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# INTEGRATED DIAGNOSTIC TECHNIQUE FOR NUCLEAR POWER PLANTS

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It is very important to detect and identify small anomalies and component failures for the safe operation of complex and large-scale artifacts such as nuclear power plants. Each diagnostic technique has its own advantages and limitations. These facts inspire us not only to enhance the capability of diagnostic techniques but also to integrate the results of diagnostic subsystems in order to obtain more accurate diagnostic results. The article describes the outline of four diagnostic techniques developed for the condition monitoring of the fast breeder reactor “Monju”. The techniques are (1) estimation technique of important state variables based on a physical model of the component, (2) a state identification technique by non-linear discrimination function applying SVM (Support Vector Machine), (3) a diagnostic technique applying WT (Wavelet Transformation) to detect changes in the characteristics of measurement signals, and (4) a state identification technique effectively using past cases. In addition, a hybrid diagnostic system in which a final diagnostic result is given by integrating the results from subsystems is introduced, where two sets of values called confidence values and trust values are used. A technique to determine the trust value is investigated under the condition that the confidence value is determined by each subsystem.

KEYWORDS : Diagnosis, Hybrid Diagnostic System, Information Integration, Subsystem, Fast Breeder Reactor

## 1. INTRODUCTION

It is very important to efficiently monitor the plant condition and to detect and identify small anomalies and component failures for the safe operation of complex and large-scale artifacts such as nuclear power plants[1]. In order to prevent accident situation from happening, the concept of defence in depth is widely applied: 1) detection and identification of an anomaly, 2) prevention of the anomaly developing into an accident, and 3) minimization of the damage and influence of an accident. For nuclear power plants, the objectives of defence in depth are specified “*to compensate for potential human and component failures, to maintain the effectiveness of the barriers by averting damage to the plant and to the barriers themselves and to protect the public and the environment from harm in the event that these barriers are not fully effective*”[2]. Diagnosing the plant condition is the first step.

In general, there are several ways of diagnosing the plant condition. First, diagnostic tests to classify the candidates of anomalies are repeated until an anomaly is identified. Second, an assumption for the detected anomaly is made and it is confirmed by diagnostic tests. Third, a standard set of diagnostic tests is applied and the anomaly is diagnosed.

The diagnostic techniques developed up to now can be categorized into several categories. The first category uses physical models or cause-effect rules of plant components based on conservation laws. A simple example is to diagnose a leak of a tank by monitoring the flow rates of its inlet and outlet. The second category uses pattern changes of measurement signals. Patterns of the values in plant conditions are usually obtained in advance theoretically, experimentally, and/or empirically. If the temperature of a building section is unusually high and its humidity is also high, then one can conclude that there is a break in the steam piping. Diagnostic techniques using discrimination functions are also included in this category. An extensive survey for the techniques of condition monitoring using empirical models is given in the literature[3]. The third category detects changes in the characteristics of measurement signals. The noise analysis[4] of BWR (Boiling Water Reactor) core is included in this category.

Each diagnostic technique has its own advantages and limitations. This fact inspires us not only to enhance the capability of diagnostic techniques but also to integrate the results of diagnostic subsystems in order to obtain more accurate diagnostic results.

This article introduces several diagnostic techniques[5-9] and an integration technique[10, 11] for diagnostic results given by subsystems. The diagnostic and integration techniques were studied in a project to develop a hybrid-type diagnostic system for the fast breeder reactor "Monju". The diagnostic techniques that were studied are introduced in Sec-tion 2. An integration technique of the results given by diagnostic subsystems is presented in Section 3. The process signal values of "Monju" are calculated by the thermal-hydraulic simulation code NET-FLOW++[12].

## 2. DIAGNOSTIC TECHNIQUES

### 2.1 Diagnostic technique based on physical model

As an example of a diagnostic technique based on a physical model, this subsection describes the outline of a diagnostic technique[5, 6] of the superheater of the fast breeder reactor "Monju" using observed process signals. The technique estimates the overall heat transfer coefficient that is an important unobserved state variable for monitoring the operation condition of the superheater.

A simplified model of the superheater is constructed by considering its structure, the flows of secondary sodium and water/steam, and the small number of process signals available to estimate the overall heat transfer coefficient as shown in Fig. 1. Based on the simplified model, the equation to calculate the overall heat transfer coefficient of the superheater, $K_{SH}$, is derived as:
where

$$K_{SH} = \frac{M_W\left(h_{W\,outSH} - h_{W\,inSH}\right)\left(\log\Delta T_{X_{SH}} - \log\Delta T_{0_{SH}}\right)}{R_{SH}X_{SH}\left(\Delta T_{X_{SH}} - \Delta T_{0_{SH}}\right)} \quad (1)$$

$M_W$: mass flow rate of steam,
$h_{W\,inSH}$: enthalpy of inlet steam,
$h_{W\,outSH}$: specific enthalpy of outlet steam,
$R_{SH}\,X_{SH}$: total heat transfer area of superheater,
$\Delta T0_{SH}$: temperature difference between liquid sodium and steam at the sodium inlet portion, and
$\Delta Tx_{SH}$: temperature difference between liquid sodium and steam at the sodium outlet portion.

