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An early warning generation and emergency advisory system and its application to power plants

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Abstract−Based on the fact that abnormal states continue prior to the breakage of the fault, an early warning system was developed by monitoring the variables in operation real-time, deciding on the operational status, and informing the operator of the process status in order to warn of an abnormal operation in advance. As the traditional system, operating based on threshold limits, separately monitors and manages each operating variable, the interaction/co-relationship among the variables is ignored. The proposed early warning system combines operating variables that interact with one another for each unit process or unit facility, producing a neural network model predicting the normal status values and generating warnings of abnormalities in the process in advance. A time extension function-linkage associative neural network model was designed and used taking consideration of the time lag. Based on the emergency advisory database established, an emergency advisory system was also developed that informs the operators of the cause, effect and emergency measures regarding abnormal operations recognized by the early warning system. The developed system was applied to the power plant operations, and it shows a good performance in early warning generation and provides good advice for the management of diagnosed abnormal situations.

Key words: Early Warning Generation, Emergency Advisory System, Power Plant Operation, Neural Network-based Modeling, Fault Detection and Diagnosis

INTRODUCTION

In numerous energy facilities, including power generation plants, enormous volumes of operating variables are monitored, controlling facilities depending on the operation status and load. When faults occur in such processes, it is not easy for an operator to figure out the right causes in a short period of time and come up with appropriate responses. In cases when the operation of the process continues in an abnormal state due to physical failures, external disturbances or human error, only after getting worse to a state recognizable by the operator through continued operations in the abnormal state, is an operational fault detected by the operator [1-3].

Various systems have been introduced that monitor operating variables in real time, decide upon the process state and provide early warnings prior to the occurrence of the faults based on the fact that the abnormal state continues prior to the process error. Generally, a process monitoring technique is used that focuses on the change of the process variable itself. It is a technique that regards changes in the statistical values including the average or the standard deviation as abnormal. However, statistical process monitoring techniques separately monitor each process variable, so in fact, it can be very difficult to judge an abnormal state that occurs amid the interactions of various operational variables.

Therefore, this study aims to conduct research on an early warning system that provides early warnings for operational faults by using techniques that combine and monitor interactive operating variables. It also seeks to establish an emergency advisory system that can promptly provide information on measures for the facilities that provide operators early emergency advice on the operational faults detected by the early warning system.

The proposed system builds a neural network-based, prediction system [4,5,10] on normal state operation values through learning from a set of data collected from a past history of normal operations. The predicted values are compared against real-time data and it decides upon the abnormal process status. Unlike previous studies that compare learned patterns of abnormal operation patterns against real-time data to detect the faults, trainings on past cases of abnormal operations are not necessary, and it is a big advantage when the system is applied to real industrial plants where collected data around abnormal operations are quite rare [6,7,9].

PROCESS MONITORING

1. Requirement for Energy Facilities

Most manufacturing facilities are equipped with superfluous inventories and buffer measures to prepare for a short-term operational stoppage, but energy facilities are one of the few exceptions. A case in point is electricity generating power plants because one cannot accumulate their inventory. As a result, an operational stoppage at energy facilities directly and instantly negatively affects revenues. Furthermore, energy facilities incur profit loss due to limited power generation capacity, and unplanned repair and maintenance costs.

As an effort to maximize availability, a maintenance program has been adopted and operated for in-depth prevention, but in the

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case of excessive preventive maintenance, the setback is an increase in maintenance costs. What is desperately needed to reduce operation stoppage time, and maintenance and other related costs in energy facilities is to warn of potential faults in advance, enabling one to timely plan for necessary maintenance.

2. Simultaneous Monitoring of Interacting Variables

Operational faults, until recognizable by the operator as the abnormal state, are continuously accumulated through continued operations where the operating conditions of the process turn abnormal due to physical failures, external disturbances and human error. The traditional control/monitoring system warns in the case of going outside the set limits, and prevents serious accidents from taking place by suspending the operation in the case of going beyond the limits. However, the traditional control/monitoring system separately monitors and manages the operating variables, and if a fault in a target facility is unnoticed until the failure occurs, a sudden operational stoppage or unplanned repair needs to be undertaken.

