THE 4TH INTERNATIONAL TOPICAL MEETING ON
NUCLEAR THERMAL HYDRAULICS, OPERATIONS AND SAFETY
April 6-8, 1994, Taipei, Taiwan

XA04N0663

DIVERSITY AND CONSENSUS AS KEY CONCEPTS FOR DESIGN OF INTELLIGENT OPERATOR SUPPORT SYSTEM

M. Kitamura, H. Furukawa and M. Sakuma

Department of Nuclear Engineering
Tohoku University
Aramaki-Aza-Aoba, Sendai, 980 JAPAN
Tel: +81-22-222-1800, ext. 4672
Fax: +81-22-268-1539

*T. Washio

*Mitsubishi Research Institute Inc.
8-1, Simomegro-Ichoume, Megro-Ku
Tokyo, 153 JAPAN
Tel: +81-3-5434-8955
Fax: +81-3-5434-8951

ABSTRACT

A general framework and guiding principles for development of intelligent operator support system in nuclear plants are proposed in this paper. The main principle is to provide advisory information to the operators through consensus of multiple agents each of which can conduct operational decision-making by focusing on mutually dissimilar symptoms obtained from the plant. The applicability and credibility of the operator support system are expected to be significantly improved by implementing the proposed scheme. An efficient procedure for diversifying the symptom descriptions was developed together with a method for autonomous consensus formation among the agents. A prototype system was developed for the subtask of fault diagnosis by emulating multiple neural networks as the diagnostic agents. The advantage of the proposed methodology over the conventional ones was clearly demonstrated through numerical evaluations simulating anomalies in a pressurized water reactor.

1.INTRODUCTION

The excellence in operational safety of large, complex and high-hazard artifacts such as nuclear power plants is a prerequisite for wider acceptance of the future technology. As the human factor is now recognized to be the most critical issue in prevention of error and enhancing the safety in these technical domains, considerable amount of research efforts have been focused on the study of this issue. The development of computer-assisted operator support system has been attempted extensively on the basis of this recognition. Within the nuclear industry, however, the performance of the systems developed up to present is, to the authors' knowledge, not sufficient for practical applications.

The expected role of operator support system is to provide information relevant to operation of the plant when the operator is truly in need of assistance by the machine-intelligence. Since the nuclear plant operators are highly trained and motivated,

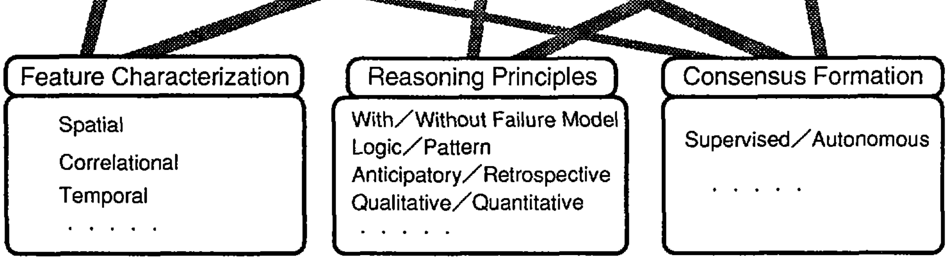

Figure 1. The Framework of the Diversity-Based Intelligent Operator Support System.

such an assistance is only needed when the situation is complicated and unexperienced. The operator support system is there fore supposed to have sufficiently high level of intelligence to cope with the difficulty in dealing with the complicated situations. To meet this technical requirement, a naive application of conventional methods of artificial intelligence, i.e. expert system, case-based reasoning, model-based reasoning including qualitative reasoning, etc. has been and will be by no means promising. The purpose of the present paper is to establish a methodology to overcome the difficulty and to further improve the operational safety of nuclear plants.

A general framework based on a concept called diversity-based decision-making has been studied in this project[1,2]. The central idea in the framework is the decision-making through consensus among multiple agents, each functioning on the basis of mutually different, i.e. diverse, principles. The task of causal identification of an anomaly, for instance, can be achieved by a wide variety of methods characterized by such attributes as absence/presence of failure mode assumption, logic-based/pattern-based causal relationships, qualitative/quantitative model descriptions, etc. The performance of the machine-intelligent operator support system is expected to be improved significantly by instantiating the problem-solving scheme by multi-perspective thinking with diversity in the functioning principles.