An example to estimate the overall heat transfer coefficient is shown in Fig. 2 for the case of a decrease of heat transfer rate in the evaporator of "Monju". The anomaly happens at 1000 [s]. The figure also shows the time responses of confidence value; a descriptor of the certainty of anomaly detection. Owing to the occurrence of the anomaly, the overall heat transfer coefficient in the superheater increases.

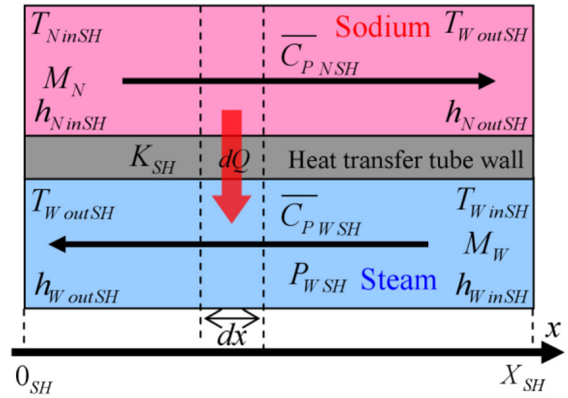



Fig. 1. Simplified Model of Superheater.

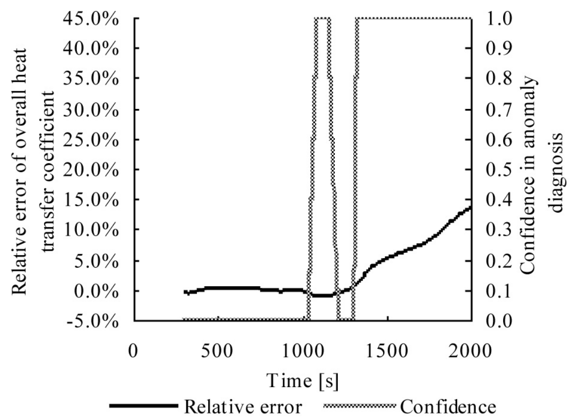



Fig. 2. Estimation Results of Overall Heat Transfer Coefficient.

### 2.2 Diagnostic technique using non-linear discrimination function

Because the SVM (Support Vector Machine)[13] can derive nonlinear identification functions from training data, it is applied to construct a state identifier[14] and a predictor[15]. The SVM has a learning function to update the identification functions when new training data are obtained. The applicability of the SVM to identify a small anomaly of "Monju" is investigated[7] with the development of a technique to select a suitable set of process signals that an SVM identifier uses.

Table 1 shows a comparison of the detection performance of SVM and a classical threshold technique to detect a small change of the operating condition of "Monju" by a partial insertion of a fine tuning control rod between using the threshold value of 2σ (σ: standard deviation

**Table 1.** Comparison of Identification Rates of Plant Condition

| Case | Diagnostic technique | True condition | Rates of identified condition [%] | |
|---|---|---|---|---|
| | | | 1 | 2 |
| A | SVM | 1 | 96.6 | 3.4 |
| | | 2 | 0.4 | 99.6 |
| | Threshold technique | 1 | 96.1 | 3.9 |
| | | 2 | 11.8 | 88,2 |
| B | SVM | 1 | 95.1 | 4.9 |
| | | 2 | 0.2 | 99.8 |
| | Threshold technique | 1 | 94.3 | 5.7 |
| | | 2 | 61.5 | 38.5 |

of noise). Cases A and B use a different set of 3 signals, which were chosen based on which give the best diagnostic performance in each case. One of the 3 signals that give the highest diagnostic performance is used in the threshold technique. As seen from the table, the SVMs give high correct identification rates.

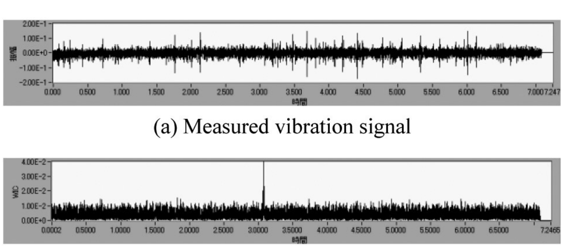
## 2.3 Diagnostic technique based on the characteristic change of measurement signals

The WT (Wavelet Transformation)[16] has a strong capability to detect the inclusion in a changing signal of a wave (short-term change pattern) similar to a reference wave called a mother wavelet (MW). The WT can analyze time-changing data in both frequency and time domains. Because of the characteristic features, the WT is widely applied to detect sudden anomalies of components with rotating parts such as pumps, motors, and so on[17]. In principle, the detection performance will increase if a MW is similar to the wave to be detected.

An anomaly detection technique[8] is developed, where a MW designed from a characteristic wave included in a real signal at an anomaly is used. To design a MW from a real signal, the technique applies a parasitic discrete wavelet transform (P-DWT) [18, 19] that can flexibly design a MW and realize a high processing speed.

