Journal of the Korean Nuclear Society
Volume 22, Number 2, June 1990

Development of an Expert System (ESRCP) for Failure Diagnosis of Reactor Coolant Pumps

Se Woo Cheon and Soon Heung Chang
Korea Advanced Institute of Science and Technology
(Received December 2, 1989)

원자로냉각재펌프 고장진단을 위한 전문가시스템의 개발

천세우 · 장순흥
한국과학기술원
(1989. 12. 2접수)

Abstract

This paper presents a prototype expert system (ESRCP) for Reactor Coolant Pumps. The purpose of this system is to diagnose RCP failures and to offer corrective operational guides to plant operators. The first symptoms for the diagnosis are the alarms which are related to the RCP domain. Alarm processing is required to find a primary causal alarm when multiple alarms occur. The system performs the alarm processing by rule-based deduction or priority factor operation. To diagnose the RCP failure, the system performs rule-based deduction or Bayesian inference. Various sensor readings are required as symptoms to infer a root cause. When the symptoms are insufficient or uncertain to diagnose accurately, Bayesian inference is performed.

요 약

본 논문에서는 원자로냉각재펌프 고장진단 전문가시스템 (ESRCP)에 대해 기술하였다. 이 시스템의 목적은 RCP의 고장진단과 함께 발전소 운전원에게 적절한 운전 조작 및 비상조치 사항 등을 알려주는데 있다. 진단을 위한 일차적 증상은 RCP 영역에 관련된 경보들이다. 경보처리는 Rule-based Deduction 또는 Priority Factor Operation에 의한다. 고장진단은 Rule-based Deduction이나 Bayesian Inference에 의해 수행된다. 각종 Sensor들의 측정값들은 정확한 원인을 진단하기 위해 필요로 하다. 증상들이 부족하거나 불확실성을 나타낼 때는 Bayesian Inference로 고장을 진단한다.

I. Introduction

Expert systems are emerging technology for organizing knowledge and applying inference, which may achieve performance comparable to human experts in closely defined domains of application. For the operation of nuclear power plants, many expert systems [1, 2] have been developed to aid operators in decisionmakings.

Most of the previously developed expert systems have been applied to the diagnosis and treatment of the infrequent accidents such as LOCA, SGTR and LOFA. Practically, these systems are not available for component specific failure. Therefore, component-wise expert systems for failure management — cause identification and treatment/recovery-may need to be developed. For the position of utilities, fast diagnosis and maintenance by use of these systems may not only save the loss of the profits, but also prevent the operator's inadvertent actions.

A prototype expert system (ESRCP) for diagnosis of RCP failure has been developed. RCP has been chosen as target domain because 1) it is an important component in maintaining a DNB limit in the NSSS and 2) its frequent failures, especially seal part, have been reported [3,4]. The RCPs in Kori-2 Nuclear Power Plant have been chosen as target domain.

In ESRCP, the diagnostic symptoms are broadly classified into two groups :*obvious* symptoms (e.g., the fired alarms associated with the RCP domain) and *non-obvious* symptoms such as parameter values and valve lineup. Due to the functional relationships between the alarms, a number of different alarms may be simultaneously or consecutively fired. In other words, a *primary causal* alarm may trigger several *consequential* alarms, i.e., symptomatic alarms. For this reason, alarm processing is required in order to find the primary causal alarm.

For cause identification, the system first tries to find a definite cause by rule-based deduction. Cause identification rules are composed of 1) the heuristic rules which are dependent on a set of symptoms and 2) the *functional* rules which describe the various operating mode logics. This rule-based deduction is only applicable to the cases of certain and sufficient symptoms.

When the symptoms are uncertain or insufficient, the diagnosis must be performed with a treatment of uncertainty. Several attempts to manage such uncertainty have been made [6,7,8,9]. The recent developments of work done by Kaplan *et al.* [10] aim to apply Bayes' theorem *straightforwardly* to diagnostic inference. Bayes' theorem provides a likelihood measure for each causal candidate. This approach deals with uncertainty in a mathematically logical way compared with the other *ad hoc* methods.

II. Description of RCP Domain

The diagnostic domain is broadly classified into two parts : the RCP and its peripheral systems. As

