FAULT DIAGNOSIS AND SEVERITY ESTIMATION IN NUCLEAR POWER PLANTS

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ABSTRACT

Signed Directed Graph (SDG) is a type of fault diagnosis method with a capability to display the complex relationship between plant parameters and reveal the potential danger and the propagation path when a fault occurs in a nuclear plant. However, the fault diagnosis method based on qualitative SDG model inevitably has a number of disadvantages, and some of these disadvantages include its inability to identify reoccurring faults; ambiguous reasoning that can result in low resolution; performance that relies on the accuracy of the model; slow diagnosis rate for large systems and poor real-time diagnosis, among others. In this paper, we propose an SDG fault diagnosis methodology based on Granular Computing Theory, referred to as Granular Computing Signed Directed Graph (GCSDG). This paper shows how knowledge reduction nature of granular computing based fault diagnosis can simplify the decision table, reduce the allocation of resources, scale-down the complexity of the problem and improve the efficiency of data processing. Then, we estimate the severity of the fault using Back Propagation (BP) neural network approach. The proposed methodology was verified by considering certain faults in the primary loop of a PWR, using PCTRAN. The result shows a considerable improvement in fault diagnosis and the severity estimated serves as a useful information for the operator, providing a firm foundation for further intervention.

Key Words: Signed Directed Graph, Granular Computing Theory, Fault Diagnosis, BP Neural Network, Severity Estimation

1 INTRODUCTION

Nuclear power plant is a complex and huge system. The equipment structures are complex and expensive, and the potential for radiological hazard is always present. Leakage of radioactive material from a nuclear plant could have disastrous consequences for the staff, the surrounding environment, and the society. Human error in plant operation has been found to be a major factor in nuclear plant accident propagation. For instance, the Japan's Fukushima nuclear power plant accident of 2011 resulted from the emergency system equipment failure as well as the slow response of the operators because they could not properly predict the fault propagation pattern, resulting in a serious nuclear accident. Hence, it is necessary to develop an effective operation support system for specific nuclear power plants. This will

help the operator to quickly and accurately obtain the abnormal state of the nuclear power plant, understand the cause, location, degree of the accident, and then take the appropriate operating action [1]. An effective fault diagnosis technology could detect the cause of the problem quickly and accurately when exceptions occurred in nuclear power plants, so as to give the operator enough time to take the corresponding safety measures to ensure the safety of nuclear power plants. Many fault diagnosis methodologies have been proposed in literature on fault diagnosis, ranging from qualitative model-based approach to quantitative data-driven methods and process history based methods [2]. In the engineering application, the single diagnosis method cannot solve the problem of fault diagnosis effectively in complex system. Therefore, the combination of multiple fault diagnosis methods is the hotspot of fault diagnosis.

Unlike the conventional quantitative-based or datadriven approaches, the SDG model does not require precise mathematical description or complete operational data, and it can be developed from the partial information of equations or the experience of operators. In addition, SDG reveals the latent dangers and the propagation rules in a simple and effective way, so it is especially suitable for fault diagnosis in the nuclear power plants. In this paper, a fault diagnosis method based on the SDG model and process historical data is proposed. In this approach, the granular computing methodology is used to scale-down the decision table, which is then applied to SDG method in order to improve the speed of the dignosis. This results in an improved SDG which is subsequently used for fault detection and the fault propagation chains obtained easily. The severity of the fault is then estimated using the BP neural network to obtain more fault information.

2 SDG FAULT DIAGNOSIS BASED ON GRANULAR COMPUTING THEORY

2.1 SDG Model

Signed directed graph is a fault diagnosis method based on qualitative model and causal analysis and it is a kind of network graph which is composed of directed lines between nodes and parameters. The definition is as follows [3]:

$$G = (V, E, \varphi, \psi)$$

where $V = \{v_i\}$ is node set, representing parameters of measure or fault root cause, $E = \{e_1, e_2, \cdots, e_m\}$ is branch set, characterizing the causal relationship between different nodes, and $\varphi : E \longrightarrow \{+, -\}$, $\varphi(e_k)(e_k \in E)$ is the sign of branch e_k ,"+" representing positive impact, On the contrary, "−" representing negative impact. $\psi{:}V \longrightarrow \{+, 0, -\}$, $\psi(v_j)(v_j \in V)$ means the sign of node v_j , representing the status of node.