This multi-agent framework was introduced on the basis of our observation that experienced specialists in most domains (e.g. technical, medical, political and administrative) are making decisions after examining the problem at hand from multiple, often mutually independent, perspectives. The intrinsic importance of combining diverse perspectives is recently pointed out by leading researchers in the artificial intelligence and relevant areas. Among such examples are the multiple-agent model of human intelligence by M. Minsky[3] and combined usage of function- and behavior-oriented description of object by Y. Iwasaki and B. Chandrasekaran[4]. The concept of cognitive diversity proposed by L. Beltracchi and R. Lindsay[5] for reduction of operator error is also closely related to the concept described in this paper.

Additional key-concept essential in this multi-agent, diversity framework is the consensus formation, since the multiple agents can provide various conclusions with inconsistency. The proce dure of consensus formation should be designed intelligent enough to reflect the difference in self-confidence of the agents engaged in the specific task. This is again a natural analogy of human problem-solving where the best solution is provided through meta-level evaluation[3] rather than direct comparison of the cost/benefit to be given by each solutions.

To model the function of the multi-perspective thinking, the multi-agent system was developed by emulating a set of neural networks, each executes diagnostic decision-making by taking into account mutually-dissimilar symptoms, or features, characterizing the disturbed state of the nuclear plant. The mechanism of consensus formation among the agents was developed in a manner to reflect the self-confidence of the neuro-agents in their diagnostic conclusion. Detailed descriptions of these methods and the performance of the prototype system developed will be given in the following sections.

2. DESCRIPTION OF GENERAL FRAMEWORK

The overall framework for development of the operator support system, and the major building blocks as well, are illustrated in Fig. 1. The task of fault management is decomposed into three subtasks, fault detection, causal reasoning and remedial procedure synthesis. In a higher level of abstraction, the fault detection is regarded as constraint violation detection. The causal reasoning and procedure synthesis are categorized as the retrospective and anticipatory hypothesis generation and testing. Most approaches to fault management cover all or a part of the subtasks. Functional relationships between these subtasks along with the evolution of anomaly are schematically given in Fig. 2.

In order to define a method of fault management more specifically, another multiple attributes of the method are taken into consideration as also given in Fig. 1. The fault detection and causal reasoning methods are characterized in terms of the fea-

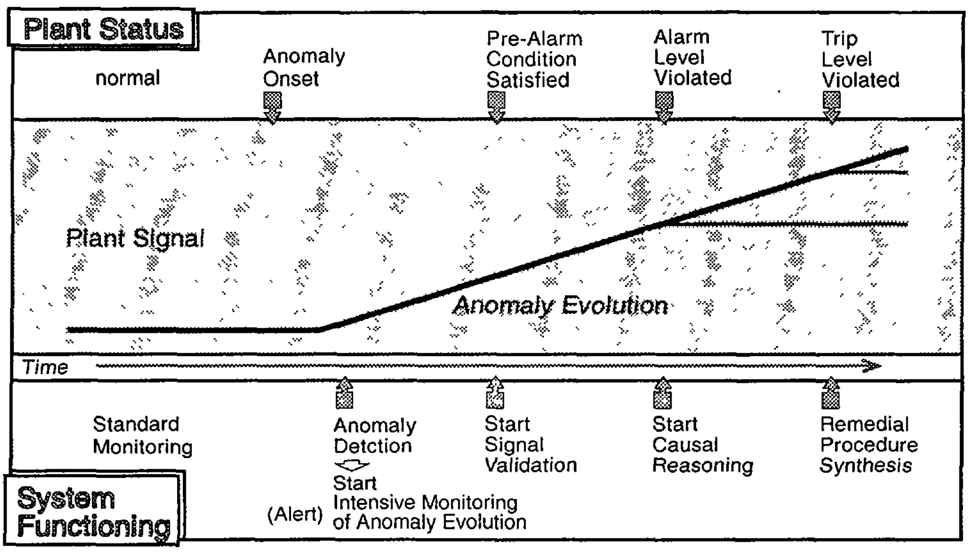

Figure 2. Functional Relationship between Subtasks along with the Evolution of Anomaly.

tures with which the departure from normal behavior is defined. The causal reasoning and procedure synthesis methods are also characterized in terms of the reasoning principle. A difference is in that fact that the former is essentially a retrospective reasoning (i. e. from observations to one or more causes) while the latter an anticipatory (i. e. from operations to possible effects).

