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Fault Diagnosis System Using Qualitative Models and Interpreters

°S. Shin*, Seon-Ho Lee*, and Zeungnam Bien*

* Department of Electrical Engineering, Korea Advanced Institute of Science and Technology
373-1 Kusong-dong, Yusong-gu, Taejon, Korea
Tel : +82-42-869-5419 Fax : +82-42-869-8750 E-mail : ssc@ctrsys.kaist.ac.kr

Abstracts This fault diagnosis system consists of qualitative models, qualitative interpreter, and inference engine. Qualitative models are formed by analysis of the relationships between faults and behaviors of sensor trends, which are described by state transition trees. Qualitative interpreter outputs confidence factors with three qualitative quantities which represent the states of sensor trends. And then, the possible faults are detected by inference module which matches the states of trends within a window size with the qualitative models using the well-known min-max operation.

Keywords Fault Diagnosis System, Qualitative Models, Qualitative Interpreter

1. INTRODUCTION

Recently, the need for efficient alarm processing in power systems is continuously increasing as the need for quality electricity is increasing. An alarm represents an abnormal state of a power plant and is an important information for the operators in the main control room. The plant operators can easily recognize the possibility of malfunctional states of the power plant when alarms occur. Note that, because of the functional relationships among alarms, multiple alarms may be fired simultaneously and consecutively[1]. In the situation of the multiple alarms, the operators should decide causal alarm(s) and take some speedy managerial action, if necessary. The original objective of an alarm is to aid the operator in decision making, but the multiple alarms can overwhelm the operators in inferencing and decision making due to heavy cognitive requirements.

It is known[6] that about 40% to 50% of the shutdowns of a nuclear power plant are attributed to operator errors, some of which are caused by the huge volume of information presented to an operator.

Because of the functional relationships among the alarms, multiple alarms may be fired simultaneously and consecutively. A number of different alarms may be fired due to the cascading effects between them. Some primary causal alarms may occur by several possible faults of the equipments or instruments and failures in the plant. Much work has been done to process abrupt alarms[1-8].

In the field of fault diagnosis, method using the qualitative models and qualitative simulations[12], method using the qualitative model and the quantitative model of the plant[13], method using the hierarchical classification based on the functional and structural analysis of the complicated plants[10], and an approach using the fuzzy neural networks[11,9]. However, the above methods show the limit points in practical applications like as power plants.

In this paper, we propose a fault diagnosis system which receives the sensor data and processed alarms from database and detects the faulty components or instruments using qualitative quantities of sensor data and prerequisite qualitative models. Moreover, this fault diagnosis system outputs inference results and operation guidances. We applied the proposed fault diagnosis system to the simulation model of unit 4 in Seoul Fossil Power Plant. In section 2, we show the developed fault diagnosis system with alarm processing system. The qualitative model and qualitative interpreter appear in Section 3. Simulation results of the fault diagnosis system are shown in Section 4 and we conclude this paper in Section 5.

2. DESIGN OF A FAULT DIAGNOSIS SYSTEM

We developed a fault diagnosis system with an alarm processing system. The total structure of alarm processing and fault diagnosis system is shown in Fig.1. The overall system accommodates the extendibility and flexibility with hierarchical distributed structures and models. In the preprocessing unit, the transferred data from the plant are changed into the desired format in the alarm processing and fault diagnosis module. The real-time database saves the data processed in the preprocessing unit and sends the data to the other parts in the system. In alarm processing module, the primary causal alarm(s) is determined by the rules of alarm processing. Moreover, the causal alarm(s) are retrieved in fault diagnosis module. The fault diagnosis module finds the fault which has the largest possibility among the faults related to the given processed causal alarm. The fault diagnosis module uses qualitative models and sensor trends which are concerned with the faults in the given causal alarm to detect the faults occurred in the plant. The user interface screen shows the results of alarm processing and fault diagnosis module, trends of sensor data, operation guidelines, instrument specifications and historical loggers of the dealt fruits previously. More detail descriptions are following.

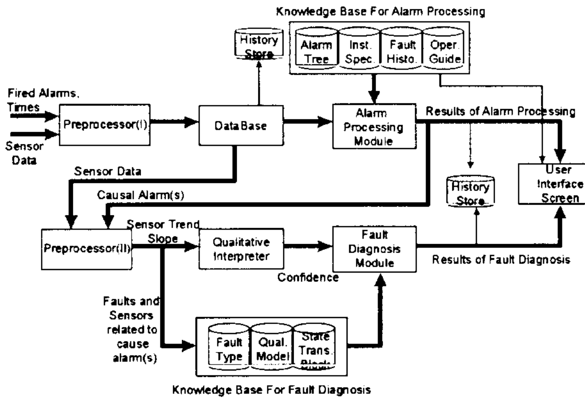


Fig. 1: Configuration of a fault diagnosis system.

