Intelligent Virtual Measurement in a Process Plant Based on Model Based Diagnosis

Takashi Washio[*1], **Kyoichi Okusa**[*2] **and Akira Endou**[*2]
*1 Institute of Scientific and Industrial Research, Osaka University
*2 Technology Development Division, Monju Construction Office
Power Reactor and Nuclear Fuel Development Corporation

Abstract

The principle of *Model Based Diagnosis* (MBD) provides a basis from which efficient fundamental techniques that are applicable to various problem tasks such as measurement, monitoring and design are derived, and it is not limited to only a stand alone diagnosis system. Consistency checking, generation of conflicts and derivation of diagnoses in the MBD principle can be used to validate a sensing system and to provide appropriate interpretations of measurement in process plant instrumentation. This idea plays an important role especially for an indirect sensing system that consists of multiple complex measurement schemes and requires high robustness in its operation. Besides, recently a new technique named as *Virtual Measurements* (VMs) has become practical in accordance with the progress of on-line computing technology. Operators of any process plant often faces a situation in which they are reqested to obtain estimates of some important physical quantities even in rough accuracy to maintain the plant in a safety state. VMs are used to indirectly obtain rough estimate of objective quantities under an even distorted and incomplete measurement environment. It is expected to support operators in making decisions by providing the credible estimation. Since the estiamted values must be ensured to be appropriate, the validity of the measurement schemes should be always monitored and diagnosed, and an appropriate interpretation of the valid measurement for each faluty candidate should be provided. The work presented here proposes a framework of the application of MBD to a VM system to measure the flow rate of the secondary sodium coolant loop of a fast breeder nuclear reactor. The role of the MBD is the diagnosis of the VM system and the interpretation of valid measurements under the candidate faults. The feasibility of the proposed framework is demonstrated by actual experimental data of the measurement signals that are associated with a secondary sodium coolant pump.

Introduction

The basic principle of *Model Based Diagnosis* (MBD)(Reiter 1987; de Kleer & Williams 1987) forms a firm foundation for efficient elementary techniques that are applicable to various problem tasks such as measurement, monitoring and design, and is not limited to only a stand alone diagnosis system(Alberts *et al.* 1993). The validation of a sensing system in process plant instrumentation is considered to be one of the candidate applications of MBD. In the operation of a process plant, operators often face situations in which they are required to obtain the credible estimates of some important physical quantities even in rough accuracy to maintain the plant safety. To support operators under these situations, a sensing system to directly measure and/or indirectly estimate some safety-related key quantities has been developed(Beltracchi & Lapinsky 1985). This type of sensing systems must be highly robust against the degradation of the quality and the loss of completeness of some measurement signals due to the faults of some components and devices that are involved in the measurement processes. Feasible interpretations of the values of the key quantities must be provided at least, even if their unique values can not be determined. Accordingly, the validation of the measurement processes should be conducted on the basis of monitoring and diagnosis, and the appropriate interpretations of the valid measurements for each candidate fault should be provided in an effective manner. The principle of the MBD is applicable to the diagnosis of the faulty processes in the sensing system and to the interpretation of the feasible values of the objective quantities.

To enhance the credibility and the robustness of the sensing system in a process plant, various techniques have been developed and actually implemented. The credibility of the direct sensing of an objective quantity by using a dedicated sensor, e.g., a flow meter to measure the flow rate of a fluid, is sensitive to the reliability of the sensor hardware. When the reliability is not sufficient enough, hardware redundancy such as 2 out of 3 logic has been applied. However, as this is costly, smarter approaches have been developed. One of the approaches is analytic redundancy in which the values of the objective quantities are indirectly estimated from other sensing information by a physical model(Gertler 1988). For instance, the flow rate of a fluid is estimated from the sensing information of the valve opening and the pressure drop between its inlet and outlet by a physical model of the valve. However, this approach requires a complete physical model and also a complete set of observed signals for the model to calculate the objective quantities. This restriction reduces the applicability of this technology in practical environments of the process plants because a complete model of the plant and the clear condition of its applicability are hardly obtained for the large scale and complex plants. Moreover, the arrangement and the quality of the sensors in the plant are not always sufficient for the purpose of indirect estimation since the specification of plant instrumentation is not designed for the technology.

This issue of the indirect estimation of physical quantities gave birth to a new technique named as *Virtual Measurements* (VMs)(Ikonomopoulos, Tsoukalas, & Uhrig 1993). It is based on the recent progress of neural network research, and does not have to use any complete model and complete observed signals to obtain the indirect estimation of the objective quantities. It has high robustness under certain assumptions to the degraded environment so that the feasible values of the objective quantities are estimated even under distorted and incomplete measurement environments without using any physical models. The feature of this technique will provide an efficient remedy to the limited applicability of the current indirect estimation methodology. One of the representative study on VMs is due to L. Tsoukalas et al.(Ikonomopoulos, Tsoukalas, & Uhrig 1993) They applied multiple neural networks to obtain an experimental model of the valve opening in a plant and to estimate the value. Their method demonstrated high applicability of VMs under the lack of some important measurement signals and the anomalous states of the plant. However, an issue remains. When some of the assumptions become no longer valid by the change of operation modes and/or when some faults occurs in the plant, the estimated values of objective quantities may also become invalid. Accordingly, the validity of the assumptions of the VM system must be always monitored. Once a violation of the assumptions are detected, the identification of the irrelevant assumptions, i.e., diagnosis, and the feasible interpretation of the objective quantities must be conducted.

