# 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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## 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 leads 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 detail monitoring can be performed. This monitoring process goes on in a recursive 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 method of handling large data set. PCA decomposes a single, dependent and highly correlated set of measurement into latent variables defined by the eigenvectors of the covariance of the data. This reduced set of latent variables summarizes most of the relevant information by projecting the original variables down onto a low dimensional subspace. In this reduced space, the reduced data set represents 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 at most source unit because of a lot of candidates. As more recycle stream 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. Consequently, 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.

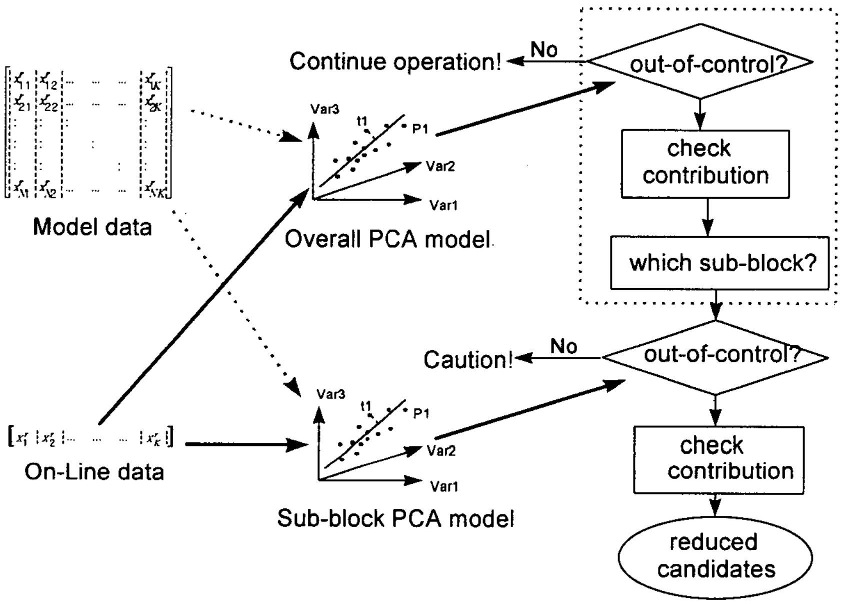


**Fig. 1 Hierarchical decomposition monitoring procedure.**

## 3. SIMULATION

Tennessee Eastman Industrial Challenge Process was proposed as a test of alternative control and optimization strategies for continuous chemical processes. 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 shows continuous fluctuation within a certain bounded range. In this experimental study, therefore, various types of disturbances within the range was considered to simulate real process behaviors. Among these simulated process measurement data, the simulated data which violate operation constraints and product variability specification is 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, statistical in-control model data of $5567 \times 41$ 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, etc. are grouped according to their process units and they are considered in modeling.

## 4. RESULTS

To test the performance of this model in detecting disturbances, three kinds of disturbances with unusual deviation excluded from the normal operation condition were studied: the feed ratio change(case1), the reactor cooling water inlet temperature change(case2), the condenser cooling water inlet temperature change(case3).

Fig. 2 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. 2 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. 2, V9(reactor temperature) has the major contribution. Because the change of reactant amount is highly related to reactions compared to separations or extractions, the reactor block shows a 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 case2.

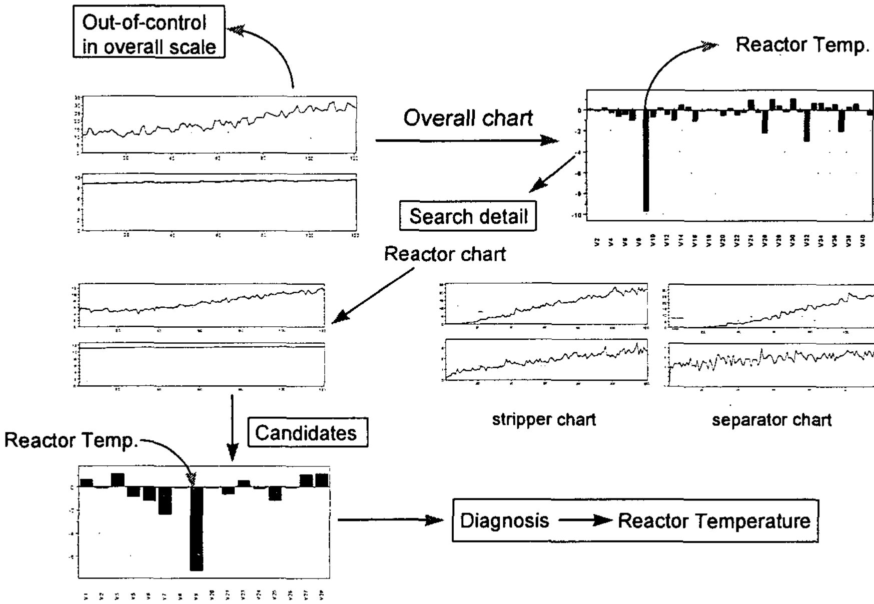


**Fig. 2 Hierarchical monitoring and diagnosis scheme for case 2.**

## 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 the performance of continuous process, three kinds of disturbances to Tennessee Eastman process were investigated. This proposed approach enables a comprehensive plant-wide monitoring scheme and greatly reduces the detection time.

## ACKNOWLEDGEMENT

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## NOMENCLATURES

| | |
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| 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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