As an example of detecting a small anomaly, the collision of a spherical plastic particle (diameter: 3.2 [mm]) with a part inside a small industrial pump (maximum flow rate: 19 [L/min]) is successfully detected as shown in Fig. 3. Although the collision of the particle with the pump is hardly observed by the measured vibration signal, the technique detects it at around 3.1 [s] as seen from the large value of fast wavelet instantaneous correlation (F-WIC)[19].

In the application of the WT, several standard MWs such as Morlet's wavelet are often utilized. In order to confirm that using MW based on a real signal increases detection performance, a parasitic filter is also constructed from Morlet's wavelet using the same procedure as the one using the real signals. Although the parasitic filter from Morlet's wavelet can detect the collision, the maximum value of F-WIC is 0.03 and is smaller than that (0.04) of the parasitic filter from a real signal.



(a) Measured vibration signal

(b) F-WIC using parasitic filter

Fig. 3. Detection of Collision of a Spherical Particle.

## 2.4 Diagnostic technique based on multi-attribute similarity

The performance of diagnosis will increase by using multiple attributes of measurement signals because the influenced attribute changes depending on the anomaly happened. A diagnostic technique based on multiple attributes has been developed [9]. The technique applies case-based reasoning (CBR)[20] inspired by the strategies that plant personnel actually applied in real world situations. The characteristic feature of the technique is

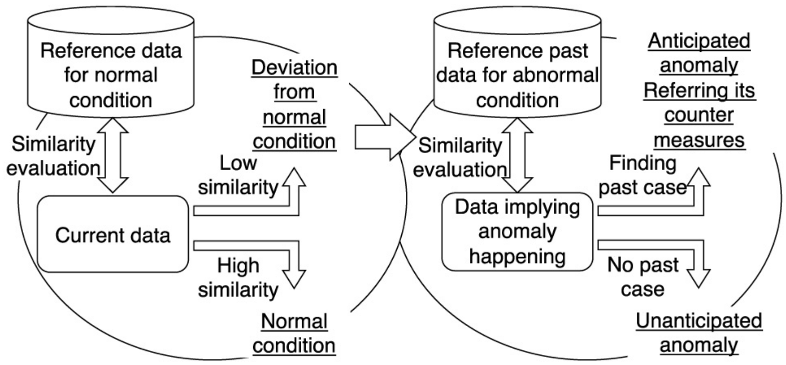



Fig. 4. Structure of Case-Based Reasoning Diagnosis System.

to use multiple attributes of process signals for similarity evaluation to retrieve a similar case stored in a case base.

The structure of the diagnostic technique is shown in Fig. 4. The reference data for attributes in the normal condition and the conditions after anomalies happen are prepared beforehand. The condition of the plant is evaluated to be normal, if the attributes of the process signals are similar to those in the normal condition. If the plant condition is diagnosed to be an anomalous one, the anomaly is identified by comparing the attributes of the process signals to those of the anomalous cases. If there is no similar case, the condition of the plant is diagnosed to be in an unanticipated anomalous condition.

The similarity to the reference data is evaluated by an exponential distribution-based similarity *EDS* [21] defined as:

$$EDS = Exp\left(-\frac{|f-g|^n}{S^n}\right), \qquad (2)$$

where $f$ and $g$ are N-dimensional attribute vectors and both $n$ and $S$ are matching parameters to adjust the severity of matching. As seen from Eq. (2), *EDS* approaches 1.0 if the similarity between $f$ and $g$ becomes high. On the other hand, *EDS* approaches 0.0 if the similarity between $f$ and $g$ becomes low.

The attributes in both frequency and time domains are used. Considering the sampling time of process data of "Monju", the spectra in low frequency between 0.001 and 0.01 [Hz], and high frequency between 0.01 and 0.5 [Hz] are utilized in the frequency domain. On the other hand, pertinent descriptors such as average, covariance, skewness, and kurtosis are utilized as attributes in the time domain. In each process signal, three similarity indices are

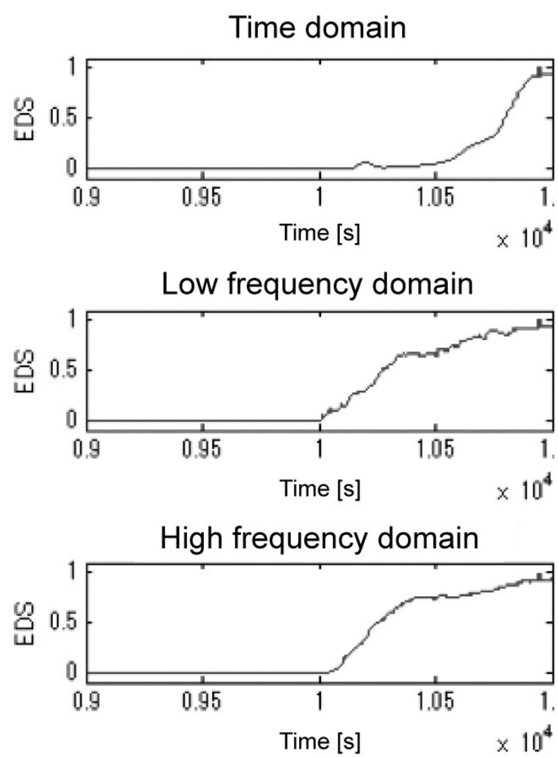



Fig. 5. Examples of Changes of Similarity Indices.

calculated for the attributes of low and high frequency bands in the frequency domain and the attributes in the time domain.