We claim that each of the subtasks needs to be carried out via multi-perspective thinking. For example, the subtask of the fault detection should be conducted by paying attention to various features. In addition to the conventional method of comparing quasi-static deviations of signals with preset thresholds, more advanced techniques focusing on signal fluctuations can also be employed to enhance the sensitivity of anomaly detection, and to derive more information on anomaly type. Possible candidates of such advanced techniques are; spectral index estimation, fractal dimension estimation and wavelet analyses. The implication of these techniques in plant anomaly detection has been already confirmed in our previous study[6].

The consensus formation in this subtask is rather naive and straightforward. In principle, an indication of anomaly from any of the agents should be regarded as a sign to "alert" the operator support system. At this stage, the consensus is equivalent to OR-type operation to determine the onset of anomaly. In another words, the consensus principle is to respect the others with the most pessimistic (or conservative) opinion.

As illustrated in Fig. 2, it is not necessary to start the causal reasoning routine, nor is it necessary to alert the operator at this stage. The system continuously monitors the time-trend of the anomaly to determine (1) if it is actually taking place and (2) if it is growing. When these two conditions are judged to be satisfied, the situation is classified to be a pre-alarm state. To determine the onset of the pre-alarm state, again a consensus is needed among the agents. The consensus principle at this stage needs to be more involved than the naive OR-operation. The simple majority voting is unacceptable since the each of the agents is sensitive to a specific class of anomalies. A rule-based consensus mechanism is one possible candidate to meet the need and is being studied within this project. Though the study of this issue is in its preliminary stage[6], the results obtained so far seem to be highly promising.

Similar statements are valid for the subtasks of causal reasoning and remedial procedure synthesis as well. Several new techniques of causal reasoning are being developed in conjunction with this project[7]. The anomaly features to be considered as input information to the causal reasoning routine could be different from the features considered in the fault detection phase. However, it is required that the features at this stage should also be diversified for higher credibility of diagnosis. By combining the multiple features and reasoning techniques, one can expect a high-level of diversity in this phase also. The consensus formation in this subtask is more crucial than that in fault detection, since the conclusions given by the multiple agents could be semantically more diverse and possibly contradictory.

Development of the techniques for remedial procedure synthesis is also attempted in this project. One of the emphasis of the study in this context is to develop a flexible scheme of anticipatory decision-making.
The word "anticipatory" is deliberately employed to highlight the relevant problem of uncertainty handling inherent in dealing with future evolution of the phenomena under consideration. Though the concept of anticipatory control is rather new in nuclear domain, importance of this novel approach to control and decision-making can be understood by the promising results to be found elsewhere[8,9]. Since the detailed discussion of this issue is beyond the scope of this paper, we will focus our attention on the problem of diversity-based fault diagnosis with consensus formation in the subsequent sections.

3. DIVERSITY IN FEATURE DESCRIPTION

The performance of the causal reasoning routine is expected to be higher if the multiple features are processed properly, since the amount of processed information is higher in the case of multiple features. We believe that more attention should be paid on this aspect. Numbers of reports dealing with elaboration of causal reasoning techniques have been published in the last decade. Nevertheless, only a limited amount of efforts has been paid on the feature characterization. However, the performance of the sophisticated techniques of causal reasoning would obviously be poor unless sufficient amount of information is supplied as the input data to the reasoning routine. The employed multiple features are illustrated in Fig. 3. For the sake of clarity, the popular word of "symptom" may be employed instead of feature as far as the discussion is relevant to the fault cause identification.

The feature characterization called <u>spatial</u> symptom stands for the representations such as [X1-high, X2-low, X3-low,...] and [X1-increase, X2-decrease...]. The former is called deviation-level-based spatial symptom while the latter incremental-change-based spatial symptom. The word "spatial" was adopted since the signals represent the variables in different locations of the plant. The time instant to define this feature is not identical but different from signal to signal. The time instant for defining the deviation of signal Xi corresponds to the time when the signal manifested its first departure from the normal value. Therefore, the spatial symptom can be regarded as the deviation profile of multiple signals in the plant.

The <u>temporal</u> symptom is characterized by the sequence of deviation descriptor such as Xi=[normal, high, high, normal, low, low, ...] or Xi=[constant, increase, increase, constant, decrease, ...]. The former is called deviation-level-based temporal and the latter incremental-change-based temporal symptom. The same set of plant signals selected to define the spatial symptom is processed to derive the temporal symptom. The time duration to define the temporal symptom is chosen long enough to cover the longest disturbance propagation time within the plant.

