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계층적 분해 방법과 PCA를 이용한 공장규모 실시간 감시 및 진단

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Plant-wide On-line Monitoring and Diagnosis Based on Hierarchical Decomposition and Principal Component Analysis

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요 약

화학 공정을 계속적으로 감시 함으로써 공정의 이상이 장치의 고장 또는 폭발에 이르지 않도록 조기에 이상을 감시하는 기술은 공장 조업의 안정성과 생산성의 측면에서 볼 때 매우 중요하다. 최근, DCS와 같은 공정 정보 시스템이 널리 보급됨에 따라서 방대한 양의 데이터들을 해석해서 실시간으로 공정을 감시하고 진단할 수 있는 기반이 마련되었다. 본 연구에서는 계층적 분해 기법과 PCA에 기반을 둔 공장 규모의 실시간 감시 기법을 제안한다. 대형 공정을 효율적으로 모니터링 하기 위하여 전체 공정은 몇 개의 군으로 나뉘며 또한 이 군은 다시 몇 개의 하위 군으로 세분하게 된다. 이렇게 전체 공정을 분해하여 계층적인 공정 모델을 구성함으로써, 전체 공정의 조업 상황을 감시할 수 있을 뿐만 아니라 이상이 발생했을 시에는 하위 계층의 조업 상황을 고려하여 보다 자세한 이상 원인을 진단할 수있다. 또한 각 세부 단위 공정들에 대한 조업 정보를 포함하고 있는 하위 모델들과 전체 조업 전반에 관한 정보를 지닌 전체 모델을 통하여 공정 이상을 조기에 감시함으로써 이상이 전파를 방지할 수 있다. 이러한 실시간 감시 및 진단 기법을 구현학 ldnl하여 기존의 SPC와 다변량 통계 기법의 하나인 PCA를 적용하였으며, 제안한 방법의 감시 및 진단 성능을 평가하기 위하여 41개의 측정 변수를 가진 Tennessee Eastman 공정에 대하여 전산 모사를 수행하였다. 세 가지 경우에 대하여 적용한 결과들은 이상의 신속한 감지와 믿을만한 원인 진단 능력을 보여 주었다.

Abstract - Continual monitoring of abnormal operating conditions i a key issue in maintaining high product quality and safe operation, since the undetected process abnormality may lead to the undesirable operations, finally producing low quality products, or breakdown of equipment. The statistical projection method recently highlighted has the advantage of easily building reference model with the historical measurement data in the statistically in-control state and not requiring any detailed mathematical model or knowledge-base of process. As the complexity of process increases, however, we have more measurement variables and recycle streams. This situation may not only result in the frequent occurrence of process perturbation, but make it difficult to pinpoint trouble-making causes or at most assignable source unit due to the confusing candidates. Consequently, an ad hoc skill to monitor and diagnose in plat-wide scale is needed. In this paper, we propose a hierarchical plant-wide monitoring methodology based on hierarchical decomposition and principal component analysis for handling the complexity and interactions among process units. This have the effect of preventing special events in a specific sub-block from propagating to other sub-blocks or at least delaying the transfer of undesired state, and so make it possible to quickly detect and diagnose the process malfunctions. To prove the performance of the proposed methodology, we simulate the Tennessee Eastman benchmark process which is operated continuously with 41 measurement variables of five major units. Simulation results have shown that the proposed methodology offers a fast and reliable monitoring and diagnosis for a large scale chemical plant.

Key word

1. INTRODUCTION

It is essential to detect and diagnose abnormal operating conditions in maintaining high product quality and safe operation because the undetected process abnormality may lead to the major failures such as equipment breakdown or explosion. Recently, as the wide deployment of distributed control system and additional process monitoring systems provide operators with huge amount of process data on-line, the most difficult task of monitoring and diagnosis has become the efficient and reliable processing and analysis of those data to extract the information about the process and monitor the process conditions. However, this task is a really challenging one due to the complexities of chemical processes such as hundreds or thousands of measurement variables and strong interactions among those measurements[1].