The node state values of the SDG model samples are determined according to the upper and lower limits of the state parameters of the respective parameters [4], as shown in formula (1):

$$\psi(v_j) = \begin{cases} -1, & if \quad x_{v_j} < x_{v_{jl}} \\ 0, & if \quad x_{v_{jl}} \leq x_{v_j} < x_{v_{jh}} \\ +1, & if \quad x_{v_j} \geq x_{v_{jh}} \end{cases} \tag{1}$$

where x_{vj} represents the actual value of the parameter node, x_{vjl} is the lower limit and x_{vjh} is the upper limit of the respective parameters.

An example of signed directed graph is shown in Fig.1, including ten nodes and three fault root causes ($F1, F2, F3$). The positive impact branches are characterized by solid lines and negative impact branch are characterized by dashed lines.

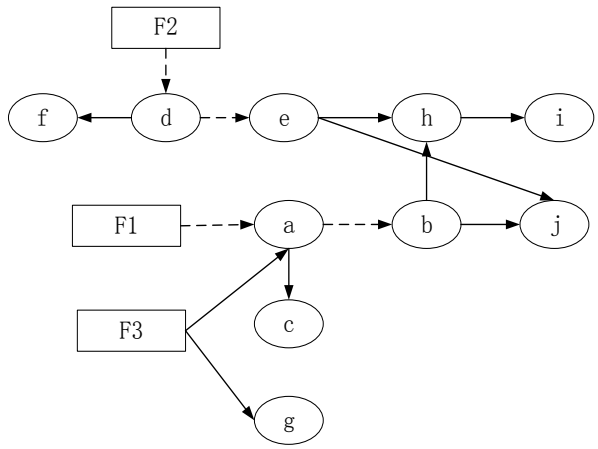

Figure 1. An example of signed directed graph

Table I contains a modified fault diagnosis decision table for SDG fault diagnosis. This modification is necessary to avoid repeated (cyclic) reasoning about the faults that have occurred. When a similar fault occurs again, the fault root cause can be easy obtained by simply matching the rules in the table. The decision table (Table I) is generated according to the ten-node SDG model in Fig.1

Table Ⅰ. Decision Table of SDG

Cases	Condition Attributes C										Decision Attributes D
U	a	b	c	d	e	f	g	h	i	j	Fault Root Causes
1	-1	+1	-1	0	0	0	0	+1	+1	+1	F1
2	0	0	0	-1	+1	-1	0	+1	+1	+1	F2
3	+1	-1	+1	0	0	0	+1	-1	-1	-1	F3

2.2 Granular Computing and Knowledge Reduction

Granular Computing is a new computational paradigm in information processing that covers all the theories, methods, techniques or tools related to grain. It is mainly used to deal with uncertain, fuzzy, incomplete and massive information [5]. The knowledge reduction capability of granular computing is based on the guarantee that the classification ability remains unchanged, and it can remove redundant attributes of the decision table and derive the minimal rules. The minimum attribute set is composed of the leading attributes and partial or all removable attributes. The dominant attributes are the indispensable attributes of the input samples, while the removable attributes are those that are not important and can even be removed from the output samples [6]. In a complex information system, some redundant attributes can be eliminated by calculating the importance of each attribute, and then simplify the complexity of the system by removing unimportant attributes.

Mathematically, the decision table is defined as follows:

$$T = (U, C \cup D)$$

where C is condition attribute set and D is decision attribute set.

The steps of a common knowledge reduction method are as follows [7]:

1. Order $\mathrm{B} = \mathrm{C}$, calculate $POS_C(D)$;
2. Calculate $POS_{B-\{a\}}(D)$, $\mathrm{a} \in \mathrm{C}$; if $POS_C(D) = POS_{B-\{a\}}(D)$, then $\mathrm{B} = \mathrm{B} - \mathrm{a}$, otherwise the attribute a is reserved;
3. Calculate each condition attribute and $\mathrm{Red}(\mathrm{C}, \mathrm{D}) = \mathrm{B}$ d is the minimum attribute set that we expect.

