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Development of Fault Diagnosis System Using Principal Component Analysis for Intelligent Operation Support System

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In this paper, it is proposed to develop the fault diagnosis system using the principal component analysis (PCA) for the intelligent operation support system that calculates the effect of fault propagation in abnormalities situation and gives appropriate information to plant operators. This proposed system using PCA discriminates a failure of equipment based on process variables. The proposed method deals with process variables in steady condition and only one type warning alarm condition that is occurred by several different failures. A set of process variables on each failure is shown as the points on 2-dimensional data space by PCA. This system judges as a failure of the equipment when a set of current process variables is closed to the point of a failure of equipment on the data space. The proposed fault diagnosis system is applied to process on a simulator and is confirm its validity.

1. Introduction

Chemical plants had become very complex for a lot of instrumentation and control systems. It is difficult for operators to predict the effect of fault and to decide corrective actions. In addition, quick response from operator is demanded as any delay response for abnormalities may expand the damage of chemical plant. Many sensors are required to monitor the chemical process for safety. It is difficult to detect the fault in the process from too many sensors. Therefore many sensors' data are reduced to less parameter by a multivariate analysis (Kano et al. 2001, 2004, Wise and Gallagher 1996). These methods detect the fault in the process, but not diagnosis the failure of equipment.

Our research is developing "Intelligent Operation Support System". This system calculates the effect of fault propagation in abnormal situations and gives appropriate information to operators. It will help operators to make quick judgments for safety. This system predicts process variables in the abnormalities situation's plant using a simulator. The states of all equipment are inputted to a simulator in order to calculate process variables correctly.

In this paper, it is proposed to develop the fault diagnosis system using the principal component analysis. This proposed system discriminates a failure of equipment in its early stage. This system is important for the intelligent operation support system. The principal component analysis discriminates a failure of equipment based on process variables from the actual plant. A data set is process variables in steady conditions and in abnormalities condition. These data sets are obtained from a simulator when the warning alarm is turned on after the selected equipment is artificially changed to a failure mode. The proposed method deals with process variables in steady condition and only one type warning alarm condition at a time. One type warning alarm is occurred by several different failures, so process variables in one failure are similar to another failure in one type warning alarm. So it is difficult to distinguish one failure among failures in one type warning alarm when the principal component analysis deals with failures in all warning alarm at a time. And the proposed method deal with selected process variables based on value changes after a failure is occurred. A set of process variables on each failure is shown as the points on 2-dimensional data space by the principal component analysis. This system judges as a failure of the

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equipment when a set of current process variables is closed to the point of a failure of equipment on the data space.
The proposed fault diagnosis system is applied to process on a simulator and is confirm its validity.

2. Intelligent operation support system

We propose the intelligent operation support system that supports the judgment of operators in abnormalities of plants.

2.1 Plant operators activity

Operators cope with the abnormal condition of the plant by their synthetic judgments. They think their synthetic judgments based on their knowledge, experiences and the manual of the plant. Their synthetic judgment is composed of 6 thinking activities (Hori et al. 1999). These activities are described in the following.
(1)Fault Detection: Operators detect a fault of the process based on the alarm and the trend of process variables. They confirm the absence of any abnormality.
(2)Prediction of Effect of Fault Propagation: Operators predict the tendency to increase a fault or to return to a normal condition based on the trend analysis, their knowledge and experiences.
(3)Judgment of Necessary of Corrective Action: Operators judge a necessary of the corrective action for operating the plant continuously or a shutdown of operations based on predictions of the effect of fault propagations and manuals.
(4)Fault Diagnosis: Operators identify hardware or software malfunction based on data of process variables, their knowledge and experiences at the same time of the previous activity.
(5)Decide the Best Corrective Action: Operators think the plural corrective actions to cope with hardware or software malfunction. They decide the best corrective action from the viewpoint of safety and validity.
(6)Circumstantial Judgment after Emergency Shutdown: Operators think the situation after the emergency shutdown.

2.2 Outline of developing system

Operators think their synthetic judgment based on their knowledge, experiences and the manuals. The most important activity is “Prediction of Effect of Fault Propagation”. If operators know the tendency of the process variables in the future, operators can recovery plant conditions by the proper corrective action.
The developing system uses the simulation for predicting the process variables in the future instead of the operator’s knowledge and experiences. The simulator requires states of all equipment to calculate process variables correctly.
We propose the intelligent operation support system that supports the judgment of operators in abnormalities of plants. Figure 1 shows the outline of the proposed system. This system is composed of the fault detection system, the fault diagnosis system, the virtual plant, the dynamic fault propagation analysis system, the fault propagation scenario and so on.
The fault detection system realizes “Fault Detection” in thinking activities, and the virtual plant is “Prediction of Effect of Fault Propagation”, the dynamic fault propagation analysis is “Judgment of Necessary of Corrective Action” and “Decide the Best Corrective Action”, the fault diagnosis system is “Fault Diagnosis”. The virtual plant is the plant simulator that is the mirror plant of the actual plant. The virtual plant can run at a high speed compared to the actual plant. Therefore this system uses the simulation instead of the operator’s knowledge and experienced for predicting the process variables. These calculated process variables are considered as the predicted process variables. The proposed system decides corrective actions in each situation based on the predicted process variables and the fault propagation scenario. These corrective actions are proposed to operators, or these are inputted to the virtual DCS. After that, some equipment in the virtual plant is controlled, and process variables change with time. Therefore the virtual plant calculates again, and the proposed system decides new corrective actions. These procedures are repeated to nearly reach the steady state.