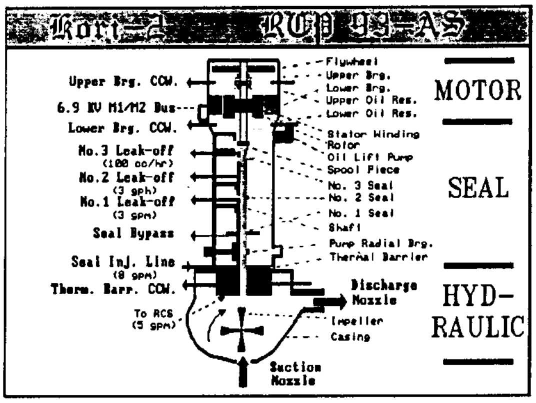

Fig. 1 The structure of RCP

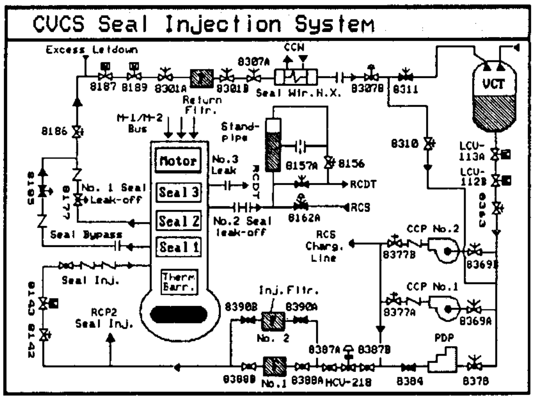

Fig.2 The Peripheral System Diagram

shown in Fig. 1, the RCP is divided into three general sections : the *hydraulic*, the *seal*, and the *motor*. Among the three sections, the seal section is an important part because severe seal damage may trigger seal-LOCA via seal leakage. In 1980, Arkansas Nuclear Plant Unit. 1 has been suffered severe seal leakages [4]. The peripheral system diagram is illustrated in Fig. 2.

The diagnostic symptoms are broadly classified into two classes, i.e., obvious symptoms and non-obvious symptoms. The obvious symptoms are 20 odd alarms which are related to the RCP domain. These symptoms are first symptoms to report RCP failures to operators. The non-obvious symptoms are instrument readings and plant computer signals. These symptoms include RCS pressure, seal injection flow, No. 1 seal leak-off flow, bearing temperature, etc.

As shown in Fig. 3, the failure modes of RCP are illustrated. The general failure modes include seal failures, vibrations, loss of seal injection flow, loss of CCW, electrical bus failure, high temperature of bearings, etc. [5].

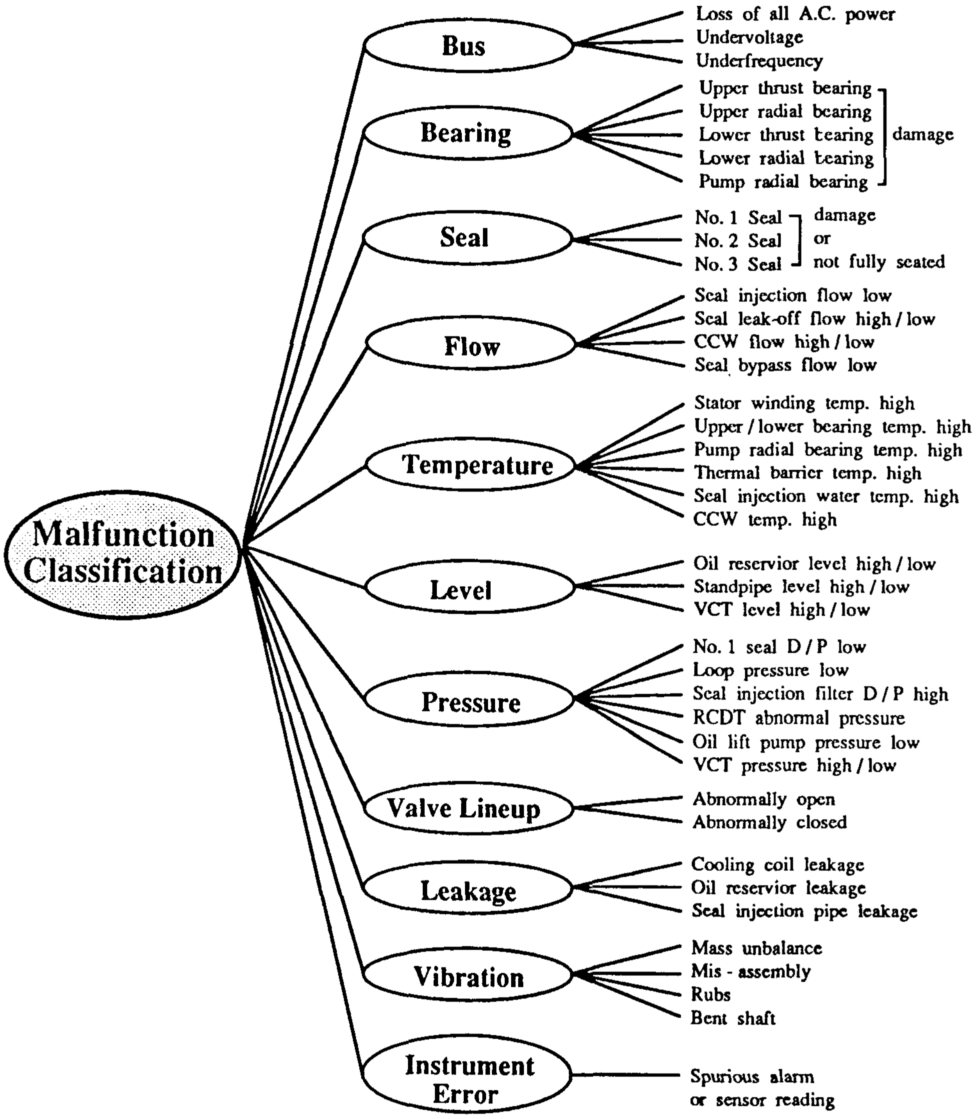

Fig.3 Malfunction Classification in ESRCP Domain

III. Development of ESRCP

III.1. The Structure of ESRCP

ESRCP was implemented on an IBM-PC/386, by using Prolog language. Prolog provides a strong capability for pattern matching and a built-in inference engine(i.e., backward-chaining and depth-first search).