In Fig. 1, if the sensor B were chosen as a major operating variable among numerous operating variables and monitored and managed alone, it could be possible that an operational fault and failure took place without any symptoms. However, if all operating variables were being monitored in an integrative way, operational faults could have been predicted in advance.

Prior to the occurrence of the operational faults, the abnormal state continued, and this is seen in various operating variables. Various techniques are introduced that monitor operating variables together to determine the operational status and provide early warnings prior to the occurrence of the operational faults.

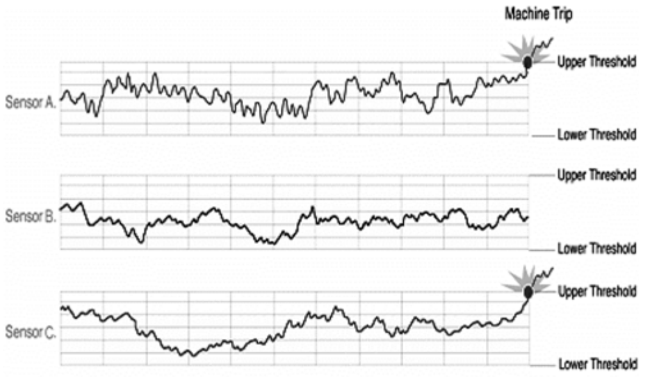

Fig. 1. Regulation monitoring and an example of an early warning system based on upper and lower threshold monitoring.

3. Operation Monitoring Based on Empirical Modeling

When empirical modeling is used without accessing first principles like physical and thermodynamic modeling for the target facilities, it is difficult to guesstimate the reliability of the method. However, if the current operational status of the plant is clearly defined, and the corresponding relationship with the target operational variables is set, a model can be standardized for the facilities.

Most of the energy facilities are very complicated, non-linear, and difficult to apply a physical interpretation to, and thus, inappropriate to completely meet the needs with the existing statistical methods.

The neural network modeling is a model that simplifies the neural transmission process of creatures and interprets it mathematically. This is to analyze the process of a kind of training that passes the neurons (the smallest unit forming a network in a neural network) that are complexly inter-wired and coordinates the intensity of the connections among neurons. Such a process is analogous to one's process of learning and remembering through which inference, classification and prediction can take place.

Using the neural network that is capable of properly interpreting the relationship between non-linear input and output, it is possible to identify a more accurate relationship with the limited data. In this respect, the neural network-based model could be better than the conventional statistical techniques.

Fig. 2 juxtaposes a multi-dimensional approximation model where simplification is made based on the past operation data against the neural network modeling: Real-time operation data is predicted to monitor the operation in a complex non-linear operation. As it shows, the neural network algorithm is widely used as a new technique.

In addition, most of the energy-related facilities face time lags among measurement variables whose influence cannot be overlooked.

As for the early warning system developed in this study, a neural network model was made for each operational unit or unit facility to predict the value of the normal state. In this case, as a neural network model is made for each operational unit or unit facility, it is beneficial not to consider a greater time lag. In this study, based on the idea that the function-linkage associative neural network model

