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Multimedia Expert System for a Nuclear Power Plant Accident diagnosis using a Fuzzy Inference Method

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퍼지 추론 방법을 이용한 원자력 사고진단 시스템을 위한 멀티미디어 전문가 시스템

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Abstract

The huge and complicated plants such as nuclear power stations are likely to cause the operators to make mistakes due to a variety of inexplicable reasons and symptoms in case of emergency. Thats why the prevention system assisting the operators is being developed for. First of all, I suggest an improved fuzzy diagnosis. Secondly, I want to demonstrate that a classification system of nuclear plants accident investigating the causes of accidents foresees possible problems, and maintains the reliability of the diagnostic reports in spite of improper working in part.

In the event of emergency in a nuclear plant, a lot of operational steps enable the operators to find out what caused the problems based on an emergent operating plan. Our system is able to classify their types within twenty to thirty seconds. As so, we expect the system to put down the accidents right after the rapid detection of the damage control-method concerned.

Keyword: Fuzzy method, Nuclear Plants, Expert system, Reasoning Algorithm

요 약

복잡한 공정계통들로 구성된 원자력 발전소에서 정상적인 운전상태를 벗어나 이상사태로 진행될때 이를 조기에 진단하고 사고를 예방할 수 있는 제반 조치를 적절히 취하는 것은 플렌트 가동율을 향상시키고 사고의 심각성을 줄이기위한 피수요건이 된다. 이상사태 발생시 과도현상의 원인과 증상은 모호하고 복잡한 인과관계를 갖기 때문에 운전원의 실수를 유발할 수 있으므로 운전원을 지원할 수 있는 사고진단 시스템의 개발이 필요하다. 따라서 본 연구에서는 일반화된 퍼지 추론 알고리즘의 개선된 퍼지진단방법론을 제시하고, 사고초기 단계에서 주요 운전변수의 거동 변화에 따른 사고원인 및 사고유형을 정확하게 예측하고 일부 입력의 오류에도 진단의 신뢰성을 유지할 수 있는 원자력 발전소 사고유형 분류 시스템을 개발하고자 하였다.

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Ⅰ. Introduction

Transient and accident conditions in NPP(Nuclear Power) rapidly progress and accordingly operation variables fluctuate severely. It is required to trace and understand behaviors of operation variables and the plant. However, the diagnosis of the plant in a very short period of time may accompany human errors easily. For complicated systems such as a NPP, Operators should detect abnormal operation condition early and then take proper actions to prevent a severe accident. Although the plant is operated fully automatically, the final decision need to be made by operators. When an abnormal situation occurs, various warning signals may arise in the main control room and therefore operators would have difficulties in making a clear decision an what to do. Generally, as earlier they want to detect abnormal conditions, the diagnostic signals would be more ambiguous. Occasionally it is necessary to take proper actions or to predict consequent conditions by judgement using such an ambiguous information. In this manuscript, we discuss the diagnosis of abnormal signals of a NPP to determine the causes . A system using fuzzy theory is developed to diagnose fast and exactly the transient and accident conditions for a NPP.

Ⅱ. Methodology

2.1 Diagnosis using Fuzzy Relationship Equation

Diagnostic fuzzy expert systems have usually used backward reasoning which can be modeled as fuzzy relationship equations. The entire space X of premise consists of m cause items and the entire space Y of conclusion consists of n diagnostic items.

$X = \{x_1, x_2, \cdot, x_m\}, Y = \{y_1, y_2, \cdot, y_n\}$

Between x_i and y_j, there exists a relationship. This relationship r_{ij} : $x_i \rightarrow y_j$ is called a fuzzy relationship between x_i and y_j. Fuzzy relationship matrix is defined as $R = \{r_{ij}\}$, $i = 1 \sim m$, $j = 1 \sim n$. For each r_{ij}, the strength of the relationship is represented a real number within the region of [0, 1].

Fig. 1 shows a Fuzzy system[1].

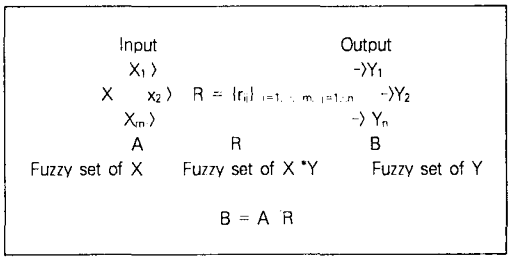

Fig. 1 Modeling by a Fuzzy system

A, B, and R are, respectively called as fuzzy set on X, fuzzy set on Y and fuzzy set on X * Y. In a fuzzy inference method, the following generalized deductive inference is used:

[Fuzzy Inference] Generalized Modus Ponens [2].