The work presented here proposes a framework of the application of MBD to a VM system. The role of the MBD is the diagnosis of the assumptions of the VM system, and the interpretation of valid measurements when some of the assumptions are thought to be fault. The feasibility of the proposed framework is demonstrated to measure the flow rate of sodium coolant using actual experimental data of the measurement signals associated with a secondary sodium coolant pump of a fast breeder nuclear reactor.

Virtual Measurements

The most of the past work to develop VMs utilized the conventional three layers feedforward neural networks(Ikonomopoulos, Tsoukalas, & Uhrig 1993; Sakuma, Kitamura, & Washio 1994). The advantages of this type of neural network are its simple implementation and the fast convergence in training. However, its ability to embed the given data is basically limited to the static relations among the data. As the virtual measurements should provide valid estimation of the objective quantities under a dynamic change in the plant state, this feature of the conventional approach easily mislead the estimation. We, therefore, adopted two layers recurrent neural networks called as *Elman networks*(Elman 1990). The outline of this network is depicted in Fig. 1. The multiple inputs are provided to each neuron in the first layer. The output function of each neuron in the first layer is a tangent sigmoid function, and the output is fed back to the inputs of all neurons in that layer. Also, the outputs are loaded to the unique neuron in the second layer. The neuron in the second layer is completely linear, and its output is the result of this entire neural network. This network has the following features.

1. The recurrent mechanism enables the learning of the highly dynamic features of given data.
2. Any relations among given data can be embedded if the sufficient number of neurons is provided in the first layer.

These features are considered to yield high applicability of VMs under dynamic and complex environments of the plant.

The inputs to the network are the sensor signals having some relations to the objective quantity which is provided at the output. The valve opening and the pressure drop between the inlet and outlet of the valve can be input signals of the Elman network to give the estimated value of the flow rate of a fluid crossing the valve at the output. The neural network needs to be trained by using the empirical data representing the relations among these inputs and the output quantities. The use of efficient learning algorithm is prerequisite to the case of the recurrent network because the convergence speed of the training is generally slow due to the compensation of the output change of each neuron by the feedback effect. Accordingly we applied an advanced back propagation algorithm using the momentum method in concert with the adaptive learning rate method(Wasserman 1989).

Though an well-trained neural network, i.e., a VM, provides an estimation of the objective quantity, the assumptions for the VM must hold to provide the

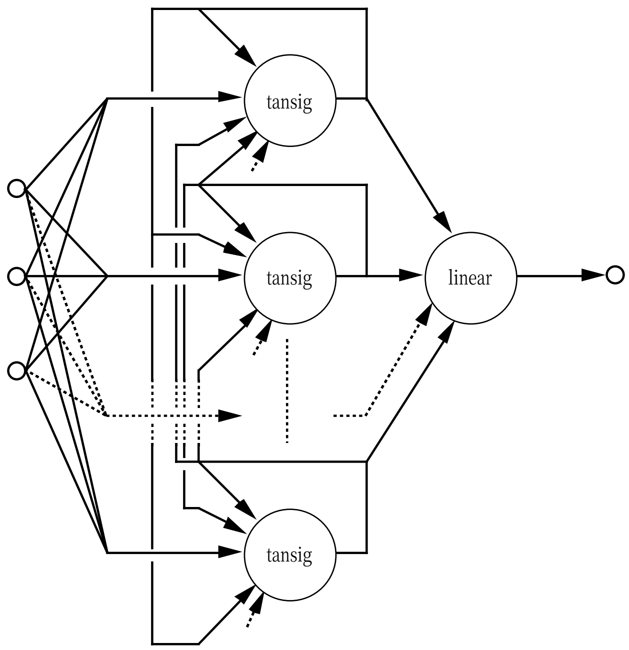

Figure 1: Outline of Elman network.

correct estimation. Accordingly, the combined use of multiple VMs mutually having different sets of assumptions is commonly adopted to enhance the credibility of the resultant estimation of an objective quantity(Ikonomopoulos, Tsoukalas, & Uhrig 1993; Sakuma, Kitamura, & Washio 1994). We also follows this approach. The possible schemes of VMs to estimate an objective quantity can be categorized into the following four types of principles.

$P1$ Direct measurement by a dedicated sensor

$P2$ Estimation based on a complete model

$P3$ Estimation based on an incomplete model but having a physical background

$P4$ Estimation based on an empirical model of some derivative relations

Though $P1$ is an ordinary approach of the instrumentation of a process plant, we include this principle in our framework of VMs. The second is the scheme used in the conventional analytical approach for the quantity estimation(Gertler 1988). The VMs also uses this principle. The neural network embedding empirical data can reduce the computational load and enhance the robustness to the measurement distortion, especially when the complete physical model is too complex and/or sensitive to the error and noise in the measurements. The third is a representative principle of the VMs. The empirical model can derive valid estimation under some assumptions even if the model and the measurements are incomplete. The forth is also useful to estimate an objective quantity under some assumption. The adoption of the third and forth principles in VMs highly enhances the applicability of the technology in practical situations.