3. QUALITATIVE MODEL AND INTERPRETER

In general, the fault diagonal system should finish its inference within needed interval, change the old data, and show the managed results to users. But, It is very difficult to construct a fault diagnosis system in a very large and complicated system such as a power plant. Most of all the subsystems are connected to each other with functional interactive relationships. Therefore, in this paper we introduce qualitative models which are founded on the experts knowledge and the qualitative interpreter deciding the behaviors of sensor trends qualitatively related to a given alarm in the plant. Through the qualitative models and qualitative interpreter, we find the faults for a given alarm.

The processed causal alarms and the sensor data become inputs of the fault diagnosis system. The preprocessor(II), in Fig. 1, brings the sensors, faults, and state transition trees concerned with a cause alarm. Moreover, it assorts the related sensors among all the sensors and measures the slope of the related sensors using the least-square algorithm to identify the present variations of the plant. For a given alarm, the related faults, sensors, and directions of the sensor trends enters into the qualitative interpreter.

3.1 Qualitative Interpreter

The qualitative inference calculates confidence factors for the qualitative states of the faults using the sensor values and their slopes. We modeled the variation of sensor data with 3 qualitative states like as ; increase, steady, and decrease. The equations about the confidence factor are given as follows[13].

$$\begin{aligned} CF_{inc} &= \frac{1}{1+\exp\alpha(1-\text{slope}/C)} \\ CF_{dec} &= \frac{1}{1+\exp\alpha(1+\text{slope}/C)} \\ CF_{steady} &= 1 - CF_{inc} - CF_{dec} \end{aligned} \tag{1}$$

Here, C is a cut-off slope, and α is a parameter which varies the sensitivity of equation (1). If α is very larger than one, then CF becomes step-function and if $\alpha = 0$, then $CF_{inc} = CF_{dec} = 0.5$ and $CF_{steady} = 0$. The feature of confidence functions with respect to $slope/C$ when $\alpha = 5$ are shown in Fig. 2. If the slope goes to negative values, then the confidence for "decrease" increases and the other confidence values dwindle. When the slope approaches to zero point, the CF_{std} increases and the others reduce. The sum of all the confidence factors is always 1. In the qualitative interpreter, we use the min-max algorithm in fuzzy logic to select the most appropriate qualitative state which has the largest confidence value.

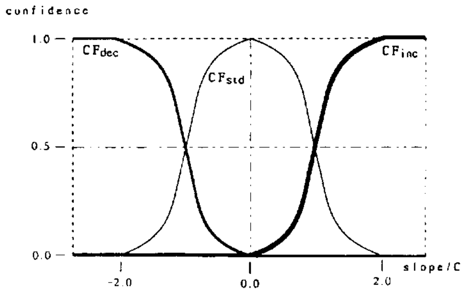


Fig. 2: Confidence factor

3.2 Qualitative Model

Qualitative model is a knowledge-base which is made off-line by the functional and structural analysis of the plant and based on the experts' experiences. In the qualitative models, firstly, we divided the faults and sensors in relation to alarms, and then modeled the motions of each related sensor data with qualitative state values. Since sensor trends are different according to each fault, we focus on the history of sensor trends. The sensors which are related to a fault are included in two class; dominant and sub-dominant sensor. The dominant sensor is connected to an alarm directly so that the alarms occurs when the value of dominant sensor exceeds set value, and the rest sensors are reserved as sub-dominant sensors. As shown in Fig. 3, we shared the operating value of dominant sensors with three parts such as high(H), normal(N), and low(L). Moreover, the operating value of sub-dominant sensors has upper portion(A) and lower portion(B) which is also depicted in Fig.3.