Premise: x is A

Implication : IF x is A, then y is B : represented by fuzzy relationship R

Conclusion : y is B'

Lukasiewicz and Mandani proposed a method to derive the relationship R as follows:

Lukasiewicz: $\mu_R(x, y)$ min{1, $1-\mu_A(x) + \mu_B(y)$}

Mandani: $\mu_R(x, y)$ min{$\mu_A(x)$, $\mu_B(y)$}

If R is given the following can be obtained by

Max-Min Composition.

$$B' = A' \circ R \text{ or, } \mu_B(y) \max(\min(\mu_R(x, y), \mu_A(x))) \quad (1)$$

Equation(1) can be expressed using a_i and b_j which are components of fuzzy sets A and B as follows:

$b_i = \max(\min(r_{ij}, a_i)),\ 1 \le i \le m,\quad 1 \le j \le n$

For the fuzzy system in Fig. 1, in some cases the fuzzy relationship R is not known, therefore, we need to determine R using x and y which are known. In some other cases, X is unknown while R and Y are known. In this case we need to determine X using R and Y. In both cases, we need to solve the fuzzy relationship equation and its solution method is an important part of the fuzzy diagnosis[3]. For a NPP accident diagnosis case, a_i and b_j are a symptom and an event, respectively. Rij determines the relationship between ith event and jth symptom. The accident diagnosis problem of a NPP searches for the event a_i when the symptom b_j and the relationship R_{ij} are given. This is the inverse problem of a fuzzy relationship equation. The fuzzy inference method using fuzzy relationship equation has a problem in determining the relationship R numerically. Using the Max-Min computation structure, the accuracy of the inference results becomes low[1]. In this paper, we extend the concept of fuzzy relationship equation and develop a new model which allows more general and flexible inference. Therefore, the proposition which can be used as knowledge database appropriate for fuzzy inferences is established.

2.2 Establishment of Knowledge data for the inference

Sets of all causes and symptoms, X and Y, are defined respectively as follows:

Cause: X={Xi (i=1, ·, m)}

Symptom: Y ={Yj (j= 1, ·, n)}

Next, propositions A_i, B_j and R_{ij} are defined as follows:

A_i : cause i exists.

B_i : symptom j is observed

R_{ij} : cause X_i is related to symptom Y_j.

All these sets include uncertainties and are fuzzy sets. The following combined propositions are defined:

$$P_j = B_j \rightarrow \text{OR } (R_{ij} \ \& \ A_i) \quad (2)$$

$$P_{ij} = (R_{ij} \ \& \ A_i) \rightarrow B_j \quad (3)$$

When "->", "OR", and "&" represent "implication", "disjunction", and "conjunction", respectively.

Proposition P_j represents the certainty of "If symptom B_j exists, there exists at least one cause A_i under relationship R_{ij}". Proposition P_{ij} represents the certainty of "If there is a cause A_i under R_{ij}, symptom B_j exists".

These propositions R_{ij}, P_j and P_{ij} are established as knowledge for the inference. The certainties of R_{ij}, P_j and P_{ij} may take the following 7 levels in the form of LTV(Linguistic Truth Value), for example.

VT : Very True, RT : Rather True, PT: Possible True

PF: Possible False, RF: Rather False, VF: Very False, UN: Unknown

2.3 Inference Algorithm

The knowledge is obtained in the form of LTV including ambiguities, but for a computation the conversion to NTV(Numerical True Value) is needed. Such a quantification is performed by using membership function. Determination of the corresponding membership function for each LTV is made using α-cut value. The inference algorithm is derived from the propositions (1) and (2). Syllogism affirmative equation. (4) and syllogism negative equation (5) are substituted into propositions P_i, (2) and P_{ij}, (3), respectively, to derive equation (6) and (7)[4].