The estimations obtained from multiple VM schemes must be synthesized into the best estimation under a certain criterion. The simplest way is to take the average of these estimated values. However, as each estimation has its own accuracy, an weighted average method reflecting the accuracy should be applied to derive the most likely estimation. We adopted the following most common method(Luo & Kay 1989).

$$\hat{x}(t) = \frac{1}{\sum_{i=1}^{n} \frac{1}{\sigma_{x_i}^2}} \sum_{i=1}^{n} \frac{1}{\sigma_{x_i}^2}(x_i(t) - e_{x_i}) \qquad (1)$$

where

$\hat{x}(t)$: most likely estimation of an objective quantity $x$at time t,

n : number of VMs to estimate x,

x_i : estimation of x by i-th VM at time t,

e_{x_i} : time averaged error of x_i,

$\sigma_{x_i}^2$: time averaged error variance of x_i,

$$e_{x_i} = \frac{1}{m}\sum_{i=1}^{m}(x_i(t) - x(t)), \qquad (2)$$

$$\sigma_{x_i}^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i(t) - \bar{x}_i)^2, \qquad (3)$$

where

$x(t)$: actual value of x at time t,

$\bar{x}_i = \frac{1}{m}\sum_{i=1}^{m} x_i(t)$,

m : total number of training data.

The parameters of e_{x_i} and $\sigma_{x_i}^2$ are determined by using the training data of the VMs.

The concrete VM schemes exemplified in our present study are to estimate the sodium flow rate in the secondary sodium coolant loop of a fast breeder nuclear reactor plant of PNC[1]. The sodium flow rate is an important quantity to monitor the plant operation and safety. Hence, its credible and robust estimation is a key issue for the reactor management. Figure 2 shows the outline of the secondary sodium coolant loop and its flow control mechanism. The fast breeder reactor has three loops to transfer the reactor core heat to the electricity generator. The secondary loop (SL) is the intermediate one, which receives the heat from the sodium coolant of the primary reactor side through Intermediate Heat Exchanger (IHX). This transfers

[1]This reactor has been developed by Power Reactor and Nuclear Fuel Development Corporation (PNC) in Japan

the heat to the tertiary water loop through Evaporator (EV) and Super Heater (SH), and generates water steams to energize the turbine connected to an electricity generator. As the rate of the heat transfer through this secondary loop depends on its sodium coolant flow, the flow rate should be appropriately maintained by the control system consisting of Master Circuit (MC), Inverter Controller (IC), Power Inverter (PI), Pump Motor (PM) and Main Pump (MP).

Figure 3 shows the causal relations among the major quantities in the control mechanism to physically determine the sodium flow rate in a secondary sodium coolant loop. Master Circuit (MC) determines a demand signal, i.e., Master Control Signal MS, while monitoring the directly measured value of the flow rate FR. By following MS, Inverter Controller (IC) tunes the voltage V and the frequency F of Power Inverter (PI) to set the rotation speed R and the torque T of Pump Motor (PM) at a desired level. These quantities finally determine the flow rate of sodium coolant FR together with the pressure drop mechanism of Secondary Loop. Also, these change the levels of sodium liquids Lp and Lo in MP and Pump Over Flow Column (POFC) respectively.

Based on the causal relations, the following five schemes to estimate the flow rate of sodium coolant FR are defined as VMs.

- $S1$ Direct estimation from a sodium flow rate sensor FR
- $S2$ Estimation from master control signal MS
- $S3$ Estimation from PI frequency F and PI voltage V
- $S4$ Estimation from pump rotation speed R and PI current I
- $S5$ Estimation from sodium level of MP Lp and sodium level of POFC Lo

The scheme $S1$ is the adoption of the principle $P1$. The scheme $S2$ is based on $P2$ since FR is completely determined by the master control signal if all the components in Fig. 3 is normal. The scheme $S3$ also belongs to $P2$ because the combination of F and V completely determines the state of PM, MP and Secondary Loop if those components are normal. The scheme $S4$ is $P2$ as well. The last scheme $S5$ is the example of $P4$, as the relations of Lp and Lo to FR are derivative, and do not have the physically firm backgrounds.

Each scheme is applied to the following case to evaluate their performance to estimate the objective sodium flow rate.

Case A case of power demand change from 50% to 100% in 10% stepwise manner. The sampling rate and the period are 1 sec and 3901 sec, respectively.

The VM of $S1$ does not use any neural network, since the sensor directly gives the value of the sodium flow rate. The Elman networks of the other schemes must be trained by the set of observed data, and thus a part of the data in the above case was used for training. The 200-300 times of the iterations of training yielded the modeling error less than 4% at the maximum per one sample datum.

Table 1: Errors and error variances of VMs.

Scheme	*Error* e_{x_i}	*Error Variance* $\sigma^2_{x_i}$
$S1$	0.00	400.0
$S2$	-0.76	1533.7
$S3$	-4.14	1026.2
$S4$	1.54	1066.0
$S5$	-17.90	16136.0
Total	0.00	168.5

An example of the resultant estimation of a VM is depicted in Fig. 4. The solid trajectory stands for the sodium flow rate estimated by the scheme $S2$, while the grey one is the directly measured sodium flow rate by $S1$. They show good agreement. The time average of error e_{x_i} and the time average of error variance $\sigma^2_{x_i}$ of the estimation for each VM are summarized in Table 1 where these are empirically estimated in the training process of VMs. The output values of $S1$, i.e., $x_1(t)$s, are considered to be the nominal values of the sensor instrument, i.e., $x(t)$s, in this case. The schemes $S3$ and $S4$ have relatively small error variances. The solid trajectory in Fig. 5 shows the total estimation synthesized by the equation (1). The values of error e_{x_i}s and error variance $\sigma^2_{x_i}$s indicated in Table 1 are used in the equation (1). The error and error variance of the total estimation shown at the bottom of Table 1 are very small, and the effect of the combined use of the multiple VMs is clear.