The third feature characterization called <u>correlational</u> symptom was introduced to supplement the spatial and temporal symptoms. The correlational symptom is derived from a trajectory in two-dimensional state space. The dynamic interactions between the two signals of interest, which are not clearly parametrized in the spatial and temporal symptoms, are properly represented in this symptom. Each state-space was defined to represent the mass and/or energy balance in main components and coolant loops.

These symptom descriptions are obtained through procedures of data compression with emphases on semantically different aspects, i.e. space, time and correlation, of the plant signals. When two symptoms represent totally independent diagnostic information, they can be viewed as semantically independent.

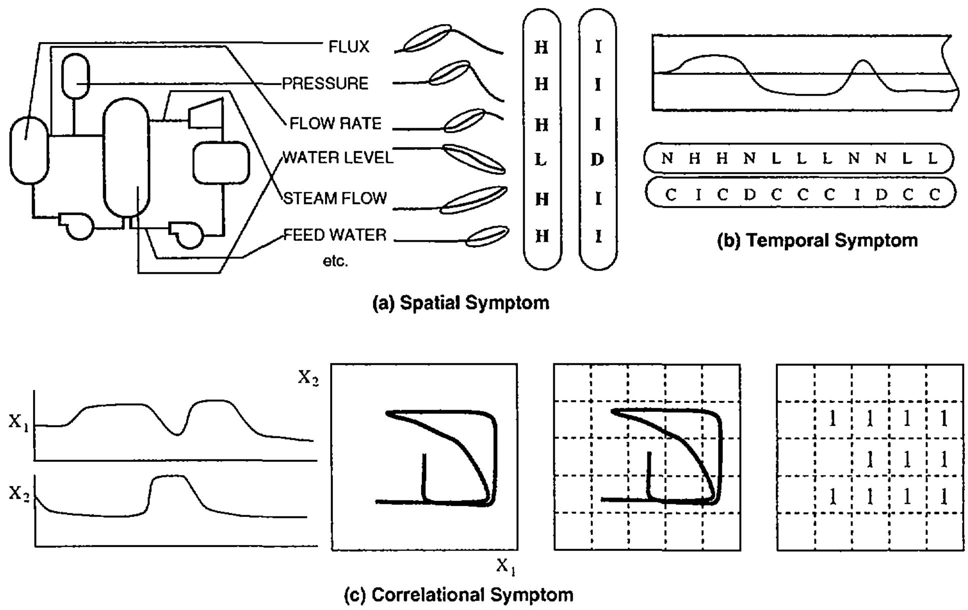

Figure 3. Illustration of Multiple Features Employed in This study.

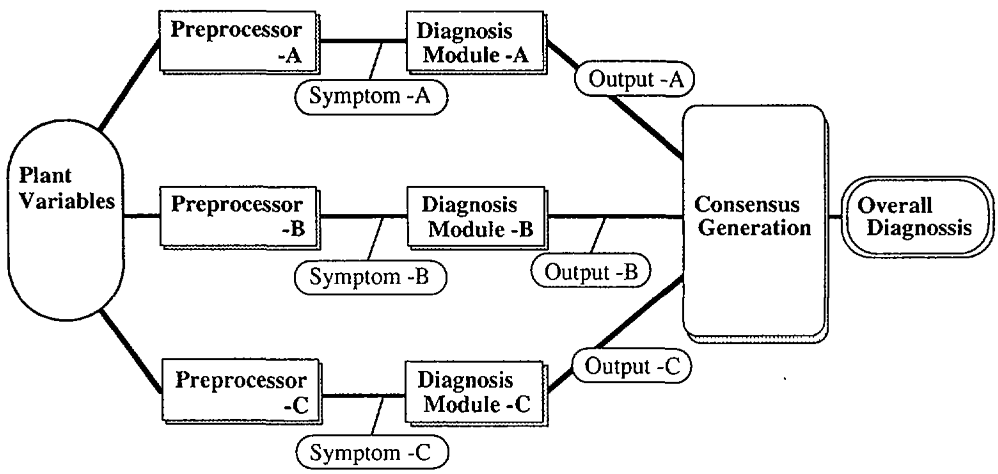

Figure 4. Causal Identification Procedure with Dedicated Diagnostic Modules.

On the other hand, the two symptoms are viewed as semantically dependent or redundant if they provide the same diagnostic information.

The semantic independence between the spatial and temporal symptom descriptions would be intuitively clear. Since the correlational symptom represents the plant behaviors that are not directly given by the spatial and temporal symptoms, it is expected to contain diagnostic information at least to some extent. Although the symptoms considered in this study are not exhaustive nor sufficient, the effectiveness of combining them together will be demonstrated through numerical tests described later.