As shown in Fig. 4, ESRCP consists of three main parts : an inferencing mechanism, a knowledge base and a user interface.

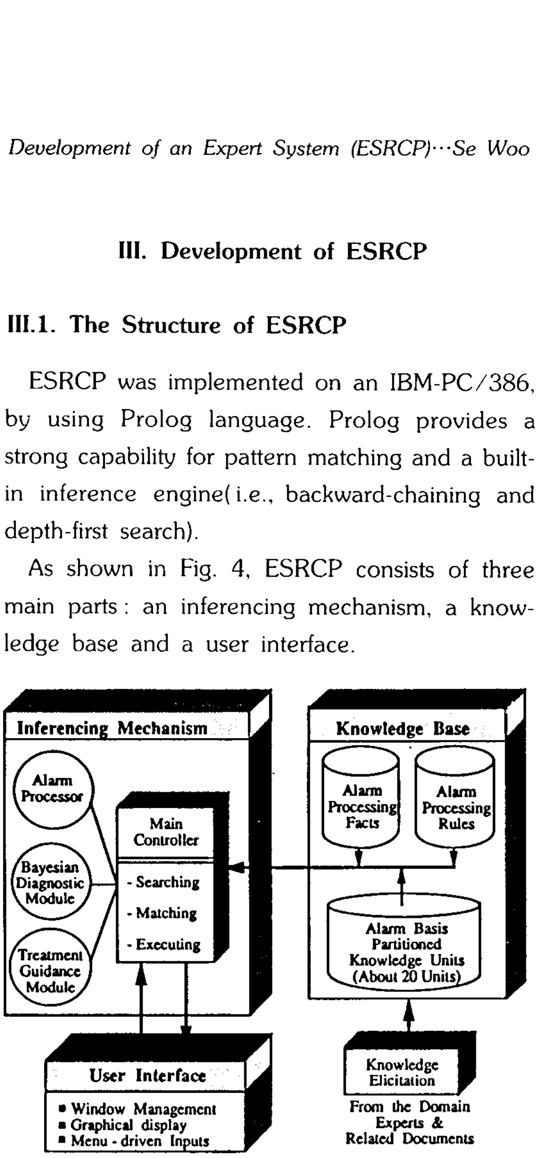

Fig. 4 The Structure of ESRCP

- The *inferencing mechanism* part which controls the search through the knowledge base, matching appropriate rules and facts, executing the rules, tracking the inference process and interacting with the user through the user interface. This part has four subcomponents : a main controller, an alarm processor, a Bayesian diagnostic module, and a treatment guidance module.
  - The *main controller* controls the whole diagnostic process.
  - The *alarm processor* finds a primary causal alarm among fired alarms by using functional rules or by priority factor operation.
  - The *Bayesian diagnostic module* infers probable causes by ranking the probabilities of their occurrences.
  - The *treatment guidance module* provides emergency actions and appropriate treatments adequate to given symptoms.
- The *knowledge base* part consists of rules and facts for alarm processing, and 20 odd partitioned knowledge units. It is available upon request to the inferencing mechanism. Each partitioned knowledge unit includes Bayesian diagnostic facts, query operation facts, cause inference rules, treatment rules, etc.
- The *user interface* part which controls window displays in a terminal and menu-driven inputs to interact with the user. This part is also essential for aiding the user to interact with the system readily.

III.2. Processing of Alarms

Alarms are generally designed to report the operator operating faults of equipment. Due to the functional relationships (e.g., flow direction, the interrelationship of parameters, pipe connectivity and time delay) between alarms, a number of different alarms may be simultaneously or consecutively fired [11, 12]. The operator must attempt to identify failed equipment and instru-

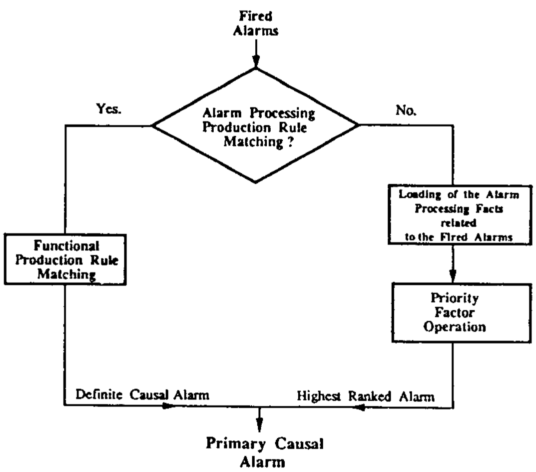

Fig.5 Flow Chart of Alarm Processing

ment and to recognize the primary causal alarm against the consequential alarms.

