Hybrid diagnostic system for nuclear power plants

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Abstract: A hybrid-type diagnostic system to give a final diagnostic result by integrating the results of sub-systems is one of promising ways to develop a flexible diagnostic system. This article describes the general configuration of a hybrid-type diagnostic system and presents the techniques for the important topics of how to integrate the diagnostic results of sub-systems and how to select suitable signals for diagnosis. The article also introduces the outline of a hybrid diagnostic agent system for the fast-breeder reactor, "Monju".
Keyword: diagnostic system; hybrid system; integration of diagnostic results; selection of signals

1 Introduction

A hybrid-type diagnostic system that a final diagnostic result is given by integrating the results of sub-systems is one of promising ways to develop a diagnostic system because such system composition has several advantageous features in adding and improving diagnostic functions in the system. However, there are two important topics to be considered in developing a hybrid-type diagnostic system. The one is how to integrate the diagnostic results from sub-systems. The other is how to select suitable process signals for plant diagnosis.

The authors studied a hybrid-type diagnostic system [1] to detect and identify early an anomaly that happens in the fast-breeder reactor "Monju". The system utilizes an agent system configuration composed of four diagnostic software agents. The advantageous characteristics of agents are: (1) easy realization of fault tolerant system by duplex systems, (2) easy system maintenance because of small program size of an agent compared with a total system including many functions, (3) easy upgrade of system function by adding only necessary agents, (4) high reusability of an agent because of the generality of the single function agent, and (5) easy localization of system trouble because of high transparency of agent function.

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The four diagnostic agents are (1) an estimation agent of overall heat transfer coefficient of evaporator and superheater, (2) a state identification agent based on SVM (Support Vector Machine) [2], (3) an anomaly detection agent by WT (Wavelet Transformation) [3], and (4) a CBR (Case-Based Reasoning) [4] agent using several attributes in both time and frequency domains.

This article describes a technique to integrate the diagnostic results given by sub-systems, a technique to select suitable process signals for plant diagnosis, and the outline of the hybrid-type diagnostic system for the fast-breeder reactor "Monju" based on the literature [1].

2 Technique to integrate diagnostic results by sub-systems

2.1 Hybrid-type diagnostic system and topics to be considered in the development

The general configuration of a hybrid-type diagnostic system is shown as Fig. 1. At the top of the system, there is an integration agent to collect diagnostic results and integrate them. In the lower, there are diagnostic agents. The integration agent may store trend data of observed signals and serve them to the diagnostic agents.

In the integration of the diagnostic results of sub-systems, several considerations are necessary. First, each diagnostic sub-system has its own applicable range due to its diagnosis principle, sensor data used in its diagnosis, and so on. Second, the accuracy of the diagnostic result of a sub-system depends on not only its diagnosis principle but also the setting of threshold values for diagnosis that are usually determined by solving the trade-off of erroneous alarm and mis-alarm. Third, it is usually hard for the integration agent to know how much a diagnostic parameter of a sub-system exceeds a threshold value.

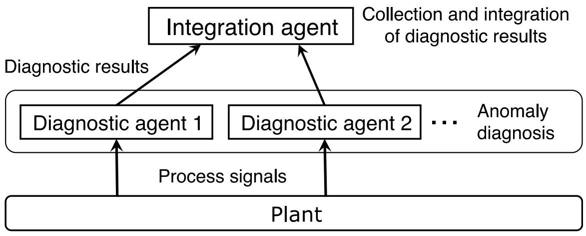


Fig. 1 Configuration of a hybrid-type diagnostic system.

2.2 Integration of diagnostic results by sub-systems

By considering the topics to be considered in the integration of diagnostic results by sub-systems, the authors propose a framework [1]. In the framework, each sub-system outputs its diagnostic result and "confidence value" for the result. On the other hand, the integration agent uses "trust values" for diagnostic sub-systems for the integration of diagnostic results by sub-systems.