3 FAULT SEVERITY ESTIMATION BASED ON BP NETWORK

The concept of severity estimation is very important because when a fault is detected, an approximate assessment of the degree of failure, such as the size of the break, avails the operators detailed information about the nature of the fault and assists in taking better safety measures. Moreover, the ability of BP neural network to map complex relation, makes it a choice method for the approximation of fault degree by establishing the mapping relation between different fault degree and system parameter change.

3.1 Artificial Neural Network

The artificial neural network simulates and simplifies the interaction of the neurons in the human brain through different network models. In the field of fault diagnosis, multilayer feedforward neural network is the most widely used. However, research improvements in the neural network algorithm gives rise to a network that often uses the error back propagation algorithm for training, and it is usually called BP neural network [8,9]. The network structure is as shown in Fig.2

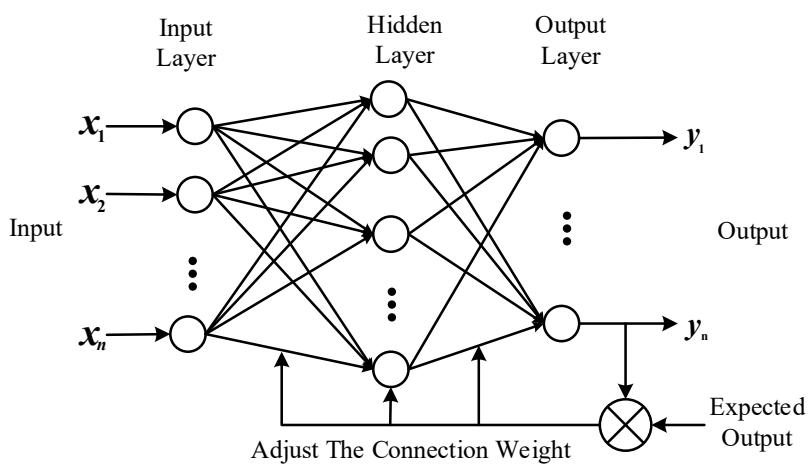

Figure 2. The architecture of three-layer BP neural network

The basic working principle of BP neural network is that when a set of signals are input to the BP neural network, the corresponding response is obtained at the output layer, passing through the hidden layer. Then, the error between the actual output of the network and the expected output is calculated and the gradient weight method of the error function is used to adjust the connection weight between the layers and the threshold of the neuron, so that the error is reduced, and the expected output is approached

continuously. When the error requirements are met, the mapping between input and output is established and the method can be used to solve the problem of pattern recognition and classification.

3.2 BP Network Based Severity Estimation

Under the same fault type, when the degree of failure is different, some changes in the monitoring parameters will be different for a period of time after the accident. Consider the following two main accident cases:

1) In the case of a Loss of Coolant Accident (LOCA), when the degree of failure is different, the rate of change of the parameter is different. Figure 3 shows the rate of change of pressurizer water level with the conditions of the break 2cm^2 and 6cm^2 in the loss of coolant accident.

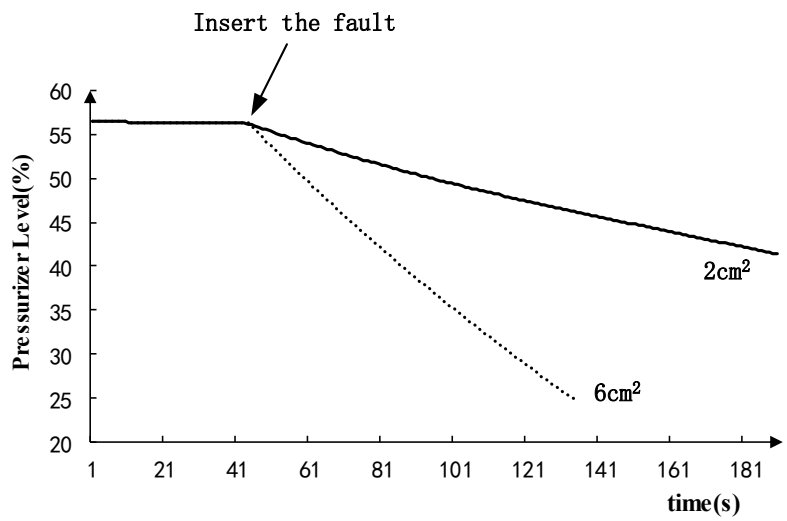

Figure 3. The pressurizer level variations in different fraction of LOCA

2) In the case of Main Steam Line Break Accident (MSLB), when the degree of failure is different, the step change of the parameter is different. Figure 4, shows the steam flow changes with the conditions of the break 25cm^2 and 75cm^2 in the main steam line break accident (inside the shell).