$$Z_i = [(B_j + P_i - 1) \vee 0,\ 1] \quad (4)$$

$$E_{ij} = [0,\ (B_j + 1 - P_{ij}) \wedge 1] \quad (5)$$

$$b_j = [\max_j(\min(r_{ij},\ a_i)),\ 1],\ 1 \le j \le n \quad (6)$$

$$a_i = [0,\ \min_j(1,\ b_j + 1 - P_{ij})],\ 1 \le i \le m \quad (7)$$

Equations(6) and (7) are the Lower Bound and Upper Bond , respectively. True value of the proposition P_j is completely true, i.e., (r_{ij} membership function is 1.0). True value of the proposition P_{ij} is a value within[0, 1] when it is close to the truth. The common solution for the cause a_i can be obtained from equations (6) and (7) . Therefore, the upper and lower bounds of a_i can be obtained by equations (8) and(9) [5].

$$0 \le b_j \le \max_j (\min(r_{ij}, a_i)),\ 1 \le j \le n. \quad (8)$$

$$0 \le a_i \le \min_j (1,\ b_j + 1 - p_{ij}),\ 1 \le I \le m. \quad (9)$$

The solution of equations (8) and(9) satisfies the following relationship:

$$\max_j\ (\inf (w_{ij}(k)))\ \ a_i\ \ \min_j\ (\sup(e_{ij}))$$

Where, $e_{ij} = [0,\ \min(1,\ b_j + 1 - p_{ij})]$,

$W_{ij}(K) = \{ U_{ij}$ for $\exists\ 1^i \in \{i \mid U_{ij} \ne 0\},\ V_{ij}$ for other i's

$$U_{ij} = r_{ij}\ \omega\ b_i = \begin{cases} b_i & \text{if } r_{ij} > b_i \\ [b_i, 1] & \text{if } r_{ij} = b_i \\ \phi & \text{if } r_{ij} < b_i \end{cases}$$

$$V_{ij} = r_{ij}\ \omega\ b_i = \begin{cases} [0,\ b_i] & \text{if } r_{ij} > b_i \\ \phi & \text{if } r_{ij} \le b_i \end{cases}$$

$$\phi \cap \phi = \phi, \quad \phi \cap G = G$$

These combination symbols are used to represent the solution algorithm in the next section

2.4 Solution Algorithm

(1) Obtain matrix U and V

$$U = \{U_{ij}\} = \{r_{ij}\ \omega\ b_j\}$$

$$V = \{V_{ij}\} = \{r_{ij}\ \omega\ b_j\}$$

(2) Obtain matrix

$$W = \{W_{ij}\}.$$

$$W_{ij}(k) = \begin{cases} U_{ij} \text{ for } \exists 1^i \in \{ i \mid U_{ij} \ne 0 \} \\ V_{ij} \text{ for other i's} \end{cases}$$

(3) Compute $\inf(W_{ij}(k))$.

(4) Compute $\max_j(\inf(W_{ij}(k)))$

(5) Compute e_{ij}

(6) Compute $\sup(e_{ij})$.

(7) Compute $\min_j(\sup(e_{ij}))$

(8) Determine the event using the following equation.

$$\max_j(\inf(W_{ij}(k)) \le a_i \le \min_j(\sup(e_{ij}))$$

2.4 An Example using the solution algorithm

Let us assume that during operation of a NPP a symptom vector $b_j = \{1,\ 0,\ 0,\ 1,\ 1\}$ is observed. For convenience of explanation binary values of 0 and 1 instead of real values in the range of [0, 1] is used for this example.

Symptom vector $b_j = \{1, 0, 0, 1, 1\}$

Relation Matrix (Completely True). Knowledge data(Discrete values are used instead of LTV)

$\longrightarrow$ symptom

case $\downarrow$

$$r_{ij} = \begin{vmatrix} 1 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 \end{vmatrix}$$

$$P_{ij} = \begin{vmatrix} 0.8 & 0.0 & 0.0 & 0.6 & 0.4 \\ 0.0 & 0.4 & 0.6 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.4 & 0.4 & 0.2 \\ 0.0 & 0.2 & 0.4 & 0.0 & 0.2 \\ 0.4 & 0.4 & 0.0 & 0.0 & 0.0 \end{vmatrix}$$

$$U_{ij} = r_{ij}\ \omega\ b_j = \begin{cases} b_j & \text{if } r_{ij} > b_j, \\ [b_j, 1] & \text{if } r_{ij} = b_j \\ \phi & \text{if } r_{ij} < b_j \end{cases}$$

$$V_{ij} = r_{ij}\ \omega\ b_j = \begin{cases} [0, b_j] & \text{if } r_{ij} > b_j \\ \phi & \text{if } r_{ij} \le b_j \end{cases}$$

