A DIAGNOSIS METHOD OF DYNAMIC SYSTEM USING THE KNOWLEDGE ON SYSTEM DESCRIPTION

Naoyuki Yamada and Hiroshi Motoda
Energy Research Laboratory,
Hitachi Ltd.
1168 Moriyamacho, Hitachi,
Iharaki 316, Japan

ABSTRACT

A method is proposed for automatic diagnosis of a dynamic system. It basically uses only the knowledge on system description and does not require any knowledge concerning failure causality. The diagnosis consists of the four steps: expectation value computation, suspects computation, suspects discrimination using observable data and suspects discrimination by test generation. Linear input resolution is used with explicit meta-level control. This method can diagnose in principle all kinds of failures that are logically diagnosable if the system description is appropriate. The capability of the method is demonstrated by an application example of a nuclear reactor feed-water system.

I INTRODUCTION

Well established approach of identifying the cause of anomaly in a dynamically changing system is to use the pre-analyzed scenario of event propagation. A typical example is Disturbance Analysis System (DAS) based on Cause-Consequence Tree (CCT) CMeijer and Frogner, 19803. DAS has useful pre-alarming and diagnosis capabilities that can cover a variety of forseen circumstances. Its efficiency comes from its use of a set of explicitly enumerated faults but building a CCT that covers almost all possible faults is a complicated and difficult task.

New approach has recently been proposed utilizing the knowledge engineering technique [Nelson, 19823CUnderwood, 19823 CChandrasekaran, 19823. Application of this technique to plant diagnosis offers the following advantages:

1) Complex phenomena that propagate through various plant components can be represented in terms of logical event chains.

2) The diagnostic ability can be easily imporved by modification of the knowledge base.

3) It can explain its line of reasoning in reaching a conclusion.

4) Knowhows that are heuristic and have been accumulated through experts' experiences can be utilized in problem solving.

This approach differs from the above in that it does not require explicit enumeration of each scenario, but it still requires cause-result relationship as a piece of knowledge. In this regards, what is not expressed in this knowledge is out of scope of diagnosis.

Another approach that has also recently been proposed is to use the knowledge about system description, i.e. intended structure and expected behavior. Application of this technique to computer hardware diagnosis showed its capability of solving the problem without requiring causality relationship CGenesereth, 1981 and 19823 CDavis etc., 19823.

This paper introduces an attempt to extend this technique to a diagnositic problem of a dynamic system that has feedback loops. The advantages listed above also apply to this approach.

II DIAGNOSIS PROBLEM

The problem to be solved is simply stated as follows:

CGiven a symptom indicating anomaly of some observable signal from some detector at some time, identify a faulty component or components of a plant that caused the observable symptom.3

The main differences of this diagnosis from that of computer hardware are:

1) The system is dynamic, i.e. the observable signals are time dependent.

2) The system forms feedback loops, i.e. inputs of some components are affected by outputs of themselves as well as of other components with some time lag.

3) Many of the important signals are observable.

4) Some of the important components are redundant.

Although the form of test generation is limited, there still are ways to do it, thereby focusing a suspect component.

III SYSTEM DESCRIPTION

The method described here expects as data a full description of a plant to be analyzed. The degree of sophistification of behavior description is determined by its capability of distinguishing a normal state from an abnormal state. The knowledge representation used for system description is based on MRS CGenesereth, 19813. Its syntax is same as that of predicate calculus.

A. Structure Description

The structure of a system is specified by describing components, interconnections and states.

1. Component Description

Each component is deisgnated by an atomic name and its type is specified by Type statement. Three examples are given below.

```
(Type A Sensor)  (Type B Selector)
(Type C Pump)
```

2. Connectivity Description

Each component has zero or more inputs and outputs. Connectivity relationship among components is specified by Conn statement. One example is given below.

```
(Conn (output 1 C) (input 2 A))
```

3. State Description

Some components need information about their states. This information refers to on/off state, observability, redundancy, swithcing condition, etc.. Four examples are given below.

```
(Value (input 1 A) on)
(Observable (value (output IB)))
(Redundant C D)
(Swltchable (value (Input IB)))
```

B. Behavior Description

The behavior of a system is specified by describing the relationship between its input(s) and output(s) of each component In terms of rules. Behavior of a component in a dynamic system is usually described by a differential equation, which is often discretized to a set of arithmetic expressions.