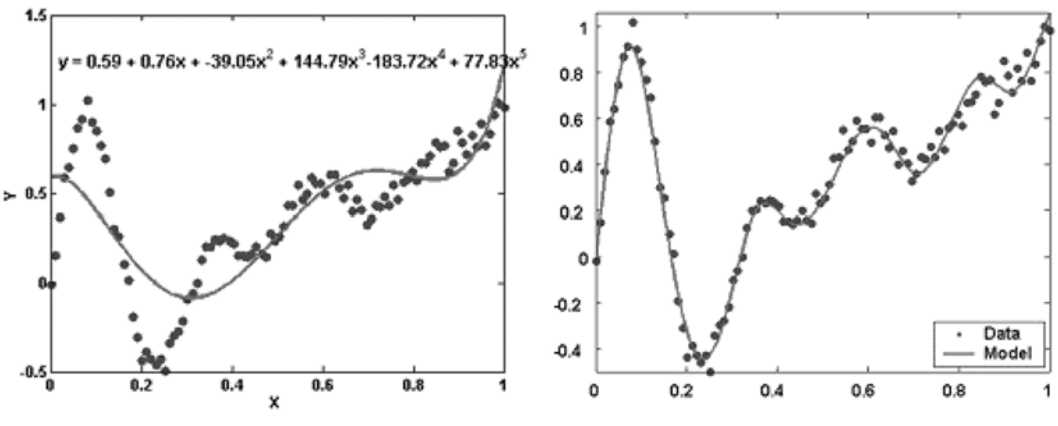

Fig. 2. Comparison of a polynomial approximate model against a neural network model.

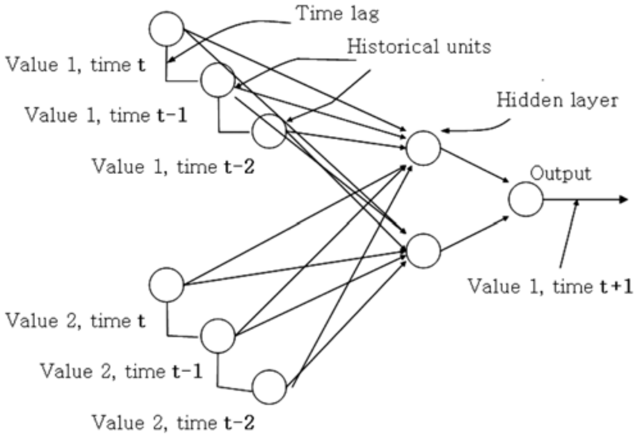

Fig. 3. Proposed neural network model.

[8] extends the input, a time extension function-linkage associative neural network model was designed and used to consider the time lag.

As shown in Fig. 3, extensions for input up to $x_i(t)$, $x_i(t-\tau)$, $x_i(t-2\tau)$ were made for each of the input variables to consider the time lag up to 2τ because the cycle time of steam is short in the selected power plant for the study. The input extension with the bigger weighting factor is to be selected eventually for the construction of the prediction model.

DEVELOPMENT OF EARLY WARNING SYSTEM USING NEURAL NETWORK MODELING

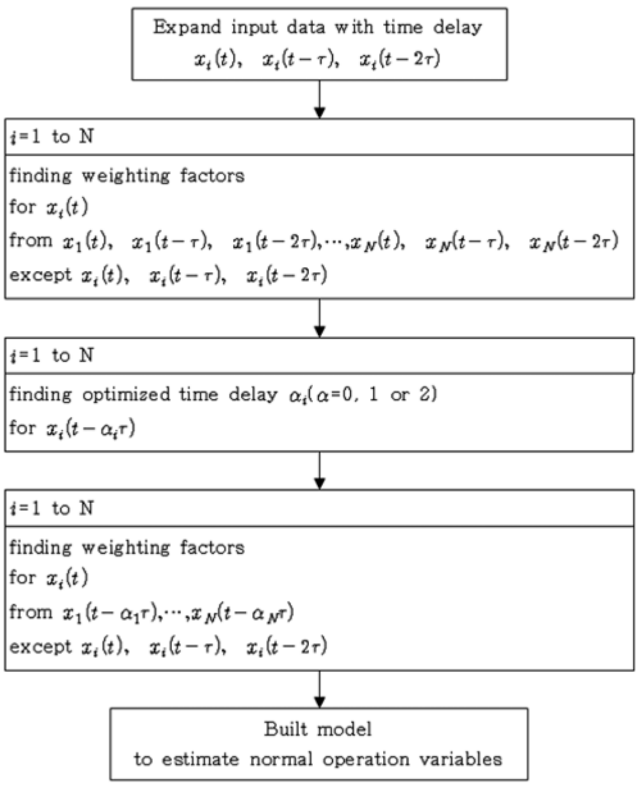

Fig. 4. Off-line training to build a prediction model.