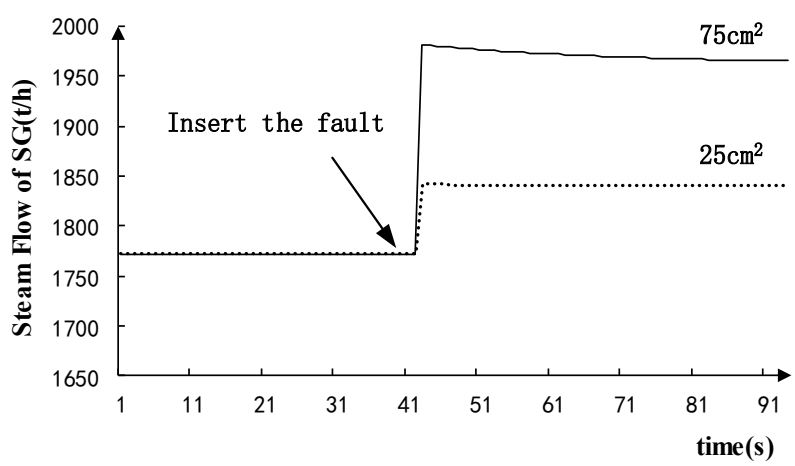

Figure 4. The steam flow variations in different fraction of MSLB

Therefore, there exist some kind of specific mapping relation between the severity and the variations of operation parameters values or gradients. That is, severity is a function of specific operational parameter values and gradients: $\text{Severity} = f(v_1, v_2, \cdots, k_1, k_2, \cdots)$.

To obtain the estimated computation of fault severity, the mapping relation between the severity and parameter values $(v_1, v_2, \cdots)$ or parameter gradients $(k_1, k_2, \cdots)$ is constructed using Elman neural network.

4 INTEGRAL DIAGNOSTIC METHOD

The evaluation of the proposed methodology was to be carried out with data from a real PWR plant. However, real operating data is not available. Thus, a PWR simulation software – PCTRAN - is adopted as the primary data source. The granular computing based SDG model is evaluated based on the analysis of PWR plant system simulated by PCTRAN.

When the PCTRAN was running in the normal operating mode, the variation of parameters and their current values are obtained by accessing the database, then the status of each parameter is confirmed. Once any abnormality is detected, the fault identification will be ascertained by matching to the rules or inferring from the established SDG model. For ruptured-type faults, the fault severity is estimated by the BP neural network. The flowchart of diagnosis process is shown in Fig.5