1. Dynamics Description

The rules relating input(s) to output(s) are denoted as forward behavior rules (FB rules) and these relating output(s) to input(s) as backward behavior rules (BB rules). Simulation of the system behavior requests use of the FB rules but inference requests use of both rules. Use of the BB rules is encountered in inferring unobervable input(s) to a component from observable output(s) of sensor(s).

a. Forward Behavior Rules

Two examples are given. The first is a sensor behavior and the second a controller behavior. OK means that a component is not faulty. Symbols starting with $ mean that these are variables. The statement (True A B) means that A is true in situation B.

The first rule says that the sensor is a two-input, one-output device, one input being an on/off switch and the other sensing a quantity mi, and that if the sensor is on and functioning normally, the output mo is mi/mr, where mr is a scale factor. This is true for every t. The second rule is more complicated. The output of the controller mo at time t is computed by a function f that requires 6 variables, one of which is the output mi itself at the previous time step s. In these rules meta-knowledge is used to determine where to perform numeric computation.

```
(if (Type $x Sensor)
  (if (and (OK $x)
        (Value (input 1 $x) on)
        (True (value (input 2 $x) $mi) $t)
        (Value (rated $x) $mr)
        (= $mo (/ $ml $mr)))
      (True (value (output 1 $x) $mo)
            $t)))

(if (Type $x Controller)
  (if (and (OK $x)
        (True (value (input 2 $x) $11) $s)
        (True (value (input 3 $x) $wfl) $s)
        (True (value (Input 4 $x) $wml) $s)
        (True (value (output 1 $x) $ml) $s)
        (Value (Input 1 $x) $ld)
        (= $t (+ $s 1))
        (True (value (input 2 $x) $lo) $t)
        (= $mo f($ml $11 $lo $ld $wfl
                 $wml)))
      (True (value (output 1 $x) $mo)
            $t)))
```

b. Backward Behavior Rules

The following rule coresponds to the first example above.

```
(if (Type $x Sensor)
  (if (and (OK $x)
     (True (value (output 1 $x) $mo) $t)
     (Value (input 1 $x) on)
     (Value (rated $x) $mr)
     (= $mi (* $mo $mr)))
    (True (value (input 2 $x) $mi) $t)))
```

2. Connectivity Description

There needs a set of rules that interprets the connectivity relationship. These are rules that if two ports are connected, they always bear the same value.

a. Forward Connectivity Rule (FC rule)

```
(if (and (Conn $x $y)
         (True (value $x $z) $t))
    (True (value $y $z) $t))
```

b. Backward Connectivity Rule (BC rule)

```
(if (and (Conn $x $y)
         (True (value $y $z) $t))
    (True (value $x $z) $t))
```

IV METHOD OF DIAGNOSIS

The diagnosis consists of the following four steps.

A. Computation of Expectation Value

Start of diagnosis is an interpretation that the symptom does not match the expectation. It is, therefore, necessary to estimate the expected value of the sensor where an anomaly is detected. To do this, plant dynamics has to be simulated starting from some initial state. It is not necessary to go back to a state where all components were normal because the input and output relationship of a normal component is consistent regardless of the value of its input(s). It is sufficient, in a dynamic system having feedback loops, to go back at least to the time t-2A and use a set of consistent observable data, where t is the time of anomaly detection and *A* is the maximum difference of time for input(s) of any component to affect output!s) of any other component including itself in solving the dynamics by time discretization.

Inference is made in two steps. First, forward chaining is applied to obtain unobservable data at time t-2 starting from the observable da£a at time t-24 using the structure data, BB and BC rules assuming all components are normal. Next, forward chaining is applied to obtain the expectation value of the anomaly detected sensor at time t starting from the estimated unobservable data using the structure data, FB and FC rules.