4. DIVERSITY IN KNOWLEDGE CHARACTERIZATION

The causal reasoning methods, or diagnostic knowledge, can be implemented in a wide variety of fashions. Different types of reasoning principles can be utilized in order to carry out this subtask. The intrinsic nature of the causal reasoning methods is characterized by various attributes such as the presence/absence of failure model, qualitative/quantitative description of the plant behavior, retrospective/anticipatory reasoning principle, etc.

Hereafter, we restrict our scope within the pattern-based fault diagnosis because the method is appropriate to highlight the effectiveness of diversification in symptom descriptions. In order to evaluate this effect independently of the effect of reasoning methods, the diagnostic contribution of each symptom was examined by utilizing the homogeneous yet customized reasoning method, i. e. dedicated neural networks. The effectiveness of diversification in reasoning principles can be evaluated after the present evaluation. Incorporation of other methods based on different causal reasoning principles is just straightforward.

The diagnostic procedure, a constituent of the overall system of Fig. 1, is schematically illustrated in Fig. 4. The symptoms obtained by the specific processing of the plant variables are fed to the diagnostic modules in parallel. Each of the dedicated neural networks is assigned to a specific symptom. The neural net employed in this study has three-layers with feedforward configuration. The number of units in the input layer is equal to the number of segmentation of the symptom description. The number of units in the output layer is equal to the number of fault causes to be identified. Each of the output unit generates the value between 0 and 1. In the learning period, the neural net is trained to provide the value 1 from the output unit #i for the input symptom correspondent to the failure mode #i. All the other output values are forced to be 0. In the testing period, output values of all units in the output layer are examined. If the output value from the unit #j is the highest of all, then it is interpreted that the failure mode #j is detected. A modification of this procedure introduced for consensus generation will be described in the next section.

The learning algorithm adopted is called adaptive structural learning with forgetting[8]. The principle of this algorithm is the conventional backpropagation (BP) with a modification term as shown below.

$$E'p = Ep + \varepsilon \Sigma \, ABS(W_{j,i}) \qquad (1)$$

where Ep is the conventional criterion (discrepancy between the network output and the desired output) in the BP algorithm, $W_{j,i}$ the magnitude of the weight of link between unit i and j, and ε defined the relative importance of the link weights. The incremental modification of the weight is then given by

$$\Delta W'_{j,i} = - \alpha \, (\delta E'p / \delta W_{j,i}) \qquad (2)$$

$$= \Delta W_{j,i} - \varepsilon \, sgn \, (W_{j,i}) \qquad (3)$$

$$sgn\,(x) = 1, \text{ if } x>0 \;;\; 0, \text{ if } x=0 \;;\; -1, \text{ if } x<0. \qquad (4)$$

where α is an adjustable parameter. Because of the second term in Eq. (1), each weight is continuously forced to decrease at every iteration. The links not reinforced by the effect of Ep will eventually become negligible. In consequence, unnecessary links and units are eliminated from the neural network along with the training in an automatic manner. Therefore, the selection of number of hidden layers and units is not a serious problem.

5. CONSENSUS FORMATION

The consensus formation, or conflict resolution, mechanism is an indispensable constituent of the diversity-based decision-making framework, because the multiple routines in the system can possibly generate outputs with mutual inconsistency. The consensus formation is therefore required at each phase of fault detection, causal reasoning, and procedure synthesis. The typical mechanisms of consensus formation such as the majority voting and parity-space method[9] can be employed to realize the function. These methods are categorized as deterministic and supervised consensus formation since the logical foundation to determine the acceptable output is prefixed with less attention on the self-confidence of each agent. To supplement the conventional mechanism, an alternate consensus method with emphasis on the self-confidence was developed in this study. The consensus is made by taking into account the inter-agent difference in self-confidence. The method is categorized as autonomous consensus formation to reflect the attitude to pay more attention to mutual relationships.

The mechanism for autonomous consensus formation is described in terms of the behavior of the multiple neuro-agents. For example, each of the neural networks in Fig. 4 is realized as an agent with a specific function. The string of output values (y_1, y_2, ..., y_N) of each neural network is interpreted as the opinion of the agent about the diagnostic conclusion. The overwhelming prominence of one output value, say y_k, over the others indicates (1) that the agent concludes that the observed symptom is caused by the failure mode #k and (2) that the agent is quite certain that the conclusion is correct. On the contrary, the non-prominence of the maximum value, y_k, indicates that the agent concludes that the ongoing failure mode is #k, yet the certainty level is modest. If the maximum value y_k is below a preselected threshold, the agent is concluding nothing. More precisely, the occurrence of the event j is considered to be negated as far as this agent is concerned.