$$\phi \cap \phi = \phi,\ \phi \cap G = G$$

(1) Obtain matrix and

$U = \{U_{ij}\} = \{r_{ij}\ \omega\ b_j\}$

$V = \{V_{ij}\} = \{r_{ij}\ \omega\ b_j\}$

$$U_{ij} = \begin{vmatrix} 1 & [0,1] & [0,1] & 1 & 1 \\ \phi & 0 & 0 & 1 & 1 \\ \phi & [0,1] & 0 & 1 & 1 \\ \phi & 0 & 0 & \phi & 1 \\ 1 & 0 & [0,1] & \phi & \phi \end{vmatrix}$$

$$V_{ij} = \begin{vmatrix} \phi & \phi & \phi & \phi & \phi \\ \phi & 0 & 0 & \phi & \phi \\ \phi & 0 & 0 & \phi & \phi \\ \phi & 0 & 0 & \phi & \phi \\ \phi & 0 & \phi & \phi & \phi \end{vmatrix}$$

(2) Obtain matrix $W = \{w_{ij}\}$.

It is noted that the circled values are U_{ij}'s selected from each columns and the other values are from V_{ij}.

$$W_{ij}(1) = \begin{vmatrix} \textcircled{1} & \textcircled{[0,1]} & \phi & \phi & \phi \\ \phi & 0 & \textcircled{0} & \phi & \phi \\ \phi & 0 & 0 & \textcircled{1} & \phi \\ \phi & 0 & 0 & \phi & \textcircled{1} \\ \phi & 0 & \phi & \phi & \phi \end{vmatrix}$$

$$W_{ij}(2) = \begin{vmatrix} \phi & \phi & 1 & \phi & \phi \\ \phi & 0 & 0 & 1 & \phi \\ \phi & 0 & 0 & \phi & 1 \\ \phi & 0 & 0 & \phi & \phi \\ 1 & 0 & \phi & \phi & \phi \end{vmatrix}$$

$$W_{ij}(3) = \begin{vmatrix} \phi & \phi & \phi & 1 & 1 \\ \phi & 0 & 0 & \phi & \phi \\ \phi & 0 & 0 & \phi & \phi \\ \phi & 0 & 0 & \phi & \phi \\ \phi & 0 & \phi & \phi & \phi \end{vmatrix}$$

$$W_{ij}(4) = \begin{vmatrix} \phi & \phi & \phi & \phi & \phi \\ \phi & 0 & 0 & \phi & 1 \\ \phi & 0 & 0 & 1 & \phi \\ \phi & 0 & 0 & \phi & \phi \\ \phi & 0 & \phi & \phi & \phi \end{vmatrix}$$

→ Min values for each row

$$W_{ij}(5) = \begin{vmatrix} 1 & \phi & \phi & \phi & \phi \\ \phi & 0 & 0 & \phi & 1 \\ \phi & [0,1] & 0 & \phi & \phi \\ \phi & 0 & 0 & \phi & \phi \\ \phi & 0 & [0,1] & \phi & \phi \end{vmatrix} \quad \begin{matrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{matrix}$$

(3) Compute $\inf(W_{ij}(k))$

X(1) = (1, 0, 0, 0, 0)

X(2) = (1, 0, 0, 0, 0)

X(3) = (1, 0, 0, 0, 0)

X(4) = (Φ, 0, 0, 0, 0)

X(5) = (1, 0, 0, 0, 0)

↓ Find max values in this direction

(4) Compute $\max(\inf(W_{ij}(k)))$, which is lower bound of a_i.

j

(1, 0, 0, 0, 0)

(5) Compute $e_{ij} = [0, \min(1, b_j + 1 - t_{ij})]$

Sup(e_{ij})

e_{11} = [0, min (1,1 + 1 - 0.8)] → 1
e_{12} = [0, min (1,0 + 1 - 0)] → 1
e_{13} = [0, min (1,0 + 1 - 0)] → 1
e_{14} = [0, min (1,1 + 1 - 0.6)] → 1
e_{15} = [0, min (1,1 + 1 - 0.4)] → 1

e_{21} = [0, min (1,1 + 1 - 0)] → 1
e_{22} = [0, min (1,0 + 1 - 0.4)] → 0.6
e_{23} = [0, min (1,0 + 1 - 0.6)] → 0.4