The monitoring method based on statistical approaches has been widely accepted as an efficient tool because it has the advantage of easily building reference model with the historical database in the statistically in-control operation state and doesn't require any detailed mathematical description and knowledge-base of process[2, 6, 8, 9].

In this paper, we propose a hierarchical plant-wide monitoring methodology based on hierarchical decomposition and principal component analysis. To handle the complexity and interactions among process units, a hierarchical decomposition is employed for the monitoring. The whole plant is decomposed into several groups and then monitored at the top level. When a disturbance or failure is detected, the monitoring goes down to the corresponding groups where more detailed monitoring can be performed. This monitoring process goes on in a ecursive manner until the right cause is identified. For the efficient monitoring of each group or the whole plant, or each subgroup, a PCA-based multivariate statistical monitoring scheme combined with SPC is employed to identify the cause. The proposed methodology is illustrated by the application to the hierarchical plant-wide monitoring of Tennessee Eastman benchmark process. Application examples are given.

2. THEORY

2.1. Process monitoring using PCA

PCA is a one of the statistical methods of handling large data set. PCA decomposes a single, dependent and highly correlated set of measurements into latent variables defined by the eigenvectors of the covariance of the data. This reduced set of latent variables summarize most of the relevant information by projecting the original variables down onto a low dimensional subspace. In this reduced space, the reduced data set represent a greatly reduced collinearity by explaining the variance of the original data in terms of a new set of independent principal components(PCs)[3, 4].

Having established a PCA model using historical data collected when process is in the NOC(Normal Operating Conditions), future behavior can be referenced against this in-control model. New multivariate observations can be projected onto the planes defined by the PCA loading vectors to obtain their scores and residuals[4, 5].

2.2 Plant-wide monitoring based on hierarchical decomposition

The increasing complexities of processes may not only lead to the frequent occurrence of process perturbation, but also make it difficult to pinpoint trouble-making causes or

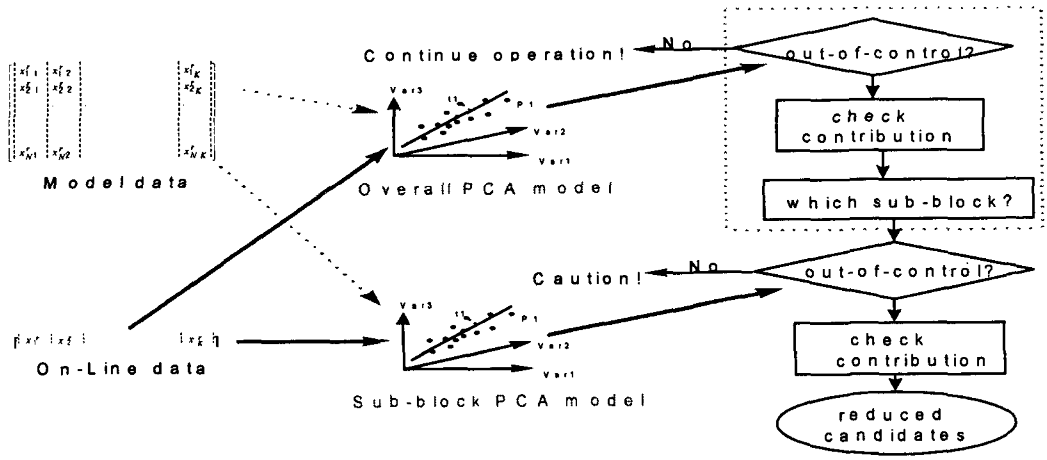


Fig. 1. Hierarchical decomposition monitoring procedure

at most source unit because of a lot of candidates. As more recycle streams have been involved, the possibility of showing poor performance of on-line monitoring and diagnosis increases. In this work, by grouping the highly correlated variables within each sub-block with the minimum interaction each other, we construct a hierarchical monitoring scheme for the overall plant and several sub-blocks. Fig. 1 shows detailed procedures. When the out-of-control state is identified by an overall monitoring chart, further inspection is focused on the sub-block corresponding to the variable with maximal contribution. Consequently, we can focus on the specific sub-block by using the hierarchical decision procedure. If we have many hierarchical levels of monitoring scheme to investigate, the decomposition and hierarchical decision procedure described as above can be repeated. In short, this have the effect of preventing special events in a specific sub-block from propagating to other sub-blocks or at least delaying transfer of an undesired state. Furthermore, fast detection and diagnosis of process malfunction can be achieved by this approach.