1. Proposed Algorithm

The early warning system is divided into two parts: an application program to establish, in off-line, prediction models for the diagnosis based on the neural network technique using the CSV file prepared by the data pre-processor; and a real-time diagnosis program where the current operational data is put in the fault diagnosis model to judge the abnormal operation, based on which the abnormal status is diagnosed.

In the off-line, prediction model building program, a time lag up to 2τ is considered to extend the data set for learning. Using those extended inputs except the values of the predicted input j, the weighting factors of the neural network model are calculated (see Fig. 4). Optimal time delays for each variable i are determined, and the final prediction model is constructed by using only those inputs having the optimal time delays. In addition, parameters are set in the fault diagnosis model, including the error range between the current operation value of each operating variable, to diagnose the fault and the output value of the neural network model and the rules that regard transcending the error range as abnormal.

According to the real-time monitoring and diagnosis program (see Fig. 5), i) real-time operation data are typed into the fault diagnostic neural network model, ii) the warning is indicated in transcending the threshold where a difference of value (2σ used in this study) between the actual operating data and the data predicted in the neural network model exists, iii) if there is continued abnormal operation for a certain period of time (8 abnormal operations in 10τ period of time) or concurrent abnormal operation takes place in various operating variables (3 used in this study), it is regarded as having faults, and iv) the user is notified.

2. Case Study

As a case study, the gas turbine of a power plant A was monitored with the Early Warning System. A fault diagnosis model was established using history data of about 86 operating variables related to the gas turbine, which includes the DCS as erroneous operation.

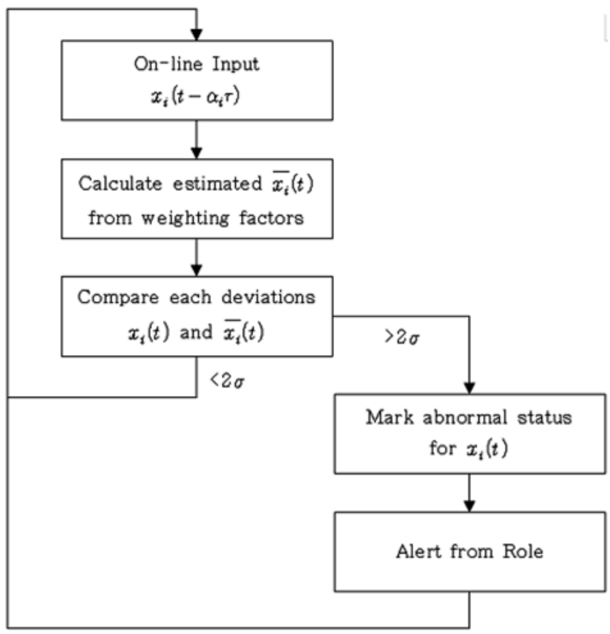

Fig. 5. On-line monitoring with the prediction model.