The mechanism for autonomous consensus formation was developed on the basis of the above interpretation. The output values are modified by a nonlinear function as

$$y'_i = f(y_i) \;;\; i = 1,2,...,N. \qquad (5)$$

to emphasize the prominent output, and also to represent the negation effect. As shown by the typical transformation function illustrated in Fig. 5, the neural network output left of the vertical dashed line is transformed to a negative value, while a large output value right of the dashed line is magnified to repre-

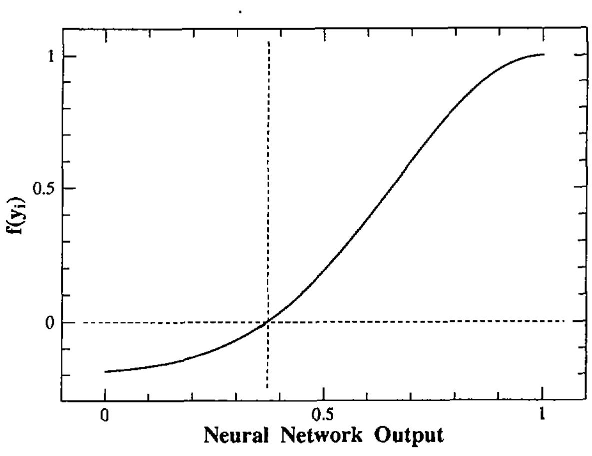

Figure 5. The Transformation Function for Consensus Formation.

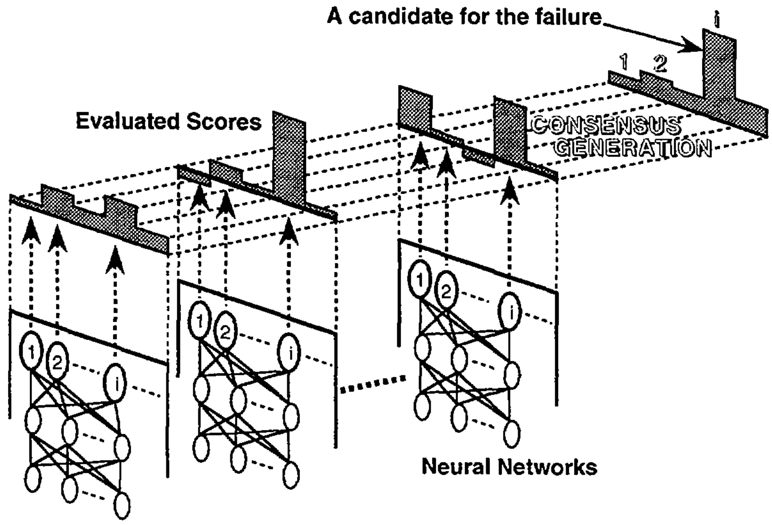

Figure 6. Illustration of the Proposed Consensus Formation Procedure.

sent the enhanced certainty. The transformation function in the figure was derived based on a gaussian, but the sigmoid function is also applicable. The selection of the transformation function is somewhat arbitrary at this stage. After the nonlinear transformation, the output values from all the agents are combined together to obtain the consensus value Z_i for each failure mode #i, i = 1,2,...N.

$$Z_i = \sum_{j=1}^{M} y'_j \qquad (6)$$

where M stands for the number of agents. The procedure is conceptually illustrated in Fig. 6.

6. EXAMPLE

A. Objective Plant

The proposed methodology was evaluated through numerical experiments with emphasis on diagnostic performance. The simulated plant is a three-loop PWR with the rated power of 820MWe. The types of anomaly events are selected to be general enough to cover malfunctions of main components in primary and secondary coolant systems, turbine and generator systems, nuclear instrumentation systems, and process control system.

A total of thirty-four anomaly events was simulated to generate dynamic responses which were processed to provide the symptoms described in 3. Since the deviation-level-based and incremental-change-based symptoms are both considered for the spatial and temporal symptoms, five symptom classes were derived and compared mutually.

The number of signals processed in the spatial and temporal symptoms is seventeen. In the former, all the 17 signals were fed as one set to the input layer of the dedicated neural network. In the latter, each one of the 17 signals was fed to the corresponding neural network. As both of the spatial and temporal symptoms have two versions, the number of dedicated neural networks is thirty-six. In addition, the correlational symptom was defined for twenty pairs of signals. Thus, the number of dedicated neural network, or number of agents, became a total of fifty-six.