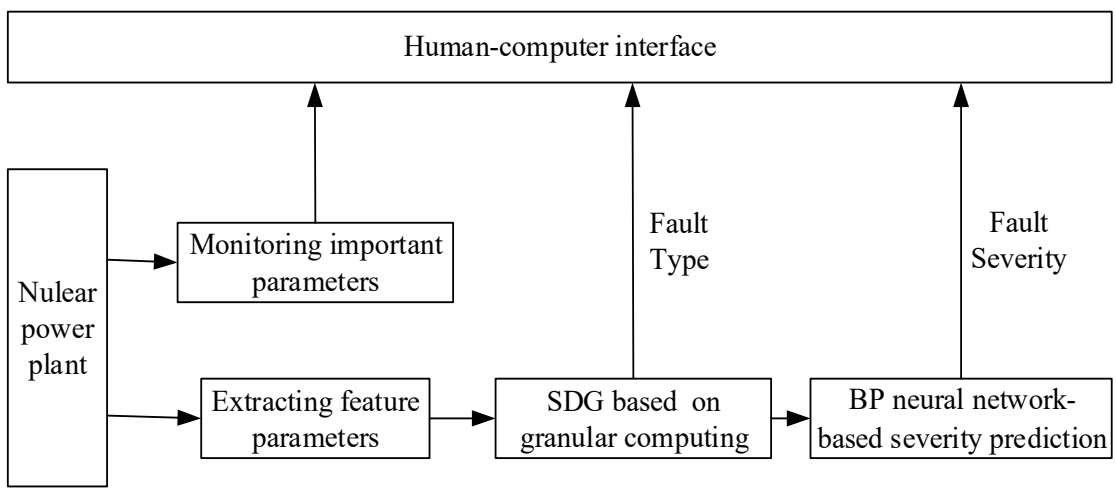

Figure 5. A general diagnostic framework for nuclear power plant

4.1 Verification of the GCSDG model

In this paper, seven different types of faults are considered to verify the SDG model. The fault types are: Loss of Coolant Accident; Steam line break inside containment; Loss of flow; Steam generator A tube rupture (SG A); Steam generator B tube rupture (SG B); Inadvertent rod insertion; and Inadvertent rod withdrawal. Then the parameters related to the designated faults are selected, and the relationship between the parameters is analyzed, according to the working principle of the system. The SDG model of the PWR primary coolant system is presented in Fig.6 and it involves 19 parameter nodes and 7 fault nodes as shown in Table Ⅱ.

Table Ⅱ. Parameter nodes and fault nodes of the SDG model of the primary coolant System

ID	Node Label	Node Name	ID	Node Label	Node Name
1	P	Pressure of RCS	14	WSTA	Steam flow of SG A
2	TCA	Temperature of Cold leg A	15	WSTB	Steam flow of SG B
3	TCB	Temperature of Cold leg B	16	TRB	Temperature Reactor building
4	QMWT	Total thermal Power	17	PRB	Pressure Reactor building
5	QMGA	Power of SG A heat removal	18	RM1	Rad Monitor Reactor building air
6	QMGB	Power of SG B heat removal	19	RM2	Rad Monitor Steam Line
7	LSGA	Level range level of SG A	20	LOCA	Loss of Coolant Accident
8	LSGB	Level range level of SG B	21	MSLB	Steam Line Break Inside Containment
9	WFWA	Feedwater flow of SG A	22	LOFA	Loss of Flow (Locked Rotor)
10	WFWB	Feedwater flow of SG B	23	SGTR(A)	Steam Generator A Tube Rupture
11	VOL	Volume of RCS liquid	24	SGTR(B)	Steam Generator B Tube Rupture
12	WRCA	Coolant Flow of loop A	25	Inserting	Inadvertent Rod Insertion
13	WRCB	Coolant Flow of loop B	26	Withdrawal	Inadvertent Rod Withdrawal

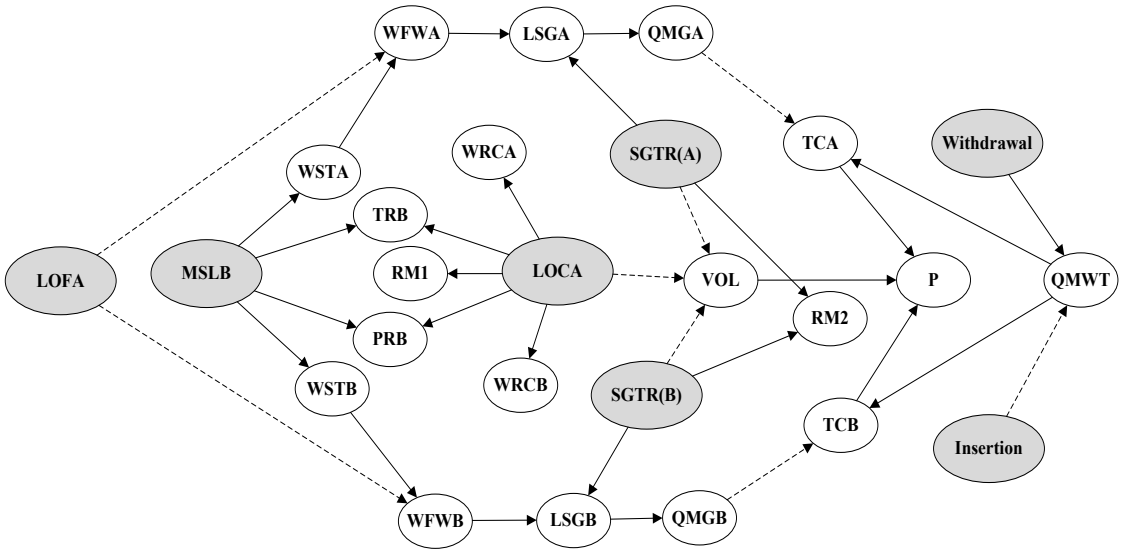

Figure 6. SDG model of the primary coolant system

The decision table in Table Ⅲ is generated according to the SDG model in Fig.6. The types of fault analyzed are represented by number 1 to 7 and the normal running state is represented by number 8.