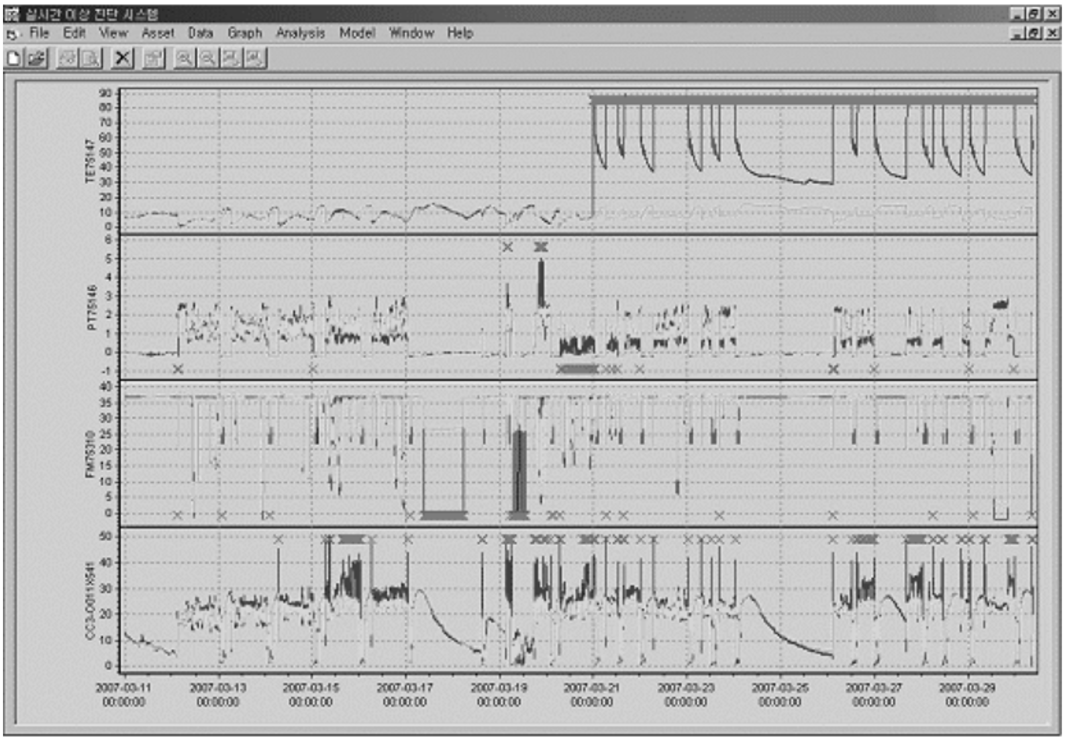

Fig. 6. Performance of the developed neural network model applied to a gas turbine.

In Fig. 6, a screen is shown of four operating variables that determined erroneous operation. The blue dotted lines are the actual operation data while the green ones are the data predicted in the fault diagnostic model. In EXHAUST PRESSURE, POSITION DEMAND TO IGV, and SPREAD BLADE PATH TEMP (second, third and fourth operating variables from the top in Fig. 6), abnormal warnings occurred in advance of 19 days to the expected erroneous operation.

In addition, COMPRESSOR INLET T/C (the top operating variable in Fig. 6) was wrongly indicated due to an error in the sensor. The model enables predicting what value it would have without errors in the sensor by regarding the predicted data in the fault diagnostic model as the value of other operating variables.

DEVELOPMENT OF EMERGENCY ADVISORY SYSTEM

1. System Development

An emergency advisory system was developed as a Web service to enable the operator to inquire and utilize specialized knowledge for the safe operation of the plant. If an erroneous operation is detected in the early warning system, the emergency action database enables inquiry of the emergency measure based on the conditions of the operation values of the equipment so that appropriate measures can be provided to the operator.

For the convenience of the operator, a database was established on the "Cause", explaining on what occasions faults recognized by the early warning system occur for the convenience of the operator, the "Effect" explaining what happens if the cause is neglected, and lastly the "Act" of the operator actions to take. Based on the established emergency advisory database, an emergency advisory system was developed that informs the operators of the cause, effect and emergency measures regarding to the abnormal operation recognized by the early warning system, as shown in Fig. 7.

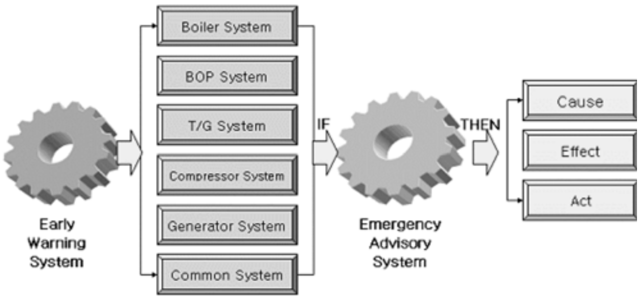

Fig. 7. Proposed emergency advisory system.

2. Case Study

As a case study, a power generation plant B's induced draft fan was set as the target, and a simulation was conducted for the early warning system (constructed using 32 operation variables) using the data right before the emergency stoppage occurred.

As a result of the test, as shown in Fig. 8, 1FG-XBTT56 operating variables informed of the abnormal operation while the warning continuously occurred for over 6 hour period starting 33 hours before the stoppage. In particular, 11 hours before stoppage, four operating variables, namely, 1FG-XBTT53, 1FG-XBTT55, 1FG-XBTT59, and 1FG-XBTT60, concurrently provided warnings. Overall, early notification prior to the emergency stoppage took place.