The alarm processing is performed by *rule matching* method or *priority factor* (PF) operation. As shown in Fig. 5, when multiple alarms occur, the alarm processor first tries to find a primary causal alarm by matching alarm processing rules. If the matching rule is not found, then the alarm processor loads alarm processing facts which are associated with the fired alarms. Next, the alarm processor performs the priority factor operation.

When the fired alarms cannot definitely show the cause-consequence relationships, i.e., uncertainty exists, the rule matching fails. In this case, the alarm processor in the inferencing mechanism performs the priority factor operation which is similar to the certainty factor operation as originated in MYCIN[6].

In Table 1, the alarm processing facts in the knowledge base are represented as:

(A_i alarm is a *causal* alarm against A_j alarm with $PF(A_i, A_j)$.)

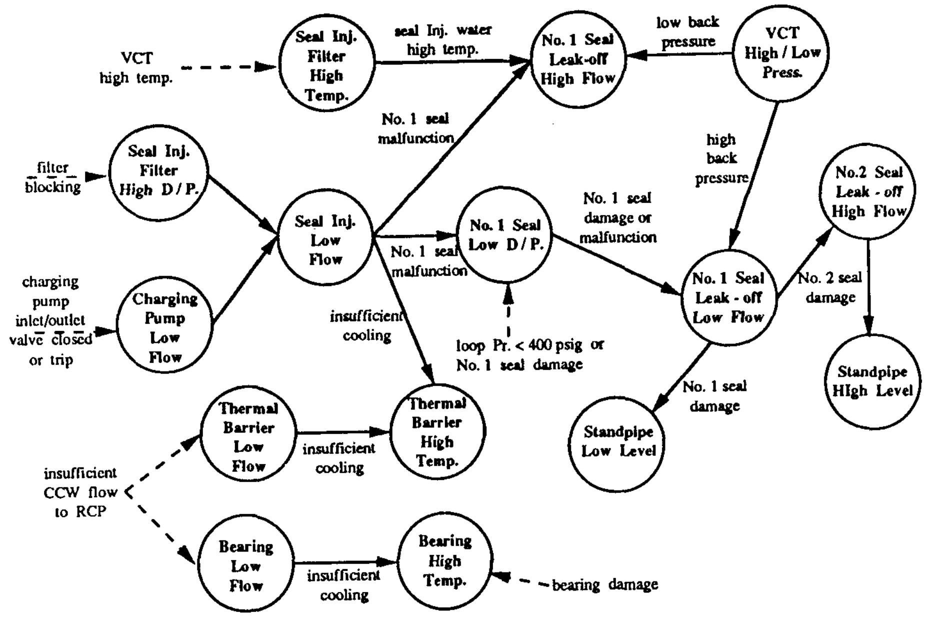

Fig.6 Cause-consequence Relationships Between the Alarms of ESRCP Domain

The priority factors vary between -1 and $+1$ The output of the rule matching is a definite primary causal alarm, while the output of the priority factor operation is the top-ranked alarm.

Alarm processing rule represents the functional relationships between the primary and the consequential alarms. This rule is only fired when multiple alarms definitely indicate the causeconsequence relationships. The causeconsequence relationships of the alarms in the RCP domain are illustrated in Fig. 6

where -1 means that the above relationship is known to be definitely false, $+1$ means definitely

Table 1. Alarm Processing Template

Consequential Alarm	Causal Alarm					
	A_1	A_2	…	A_i	…	A_n
A_1						
A_2						
⋮						
A_j				$PF(A_i, A_j)$		
⋮						
A_n						

true, and 0 corresponds to the unknown (complete uncertainty) or meaningless case. That is, positive numbers correspond to an increase in belief in the causal alarm A_i, while negative numbers correspond to a decrease in belief. In the case of $i=j$, the $PF(A_i, A_i)$ is always *zero* because the cause-consequence relation between the same alarms is meaningless.

Suppose three alarms, A_1, A_2 and A_3, are fired. In this case, the global priority factor of the A_3 alarm is obtained by the following operation.

(A_3 is a *causal* alarm against A_1 with $PF(A_3, A_1)$.
A_3 is a *causal* alarm against A_2 with $PF(A_3, A_2)$.)