2.3 Fault diagnosis system

The fault diagnosis system discriminates a failure of equipment in its early stage. This system is important for the intelligent operation support system. Because the states of all equipment are inputted to a simulator in order to calculate process variables correctly.
The fault diagnosis system identifies the failure of equipment based on data of process variables. Data of process variables should be characterized for identifying a failure of equipment. Furthermore it is necessary to detect a fault in its early stage in order to gain an extension of simulation time.

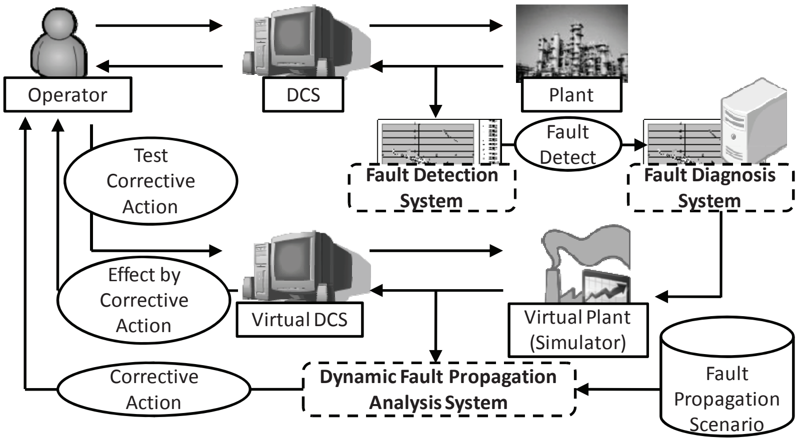


Figure 1: Outline of the intelligent operation support system

3. Proposed Method

The proposed method prepares the 2-dimensional data space and the failure judging area before monitoring the process. The data space shows process states that are converted from all sensors' data based on the principal component scores. The failure judging area on the data space is used as one of criteria for discriminating the failure.

After the fault diagnosis system using the proposed method starts to monitor the process, the measuring process variables from sensors are converted to the principal component scores in real time. These scores are evaluated based on the failure judging area and so on.

3.1 Symbols

The following symbols are used in this paper.

A_i i-th fault (i = 1,…, IN). 1 warning alarm warns an occurrence of A_i.

C_{ij} j-th cause of A_i (j = 1,…, JN_i). A_i is occurred by several causes. Operators don't discriminate a cause based on the warning alarm. In this paper, causes are assumed as failures of equipments.

S_p p-th sensor (s = 1,…, PN). S_p observes 1 process variable in the process.

X_{pt} Measuring data of S_p at time t. In case of C_{ij} for n-th time, Measuring data is represented as $X_{pt}(C_{ij}, n)$, (n = 1,…, NN_{ij}).

$\bar{x}_{ip}$ Average of $X_{pt}(C_{ij}, n)$ for S_p in case of A_i.

$\bar{\sigma}_{ip}$ Standard deviation of $X_{pt}(C_{ij}, n)$ for S_p in case of A_i.

wx_{ip} 1st principal component loadings of S_p in case of A_i.

wy_{ip} 2nd principal component loadings of S_p in case of A_i.

x_{it} 1st principal component score in case of A_i at time t.

y_{it} 2nd principal component score in case of A_i at time t.

3.2 Data space

The proposed method converts all sensors' data into principal component score by the principal component analysis. 1st principal component score is calculated by Equation (1), 2nd one is calculated by Equation (2).

$$x_{it} = \sum_{p=1}^{PN} \left(\frac{X_{pt} - \bar{x}_{ip}}{\sigma_{ip}} \times wx_{ip} \right) \tag{1}$$

$$y_{it} = \sum_{p=1}^{PN} \left(\frac{X_{pt} - \bar{x}_{ip}}{\sigma_{ip}} \times wy_{ip} \right) \tag{2}$$

There are some types of sensors that measure different order of magnitude and units. Therefore X_{pt} is normalized in Equations (1), (2). Any sensors don't observe the change in measurements after occurring a failure, then Equations (1), (2) are not solved. In this case, the proposed method excludes these sensors' data.