Table Ⅲ. Decision Table of GCSDG model

U	Condition Attributes C																			D
	P	TCA	TCB	QMWT	QMGA	QMGB	LSGA	LSGB	WFWA	WFWB	VOL	WRCA	WRCB	WSTA	WSTB	TRB	PRB	RM1	RM2	
1	-	0	0	0	0	0	0	0	0	0	-	+	+	0	0	+	+	+	0	1
2	-	-	-	0	+	+	+	+	+	+	0	0	0	+	+	+	+	0	0	2
3	+	+	+	0	-	-	-	-	-	-	0	0	0	0	0	0	0	0	0	3
4	-	-	0	0	+	0	+	0	0	0	-	0	0	0	0	0	0	0	+	4
5	-	-	0	0	0	+	0	+	0	0	-	0	0	0	0	0	0	0	+	5
6	-	-	-	-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
7	+	+	+	+	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8

The condition attributes are calculated, and the redundant attributes are removed. The minimal attribute set Red $= \{P, TCB, QMWT, QMGA, QMGB, VOL, WSTA, RM1\}$, and the decision table after reduction is shown in Table Ⅳ.

Table Ⅳ. Decision Table of GCSDG model after Reduction

U	Condition Attributes C								D
	P	TCB	QMWT	QMGA	QMGB	VOL	WSTA	RM1	
1	-1	0	0	0	0	-1	0	+1	1
2	-1	-1	0	+1	+1	0	+1	0	2
3	+1	+1	0	-1	-1	0	0	0	3
4	-1	0	0	+1	0	-1	0	0	4
5	-1	0	0	0	+1	-1	0	0	5
6	-1	-1	-1	0	0	0	0	0	6
7	+1	+1	+1	0	0	0	0	0	7
8	0	0	0	0	0	0	0	0	8

4.2 Modeling and Training of Severity Estimation

4.2.1 Sample set building

The training samples include inputs and outputs. Input samples are the values or variation gradients of the selected parameters relate to the specific fault type and the output samples are the failure fraction. Inputs and outputs are shown in Table Ⅴ. The process data under faulty condition are obtained with the PCTRAN running in a certain span. The value of the selected evaluation parameters can be obtained and the variation gradients of this parameter should be calculated. Then, the input data sample is obtained, and the corresponding output is the predefined failure fraction. What's more, both the inputs and outputs need to be normalized.

Table Ⅴ. The selected parameters of severity estimation for rupture fault

Fault Type	Estimate Parameter(Inputs)	Severity Range(Outputs)
LOCA	P, LVPZ, TRB, RM1	[0,200] /cm^2
MSLB	PRB, TRB, WSTA*, WSTB*	[0, 200] /cm^2
SGTR(A)	WFWA, P, LVPZ, RM2	[0, 40] / of full tube rupture
SGTR(B)	WFWB, P, LVPZ, RM2	[0, 40] / of full tube rupture

Note: the parameters with asterisk mean their value are the inputs of the network, those without asterisk means their variation gradients are the inputs of the network.

4.2.2 Modeling and training

The neurons number of the input layer and output layer in neural network is determined by the date samples. As the number of input parameters is small, the neural network is designed to be one hidden layer structure, and the neurons number of the hidden layer is calculated through empirical formula (2) [10].

$$h = 0.51 + \sqrt{0.12n^2 + 0.43mn + 2.54m + 0.77n + 0.35} \tag{2}$$

where h *is* the neurons number of hidden layer, n is the neurons number of the input layer, m is the neurons number of the output layer.

The training of BP neural network is a process that results to the mapping relation between the inputs and the outputs. The back propagation (BP) learning and its improvement are the common learning algorithms.

