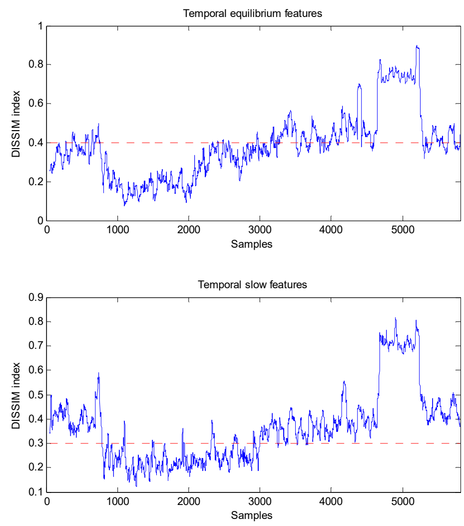


Fig. 5. Online CPM for one fault case (data set 1.1) based on two types of temporal features

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