3. SIMULATION

Tennessee Eastman Industrial Challenge Process was proposed as a test of alternative control and optimization strategies for continuous chemical processes. As shown in Fig. 2, it includes an exothermic irreversible two-phase reactor, a reactor-product condenser, a flash vapor-liquid separator, a reboiled product stripper, and a recycle compressor. There are 41 measurements and 12 manipulated variables (11 valves and reactor agitation speed)[10].

In building model. it is important to define a normal operating condition. Actually, the data sampled at the plant by an on-line sensor show continuous fluctuation within a certain bounded range. In this experimental study, therefore, various types of disturbances within the range were considered to simulate real process behaviors. Among these simulated process measurement data, the simulated data which violate operation constraints and product variability specification are excluded from in-control model data set.

The reference model data should satisfy the specified production mass ratio and the convergence of all measurement variables as well. With these criteria of selecting successfully operating normal conditions, model data of 5567×41 were obtained after more than 24 hours of simulation. In these model data, three or four PCs explain the systematic variations in overall plant and sub-blocks. We divide whole processes into three major operational units: the reactor unit, the separator unit and the stripper unit. The variables of each unit, i.e., temperature, pressure, level,

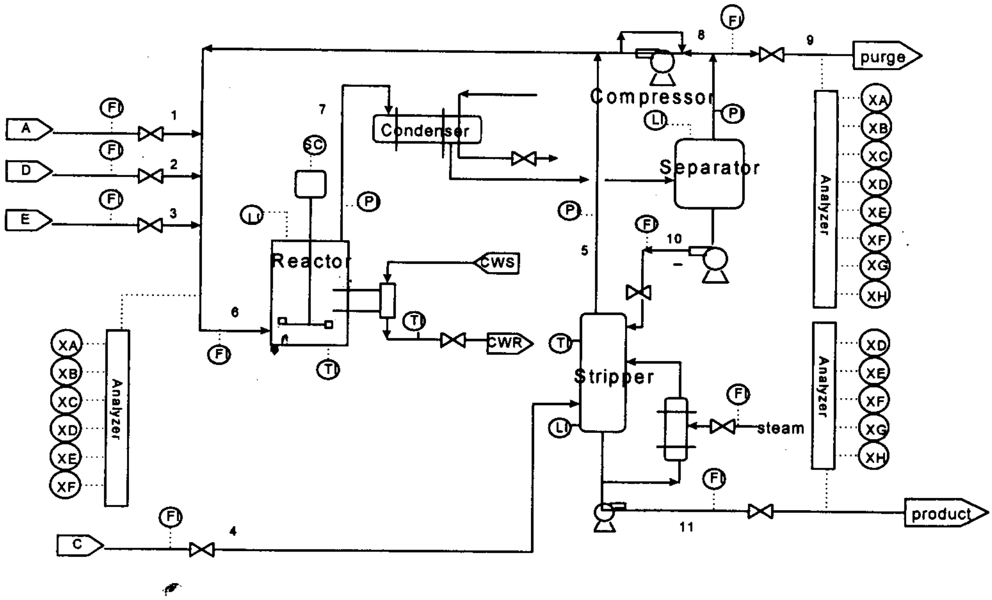


Fig. 2. Schematic of Tennessee Eastman process

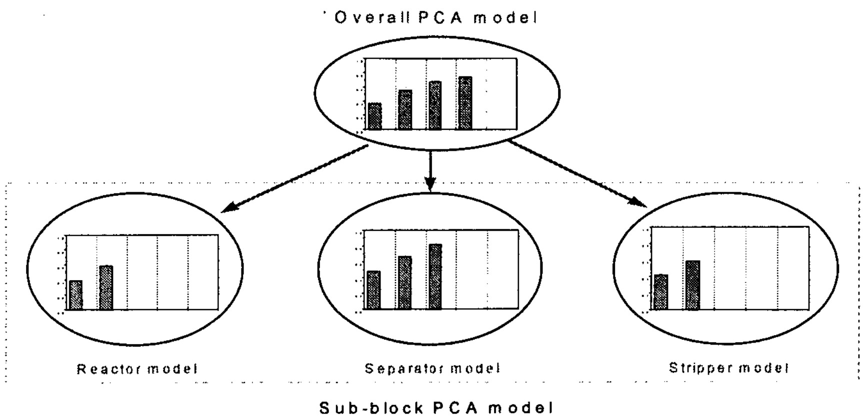
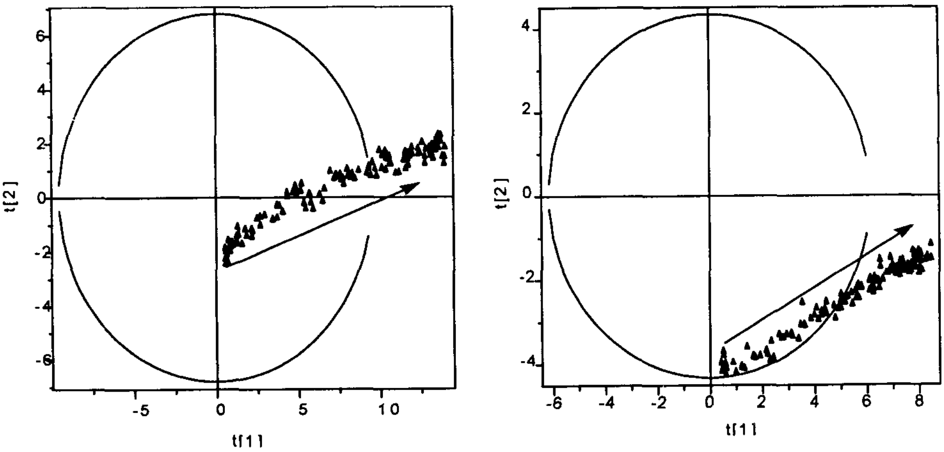


Fig. 3. Hierarchical PAC model and cumulative explained variance in each model.

etc., are grouped according to their process units and they are considered in modeling. As shown in Fig. 3, four PCs explain the systematic variations in Tennessee Eastman process, and so dimension reduction form 41 to 4 is achieved in the overall PCA model. There are number of PCs used for model development and cumulative explained variance for each sub-blocks in the lower Fig. 3

4. RESULTS

To test the performance of this model in detecting disturbances, three kinds of dusturbances with unusual deviation excluded from the normal operation condition were considered: the feed ratio change(case 1), the reactor cooling water inlet temperature change(case 2), the condenser cooling water



(a) (b)

Fig. 4. Predicted t score plot of case 2 for (a) overall model (b) reactor model (t[1]:1st score, t[2]:2nd score).