In this case, these relations are combined into an effective single relation with priority factor $PF(A_3, A_1A_2)$ by using the following combination function [6].

$$
\begin{aligned}
&PF(A_3, A_1A_2) \qquad (1)\\
&= PF(A_3, A_1)+PF(A_3, A_2)-PF(A_3, A_1)\times PF(A_3, A_2)\\
&\quad \text{if } PF(A_3, A_1)\geq 0 \text{ and } PF(A_3, A_2)\geq 0\\
&= PF(A_3, A_1)+PF(A_3, A_2)+PF(A_3, A_1)\times PF(A_3, A_2)\\
&\quad \text{if } PF(A_3, A_1)<0 \text{ and } PF(A_3, A_2)<0\\
&= \frac{PF(A_3, A_1)+PF(A_3, A_2)}{1-\min\{|PF(A_3, A_1)|,\ |PF(A_3, A_2)|\}}\\
&\quad \text{if } -1<PF(A_3, A_1)\times PF(A_3, A_2)<0
\end{aligned}
$$

By applying this function, the above two relations are combined into one as :

(A_3 is a *causal* alarm against the other alarms with $PF(A_3, A_1A_2)$.)

For illustrative example, suppose three fired alarms, 'No. 1 seal D/P. low', 'No. 2 seal leak-off flow high' and 'Standpipe level high'. In this case, the alarm processor performs the priority factor operation because the functional rule matching fails. In Table 2, the results of this operation shows that the 'No. 1 seal D/P. low' is the top-ranked alarm.

III.3. Bayesian Inference

In ESRCP, diagnosis is performed in terms of levels of confidence when symptoms are uncertain or insufficient for the inferencing mechanism to find a definite cause. This system applies Bayes' theorem straightforwardly to the diagnostic inference. Bayesian inference deals with uncertainty in a mathematically logical way.

Table 2. Example of PF Operation

Consequential Alarm	Causal Alarm		
	No.1 Seal D/P. Low	No.2 Seal Leak-off High	Standpipe Level High
No.1 Seal D/P. Low	0.00	-0.60	-0.40
No.2 Seal Leak-off High	0.60	0.00	-0.80
Standpipe High Level	0.40	0.80	0.00
Global PF	0.76	0.50	-0.88

S. Kaplan *et al.* have proposed a method of inference by full use of Bayes' theorem [10]. They called this concept of inferential mechanism as the Bayesian Diagnostic Module (BDM) and provided a complete theoretical foundation and description of it. It is summarized in the followings.

For the diagnosis of system failure, Bayes' theorem takes the form :

$$p(x_i\,|\,E)=\frac{p(x_i)p(E\,|\,x_i)}{\Sigma\, p(x_i)p(E\,|\,x_i)} \qquad (2)$$

where

E : evidence observable
$p(x_i)$: prior probability of cause x_i
$p(E\,|\,x_i)$: likelihood function
$p(x_i|E)$: probability that cause x_i is true cause given evidence E

The evidence E consists of a set of evidence variables, V^k, $k=1,\ldots, K$, each of which may take on one of several possible values, v^k_j, $j=1,\ldots, J$. In Table. 3, the probable cause lists of failure, x_i, are shown across the top side. Down the left side of the table, it lists the discrete evidence variables, V^k. For each variable V^k, it lists also the possible values, v^k_j, that the V^k may take on. In each box of

Table 3. Bayesian Template

Evidence Variable V^k	Possible Values	Probable Causes x_1	x_2	$\cdots$	x_i	$\cdots$
V^1	v_1^1 $\vdots$ v_j^1 $\vdots$ v_J^1					
$\vdots$						
V^k	v_1^k $\vdots$ v_j^k $\vdots$ v_J^k				$p(v_j^k \mid x_i)$	
$\vdots$						
Prior					$p(x_i)$	

the table, it enters the number $p(v_j^k|x_i)$, i.e., the probability that the kth evidence variable, V^k, would take on the value v_j^k, given that the cause x_i is the true cause of failure. This table, in effect, is presentation of the likelihood function $p(E|x_i)$ of Bayes' theorem. It may think of the evidence at any moment as encoded in the set of values v_j^k, i.e., in the specializations taken on by the variables V^k at that moment. Therefore, the evidence E now consists of the set of values v_j^k:

$$E=[v_j^1, v_j^2, \ldots, v_j^k, \ldots, v_j^K] \tag{3}$$

Assume that individual evidence items v_j^k are independent to each other, then the likelihood function in Eq (2) can be represented as

$$\begin{aligned} p(E|x_i) &= p(v_j^1, \ldots, v_j^K|x_i) \\ &= p(v_j^1|x_i)p(v_j^2|x_i)\cdots p(v_j^K|x_i) \\ &= \prod_{k-1}^{K} p(v_j^k|x_i) \end{aligned} \tag{4}$$

Therefore, it can implement Bayes' theorem directly from Table 3 in the following form.

$$p(x_i|E)=\frac{p(x_i)\prod_{k=1}^{K} p(v_j^k|x_i)}{\sum_i p(x_i)\prod_{k=1}^{K} p(v_j^k|x_i)} \tag{5}$$

Thus, given the values v_j^k of the evidence variables, it can calculate the probability distribution over the x_i in a simple way using Eq. (5) and the numbers $p(v_j^k|x_i)$. Table 3 is effectively the diagnostic knowledge base.