$e_{21} = [\ 0,\ \min\ (1.1 + 1 - 0)\ ] \rightarrow 1$
$e_{25} = [\ 0,\ \min\ (1.1 + 1 - 0)\ ] \rightarrow 1$
$e_{31} = [\ 0,\ \min\ (1.1 + 1 - 0)\ ] \rightarrow 1$
$e_{32} = [\ 0,\ \min\ (1.0 + 1 - 0)\ ] \rightarrow 1$
$e_{33} = [\ 0,\ \min\ (1.0 + 1 - 0.4)\ ] \rightarrow 0.6$
$e_{34} = [\ 0,\ \min\ (1.1 + 1 - 0.4)] \rightarrow 1$
$e_{35} = [\ 0,\ \min\ (1.1 + 1 - 0.2)] \rightarrow 1$

$e_{11} = [\ 0,\ \min\ (1.1 + 1 - 0)\ ] \rightarrow 1$
$e_{12} = [\ 0,\ \min\ (1.0 + 1 - 0.2)\ ] \rightarrow 0.8$
$e_{13} = [\ 0,\ \min\ (1.0 + 1 - 0.4)\ ] \rightarrow 0.6$
$e_{14} = [\ 0,\ \min\ (1.1 + 1 - 0)\ ] \rightarrow 1$
$e_{15} = [\ 0,\ \min\ (1.1 + 1 - 0.2)\ ] \rightarrow 1$

$e_{51} = [\ 0,\ \min\ (1.1 + 1 - 0.4)\ ] \rightarrow 1$
$e_{52} = [\ 0,\ \min\ (1.0 + 1 - 0.4)\ ] \rightarrow 0.6$
$e_{53} = [\ 0,\ \min\ (1.0 + 1 - 0)\ ] \rightarrow 1$
$e_{54} = [\ 0,\ \min\ (1.1 + 1 - 0)\ ] \rightarrow 1$
$e_{55} = [\ 0,\ \min\ (1.1 + 1 - 0)\ ] \rightarrow 1$

(6) Compute $\sup(e_{ij})$

$\longrightarrow$ Min values for each row.

$$\sup(e_{ij}) = \left| \begin{array}{ccccc|c} 1 & 1 & 1 & 1 & 1 & 1.0 \\ 1 & 0.6 & 0.4 & 1 & 1 & 0.4 \\ 1 & 1 & 0.6 & 1 & 1 & 0.6 \\ 1 & 0.8 & 0.6 & 1 & 1 & 0.6 \\ 1 & 0.6 & 1 & 1 & 1 & 0.6 \end{array} \right.$$

(7) Compute $\min_j(\sup(e_{ij}))$, which is upper bound of a_i

(1, 0.4, 0.6, 0.6, 0.6)

(8) Determine which event occurs

$$\left| \begin{array}{c} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{array} \right| \le \left| \begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array} \right| \le \left| \begin{array}{c} 1 \\ 0.4 \\ 0.6 \\ 0.6 \\ 0.6 \end{array} \right|$$

Therefore presently the event a_1 occurs

Ⅲ. Accident Diagnosis of a NPP

For the analysis of transient and accident conditions of a NPP, the NPP system is modeled as several separate volumes and connecting junctions inside which the reactor coolant flows using a special computer code such as RETRAN. The RETRAN model of NPP is shown in Fig. 2.

Firstly normal operation conditions are simulated using this NPP model by setting the operation variables such as temperature, pressure, thermal power output, and flow rate, etc. Then transient or accident condition may be simulated for a specific case to be studied. The trends of various parameters such as temperature and pressure can be observed as the simulated transient or accident event progresses.

3.1 Selection of accident event cases

The following 7 events are analyzed in this paper.

(1) FLB: Feed water line break

In a NPP, the heat from the nuclear fission energy is transferred from the primary system to the secondary system in order to make steams in the steam generator. Feed water is supplied to the steam generator. FLB occurs when the feed water pipe line breaks, consequently, feed water can not be supplied to the steam generator.

(2) SLB: Steam Line Break

Steam line carries steam from the steam generator to the turbine generator. SLB occurs when there occurs a break in the steam line.

(3) SGLR : Steam Generator Tube Rupture

The steam generator has thousands of fine tubes to make a effective heat transfer in the primary side. SGLR occurs when one of those fine tubes breaks.

(4) SBLOCA: Small Break Loss of Coolant Accident

The primary system is highly pressurized, therefore, if there is a break in the primary system the coolant leaks abrutly. SBLOCA occurs when there is a small size break in the primary system.