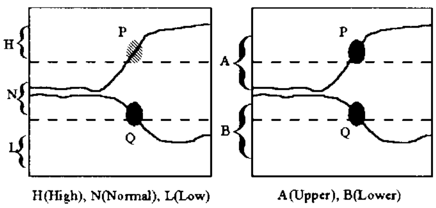
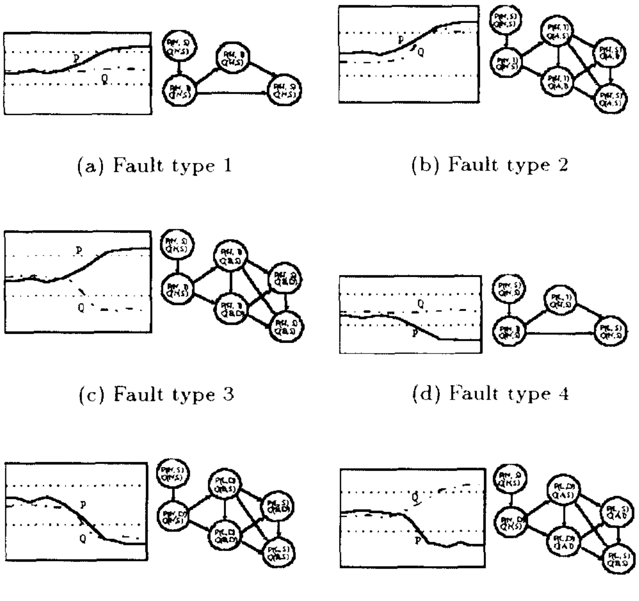


Fig. 3: Qualitative interval of dominant and sub-dominant sensor data

If the value of dominant-sensor hits a high/low set bound, the corresponding high/low alarm occurs, but there are no established alarms in the case of sub-dominant sensors directly. Thus, we divided the value of dominant sensors into 3 parts and two parts for sub-dominant sensors with considering the flexibility, i.e., the present states have more information on the present



(a) Fault type 1 (b) Fault type 2

(c) Fault type 3 (d) Fault type 4

(e) Fault type 5 (f) Fault type 6

Fig. 4: Trend variations and state transition tree for one dominant sensor and one sub-dominant sensor values in the case of sub-dominant sensors. In Fig. 4, we showed all the possible trend variations in two sensors, i.e., one is dominant and the other is sub-dominant sensor. There are 6 types for the above case as in Fig. 4. Using the qualitative states and the present sensor values, we determine the fault types and state transition trees appeared in Fig. 4 according to the fault types, respectively. As an instance, the trend of sub-dominant sensor didn't vary but the trend of dominant sensor increased in fault type-1, and both the sensor values increase in the fault type-2. Also, the others are arranged by the same manner.

3.3 Inference Procedure

In this procedure, we match the present values and states with the qualitative models in the knowledge for fault diagnosis. As the output of the qualitative interpreter in table 1, the sensor-1 is increasing, sensor-2 is decreasing, and the sensor-3 retains in steady state which are observed by the confidence factors in table 1. In table 2, qualitative states of the sensors for the inherent faults are represented. It says that the trends of sensor-1 and sensor-2 increase and sensor-3 decreases when a fault occurs.

Table 1: An example of the qualitative inference outputs

sensor \ state	increase	steady	decrease
sensor 1	0.5	0.3	0.2
sensor 2	0.1	0.2	0.7
sensor 3	0.2	0.5	0.3

From the two tables, we find that the confidence for normal operation is $\min(0.3, 0.2, 0.5) = 0.2$ and 0.5 for fault-1, 0.1 for fault-2. Therefore, $\max(0.2, 0.5, 0.1) = 0.5$, hence the fault, fault-1, is inspected through these procedures. If the present states of sensors are matched to certain faults, then we traces the histories of sensor data. Some simulation results are following in next section.

Table 2: An example of qualitative model for some fault

sensor \ state	normal	fault 1	fault 2
sensor 1	normal	increase	increase
sensor 2	normal	decrease	increase
sensor 3	normal	normal	decrease

4. SIMULATION RESULTS

We applied the proposed fault diagnosis system to a simulation system of the unit 4 in Seoul Fossil Power Plant. As one abrupt fault occurs in the auxiliary system, the related sensor values move up and down which motions are shown in the user interface screen of Fig. 5.