This inference method is employed to ESRCP. The Bayesian diagnostic template for the diagnosis of 'No. 2 seal leak-off flow high' alarm is shown in Table 4.

Table 4. Example of Bayesian Template

Evidence Variables	Selected Values	Probable Causes: No.1 Seal Damaged	No.2 Seal Damaged	No.2 Seal Not Seated	Instrument Error
Operation Time	v_2^1) > 24 hr	0.600	0.600	0.300	0.400
Standpipe level	v_1^2) high	0.500	0.500	0.500	0.200
No.1 Seal D/P.	v_3^3) ≥ 450 (in psi)	0.200	0.400	0.300	0.500
Prior Prob.		0.270	0.270	0.250	0.200
Final Prob.		0.239	0.477	0.166	0.118

In this case, the evidence variable V^1 stands for 'RCP operation time' which takes on the values: v_1^1='time≤24hrs.' and v_2^1='time>24hrs.'. V^2 is the variable 'standpipe level' which takes on the values: v_1^2='high', v_2^2='normal' and u_3^2= 'low'. V^3 is the variable 'No. 1 seal D/P.' which takes on the values: v_1^3='D/P.≤210 psi', v_2^3='210<D/P.<450' and v_3^3='D/P.≥450'. In the case of the evidence $E=[v_2^1, v_1^2, v_3^3]$, the Bayesian diagnostic module infers the probable causes by using the Eq. (5) and the numbers in the template. In this case, the most probable cause is determined as "No. 2 Seal Damaged".

III.4. Diagnostic Control Strategies

As shown in Fig. 7, a flow chart of the diagnostic control process is illustrated. First, fired alarms are inputted. Next, the alarm processing is introduced. From the result of the alarm processing, the main controller loads the partitioned knowledge unit of the primary causal alarm into working memory.

The diagnosis about the primary causal alarm begins with query operation. The system interrogates various symptoms (e.g., parameter values, states of valves). During the query operation, if an inputted parameter is dangerous to the RCP, the

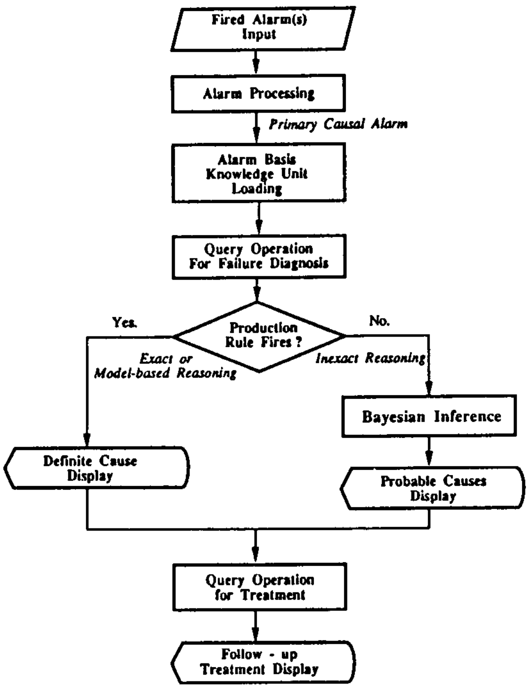

Fig.7 Flow Chart of Diagnostic Control Process

system messages the operator to take an emergency action.

When the query operation is finished, the inferencing mechanism first tries to find a cause using the production rules. If one of these rules is matched, the system displays a definite cause. If matching rule is not found, whereas, then Bayesian inference is introduced to the diagnosis. The result of this inference shows probable causes by ranking their probabilities. Next, the system displays follow-up treatments using treatment rules.

III.5. Knowledge Base of ESRCP

(a) Functional Rules

By using these rules the operating mode and component states can be definitely identified. The logic circuit of RCP underfrequency signals are illustrated in Fig. 8. In this figure, the functional rules at each gates are described in Table 5.

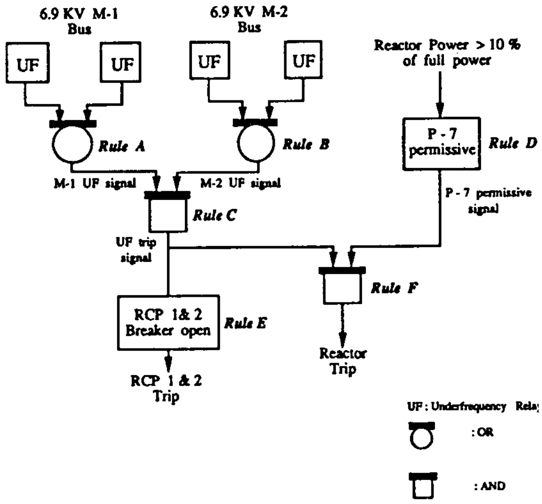

Fig.8 The Logic Diagram of RCP UF Trip

Table 5. Functional Logic Rules

Rule No.	Rule Description
A	[IF] One or two of M-1 bus UF relay is operated [THEN] M-1 bus UF signal is generated.
B	[IF] One or two of M-2 bus UF relay is operated [THEN] M-2 bus UF signal is generated.
C	[IF] M-1 bus UF signal is generated and M-2 bus UF signal is generated [THEN] UF trip signal is generated.
D	[IF] Reactor power level is above 10 % of full power [THEN] P-7 permissive signal is generated.
E	[IF] UF trip signal is generated [THEN] RCP 1 & 2 are tripped.
F	[IF] UF trip signal is generated and P-7 permissive signal is generated [THEN] Reactor trip occurs.