The confidence value is given between 0.0 and 1.0. The confidence values of 1.0 and 0.0 mean that the sub-system has absolute confidence and no confidence, respectively. In the framework, the determination of the confidence value is left to each sub-system. The confidence value may be determined base on the following evaluation value depending on the diagnosis principle of a sub-system:

1) an exceeding or underrating value for a threshold value when the sub-system uses a threshold value,
2) a distance from a discrimination function when the sub-system makes a state classification by the function,
3) a coincidence value for a typical pattern when the sub-system checks some attributes with those of past cases.

On the other hand, the trust value is given between 0.0 and 1.0. The trust values of 1.0 and 0.0 mean that the integration agent absolutely trusts the result and ignores the result of the corresponding diagnosis sub-system, respectively. In the authors' study, a sub-system outputs its diagnostic result as a category of plant condition such as normal, anomaly 1, anomaly 2, and so on with a confidence value. Thus, the trust value is predetermined for each category of plant condition that a sub-system identifies.

The integrated diagnosis result is given to be a plant condition whose evaluation value is highest as calculated by the following equation:

$$E_i = \sum_a C_{ai} \cdot T_{ai} \tag{1}$$

where E_i, C_{ai}, and T_{ai} are evaluation value for plant condition i, confidence value of sub-system a for plant condition i, and trust value for the diagnostic result of sub-system a in its diagnostic result of plant condition i.

It is considered as reasonable that the trust value is determined by the diagnostic performance of a sub-system in the past if the confidence value of the sub-system is given in an unchangeable way. From this consideration, the trust value is calculated by

$$T_{ai} = \frac{1}{2}\left(\frac{\sum_j C_{aij} - \sum_k C_{aik}}{\sum_j C_{aij} + \sum_k C_{aik}} + 1 \right) \tag{2}$$

where C_{aij} and C_{aik} are a confidence value of correct diagnostic result for plant condition i of sub-system a and a confidence value of wrong diagnostic result in past diagnoses. The meaning of the trust value defined by Eq. (2) is clear and the value is easy to update on line by keeping the values of the summations of C_{aij} and C_{aik}.

The theoretical value of trust value can be calculated easily if a sub-system gives its diagnostic result at random and the plant condition is also given at random. For example, there are four plant conditions and the happening probabilities of the conditions are 0.6, 0.2, 0.1 and 0.1 and the diagnostic performance of sub-systems are given as shown in Table 1. Then, the theoretical values of trust values are calculated as shown in Table 2.

Table 1 Diagnostic performance of sub-systems

Sub-system	True condition	Identification probability [%]				Confidence value
		1	2	3	4	
A	1	95	3	2	0	0.8-1.0
	2	0	100	0	0	
	3	3	2	95	0	
	4	5	0	5	90	
B	1	98	2	0	0	0.8-1.0
	2	3	95	2	0	
	3	10	20	70	0	0.6-0.9
	4	25	0	25	50	0.3-0.6

Table 2 Theoretical values of trust values

Sub-system	True condition	Probability of correct identification [%]	Trust value
A	1	98.6	0.986
	2	90.9	0.909
	3	84.8	0.848
	4	100	1.000
B	1	93.5	0.957
	2	85.6	0.869
	3	70.7	0.780
	4	100	1.000

Trust values of both sub-systems for condition 4 are 1.000 because the results of condition 4 by the sub-systems are always correct although sub-system B has high probability of mis-identification for condition 4. If the confidence value is the same independent on the true condition, the trust value is the same as the probability of correct identification. It is interesting that the trust values of sub-system B are higher than the probabilities of correct identification except for condition 4. This is because that sub-system B gives high confidence values for the conditions of high diagnostic performance and middle and low confidence values for the conditions of low diagnostic performance. The theoretical values of trust values for the stochastic case suggest the adequacy of the determination of trust values by *Eq.* (2)

3 Selection of suitable plant variables for diagnosis

The selection of suitable plant variables is important in diagnosis because the performance of diagnosis depends on the selection. Usually, designers of a diagnosis system select plant variables to be used by their experiences of plant diagnosis and knowledge of both the principles of diagnostic techniques and components to be diagnosed.

A technique to select a suitable combination of process signals based on the performance of the diagnostic system is developed [1]. Although the technique utilizes “model score” for evaluating the performance of a diagnostic system and SVM (Support Vector Machine) [2] for predicting diagnostic performance of the system using more process signals, this subsection presents a general algorithm based on the technique.