As an example of diagnostic results, Fig. 5 shows the trend graphs of similarity indices to normal operating condition. The EDS for similarity evaluation is calculated every 1 [s] for the time window of 1000 [s]. The anomaly is a small decrease of feedwater temperature. The anomaly occurs at 10000 [s]. As seen from the figure, the similarity indices for the attributes in the time domain, the attributes of low and high frequency bands in the frequency domain gradually increase from 0.0 to 1.0 after the anomaly happens. The technique is also confirmed to detect other anomalies a short time after they happen.

## 3. A HYBRID DIAGNOSTIC SYSTEM

### 3.1 General configuration and advantages

A hybrid diagnostic system[22] in which a final decision is given by integrating the results of subsystems is one of the promising ways to develop a diagnostic system because the applicable range of the system can be wide compared with that of a single system.

A hybrid diagnostic system is generally composed of an integration system and diagnostic subsystems as shown in Fig. 6. Each diagnostic subsystem diagnoses the plant condition from measurement signals, such as process signals of the plant, based on their own diagnostic principles. The diagnostic results are sent to the integration system and are integrated to obtain a diagnostic result on plant condition. The integration agent may store trend data of observed signals and serve them to the subsystems.

The advantages of the hybrid system are:

1) easy realization of fault tolerance by duplex systems,
2) easy maintenance because of small program size of a subsystem compared with a total system implementing many functions,
3) easy upgrade of the function by adding or replacing subsystems that are required,
4) high reusability of a subsystem based on the modularity of the subsystem, and
5) easy localization of system trouble because of high transparency and modularity of subsystem functions.

### 3.2 Problems in integrating diagnostic results by subsystems

A critical issue in the development and application of a hybrid diagnostic system is how to integrate the diagnostic results from subsystems. Usually, the diagnostic performance of a subsystem depends on the following features. First, the applicable range of each subsystem is restricted due to its diagnosis principle, measurement signals used, noise in measurement signals, and so on. Second, the anomalies that can be diagnosed by a subsystem and the accuracy of its diagnostic results depend not only on its diagnostic principle but also on the setting of thresholds for diagnosis because they are usually determined by solving the trade-off of erroneous alarm and missed alarm. Moreover, it is usually hard for the integration system to know how much a diagnostic parameter of a subsystem exceeds the thresholds used in diagnosis because the information is local to a particular subsystem.

The handling of the information of subsystems is difficult for the integration system due to the variety of diagnostic principles, measurement signals, and structures of subsystems. However, in the integration of the diagnostic results of subsystems, these topics should be addressed because they influence the accuracy of integrated diagnostic results.

## 4. AN INTEGRATION TECHNIQUE OF DIAGNOSTIC RESULTS BY SUBSYSTEMS

### 4.1 Integration framework of diagnostic results

By considering the topics to be addressed in the integration of diagnostic results of subsystems by an integration system, the integration technique[9, 10] shown in

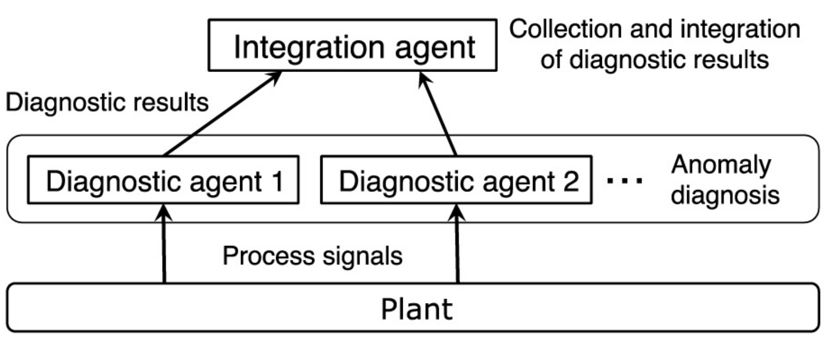



Fig. 6. General Configuration of a Hybrid-Type Diagnostic System.