The principal component loadings are obtained based on PCA. 2-dimensional data space is made with 1st principal component score as abscissa against 2nd principal component score as ordinate. The measuring process data is converted to principal component scores in real time, and these scores are plotted on the data space. Figure 2 shows the data space. The same failure is applied to the steady process at different time (Case 1-5) in Figure 2. The starting points are different, but the end points gather at same point. When the point reaches the end point, a warning alarm is turned on. The proposed method makes use of this characteristic.

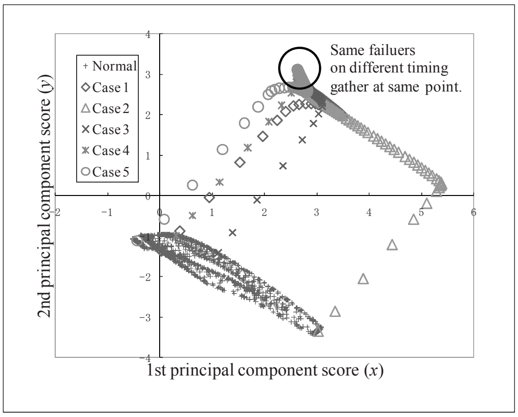


Figure 2: 2-dimensional data space

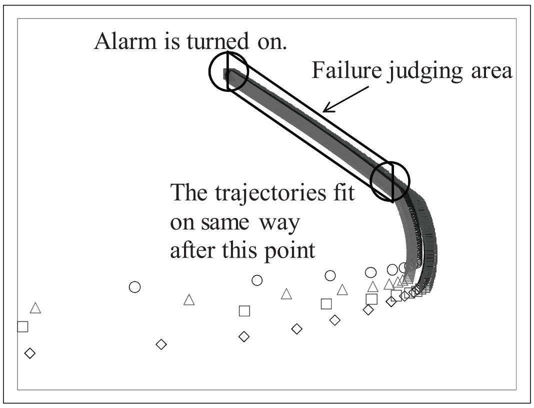


Figure 3: Failure judging area

3.3 Failure judging area

It is difficult to discriminate a failure in the early stage when the point reaches the end point. Therefore failure judging areas are established on data space in Figure 3. This area includes a part of every trajectory that are close each other.

The time of turned on a warning alarm is represented as T, and n points near (x_{iT}, y_{iT}) are selected from all points including different starting time. The linear approximation is formularized from n points based on the least-squares method. This equation is shown in Equation (3).

$$y = a_{ij} x + b_{ij} \tag{3}$$

where a_{ij}, b_{ij} are coefficients in case of C_{ij}. The residual between q-th point and this linear approximation is represented as d_{ijq} in Equation (4).

$$d_{ijq} = y_{ijq} - \left(a_{ij} x_{ijq} + b_{ij}\right) \tag{4}$$

The standard deviation from d_{iT} to d_{iq} is represented as σ_{ijn}. The failure judging area includes n points that are satisfied in Equation (5).

$$\left|3\sigma_{ijn}\right| \geq \left|d_{ijn+1}\right| \tag{5}$$

where d_{ijn+1} is far next to d_{ijn} from (x_{iT}, y_{iT}). The failure judging area is made as a parallelogram with an altitude 6 σ_{ijn} and along the linear approximation.

The proposed method judges as a failure of the equipment when a point of current process variables exists in a failure judging area within a given period.

4. Application

The proposed method is applied to the process model on Visual Modeler created by Omega Simulation Co., Ltd. in Japan.

4.1 Process

The proposed method is applied to the polymerization process in PVC plant. There are the automatic valve for cooling water, the bypath valve for cooling water, the product valve, the steam supply valve, the steam drain valve and so on in the this process. This process is monitored by 32 sensors (S_1-S_{32}); 19 flowmeters (S_1:FL1-S_{19}:FL19), 7 level gages (S_{20}:L1-S_{27}:L7), 3 pressure gages (S_{28}:P1-S_{30}:P3) and 3 thermometers (S_{31}:T1-S_{33}:T3). The temperature in the reactor is controlled around 55°C during polymerizing materials.

4.2 Conditions

In this application, 1 fault is assumed as abnormal situations. It is that the temperature in the reactor drops down under 50°C. When these faults are occurred, a warning alarm is turned on. A fault is occurred by 3 different causes.

(1)There occurs by the failure to open the automatic valve for cooling water. This failure is represented as C_{11} and F1.

(2)There occurs by the failure to open the bypath valve for cooling water. This failure is represented as C_{12} and F2.

(3)There occurs by the failure to open the product valve. This failure is represented as C_{13} and F3.

4.3 Input data set

The specific failure is artificially applied to the steady process on the simulator, and 32 process variables are observed. When the warning alarm is turned on, data of all sensors are recorded as an input data set for PCA. One failure is generated 10 times at different times, because process variables on the steady state change within a control limit. All failures (F1-F3) are calculated one by one.