As the warning took place concurrently on four operating variables including 1FG-XBTT53, the emergency advisor system searched for the information on emergency measures reflecting the current

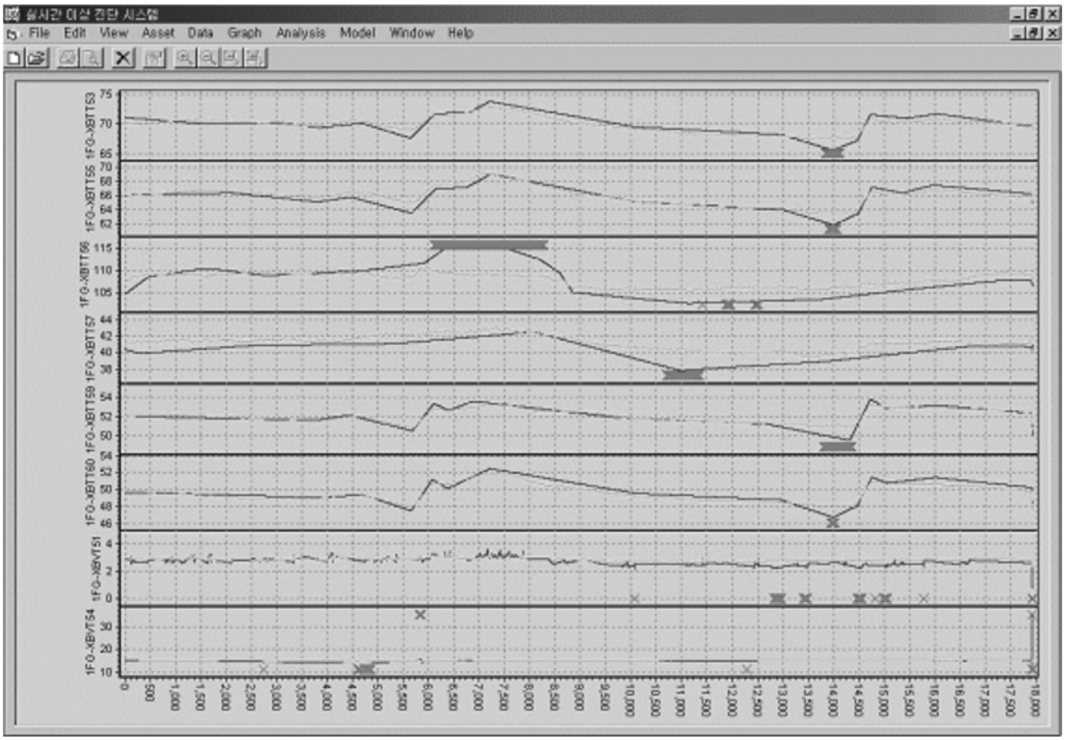

Fig. 8. Test of the emergency advisory system against the history data (An early warning is generated before the trip occurs).