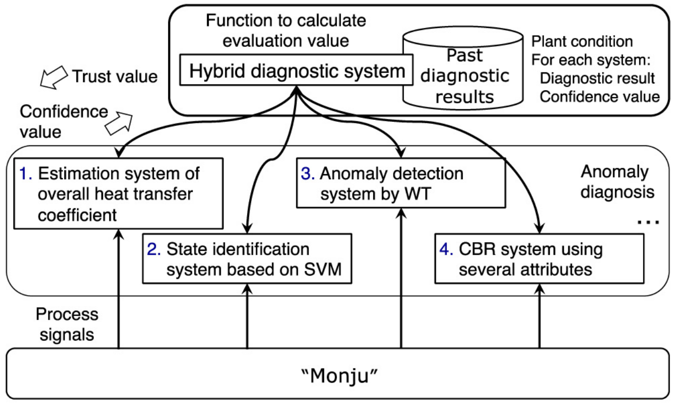



Fig. 7. Hybrid Diagnostic System for "Monju".

Fig. 7 is proposed and applied to study a hybrid diagnostic system for the fast breeder reactor "Monju".

In this technique, each subsystem outputs its diagnostic result and a confidence value that is a descriptor of the certainty of the result. The confidence value is given between 0.0 and 1.0. Confidence values of 1.0 and 0.0 mean that the subsystem has absolute confidence and no confidence, respectively.

On the other hand, the integration system (hybrid diagnostic system) uses trust values that are descriptors of trust in the results of subsystems by the integration system. The trust value is given between 0.0 and 1.0. Trust values of 1.0 and 0.0 mean that the integration agent absolutely trusts the result and ignores the result of the corresponding subsystem, respectively. The integration system obtains an integrated diagnostic result by using the diagnostic results and confidence values given by subsystems and its own trust values.

It will be better to leave the determination of the confidence value to each subsystem because there are many kinds of diagnostic techniques and it is difficult for the integration system to grasp the characteristic features of subsystems. Instead, it is reasonable to focus on the development of a technique for determining the trust values.

When a subsystem is supposed to output its diagnostic result as a category of plant condition such as state 1, state 2, and so on, with a confidence value, the trust value is predetermined for each category of plant condition that a subsystem identifies.

To integrate the diagnostic results given by subsystems, an evaluation value is defined as:

$$E_j = \sum_k C_{kij} \cdot T_{kj} \tag{3}$$

where $E_j$, $C_{kij}$, and $T_{kj}$ are the evaluation value for identified condition $j$, the confidence value of subsystem $k$ for plant condition $i$ and identified condition $j$, and the trust value for the diagnostic result of subsystem $k$ for identified condition $j$, respectively. The integrated diagnostic result is given to be a plant condition $j$ that the evaluation value $E_j$ is the highest.

Although the integration system does not know how a subsystem determines the confidence value, it will be reasonable that the integration system determines the trust value of a subsystem by its past diagnostic performance if its confidence value is supposed to be given in an unchangeable way. From this consideration, the trust value $T_{kj}$ is calculated by:

$$T_{kj} = \frac{\sum_T C_{kijT}}{\sum_T C_{kijT} + \sum_F C_{kijF}} \tag{4}$$

where $C_{kijT}$ and $C_{kijF}$ are the confidence value of subsystem $k$ at diagnosis round $T$ giving the correct diagnostic result for plant condition $i$ and identified condition $j$, and the confidence value at diagnosis round $F$ giving the wrong diagnostic result.

The trust value defined by Eq. (4) means the ratio between the total confidence value of past diagnoses giving correct results by a subsystem and the total confidence value of its past diagnoses. In an online system application, the trust value is easy to update by keeping the values of the summations of $C_{kijT}$ and $C_{kijF}$.

## 4.2 Applicability evaluation

### 4.2.1 Purpose and conditions of applicability evaluation

The applicability of the technique of trust value determination is examined by several case studies. The con-