The number of segmentations in the temporal symptom is twenty-five with five second interval. The number of segmentations of the two-dimensional state space is forty-nine (7 times 7). The number of units in the input layer of the neural network is set equal to these numbers. The number of units in the hidden layer is one half of the input layer units. Although the number of the hidden layer units was selected without cautious tuning, the results were expected to be insensitive to this number by virtue of the adaptive learning algorithm.

B. Results

<u>Training Results</u>

The performances of the diagnostic modules dedicated for one of the five symptoms are summarized in Table-1 for the training phase. The five symptoms are denoted spatial H/N/L, spatial I/C/D, temporal H/N/L, temporal I/C/D and correlational symptoms in these tables. It might be felt strange that the diagnostic

Table 1. Results of Diagnosis(Training).

Number of Success Cases	Each Symptom	Overall Diagnosis
Spatial H/N/L	32	34
Spatial I/C/D	32	
Temporal H/N/L	31	
Temporal I/C/D	34	
Correlational	33	

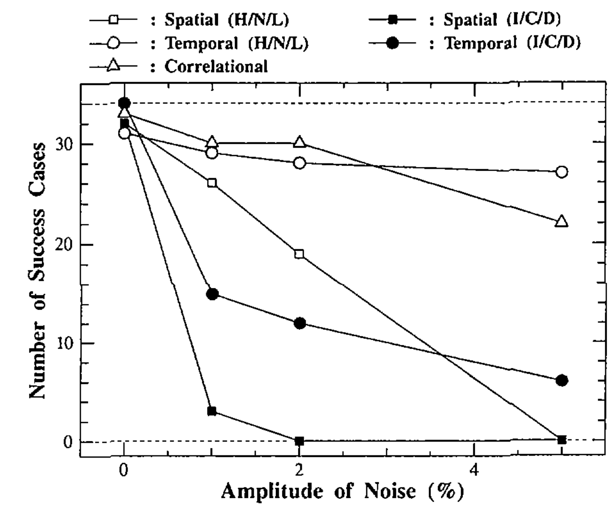

Figure 7. Diagnostic Performance Degradation for Increase in Noise Magnitude.

performance is sometimes below 100% even for the training data. The faulty diagnosis is attributed to the similarity of multiple failure modes observed via specific symptom descriptions. The main reason of this apparent similarity is the coarse segmentation in magnitude and time of the symptom characterization. This defect can be mitigated by elaborating the segmentation in a suitable manner. However, as the purpose of the study is to evaluate the effect of symptom diversification rather than to attain high diagnostic performance, the elaboration of the symptom characterization was not attempted in this phase. As expected, the diagnostic performance was 100% after consensus formation of the multiple agents.

Testing Results

The testing of the trained neural networks was carried out for the plant responses distorted by additive noise components with specified amplitudes. The amplitude of the distortion noise was modified up to 5% of the original signal magnitude in order to examine the robustness of the diagnosis system. The number of cases in which the true fault cause was successfully identified decreased monotonically along with the increase in the noise magnitude as depicted in Fig. 7. The performance degradation of the agents based on the incremental-change-based symptoms is particularly significant. This degradation is attributable to the fact that the change in the feature description is most drastic in the incremental-change-based symptom.

On the other hand, the degradation is less significant with the deviation-level-based temporal and correlation-based symptoms. The robustness of these symptom representation is attributable to the segmentation of the dynamic response with an appropriate coarse grain size. It should be noted that the results in Fig. 7 are given after consensus formation among the agents within the corresponding symptom descriptions. In other words, these results provide a relative evaluation of information values reflected in these symptom descriptions.

Table 2. Results of Diagnosis (Testing with Perturbated Data).

Number of Success Cases		Each Symptom		Overall Diagnosis	
		Linear Average	Autonomous	Linear Average	Autonomous
1%	Spatial H/N/L	28	26	34	34
	Spatial I/C/D	3	3		
	Temporal H/N/L	29	29		
	Temporal I/C/D	9	15		
	Correlational	33	30		
2%	Spatial H/N/L	22	19	31	34
	Spatial I/C/D	0	0		
	Temporal H/N/L	26	28		
	Temporal I/C/D	5	12		
	Correlational	30	30		
5%	Spatial H/N/L	1	0	19	32
	Spatial I/C/D	0	0		
	Temporal H/N/L	17	27		
	Temporal I/C/D	0	6		
	Correlational	8	22		

Effect of Consensus Formation

The results described in the above paragraph were further processed to derive the final conclusion through the overall consensus formation. The results are summarized in Table-2 together with the results obtained from the simple majority voting and the linear averaging. The latter is equivalent to the consensus without the nonlinear transformation.