(5) ATWT: Anticipated Transients Without Trip

In this event, the reactor core still generates much heat although the steam can not circulate because the turbine value is closed.

(6) LOFA: Loss of Flow Accident

In this event, all reactor coolant pumps stop because the electric power is out. Therefore, the reactor core is over-heated.

(7) RTWT: Reactor Trip Without Turbine Trip

In this event, while the reactor core does not generate heat the steam still circulates in the secondary system because the turbine value is not closed. Therefore, the primary system is overcooled.

3.2 Selection of symptom Inputs

The following symptom inputs are selected based on the change rates of the variables during 20 seconds. After an accident, abrupt changes of the operation variables occur, therefore, the use of change rates for 20 seconds duration is reasonable.

[Symptom Input]

1) Pressure increase rate of the pressurizer is large
2) Pressure decrease rate of the pressurizer is large
3) Water level increase rate of the pressurize is large
4) Water level decrease rate of the pressurize is large
5) Average temperature increase rate of the reactor coolant is large
6) Average temperature decrease rate of the reactor coolant is large
7) Water level decrease rate of the steam generator is large
8) Pressure increase rate of the steam line is large
9) Pressure decrease rate of the steam line is large
10) Flow rate decrease rate of the reactor coolant is large
11) Radiactivity detection in the secondary system

3.3 Knowledge data

For the relation matrix r_{ij}, using completely true in case there is a relation between the event a_i and the symptom b_i, the membership function is set to 1. 0. True value of P_{ij} uses discrete values as shown in the following table. In order to determine the truth values in the table, RETRAN code is used to calculate the change rates during 20 seconds of symptom inputs for each accident. Then the normalization is performed based on the parameters of events which show largest change rates. The P_{ij} values are calculated as proportions to the base value.

Knowledge data (p_{ij}) from the RETRAN analysis results

Symptiom Events	1	2	3	4	5	6	7	8	9	10	11
FLB	0.0	0.02	0.0	0.0	0.0	0.0	0.98	0.0	0.02	0.0	0.0
SLB	0.98	0.0	0.98	0.0	0.98	0.0	0.4	0.98	0.0	0.2	0.0
SGTR	0.0	0.03	0.0	0.03	0.0	0.0	0.0	0.0	0.0	0.0	0.98
SBLOCA	0.0	0.98	0.0	0.98	0.6	0.0	0.0	0.0	0.14	0.27	0.0
ATWT	0.46	0.0	0.4	0.0	0.35	0.0	0.2	0.0	0.98	0.1	0.0
LOFA	0.04	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.19	0.98	0.0
RTWT	0.0	0.44	0.0	0.5	0.5	0.98	0.04	0.08	0.0	0.53	0.0

3.4 Sample Calculation

The P_{ij} values in the above table are substituted into the solution algorithm and r_{ij} is set to 1.0 (Completely true) for the related items.

Symptom: b_j = (0.05, 0.0, 0.1, 0.0, 0.03, 0.0, 0.16, 0.0, 0.2, 0.9, 0.0)

Inference Result :

Results are as follows:

max (inf(w_{ij} (k) 〈 Accident 〈 min(sup(e_{ij})):

0.00 〈 Feed Line Break 〈 0.18
0.00 〈 Steam Line Break 〈 0.02
0.00 〈 S/G Tube Rupture 〈 0.02
0.00 〈 Small Break LOCA 〈 0.02
0.03 〈 ATWT 〈 0.22
0.05 〈 Loss of Flow Accident 〈 0.92
0.00 〈 R x Trip Without TBN Trip 〈 0.02

symptom : b_j = (0.95, 0.0, 0.9, 0.0, 0.9, 0.3, 0.89, 0.1, 0.1, 0.0)

Inference result:

Results are as follows:

max (inf(w_{ij} (k) 〈 Accident 〈 min(sup(eij)) :

0.00 〈 Feed Line Break 〈 0.32
0.10 〈 Steam Line Break 〈 0.90
0.00 〈 S/G Tube Rupture 〈 0.02
0.00 〈 Small Break LOCA 〈 0.02
0.10 〈 ATWT 〈 0.12
0.10 〈 Loss of Flow Accident 〈 0.12
0.00 〈 R x Trip Without TBN Trip 〈 0.02

symptom : b_j = (0.0, 0.9, 0.0, 0.89, 0.5, 0.0, 0.1, 0.1, 0.1, 0.2 , 0.0)

Inference result :