**Table 2.** Diagnostic Performance of Subsystems

| Subsystem | Plant condition | Identification probability [%] | | | | Confidence value for plant condition |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | |
| A1 | 1 | 98 | 1 | 1 | 0 | *CH* |
| | 2 | 2 | 95 | 2 | 1 | *CH* |
| | 3 | 1 | 1 | 97 | 1 | *CH* |
| | 4 | 1 | 1 | 3 | 95 | *CH* |
| A2 | 1 | 98 | 1 | 1 | 0 | *CL* |
| | 2 | 2 | 95 | 2 | 1 | *CL* |
| | 3 | 1 | 1 | 97 | 1 | *CL* |
| | 4 | 1 | 1 | 3 | 95 | *CL* |
| A3 | 1 | 98 | 1 | 1 | 0 | *CH* |
| | 2 | 2 | 95 | 2 | 1 | *CL* |
| | 3 | 1 | 1 | 97 | 1 | *CH* |
| | 4 | 1 | 1 | 3 | 95 | *CL* |
| A4 | 1 | 60 | 20 | 10 | 10 | *CH* |
| | 2 | 30 | 50 | 10 | 10 | *CH* |
| | 3 | 20 | 20 | 55 | 5 | *CH* |
| | 4 | 30 | 10 | 10 | 50 | *CH* |
| A5 | 1 | 60 | 20 | 10 | 10 | *CL* |
| | 2 | 30 | 50 | 10 | 10 | *CL* |
| | 3 | 20 | 20 | 55 | 5 | *CL* |
| | 4 | 30 | 10 | 10 | 50 | *CL* |
| A6 | 1 | 60 | 20 | 10 | 10 | *CH* |
| | 2 | 30 | 50 | 10 | 10 | *CL* |
| | 3 | 20 | 20 | 55 | 5 | *CH* |
| | 4 | 30 | 10 | 10 | 50 | *CL* |
| A7 | 1 | 98 | 1 | 1 | 0 | *CH* |
| | 2 | 20 | 55 | 20 | 5 | *CH* |
| | 3 | 2 | 2 | 95 | 1 | *CH* |
| | 4 | 30 | 10 | 10 | 50 | *CH* |
| A8 | 1 | 98 | 1 | 1 | 0 | *CL* |
| | 2 | 20 | 55 | 20 | 5 | *CL* |
| | 3 | 2 | 2 | 95 | 1 | *CL* |
| | 4 | 30 | 10 | 10 | 50 | *CL* |
| A9 | 1 | 98 | 1 | 1 | 0 | *CH* |
| | 2 | 20 | 55 | 20 | 5 | *CL* |
| | 3 | 2 | 2 | 95 | 1 | *CH* |
| | 4 | 30 | 10 | 10 | 50 | *CL* |
| A10 | 1 | 98 | 1 | 1 | 0 | *CL* |
| | 2 | 20 | 55 | 20 | 5 | *CH* |
| | 3 | 2 | 2 | 95 | 1 | *CL* |
| | 4 | 30 | 10 | 10 | 50 | *CH* |

ditions of all case studies are as follows. Diagnoses by subsystems are assumed to be random processes under predefined probabilities and the plant condition is also given as random. Four plant conditions and ten subsystems are considered. The occurrence probability of each condition is assumed to be 0.6 (Condition 1), 0.2 (Condition 2), 0.1 (Condition 3), and 0.1 (Condition 4). The diagnostic performances of the subsystems are given as shown in Table 2, where two confidence values of high (*CH*) or low (*CL*) for identified conditions are used.

The subsystems A1 to A3 exhibit high diagnostic performances. On the other hand, the diagnostic accuracies of subsystems A4 to A6 are low. The subsystems A7 to A10 exhibit high or low diagnostic performances depending on the current plant condition.

#### 4.2.2 Relations between diagnostic characteristics of subsystems and determined trust values

The diagnostic characteristics of subsystems are specified by the probabilities of correct identification and confidence values. The first evaluation investigates the relations between diagnostic characteristics of a subsystem and determined trust values by the proposed technique.

In a random process, the theoretical probability of correct identification $P_{kj}$ of subsystem k for identified condition j is given by:

$$P_{kj} = \frac{H_j * I_{kjj}}{\sum_i H_i * I_{kij}} \tag{5}$$

where $H_i$ and $I_{kij}$ are the happening probability of plant condition $i$ and the identification probability of subsystem $k$ as identified condition $j$ when the plant condition is $i$, respectively. On the other hand, the theoretical values of trust values $T_{kj}$ are given by:

$$T_{kj} = \frac{H_j * I_{kjj} * \bar{C}_{kjj}}{\sum_i H_i * I_{kij} * \bar{C}_{kij}} \tag{6}$$

where $\bar{C}_{kjj}$ and $\bar{C}_{kij}$ are averages of the confidence values $C_{kjj}$ and $C_{kij}$, respectively when the confidence values of a subsystem change depending on diagnosis rounds and the probability density functions to determine the confidence values are symmetrical around their averages.

As an example of calculated theoretical values, Table 3 shows the correct identification probabilities and trust values for subsystem A1 and A9. In the calculation, the confidence value *CH* is set to be 0.80 and *CL* is set to be 0.20.

As seen from Table 3, the trust values for subsystem A1 are the same as the probabilities of correct identification for plant conditions. This is obvious from Eq. (6) because the confidence value is the same independent of the identified plant condition. The trust values of subsystem A9 are higher than the probabilities of correct identification except for plant conditions 2 and 4. This is because subsystem A9 gives low diagnostic performance and low confidence values for plant conditions 2 and 4. The theoretical values of trust values for the random process case suggest the adequacy of the determination of trust values by this technique.

#### 4.2.3 Comparison with other integration techniques

The diagnostic performances by the proposed technique are compared with other integration techniques by changing the confidence values (*CH* and *CL*). The confidence value *CH* is set to be 0.80 or 0.90. On the other hand, the confidence value *CL* is changed from 0.30 to 0.60 by steps of 0.10. It is assumed that there are four subsystems in a hybrid diagnostic system. The diagnostic performance of a subsystem is selected to be one from A1 to A10 in Table 2.

Two types of straightforward integration techniques are considered. The first one is the decision by majority. This technique is often used for decision making in human society. The other is to give an integrated diagnostic result by considering only confidence values of subsystems. This case corresponds to the one where all trust values in Eq. (4) are set to 1.0.