The technique is based on several empirical rules for the combinations of process signals on diagnostic performance: (1) the diagnostic performance will not increase so much if the process signals that give high diagnostic performance are combined, (2) a combination of the process signals that do not give high performance does not give high performance, (3) an addition of the process signal that give low diagnostic performance will not increase the performance, (4) the performances of the two diagnostic systems using the same kinds of signals measured at similar places by the same measurement principle are almost the same.

The technique uses a predictor that learns the performance of a diagnostic system with each combination of less process signals and predicts the performance of the diagnostic system using a combination of more process signals. The SVM and other techniques of machine learning and function fitting can be applied as the predictor.

The generalized signal selection technique based on the technique [1] is outlined as follows, where the performance index is an index to evaluate the performance of a diagnostic system such as accuracy, detection time, *etc.* depending on the purpose of diagnosis:

<u>Step 1</u>: Selection of useful signals.

<u>Step 1.1</u>: Calculate a base performance index M_B of diagnostic system using all process signals.

<u>Step 1.2</u>: Calculate performance index M_i of the diagnostic system using a process signal i.

<u>Step 1.3</u>: Select the signal if the performance index of the diagnostic system using the signal is higher than M_B or the order of the performance index in arranging performance indices from the highest is smaller than a predetermined order. The number of selected signals is set to m.

Step 2: Optimization of signal combination.

Step 2.1: Obtaining the set of signal combinations by using the signals selected in Step 1.

Step 2.2: For a given j (initially 2), construct ${}_mC_j$ diagnostic systems using j signals and calculate their performance indices.

Step 2.3: Construct a predictor to estimate the performance indices of diagnostic systems using $j+1$ signals from the performance indices of diagnostic systems using 1 to j signals and estimate the performance indices $M_k^{E(j+1)}$ of diagnostic systems using $j+1$ signals.

Step 2.4: Construct ${}_mC_{j+1}$ diagnostic systems using $j+1$ signals and calculate their performance indices $M_k^{C(j+1)}$.

Step 2.5: Move to Step 2.6 if the termination condition is satisfied. Otherwise, return Step 2.2 after incrementing j. The termination condition is that the increase of highest performance index is small by the increase of the number of signals.

Step 2.6: Estimate the performance indices of diagnostic systems using $j+1$ to m signals by the predictor.

Step 2.7: Select a combination of signals that gives highest estimated or calculated performance index.

For example, Table 3 shows the comparison of the performance SVM diagnostic systems [1] in the cases of using all signals and selected signals. The "Basic SVM" in the table uses 16 signals. From the table, the SVM diagnostic systems using the signals selected by the technique show comparative diagnostic performance.

Table 3 Example of comparison of diagnostic performance

Case	Anomaly	Opt-SVM (sec)	Selected signals	Basic SVM (sec)
1	Decrease of feedwater temp.	10057	3	10036
2	Decrease of heat transfer at evaporator	10031	4	10031
3	Decrease of feedwater flow rate	10240	8	10257
4	Decrease of Primary Na flow rate	10167	4	10151

4 Hybrid diagnostic agent system for "Monju"

4.1 Diagnostic techniques developed

A hybrid diagnostic agent system for "Monju" is developed as shown in Fig. 2. It consists of the diagnosis integration sub-system and four diagnostic sub-systems to detect small anomalies using process signals. The sub-systems are: (1) an estimation agent of overall heat transfer coefficient of evaporator and superheater, (2) a state identification agent based on SVM, (3) an anomaly detection agent by WT, and (4) a CBR diagnostic agent using several attributes in both time and frequency domains.