Framework of Diagnosis and Fault Isolation

The role of the MBD is the diagnosis of the VM system and the interpretation of valid measurements under the candidate faults. In the framework of MBD, the system is a triple $(SD, COMPS, OBS)$ where they stand for the system description, the system components and a set of observations, respectively(Reiter 1987; de Kleer & Williams 1987). The method of *minimal diagnosis* is used in this application. The generic procedure of the minimal diagnosis consists of three stages(Reiter 1987; de Kleer & Williams 1987). The first stage is to compare the estimated objective quantity among the schemes. We apply the standard statistical test on the discrepancy between the outputs of each pair of the schemes. The information of error e_{x_i} and error variance $\sigma^2_{x_i}$ in Table 1 enables the judgement if the discrepancy is meaningful under the assumption of Gaussian error distributions. When the

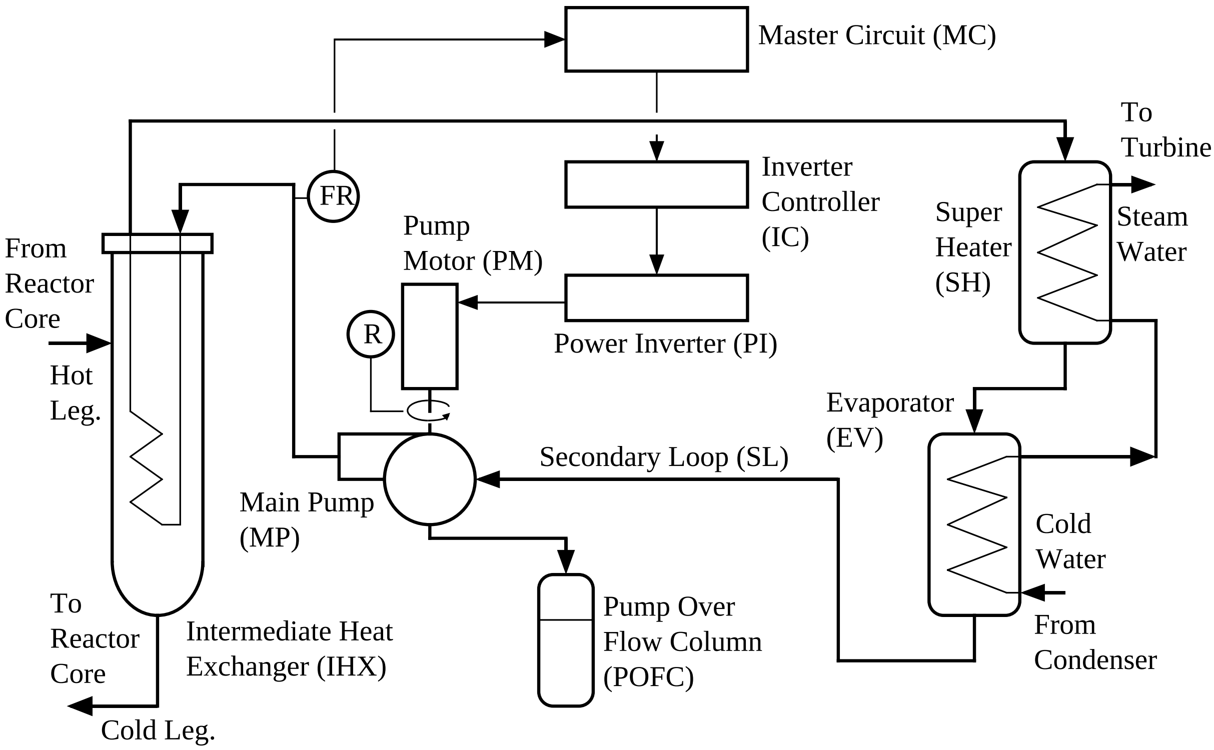

Figure 2: Outline of secondary sodium coolant loop.