4.4 2-dimensional data space

Table 1 shows 1st and 2nd principal component loading that are analyzed by PCA in case of the fault of dropping down under 50°C (A_1). 'Other' in Table 1 includes other sensors that don't indicate different value among each failure (F1-F3). Therefore 11 sensors' data are analyzed by PCA. 1st and 2nd principal component scores are calculated based on these loadings.

Figure 4 shows 2-dimensional data space of A_1. The position of each failure is calculated to substitute the average value for 10 times into equations (1), (2).

4.5 Failure judging area on data space

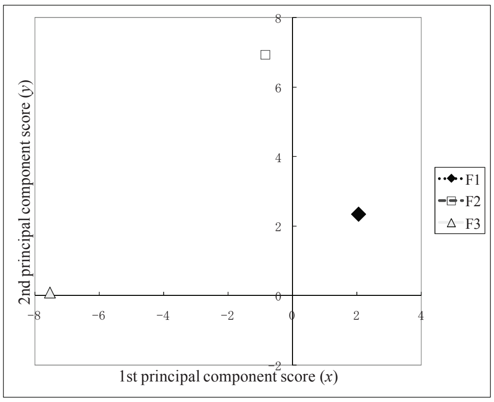
Table 2 shows parameters for making the failure judging area of fault A_1 on data space. These parameters are calculated based on data set from applying the failure to turning on the waning alarm. Figure 5 shows to add the failure judging area on data space of A_1.The standard deviation in Table 2 is very small. Therefore these areas are very narrow, and are drawn as the straight line on data space.

Table 1. Principal component loadings in A_1

Sensor	1st principal component loadings wx_{1p}	2nd principal component loadings wy_{1p}
S_{10}:FL10	0.362	-0.075
S_{11}:FL11	0.362	-0.075
S_{12}:FL12	-0.043	0.475
S_{13}:FL13	-0.043	0.475
S_{14}:FL14	0.337	0.273
S_{17}:FL17	0.314	0.286
S_{20}:L1	0.129	0.466
S_{26}:L7	0.389	-0.015
S_{27}:P1	0.386	-0.066
S_{30}:T1	0.212	-0.391
S_{32}:T3	-0.401	0.079
Other	none	none

Table 2: Parameters for failure judging area in A_1

Failure mode	Linear approximation	Min. x	Max. x	SD.
F1	$y = -1.63x+5.69$	2.06	2.84	1.66×10^{-2}
F2	$y = -1.52x+5.65$	-0.85	-0.34	1.43×10^{-2}
F3	$y = -1.59x-11.87$	-7.52	-7.17	0.08×10^{-2}



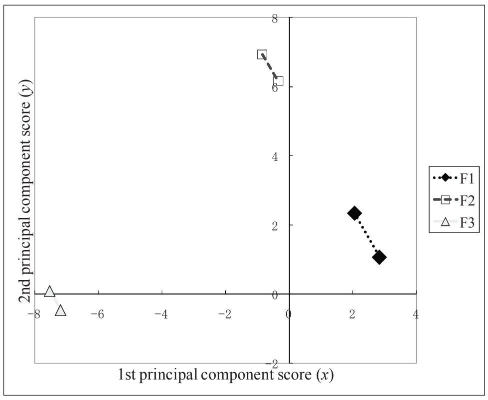


Figure 4: 2-dimensional data space of A_1

Figure 5: Failure judging area on data space of A_1

Table 3: Result of Experiment

Failure mode	Proposed method (min.)	Alarm (min.)
F1	4	11
F2	4.5	11
F3	29	34

4.6 Experiment

In this experiment, the times to discriminate the failure by proposed method and to turn on the warning alarm are measured. The failure is applied at different time from making the input data set. The measuring process variables are converted to the principal component scores of A_1 in real time. And these scores are evaluated whether this state is the specific failure.

4.7 Results and discussions

Table 3 shows the results of the experiments. All failures are discriminated less than 5-10 minutes before detecting the fault and turning on the warning alarm. If operators don't use this system, they spend to identify the failure after turning on the warning alarm.

5. Conclusion

In this paper, it is proposed to develop the fault diagnosis system using PCA for the intelligent operation support system that calculates the effect of fault propagation in abnormalities situation and gives appropriate information to plant operators.
(1)This proposed system using PCA discriminates a failure of equipment based on process variables. The proposed method deals with process variables in steady condition and only one type warning alarm condition that is occurred by several different failures.
(2)A set of process variables on each failure is shown as the points on 2-dimensional data space by PCA. This system judges as a failure of the equipment when a set of current process variables is closed to the point of a failure of equipment on the data space.
(3)The proposed fault diagnosis system is applied to process on a simulator and is confirmed its validity.

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