The overall diagnostic performance after consensus was certainly improved. When the noise magnitude is as low as 1%, the diagnostic credibility is 100% irrespective of the consensus strategy. On the contrary, the advantage of the autonomous consensus is significant when the noise magnitude is increased. The performance for 5% noise is particularly outstanding. The usefulness of the proposed method of consensus formation was clearly shown in these example. Since no single symptom description alone could reach the 100% performance, the advantage of diversification in symptom description is, we believe, well demonstrated by the above results.

7. CONCLUDING REMARKS

A general framework based on the diversification of symptom description and causal reasoning was proposed as a guiding principle for future development of intelligent and dependable operator support system in nuclear power plants. The essential nature of the framework is a distributed multi-agent system each of which can conduct operational decision-making from a specific perspective. An accompanying key concept called autonomous consensus formation was also proposed for efficient incorporation of the multiple conclusions provided by the multi-agents. The concept of diversification was introduced based on extensive survey of decision-making strategy by human experts in various domain.

The advantage of implementing the diversity in symptom description, and the importance of the autonomous consensus formation as well, were evidently demonstrated through numerical experiments simulating nuclear plant anomalies. The obtained results validate, at least to some extent, the present claim of combining multiple and diverse perspectives for reliable decision-making in high-potential-hazard artifacts. Further development of key techniques to be implemented in the general framework of Fig. 1 is currently in progress.

ACKNOWLEDGMENTS

The central concept in this paper, diversification of symptom description and method of causal identification, was formulated through intensive discussions in the Cross-over Research Group on Artificial Intelligence sponsored by Science and Technology Agency, Japan. The authors would like to express their sincere thanks to those contributed to the discussions in the group meetings. The authors are also grateful to K.Yoshida of JAERI for providing them the simulation code, and to T.Baba, H.Takada and O.Dairiki of Nippon Steel Corp. for providing the AMI/AMIMADO system for neural networks development. The present work was partially supported by the Ministry of Education grand-in-aid for scientific research (C) 04680220.

REFERENCES

1. M.Kitamura, K.Kuchimura, and H.Furukawa, "Information Diversification for Improving Diagnostic Reliability in Complex Dynamic Processes", Proc. IMACS/SICE Intern'l Symp. on Robotics, mechatronics and Manufacturing, 92'KOBE, 823-830 (1992).
2. M.Kitamura, H.Furukawa, K.Kuchimura and T.Washio, "Diversification of Symptom Description and Causal Reasoning for Higher Credibility of Computer-Assisted Diagnosis in Nuclear Plants", Proc. ANS Topical Meeting on Nuclear Plant Instrumentation, Control and Man-Machine Interface Technologies, Oak ridge, 427-434 (1993).
3. M.Minsky, The Society of Mind, Simon and Schuster (1986).
4. Y.Iwasaki and B.Chandrasekaran, "Design Verification Through Function- and Behavior-Oriented Representations: Bridging the Gap Between Function and Behavior", paper presented in AAAI-1992.
5. L.Beltracchi and R.W.Lindsay, "A Strategy for Minimizing Common Mode Human Error in Executing Critical Functions and Tasks," Proc. 8th Power Plant Dynamics, Control and Testing Symposium, Knoxville, 19.01 (1992)
6. M.Sakuma, Y.Yokoyama, M.Takahashi and M.Kitamura, "Pattern Characterization of Signal Fluctuation for Automation of Fault Detection in Complex Dynamic Processes", Paper presented at SICE Tohoku Branch Seminar, May (1993) (in Japanese).
7. T.Washio, M.Sakuma and M.Kitamura, "A Diagnosis Method for Multiple Process Failures Based on Physical Constraints, Kernel Diagnosis and Causal Ordering", paper to be presented at DX-93, The Fourth International Workshop on Principles of Diagnosis, Univ. Wales, Sept. (1993).
8. M.Ishikawa, "A Structural Connectionist Learning Algorithm with Forgetting," J. of Soc. of AI in Japan, 595 (1990) (in Japanese)
9. B.R.Upadhyaya, "Sensor failure Detection and Estimation", Nuclear Safety, 26, 32-43 (1985).