5 VERIFICATION CASE STUDIES

A fault diagnosis system for nuclear power plant is developed based on the GCSDG diagnosis method and BP Neural Network. The diagnosis system is linked to PCTRAN. The responses of the system are tested by inserting different faults in the PCTRAN to verify the feasibility of the method.

5.1 Loss of Coolant Accident

The loss of coolant accident is inserted after PCTRAN steadily running with full power for 20s, and the failure fraction is set to 20cm^2. The LOCA was detected promptly as it was inserted for 2s. Then the failure fraction is estimated by the relevant trained BP neural network every second. The fault detail is shown in Fig.7

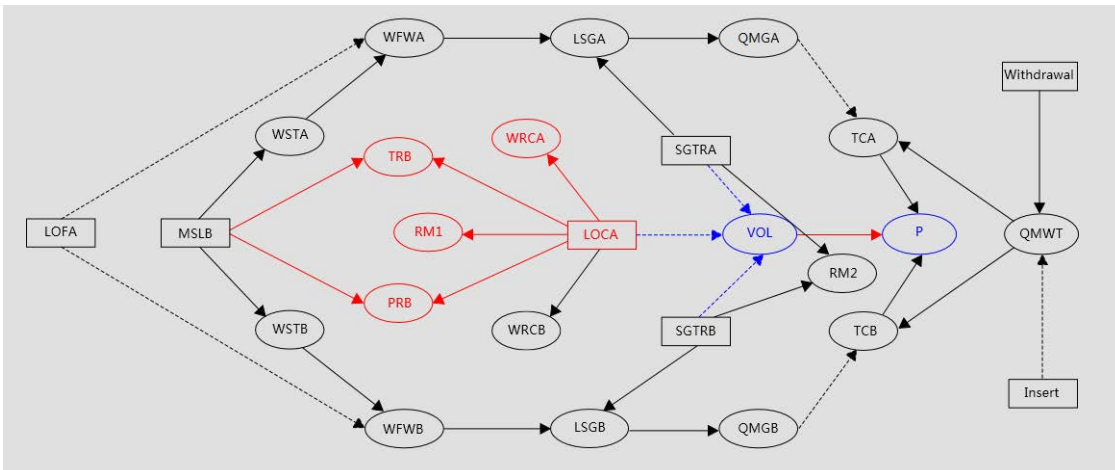

Figure 7. GCSDG diagnostic result for LOCA

Fault propagation chains inferred from the GCSDG model are as follow:

(1) Loss of Coolant Accident → Volume of RCS liquid → Pressure of RCS;

(2) Loss of Coolant Accident →Radiation monitors reactor building air;

(3) Loss of Coolant Accident → Temperature reactor building;

(4) Loss of Coolant Accident → Coolant flow of loop A;

(5) Loss of Coolant Accident → Pressure reactor building.

Consequently, the severity of the fault injected was successfully estimated. Figure 8 below shows the estimation curve of the severity of the LOCA.

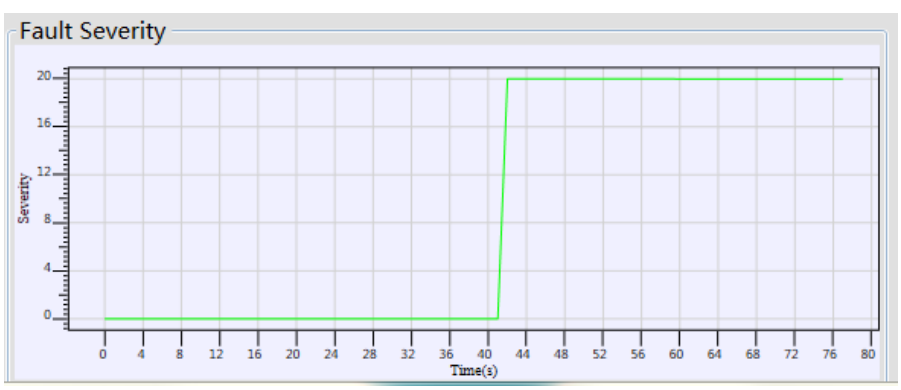

Figure 8. Estimating curve of LOCA

5.2 Steam Generator Tube Rupture

The fault of steam generator A tube rupture was injected after PCTRAN steady running on full power for 20s, and the failure fraction is set to 25 full tube rupture. The fault is detected and identified as SGTR A in 1s. The fault propagation chains inferred from SDG model (shown in Fig.9) are as follow:

(1) Steam Generator A Tube Rupture → Volume of RCS liquid → Pressure of RCS;

(2) Steam Generator A Tube Rupture → Radiation monitor steam line;

(3) Steam Generator A Tube Rupture → Level range level of SG A.