(b) Alarm Processing Rules

When the fired alarms can indicate deterministic relationship between the causal and consequential alarms, this rule can be fired. For example, the rule for

[IF] Only two alarms, 'No. 2 seal leak-off flow high' and 'Standpipe level high', occur

[THEN] The causal alarm is definitely 'No. 2

seal leak-off 'flow high'.

(c) Emergency Action Rules

During the query operation, if a parameter value is dangerous to RCP, the system can message to the operator with allowable emergency actions by using these rules.

(d) Bayesian Diagnostic Facts

Bayesian diagnosis is performed using the prior probabilities and the likelihood functions of causal candidates. For a given evidence, the discretized likelihood functions are represented as :

```
sub–likelihood(
  evidence(time–less–than–24hrs, yes), [
   nol–seal–damage : 0.4,
   no2–seal–damage : 0.5,
   not–fully–seat : 0.7,
   instrument–error : 0.3] ).
```

This fact is fired when the value of the 'time_less_than_24hrs' query item is 'yes'. The crucial contributors of the Bayesian inference are the discretized likelihood functions.

(e) Cause Inference Rules

Some given set of symptoms can definitely draw a hypothesis. Therefore, these rules are only fired when there is no uncertainty in solving a hypothesis. For example, in the case of the diagnosis of 'Seal injection flow low' alarm, a sample rule is as follows.

[IF] Seal injection flow is truly below normal rate and
Charging pump is operated well and
Seal injection valve lineup is correct and
Seal injection filter D/P. is more than 19.2 psig
[THEN] The definite cause is 'filter blockage'

This rule consists of the [IF] clause that represents a set of discretized evidences and the [THEN] clause that represents a definite cause.

(f) Follow-up Treatment Rules

This rule can infer appropriate follow-up treatment according to RCP trend. This rule is fired with a set of operational guidances to restore abnormal RCP state to normal.

IV. Results and Discussions

IV.1. Single Alarm Diagnosis

When 'No. 1 seal leak-off low flow' alarm occurs, the diagnostic procedure is as follows.

The operator inputs this alarm through the checker alarm menu as shown in Fig. 9. Because a single alarm is inputted, the system skips the alarm processing step and loads this alarm's partitioned knowledge unit. Next, the system requires to input several symptoms. After the query operation, the system tries to find a definite cause by the rule-based deduction. In this case, since the symptoms are insufficient and uncertain to determine a definite cause, a rule is not fired. Therefore, the system performs the Bayesian inference. The result is shown in Fig. 10.

IV.2. Multiple Alarm Diagnosis

When 'No. 1 seal D/P. low', 'Thermal barrier temperature high' and 'Seal injection flow low' alarms occur, the diagnostic procedure is as follows.

The alarm processor tries to find the primary causal alarm by the rule-based deduction. In this case, the matching functional rule is not found. In turn, the alarm processor ranks three alarms by the priority factor operation. From the result of this, the 'Seal injection flow low' alarm is chosen as the primary causal alarm. Next, the system provides the ranked alarm menu as shown in Fig. 11. The first option is the highest ranked alarm. By selection of this option, the diagnosis of the primary causal alarm can be performed. During query operation, if symptoms are dangerous to the RCP, the system messages the operator to take an emergency action as shown in Fig. 12. After the query operation, the system tries to find a definite