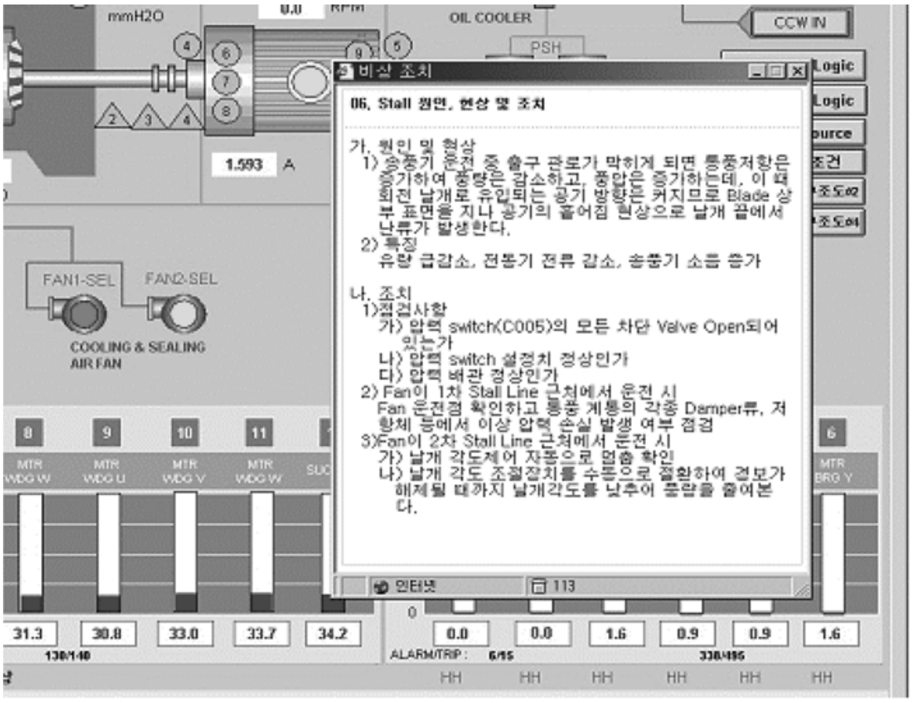

Fig. 9. Window of an emergency action for a real-time detected fault.

status, and showed it on the operation monitoring screen as a pop-up as shown in Fig. 9.

DISCUSSION ON MORE INDUSTRIAL APPLICATION STUDIES

Table 1 shows the result obtained for more industrial application studies. When the proposed method was tested against the past operational data of each application, drifting alarms were sometimes generated earlier than the result shown. However, to reduce the chance of the generation of false warnings, the installed system reports the

Table 1. Result of more industrial application studies

Area of application	Type of equipment	Alarm generation confirmed before the failure
Semiconductor wafer manufacturing plant	Vacuum pump	5 min before the failure
Power plant	Boiler tube	32 hrs before the failure
	Turbine	6.5 days before the failure
	Pump	1 hr before the failure
Combined cycle power plant	Gas turbine	10 days before the failure
Petrochemical plant	Dryer	5 days before the failure

early detection of the trouble only when the alarm is being continuously generated or simultaneous alarms are obtained from multiple sources. Of course, no alarms were generated when tested against normal operation data without any on-coming failure.

This system is based on the training of previous data of normal operations. Thus, if there is a type of normal operation mode which has not been considered during the training phase, there is some chance that the system may diagnose that operation as abnormal. So the operators are always informed of this kind of case, and once a warning is reported it is always checked if the plant is being operated differently from the past patterns of normal operations. After that, the mitigation action part for the suspected failure is performed.

CONCLUSION

Various systems are introduced that monitor operating variables in real-time, decide upon the process state and provide early warnings prior to the occurrence of the faults based on the fact that the abnormal state continues prior to the process error. Generally, the process monitoring technique is used that focuses on the change of the process variable itself. It is a technique that regards changes in the statistical values including the average or the standard deviation as abnormal. However, statistical process monitoring techniques separately monitor each of the process variables, so in fact it is very difficult to judge an abnormal state that occurs amid the interaction of various operational variables.

Therefore, in this research, among techniques which combine and monitor interactive operating variables, a method combining various variables using the neural network and a monitoring technique using that model were identified. The developed early warning system provides early warnings on operational faults using the prediction from the neural network, and it was applied to the gas turbine, deciding on the operating faults resulting from the continued abnormal operation and notifying the operator. Furthermore, support was made to enable proper operation by predicting the measurement value when an abnormal value comes in due to faults in the measurement equipment. The emergency advisory system was also developed that concurrently monitors various operating variables in real time in the early warning system, and searches for information on emergency measures for the current status in the emergency measure database upon the occurrence of the warning for operational fault. The system shows the resulting outcome on the pop-up screen of the operation monitoring screen.

There is a need to come up with measures that objectively calculate the error range between the actual operation values and the predicted operation values in order to determine the abnormal operating state. Furthermore, research is required on the objective determining methods to distinguish abnormal operations from erroneous ones.

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