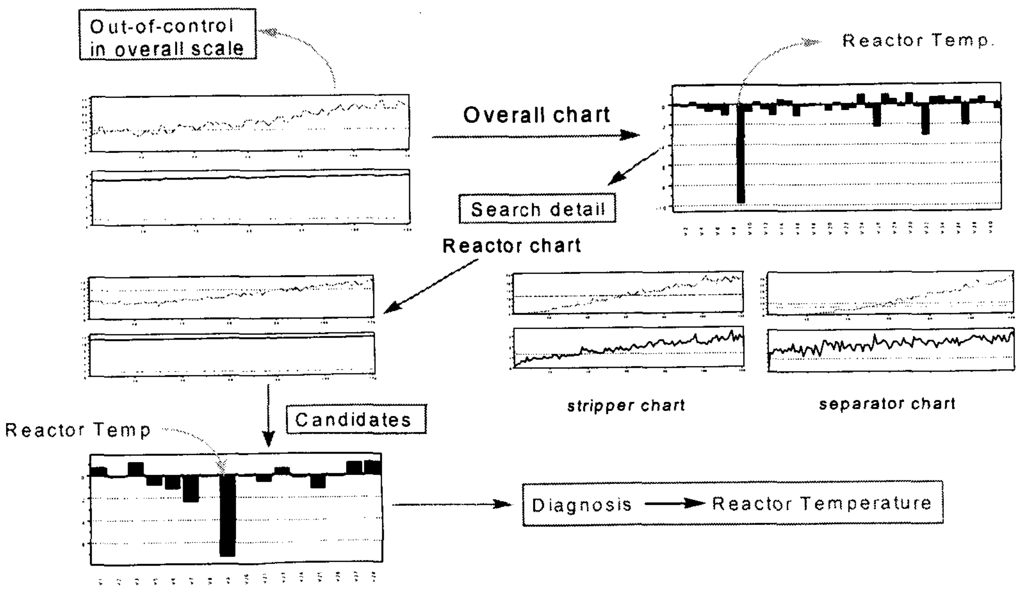


Fig. 5. Hierarchical monitoring and diagnosis result for case 2l.

inlet temperature change(case 3). Fig. 4 shows the predicted t score of case 2 for overall model and reactor model. As redexpected, the uced representations, t scores, of measurements in case 2 move out of normal operation region with time.

Fig. 5 shows the result of case 2. First, to investigate whether abnormality occurs in terms of overall operation, multivariate charts for the overall block are verified as described in Fig. 1. For this overall block, Hotelling's

T^2 chart and SPE chart are in the upper left corner and contribution chart in the upper right corner. While sub-block's monitoring charts are located in the middle, contribution for the specific sub-block showing abnormal deviation is shown in the bottom. Fig. 5 shows an out-of-control state in the overall monitoring charts. Therefore, referring to the contribution chart for overall abnormality, it is necessary to observe whether sub-block is in-control state or not. The fact that the out-of control state is detected only in the reactor block agrees with the result of the overall contribution. That is, the reactor temperature showing maximal contribution for the overall deviation is largely related to reactor unit. Therefore it can be concluded that disturbance is initiated in the reactor. For more detailed diagnosis, it is necessary to know which variables are responsible for the occurrence of the out-of-control state in the reactor unit. As shown in Fig. 5, V9 (reactor temperature) has the major contribution. Because the change of reactant amounts is highly related to reactions compared to separations or extractions, the reactor block shows more deviation from normal operation state than the stripper or the separator section. Therefore, assignable causes based on the contribution chart are reasonable, and monitoring schemes show relatively good performance of detection and diagnosis of abnormality. In other simulation cases which are not included in this paper, similar results were obtained as in case 2.

5. CONCLUSIONS

In this paper, methodology of a hierarchical decomposition monitoring is proposed to extract latent information from a massive amount of data and to diagnose process malfunctions in a plant-wide scale. To verify its performance with continuous process, three kinds of disturbances to Tennessee Eastman process were investigated. The proposed methodology based on hierarchical decomposition showed an improved performance in detecting out-of-control state more quickly and more easily by focusing on the specific block where SPC charts show out-of-control state. Also, by using contribution chart and SPC chart together, the systematic detection of out-of-control state and diagnosis are achieved in plant-wide scale. Therefore, methodology proposed here suggests a good solution for monitoring and diagnosis in terms of the increasing complexity of industrial chemical processes.

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NOMENCLATURES

NOC	: Normal Operation Conditions
PC	: Principal Component
PCA	: Principal Components Analysis
SPE	: Squared Prediction Error
T^2	: Hotelling's T^2 statistic

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