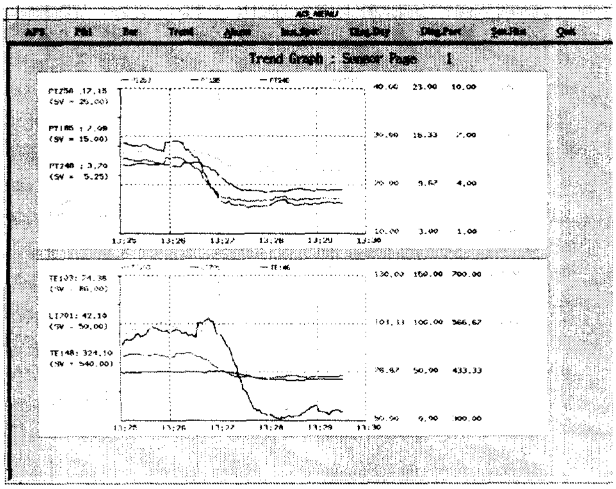


Fig. 5: Sensor Trends for one fault in auxiliary system

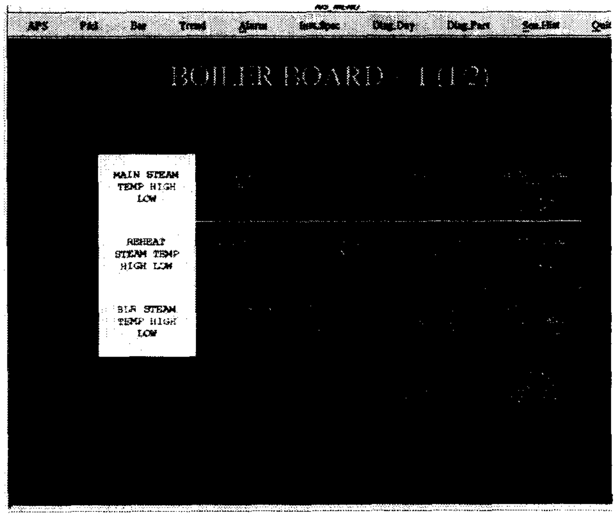


Fig. 6: Bar graphs

An alarm panel is shown in Fig. 6 and the fired alarms and the processed cause alarm are drawn in

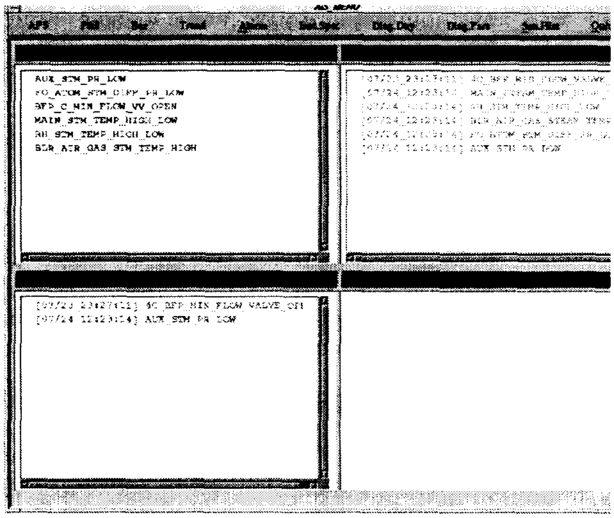


Fig. 7: Alarm processing window

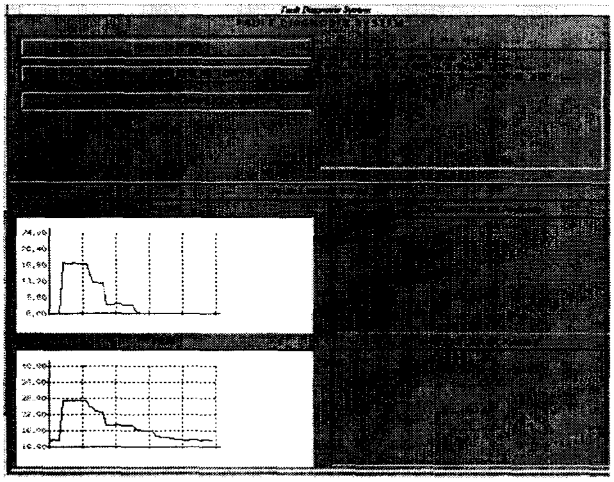


Fig. 8: Fault diagnosis window

the windows of Fig. 7. The primary causal alarm is "Aux-Stm-Press-Low" which alarm means the drop of auxiliary steam pressure. The fault diagnosis results are depicted in Fig. 8. It shows the history of related sensors, occurred-fault, and the operation sequences. By using the results, operator can control the status of power plant.

5. CONCLUDING REMARKS

In this paper, we sketched a fault diagnosis system with qualitative models and qualitative interpreter. The qualitative models are made by analysis of plant functions and operational experts' experimental knowledges according to alarms. We match qualitative states of the qualitative interpreter with the qualitative models so that detect occurred faults in the plants. For the convenience of users, we designed several windows in MMI screen. We expect that the proposed fault diagnosis system can be applied to the actual plants after some requisites are satisfied.

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