Examples of comparison results are shown in Tables 4 to 6. In Tables 4 and 6, the combination of subsystems is shown as "[$n_a$,$n_b$,$n_c$,$n_d$]", where $n_a$,$n_b$,$n_c$,and $n_d$ are identification numbers of subsystems.

Table 4 summarizes the best five combination patterns in the case of *CH*=0.90. In the table, the value in the second line of each cell is the correct identification probability by the integration technique. The table shows that the correct identification probability is slightly higher than that of the technique using only confidence values. Although the best correct identification probability of decision by majority is highest in the case of *CL*=0.30, the probability drops when descending the order.

Table 5 shows the total number of combination cases of subsystems that give better diagnostic results by the proposed technique than the compared integration technique at the confidence value *CH* of 0.90. There are 715 combination cases of four subsystems because combination cases containing the same subsystems are permitted. As seen from the table, the proposed technique tends to give better integration results than the straightforward integration techniques according to the increase of the confidence value *CL* for plant conditions. It is interesting that the decision by majority gives slightly better integration results than the proposed technique at a low *CL*.

In order to confirm the tendency of combination pat-

**Table 3.** Theoretical Trust Values of Subsystem in the First Simulation

| Subsystem | Identified condition | Probability of correct identification [%] | Trust value |
|---|---|---|---|
| A1 | 1 | 99.0 | 0.990 |
| | 2 | 96.0 | 0.960 |
| | 3 | 88.2 | 0.882 |
| | 4 | 96.9 | 0.969 |
| A9 | 1 | 89.1 | 0.968 |
| | 2 | 85.9 | 0.724 |
| | 3 | 62.9 | 0.837 |
| | 4 | 82.0 | 0.781 |

**Table 4.** Best Five Combinations of Diagnostic Subsystems Giving High Performances by an Integration Technique without Permitting the Combination of Same Diagnostic Subsystems

| *CL* | Order from best case | Integration technique | | |
|---|---|---|---|---|
| | | Proposed technique | Decision by majority | Considering only confidence value |
| 0.30 | 1 | [A1, A2, A3, A10]<br>0.992 | [A1, A2, A3, A7]<br>0.995 | [A1, A2, A3, A7]<br>0.990 |
| | 2 | [A1, A2, A3, A7]<br>0.992 | [A1, A2, A3, A4]<br>0.992 | [A1, A2, A3, A10]<br>0.990 |
| | 3 | [A2, A3, A8, A9]<br>0.991 | [A1, A2, A7, A8]<br>0.978 | [A1, A2, A3, A4]<br>0.985 |
| | 4 | [A1, A3, A8, A10]<br>0.990 | [A1, A2, A4, A7]<br>0.974 | [A1, A2, A3, A9]<br>0.985 |
| | 5 | [A1, A2, A9, A10]<br>0.990 | [A1, A2, A4, A5]<br>0.947 | [A1, A3, A8, A9]<br>0.984 |
| 0.60 | 1 | [A1, A2, A3, A7]<br>0.996 | [A1, A2, A3, A7]<br>0.995 | [A1, A2, A3, A8]<br>0.996 |
| | 2 | [A1, A2, A3, A8]<br>0.996 | [A1, A2, A3, A4]<br>0.992 | [A1, A2, A3, A9]<br>0.996 |
| | 3 | [A1, A2, A3, A4]<br>0.996 | [A1, A2, A7, A8]<br>0.978 | [A1, A2, A3, A10]<br>0.994 |
| | 4 | [A1, A2, A3, A10]<br>0.996 | [A1, A2, A4, A7]<br>0.974 | [A1, A2, A3, A7]<br>0.994 |
| | 5 | [A1, A2, A3, A9]<br>0.996 | [A1, A2, A4, A5]<br>0.947 | [A1, A2, A3, A5]<br>0.994 |

**Table 5.** Comparison Results of Diagnostic Performances Among Three Integration Techniques by Changing Lower Confidence Values for Plant Conditions with Permitting the Combination of Same Diagnostic Subsystems

| Comparison case | Integration technique | $CL$ (Lower confidence values for plant conditions) | | | |
|---|---|---|---|---|---|
| | | 0.30 | 0.40 | 0.50 | 0.60 |
| 1 | Proposed technique | 329 | 381 | 471 | 544 |
| | Decision by majority | 386 | 334 | 244 | 171 |
| 2 | Proposed technique | 611 | 600 | 577 | 621 |
| | Considering only confidence value | 104 | 115 | 138 | 94 |