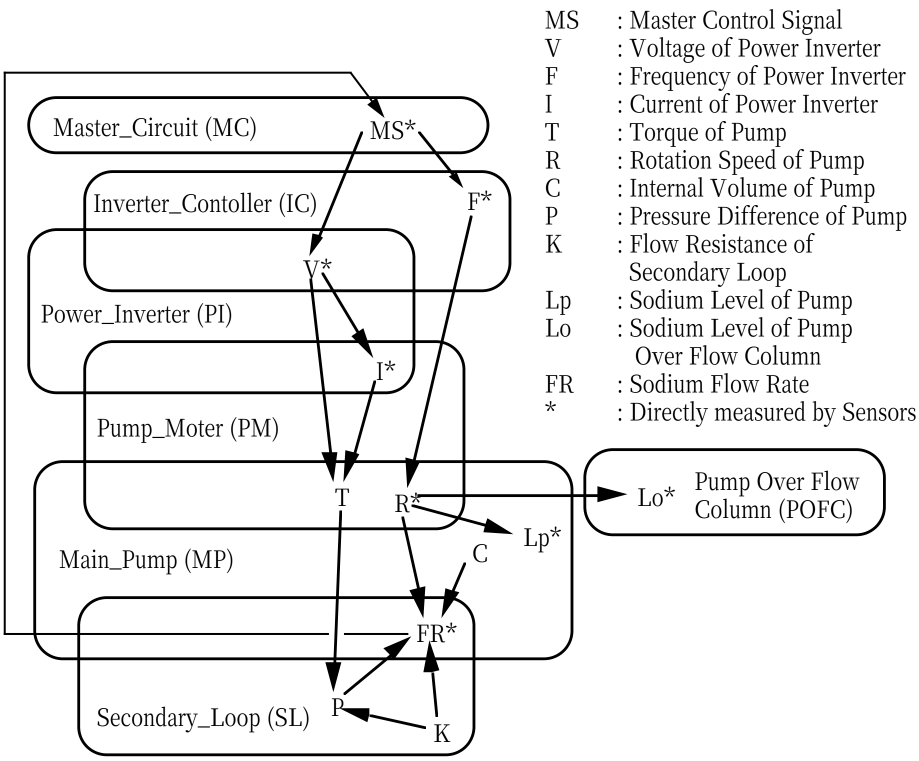

Figure 3: Causal relations to determine secondary sodium flow rate.

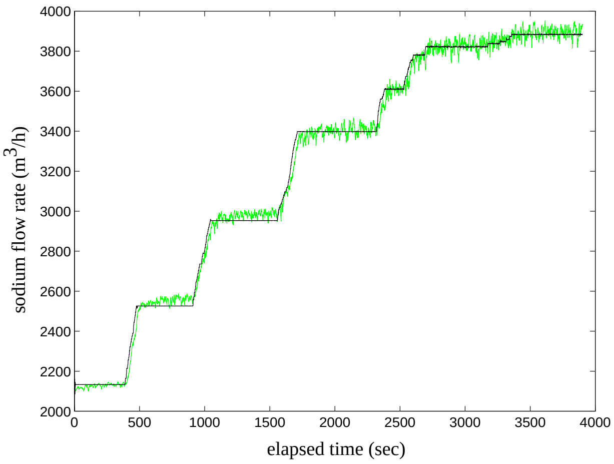

Figure 4: Resultant estimation by $S2$.

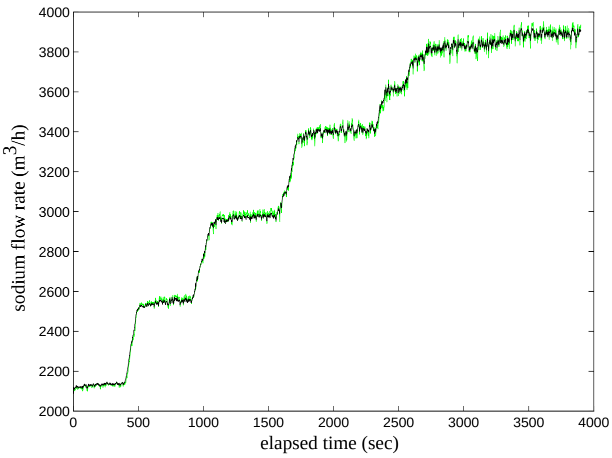

Figure 5: Synthesized estimation of $S1 - S5$.

discrepancy is not negligible, the pair of the schemes are considered to be inconsistent. The second is to generate minimal conflicts based on the result of the consistency checking. Suppose a scheme of the VM Si $(i = 1, 2, ..., n)$ assumes the validity of a set of components $COMPS(Si)$. When we observe inconsistency between the estimations of the different schemes Si and Sj, the following logical disjunctive form is stated.

$$\vee_{\forall c \in COMPS(Si) \cup COMPS(Sj)} AB(c). \quad (4)$$

The literal AB(c) stands that the component c is faulty. This expression is valid, since at least one of the components in $COMPS(Si) \cup COMPS(Sj)$ must be operating abnormally to cause the discrepancy between the estimations of the two schemes. When some inconsistencies are observed for multiple pairs of the schemes, the disjunctive form (4) is also derived for each inconsistency. Then, only the disjunctive forms which do not subsume any other disjunctive forms, i.e., *minimal conflicts*, are taken. A minimal conflict states the set of candidates of faulty components having minimal cardinality derived from the inconsistency between a given set of pairs of schemes. The third stage is to derive probable diagnoses based on these minimal conflicts. Given a set of minimal conflicts, the Cartesian conjunctions of the literals over the minimal conflicts are taken, and the conjunctive forms involving all literals in the other conjunctive forms are removed. The remaining conjunctive forms are called as *minimal diagnoses*. As the operation of the Cartesian conjunctions is to take a literal AB(c) from each minimal conflicts, the conjunctive forms stand for the interpretations of possible multiple faults of components.

Once a set of minimal diagnoses are obtained, the anomalous schemes of VMs are identified for each minimal diagnosis. The identification procedure is quite simple where a scheme Si is judged to be anomalous when $COMPS(Si)$ involves any abnormal components in a minimal diagnosis. Subsequently, the anomalous schemes are excluded from the VM system for each diagnosis, and the synthesized estimation of the rested schemes gives the optimum value of the objective quantity as an interpretation under the diagnosis.