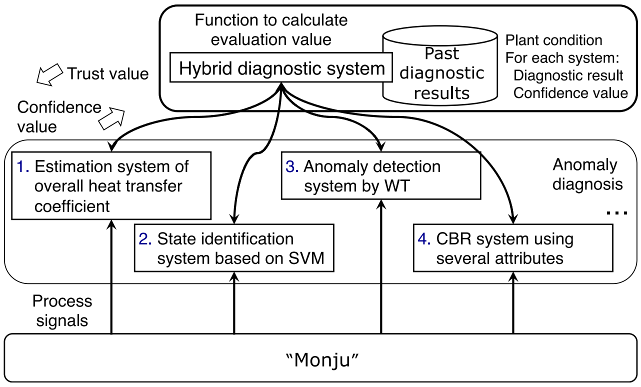


Fig. 2 Hybrid diagnostic system for "Monju".

4.2 Estimation technique of overall heat transfer coefficients of evaporator and superheater

Diagnostic techniques of evaporator and superheater using observed process signals are developed to monitor their operation conditions [5,6]. The techniques estimate the overall heat transfer coefficients that are important unobserved state variables for evaporator and superheater.

Simplified models of the evaporator and superheater of "Monju" are constructed by considering their structures, the flows of secondary sodium and water/steam, and small number of process signals available to estimate the overall heat transfer coefficients. Based on the simplified models, equations to calculate overall heat transfer coefficients of evaporator and superheater are derived.

As an example to estimate the overall heat transfer coefficient, Fig. 3 shows estimation results in the case of a decrease of heat transfer rate in evaporator. The figure also shows the time responses of confidence value; a descriptor of the certainty of anomaly detection. The anomaly happens at 1000 [**s**]. Owing to the occurrence of the anomaly, the overall heat transfer coefficient in the evaporator decreases.

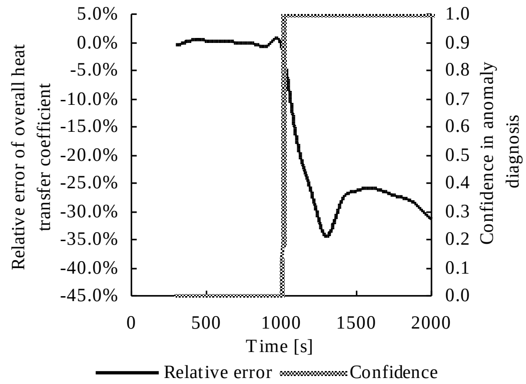


Fig. 3 Estimation results of overall heat transfer coefficient of evaporator.

4.3 State identification technique based on support vector machine

The SVM is a kind of machine learning technique and is widely applied to construct a state identifier [2]. The SVM has a characteristic feature to derive nonlinear identification functions from training data. It can update the identification functions when new training data are obtained.

As an example for showing high performance of anomaly detection, Table 4 shows comparisons of the performance of the detection of a small change of operating condition of “Monju” by a small insertion of fine tuning control rod between SVM and a classical threshold technique using the threshold value of $2s$ (s: standard deviation of noises). The selected 3 signals used in the identification of plant condition are different in the cases A and B. One of 3 signals that give highest diagnostic performance is used in the threshold technique. As seen from the table, the identification results by SVMs give high correct identification rates.

Table 4 Comparison of identification rates of plant condition

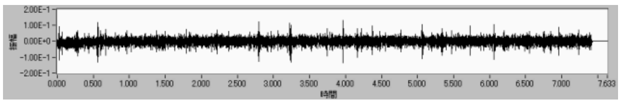
Case	Diagnostic technique	True condition	Rates of identification [%]	
A	SVM	1	96.6	3.4
		2	0.4	99.6
	Threshold technique	1	96.1	3.9
		2	11.8	88,2
B	SVM	1	95.1	4.9
		2	0.2	99.8
	Threshold technique	1	94.3	5.7
		2	61.5	38.5

4.4 Anomaly detection technique by wavelet transform

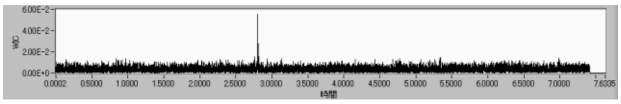
A WT [3] has a strong capability to detect the inclusion of a similar wave (short-term change pattern) in a changing signal to a reference wave called a mother wavelet (MW). WT can analyze time-changing data in both frequency and time domains. Therefore, WT is widely applied to detect a sudden anomaly of a component with rotating parts such as pump, motor, and so on. In principle, the detection performance will increase if a MW is similar to the wave to be detected.