**Table 6.** Worst Five Combinations of Diagnostic Subsystems Giving Lower Performances by the Proposed Technique with Permitting the Combination of Same Diagnostic Subsystems

| Comparison case | Order from worst case | $CL$ (Lower confidence values for plant conditions) | | | |
|---|---|---|---|---|---|
| | | 0.30 | 0.40 | 0.50 | 0.60 |
| 1 (Proposed technique and decision by majority) | 1 | [A2, A3, A6, A7] 0.884, 0.973 | [A3, A6, A6, A7] 0.853, 0.908 | [A6, A6, A6, A8] 0.765, 0.797 | [A6, A6, A6, A10] 0.765, 0.797 |
| | 2 | [A2, A3, A5, A7] 0.884, 0.973 | [A2, A6, A7, A9] 0.886, 0.936 | [A3, A6, A6, A7] 0.882, 0.908 | [A4, A6, A9, A9] 0.846, 0.862 |
| | 3 | [A2, A2, A6, A10] 0.884, 0.973 | [A3, A6, A7, A9] 0.886, 0.936 | [A2, A6, A6, A7] 0.882, 0.908 | [A4, A4, A4, A10] 0.781, 0.797 |
| | 4 | [A3, A3, A6, A7] 0.885, 0.973 | [A2, A5, A6, A7] 0.860, 0.908 | [A6, A6, A7, A9] 0.841, 0.862 | [A6, A7, A7, A9] 0.875, 0.890 |
| | 5 | [A3, A3, A5, A7] 0.885, 0.973 | [A2, A5, A5, A7] 0.861, 0.908 | [A4, A6, A8, A8] 0.843, 0.862 | [A6, A8, A8, A9] 0.877, 0.890 |
| 2 (Proposed technique and technique only considering confidence value) | 1 | [A5, A5, A5, A9] 0.825, 0.871 | [A5, A5, A5, A9] 0.839, 0.867 | [A5, A6, A7, A9] 0.856, 0.886 | [A5, A6, A7, A9] 0.861, 0.886 |
| | 2 | [A5, A6, A6, A6] 0.676, 0.711 | [A5, A6, A9, A9] 0.857, 0.883 | [A3, A5, A6, A7] 0.898, 0.925 | [A5, A5, A7, A9] 0.862, 0.886 |
| | 3 | [A5, A6, A9, A9] 0.852, 0.883 | [A2, A5, A5, A7] 0.861, 0.881 | [A4, A5, A9, A9] 0.858, 0.883 | [A5, A5, A7, A8] 0.867, 0.886 |
| | 4 | [A6, A9, A9, A9] 0.859, 0.890 | [A3, A5, A5, A7] 0.865, 0.885 | [A6, A6, A7, A9] 0.841, 0.864 | [A5, A5, A9, A10] 0.869, 0.886 |
| | 5 | [A3, A4, A5, A7] 0.875, 0.903 | [A3, A5, A6, A7] 0.865, 0.885 | [A2, A5, A5, A7] 0.904, 0.924 | [A4, A5, A7, A7] 0.868, 0.886 |

terns that the proposed technique gives worse integrated diagnostic results, Table 6 summarizes the worst five combination patterns in the case of $CH$=0.90. In the table, the values in the second line of each cell are correct identification probabilities by the proposed technique and by the compared straightforward integration technique.

The table suggests that the worse cases include the subsystems that give low confidence values at high diagnostic performance and/or give high confidence values at low diagnostic performance, especially in comparison case 1. Subsystems A2, A3, and A8 tend to give low confidence values at high diagnostic performance. Subsystems A6 and A7 tend to give high confidence values at low diagnostic performance. On the other hand, subsystem A5 gives low confidence values at low diagnostic performance, so subsystem A5 is hardly referred to when the integration agent integrates the results of the subsystems.

Similar tendencies are seen in the cases of $CH$=0.80. The comparison results show the applicability of the proposed technique if each diagnostic subsystem gives high confidence values for the conditions diagnosed at high diagnostic performance.

## 5. CONCLUSIONS

It is crucial to improve the performance and applicable range of diagnostic systems for a large-scale safety critical system. This article describes the outline of four diagnostic techniques and a hybrid diagnostic technique developed for condition monitoring of the fast breeder reactor "Monju".

The developed four diagnostic systems are (1) estimation technique of important state variables based on a physical model of the component, (2) a state identification technique by non-linear discrimination function applying SVM, (3) a diagnostic technique applying WT to detect changes in the characteristics of measurement signals, and (4) a state identification technique effectively using past cases. The high performances of the techniques are confirmed by diagnostic experiments using the data generated by NETFLOW++ and real noise data of "Monju" process signals. Each diagnostic technique will improve the condition monitoring capability of a plant such as "Monju".

An integration technique of the results of diagnostic subsystems is described. Its applicability is confirmed by several case studies assuming that subsystems diagnose the plant condition as a random process. The integrated technique gives more accurate results than straightforward integration techniques.

Future works for the integration technique include an extension of the calculation of trust values for extending the applicability, for example renewing confidence values of subsystems based on diagnostic performance, and applicability evaluations under the conditions of real diagnostic cases rather than random process cases. Applicability evaluation of the developed hybrid diagnostic system through the condition monitoring of "Monju" is also a future topic. Because engineering plants have similar components to "Monju", it will be easy to apply the developed diagnostic techniques to an engineering plant with some minor modifications.

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