In our application, a triple $(SD, COMPS, OBS)$ is as follows.

$$\begin{aligned} SD &= \{S1,\ S2,\ S3,\ S4,\ S5\}, \\ COMPS &= \{MC,\ IC,\ PI,\ PM,\ MP,\ SL,\ POFC, \\ &\quad\ V,\ F,\ I,\ R,\ Lp,\ Lo,\ FR\}, \\ OBS &= \{MS,\ V,\ F,\ I,\ R,\ Lp,\ Lo,\ FR\}. \end{aligned}$$

The sensors are added as components to include the possibility of sensor faults. The sets of components associated with the schemes $S1 - S5$ are summarized as follows based on Fig. 3.

$$\begin{aligned} COMPS(S1) &= \{FR\}, \\ COMPS(S2) &= \{MC,\ IC,\ PI,\ PM,\ MP,\ SL\}, \\ COMPS(S3) &= \{F,\ V,\ IC,\ PI,\ PM,\ MP,\ SL\}, \\ COMPS(S4) &= \{R,\ I,\ PI,\ PM,\ MP,\ SL\}, \\ COMPS(S5) &= \{\ Lp,\ Lo,\ MP,\ SL,\ POFC\}. \end{aligned}$$

In our experiment of the sodium coolant flow control, we introduced a slight anomalous reduction of the output gain of the sodium flow sensor FR from 100% to 96%. Figure 6 shows the synthesized estimation of the VM system without diagnosis in a solid line and the raw FR in a grey line. The output of the VM system is underestimated due to the influence of the gain reduction of FR.

By applying the consistency checking, we observed the inconsistency of pairs of $S1\&S3$ and $S1\&S4$. Ideally, the inconsistency should be also observed in the other pairs associated with $S1$. However, the inconsistencies were detected only in these pairs because of the high sensitivity of the detection yielded by the small

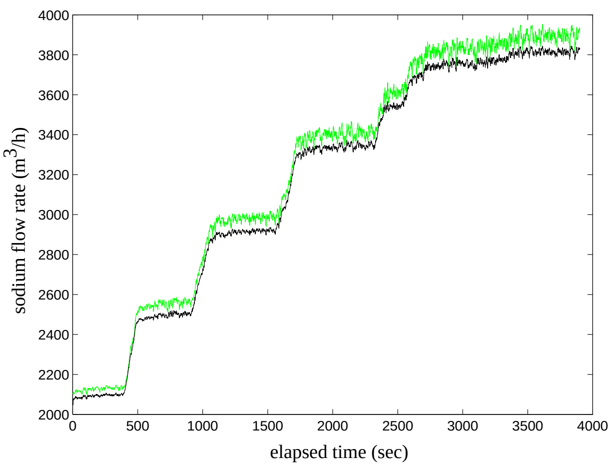

Figure 6: Synthesized estimation and raw value of sodium flow rate for 4% gain reduction.

error variances of $S3$ and $S4$ as indicated in Table 1. The monotonic characteristic of the minimal diagnosis derives the appropriate candidate diagnoses, since this incompleteness of the consistency checking does not rule out possible diagnoses.

In this case, the following two disjunctive forms are derived based on the sets $COMPS(S1)$, $COMPS(S3)$ and $COMPS(S4)$.

$$AB(FR) \vee AB(F) \vee AB(V) \vee AB(IC) \vee$$
$$AB(PI) \vee AB(PM) \vee AB(MP) \vee AB(SL),$$
$$AB(FR) \vee AB(R) \vee AB(I) \vee AB(PI) \vee$$
$$AB(PM) \vee AB(MP) \vee AB(SL).$$

Each of these forms does not subsume each other. Thus, they are minimal conflicts. By taking the Cartesian conjunctions of these minimal conflicts and resting only minimal diagnosis, we obtain the following 11 diagnoses.

$$AB(FR),\ AB(PI),\ AB(PM),\ AB(MP),$$
$$AB(SL),\ AB(F) \wedge AB(R),\ AB(F) \wedge AB(I),$$
$$AB(V) \wedge AB(R),\ AB(V) \wedge AB(I),$$
$$AB(IC) \wedge AB(R),\ AB(IC) \wedge AB(I).$$

The anomalous VMs involving the components in each diagnosis are summarized in Table 2. Totally, five interpretation of the anomalous schemes are figured out. By isolating the anomalous schemes in each interpretation, five optimal estimations are derived. Figure 7 and 8 depicts two of them. The former is the correct interpretation No. 1. It is estimated through the synthesis of

$$\hat{x}(t) \quad = \quad \frac{1}{\sum_{i=2}^{n} \frac{1}{\sigma_{x_i}^2}} \sum_{i=2}^{n} \frac{1}{\sigma_{x_i}^2}(x_i(t) - e_{x_i}), \qquad (5)$$

where the first scheme $S1$ is excluded from eq. 1, and gives the exact sodium flow rate. The latter interpretation No. 3 is estimated by

$$\hat{x}(t) \quad = \quad x_1(t) - e_{x_1}, \qquad (6)$$

in which the terms for $S2, S3, S4 and S5$ are omitted from eq. 1. It is completely wrong giving the degraded FR sensor output. The choice of the best interpretation may be suggested by the knowledge of the reliability of each component and the situation of the plant. However, it is out of the scope of this diagnosis, and the work on this part is omitted in this paper.