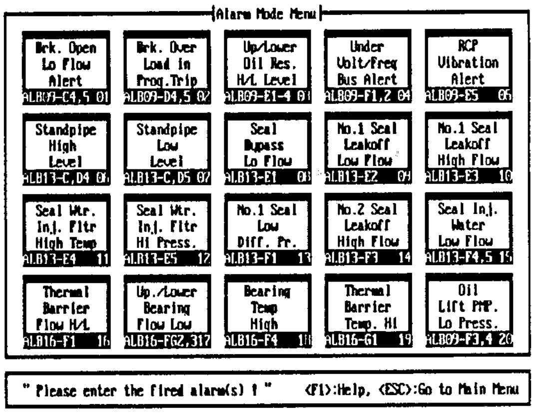

Fig.9 Checker Alarm Menu

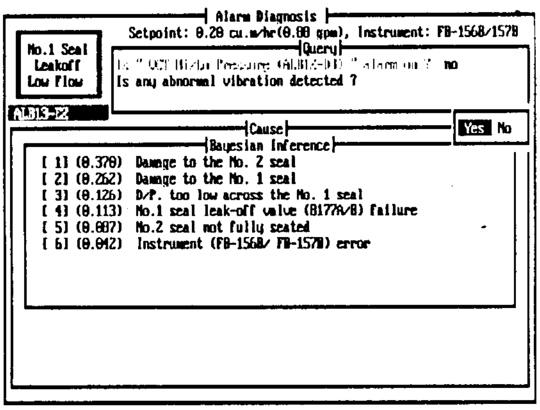

Fig.10 The Result of Bayesian Inference in the Case of Single Alarm

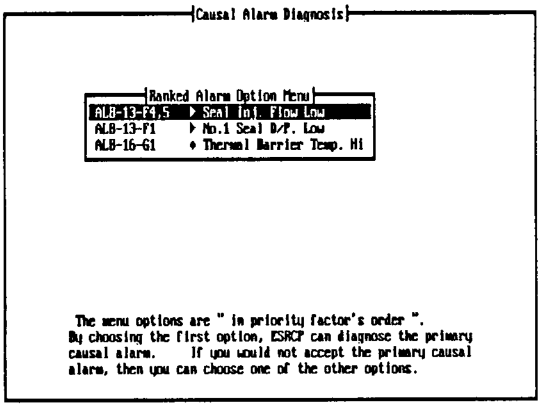

Fig.11 Ranked Alarm Menu

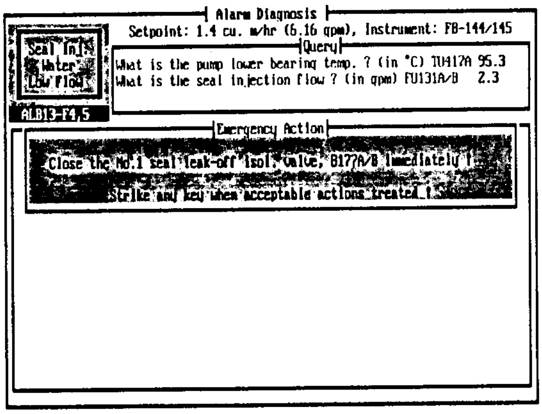

Fig.12 Display of an Emergency Action During Diagnosis

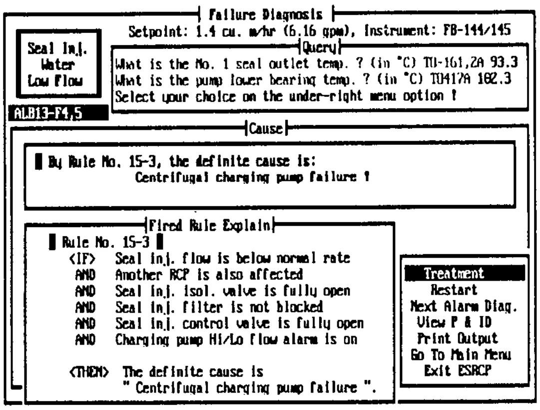

Fig.13 The Result of Fule-based Deduction in the Case of Multiple Alarm

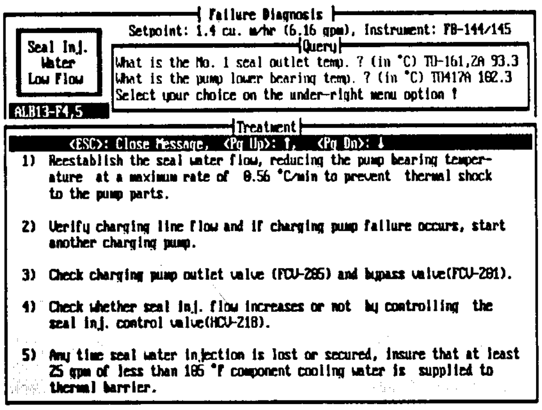

Fig.14 Follow-up Treatment Messages

cause using the cause inference rules. In this case, one of these rules is fired. Therfore, the system displays a definite cause as shown in Fig. 13 and skips the Bayesian inference step. Finally, the system provides appropriate follow-up treatments to the operator as shown in Fig. 14.

V. Conclusions

A component-wise expert system (ESRCP) for RCP failure diagnosis and operational guidances has been developed for Kori-2 Nuclear Power Plant. This system can aid operators to diagnose RCP malfunction quickly.

Partitioning of the knowledge base into the alarm basis knowledge units enables the system to diagnose RCP malfunction quickly. Moreover, updating of the knowledge base is easy and simple. This system diagnoses malfunction in parallel with the generation of operational guidance.

The knowledge elicitation process plays an important role in the accuracy and integrity of the knowledge base. The priority factors and the likelihood functions are ranked by means of the empirical knowledge elicited from the domain experts. Fine tuning of these values is performed by several tests of execution results. If the diagnostic results are not reasonably accepted under a given set of symptoms, revision of these values enables the system's performance to be increased.

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