Results are as follows:

max (inf(w_{ij} (k) 〈 Accident 〈 min(sup(e_{ij})) :

0.10 〈 Feed Line Break 〈 0.12
0.00 〈 Steam Line Break 〈 0.02
0.00 〈 S/G Tube Rupture 〈 0.02
0.10 〈 Small Break LOCA 〈 0.90
0.10 〈 ATWT 〈 0.12
0.00 〈 Loss of Flow Accident 〈 0.22
0.00 〈 R x Trip Without TBN Trip 〈 0.02

symptom : b_j = (0.8, 0.1, 0.9, 0.12, 0.85, 0.0, 0.3, 0.86, 0.1, 0.3 , 0.0)

Inference result :

max (inf(w_{ij} (k) 〈 Accident 〈 min(sup(eij)) :

0.10 〈 Feed Line Break 〈 0.32
0.30 〈 Steam Line Break 〈 0.82
0.00 〈 S/G Tube Rupture 〈 0.02
0.10 〈 Small Break LOCA 〈 0.12
0.10 〈 ATWT 〈 0.12
0.10 〈 Loss of Flow Accident 〈 0.32
0.00 〈 R x Trip Without TBN Trip 〈0.02

Ⅳ. Conclusions

In this manuscript, we have improved the fuzzy inference function in the diagnosis of abnormal conditions of complicated systems. In order to do this we simulated fuzzy relationship equation by establishing knowledge data and then developed fuzzy inference algorithm. The proposed method was applied to the accident diagnosis of a nuclear power plant. As a result of the application the diagnosis of the accident was performed satisfactorily, and even in the case that the input values are quite different from knowledge data the accident type was well identified.

When an accident occurs in the nuclear power plant the causes of the accident are to be identified according to the emergency operation guideline, and the causes can be identification after the accident progresses significantly. However, if the proposed method is applied, the accident type can be identified within 20 or 30 seconds, therefore, the corresponding operation guideline can be short time so that the appropriate actions to the accident can be taken promptly. If the proposed diagnostic system is incorporated into the expert system which protects a nuclear power plant against accidents, appropriate operators actions as well as the fast identification of the accident type can be provided, therefore, the safety of the nuclear power plant could be improved significantly

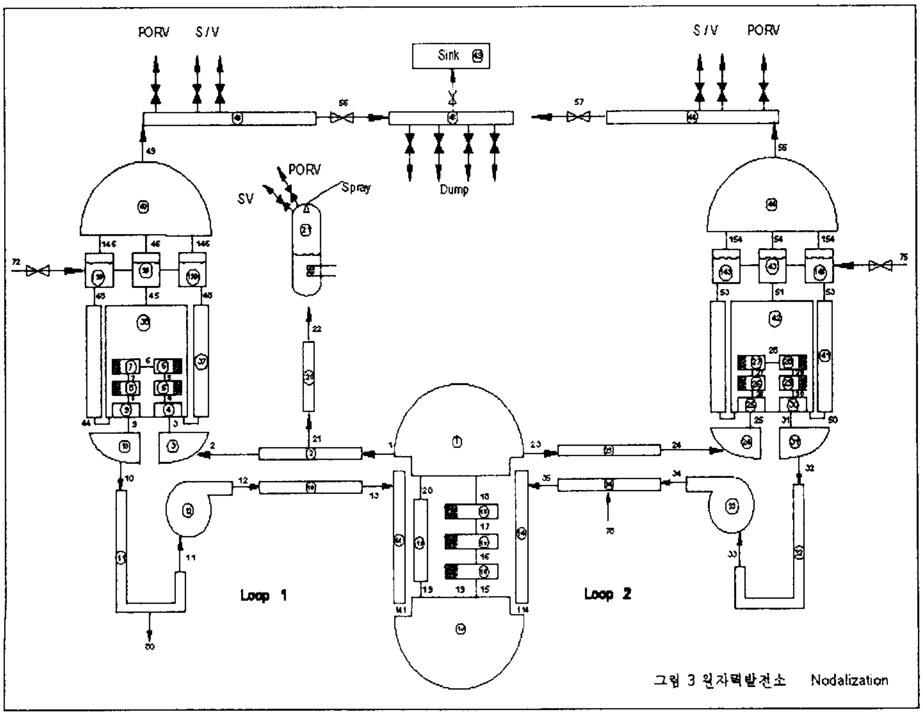

Fig 2. RETRAN model of NPP

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