Discussion

The main purpose of the study of L. Tsoukalas et al.(Ikonomopoulos, Tsoukalas, & Uhrig 1993) was to develop the robust virtual measurement. However, their framework does not involve the diagnosis and the isolation process of the faulty schemes. Accordingly, the robustness is limited to small distortions. The distortions over a certain scale such as severe faults of components may cause some significant error of the estimation. In contrast, our approach works correctly even under large distortions to the VM system in principle. We tested the validity of our result under larger distortion such as 30% gain reduction of the FR sensor. In this case, the four conflict sets

$$\vee_{\forall c \in COMPS(S1) \cup COMPS(Si)} AB(c) \qquad (i = 2, 3, 4, 5), \qquad (7)$$

are given by the consistency checking, and the total number of feasible interpretations of the optimum estimation becomes 27. Figure 9 shows the synthesized estimation without any isolation of VMs. The value of the FR, i.e., a solid line, shows a significant discrepancy from the true value of the FR, i.e., a grey line. Two representative interpretations of this example are depicted in fig. 10 and 11 similarly to the example of 4% gain reduction. The former appropriate interpretation derives a valid estimation of FR again. Though the ambiguity of the reasoning, i.e., the multiple candidates of the interpretations, may not be completely removed within the framework of the diagnosis only, the combined use of the knowledge of the component reliability and some other expertise would enhance the value of this type of information.

The characteristics of the minimal diagnosis is well suited to this application. If we apply the information of consistency, obtained from the consistency checking, to the diagnosis such as the methods of kernel diagnosis(de Kleer, Mackworth, & Reiter 1992) and Raiman's(Raiman 1990), the number of candidate interpretations can be reduced in some cases. However, because of the incompleteness of the consistency checking as demonstrated in our example, this approach will exclude some feasible interpretations of the estimation.

Table 2: Interpretations of anomalous VMs.

Interpretation No.	*Diagnoses*	*Anomalous VMs*
1	$AB(FR)$	$AB(S1)$
2	$AB(PI), AB(PM)$	$AB(S2) \wedge AB(S3) \wedge AB(S4)$
3	$AB(MP), AB(SL)$	$AB(S2) \wedge AB(S3) \wedge AB(S4) \wedge AB(S5)$
4	$AB(F) \wedge AB(R), AB(F) \wedge AB(I),$ $AB(V) \wedge AB(R), AB(V) \wedge AB(I)$	$AB(S3) \wedge AB(S4)$
5	$AB(IC) \wedge AB(R), AB(IC) \wedge AB(I)$	$AB(S2) \wedge AB(S3) \wedge AB(S4)$

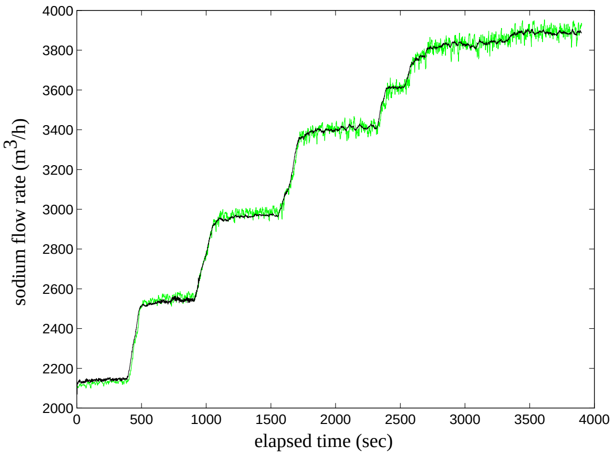

Figure 7: Optimal estimation under assumption AB(S1) for 4% gain reduction.

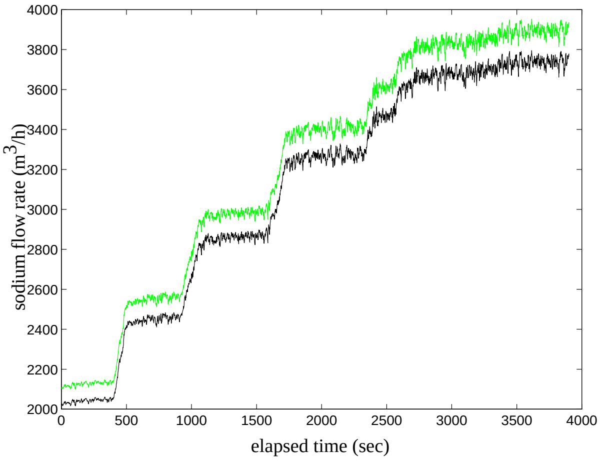

Figure 8: Optimal estimation under assumption $AB(S2) \wedge AB(S3) \wedge AB(S4) \wedge AB(S5)$ for 4% gain reduction.

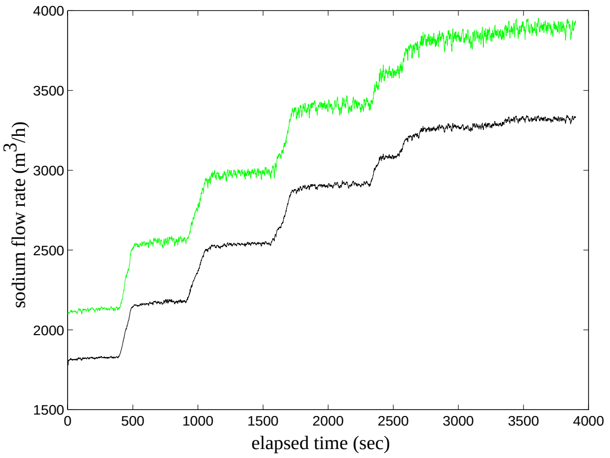

Figure 9: Synthesized estimation and raw value of sodium flow rate for 30% gain reduction.