An anomaly detection technique [7] 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) [8] that has a large flexibility in the design of a MW and a high processing speed.

As an example to detect a small anomaly, the collision of a spherical particle is successfully detected as shown in Fig. 4. Although the collision of the particle to the pump is hardly observed by the measured vibration signal, the technique detects it at around 2.8 [**s**] as seen from a large value of WIC.



(a) Measured vibration signal



(b) WIC using parasitic filter

Fig. 4 Detection of collision of a spherical particle.

4.5 Case-based reasoning diagnostic technique based on multi-attribute similarity

A diagnostic technique applying CBR is developed. The characteristic feature of the technique is 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. 5. The plant condition is evaluated in the normal condition, if the attributes of 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 process signals to those of the anomalous cases. If there is no similar case, the plant condition is diagnosed to be in a different anomalous condition from those of past cases.

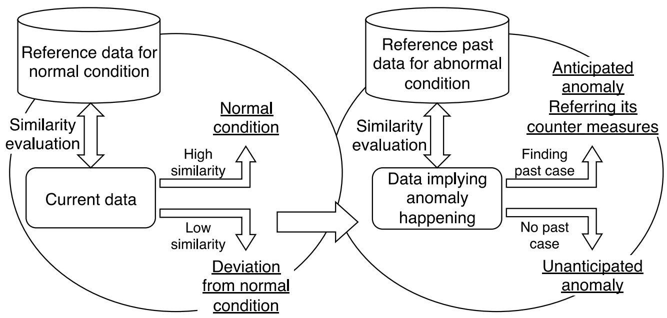


Fig. 5 Structure of case-based reasoning diagnosis system.

In the diagnostic technique, the similarity index is calculated by an exponential distribution-based similarity EDS [9] defined as:

$$EDS = Exp\left(- \frac{|f - g|^n}{S^n} \right) \tag{3}$$

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. (3), 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. In frequency domain, the spectra in low frequency between 0.001 and 0.01 [**Hz**], and high frequency between 0.01 and 0.5 [**Hz**] are utilized. On the other hand, pertinent descriptors such as average, covariance, skewness, and kurtosis are utilized as attributes in time domain. In each process signal, three similarity indices are calculated for the attributes of low and high frequency bands in frequency domain and the attributes in time domain.

As an example of diagnostic results, Fig. 6 shows the trend graphs of similarity indices for four process signals at the anomaly case of a small decrease of feedwater temperature. The similarity indices for three of the four process signals change from 1.0 to 0.0, implying the occurrence of an anomaly of decreasing feedwater temperature. This means that the technique can identify the anomaly that happened.

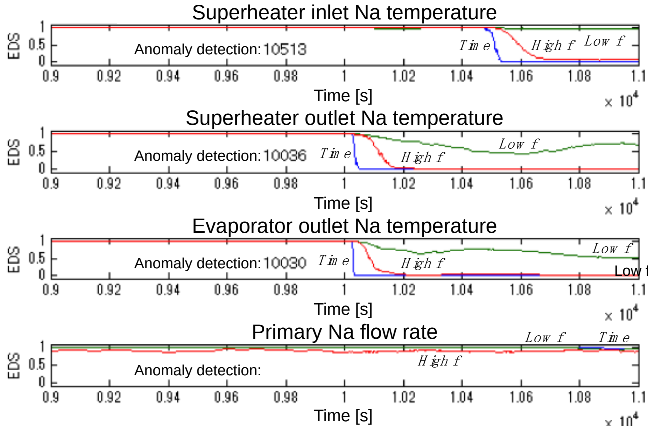


Fig. 6 Similarity indices to a case of small feedwater temperature decrease.

5 Concluding remarks

The article describes the general configuration of a hybrid-type diagnostic system and presents the techniques for the important topics of how to integrate the diagnostic results of sub-systems and how to select suitable signals for diagnosis. The article also introduces the outline of a hybrid diagnostic agent system for “Monju”.

Although the techniques of integration and signal selection are applicable to any engineering plant, further investigation and extension may be made for a real implementation of hybrid-type diagnostic system.

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