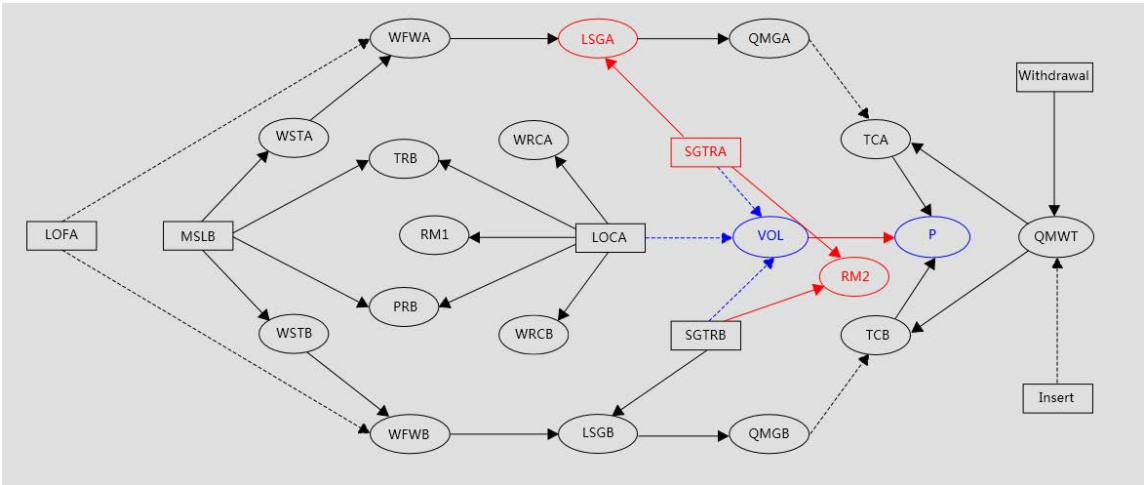

Figure 9. SDG Diagnostic result for SGTR

Obviously, the result of estimation is around 25 full tubes rupture, and the fault severity is approximated. Figure 10 shows the severity estimation curve for the Steam Generator Tube Rupture fault.

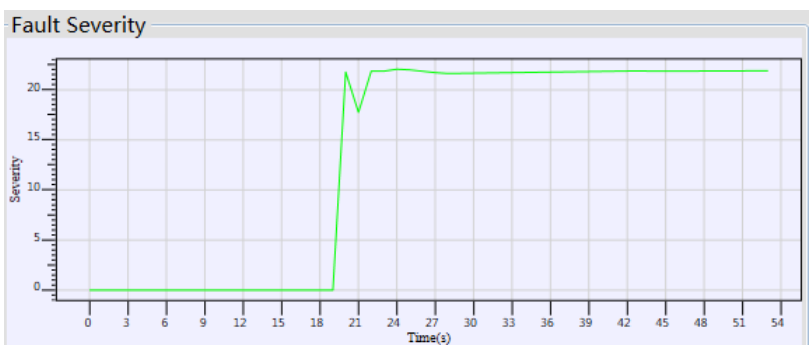

Figure 10. Estimating curve of SGTR

6 CONCLUSIONS

This research work proposed and introduced the decision table into SDG fault diagnosis and the table was simplified by application of the knowledge reduction granular computing theory to identify and remove redundant attributes. Once the redundant attributes were removed, the minimum rules were derived. The improved SDG based fault diagnosis method, referred to as the Granular Computed Signed

Directed Graph (GCSDG) is then applied to diagnose fault in the primary coolant loop of a simulation based nuclear power plant, using PCTRAN. The result shows that all considered faults were successfully detected and identified, and the fault propagation chains were determined. On the basis of the identified faults, the severity of the faults was quantitatively estimated by BP network. Hence, the verification results show that the proposed methodology can be used to diagnose faults accurately and timely, and the severity of the faults can be successfully estimated.

7 ACKNOWLEDGMENTS

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