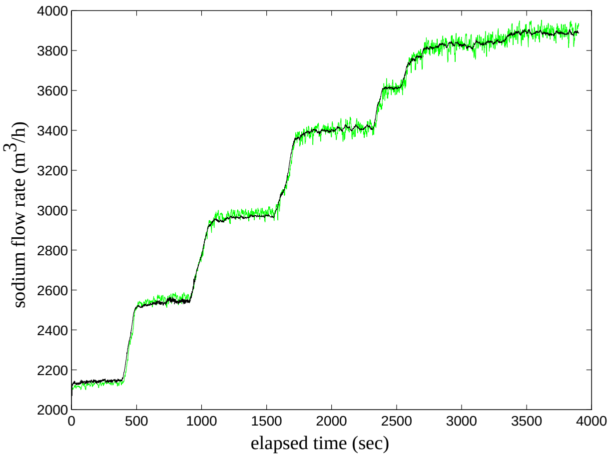

Figure 10: Optimal estimation under assumption AB(S1) for 30% gain reduction.

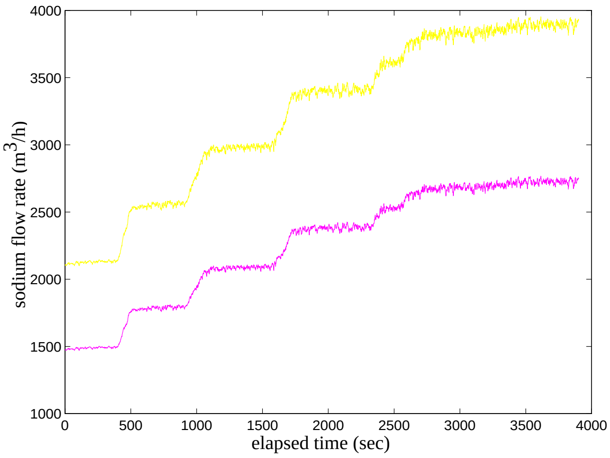

Figure 11: Optimal estimation under assumption $AB(S2) \wedge AB(S3) \wedge AB(S4) \wedge AB(S5)$ for 30% gain reduction.

The monotonicity of the reasoning of the minimal diagnosis, i.e., only the knowledge of inconsistency is used, does not cause this difficulty.

Conclusion

The objectives of this study were to proposes a framework of the application of MBD to a VM system. The feasibility of the proposed framework is demonstrated to measure the flow rate of sodium coolant by using actual experimental data of the measurement signals associated with a secondary sodium coolant pump of a fast breeder nuclear reactor. The following topics still remain for the future study.

1. More robust and sensitive method of the consistency checking must be developed.
2. The framework to preserve the knowledge of component reliability and the other expertise with the interpretations of the VMs estimation must be established.

The work presented in this paper is now under evaluation for a possible future instrumentation of the plant.

References

Alberts, L.; Bakker, R.; Beekman, D.; and Wognum, P. 1993. Model-based Redesign of Technical Systems. In *Working papers of DX-93: Fourth Intermational Workshop on Principles of Doagnosis*, 201–211.

Beltracchi, L., and Lapinsky, G. 1985. Safety Parameter Display System. NRC Perspective. In *1985 IEEE 3rd Conference Humman Factors Nuclear Safety*, 150–153.

de Kleer, J., and Williams, B. 1987. Diagnosing Multiple Faults. *Artificial Intelligence* 32:97–130.

de Kleer, J.; Mackworth, A.; and Reiter, R. 1992. Characterizing diagnosis and systems. *Artificial Intelligence* 56:197–222.

Elman, J. 1990. Finding structure in time. *Cognitive Science* 14:179–211.

Gertler, J. 1988. Survey of Model-Based Failure Detection and Isolation in Complex Plants. *IEEE Control Systems Magazine* (12):3–11.

Ikonomopoulos, A.; Tsoukalas, L.; and Uhrig, R. 1993. Measuremet of Fuzzy Values Using Artificial Neural Networks and Fuzzy Arithmetic. In *1993 2nd IEEE International Conference on Fuzzy Systems*, 357–362.

Luo, R., and Kay, M. 1989. Multisensor Integration and Fusion in Intelligent Systems. *IEEE Trans. Sys., Man, Cybern.* SMC-19(5):901–932.

Raiman, O. 1990. A circumscribed diagnosis engine. In *Proc. of International Workshop on Expert Systems in Engineering: Lecture Notes in Artificial Intelligence*, volume 462, 90–101. Berlin: Springer.

Reiter, R. 1987. A Theory of Diagnosis from First Principles. *Artificial Intelligence* 32:57–95.

Sakuma, M.; Kitamura, M.; and Washio, T. 1994. A Systematic Method for Signal Validation Based on the Minimal Over-constrained Subsets and the Neural Networks (in Japanese). In *19th SICE Intelligent System Symposium*, 167–171.

Wasserman, P. D. 1989. *Neural Computing -Theory and Practice-*. New York: Van Nostrand Reinhold.