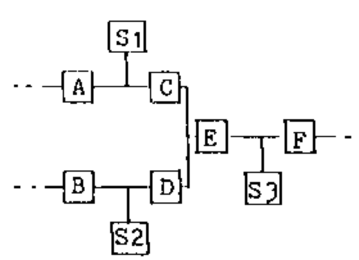
B. Computation of Suspects

Using the fact that the symptom is against the expectation, all components that can logically be responsible for the symptom are picked up as suspects. Linear input resolution is applied starting from the expectation violation at time t until it reaches the estimated unobservable data at time t-2/\ using the structure data, FB and FC rules. All rules are converted to conjunctive normal form.

C. Discrimination of the Suspects Using Observable Data

It is possible to discriminate the suspects by checking the consistency of the available observable data. Here, consistency means that the observed output(s) can be expected from the observed input(s) using the knowledge on system description. The knowledge required in this step is the structure data, FB, BB, FC and BC rules.

Inference is made in two steps. First, a set of observable data required to identify the anomaly of one or more components is searched. Symbolic simulation is performed by resolution starting from the FB rule of any one of the suspect candidates. Because the feedback nature of the system necessitates concurrent use of both forward and backward rules, inference should be controlled to avoid to get into an infinite loop. In Fig. 1, for example, starting the resolution from the component C, the sensors SI, S2 and S3 are picked up as the data that



Si : Sensors
..A - F.. : Suspects

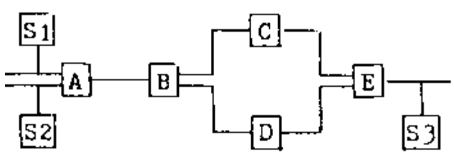
Fig. 1
An example of the suspect discrimination by observable data

can be used to identify anomaly in the components C, D and E. The sensors themselves can also be suspects in this case. This process is repeated until all suspects are grouped into smaller sets. Next, numeric simulation is performed for each set again using resolution to sheck if the observable data are consistent to each other. If they are not consistent, at least one of the components for that set is faulty.

D. Discrimination of the Suspects by Generating Tests

It is possible to further discriminate the suspects by placing single fault and non-intermittency assumptions for each set if a meaningful test can be generated and if it is successful. Use of the redundant component or valve open/close can be a realizable test in a plant disgnosis.

Inference is made in two steps. First, test form is generated. The knowledge required and the inference procedure used in this step are the same as in IV C. Figure 2 is an example of a set of suspects in which a test is possible.



Si : Sensors
E : Selector

Fig. 2
An example of the suspect discrimination by generating a test

The components C and D are redundant. Assume that the component C has been selected. The suspects at this stage are A, B, C and E. If there is still inconsistency among the data when the selector E is switched from C to D, the compponent C is exonerated from the suspects. Otherwise, the component C is faulty. The resolution starts from the redundant component D which is selected by the knowledge that C and D are redundant, the selector E is switchable and now C is selected, and is continued until the test form is obtained. Similar test can be generated in case of valve control. Next, numeric simulation Is performed using resolution, and the simulated results is evaluated against the observable data.

V APPLICATION TO A DIAGNOSIS OF A NUCLEAR REACTOR POWER PLANT

The above method is applied to a simplified model of feed-water system of a boiling water reactor shown in Fig. 3. Steam going out of the core is returned to the core by the feed-water pump after being condensed to water. Small fraction of the vapor is used to drive a turbine-driven feed-water pump. The power level is controlled by recirculation flow rate. The water level is kept constant by the controller which uses signals from water level sensor, feed-water flow meter and main steam flow meter. The condensor is assumed to serve as a source and a sink of water and vapor. The system dynamics are, thus, determined by those of the core, the controller and the pumps. The water level sensor 1 (S3) and 2 (S4), and the turbine-driven (J) and motor-driven (L) pumps are redundant components. In the normal operating condition, S3 and J are used. When S3 is used, S4 is not observable.

The following hypothetical situation is assumed. The component S3 happened to fail. The anomaly was first detected by the alarm signal of S9 at the feed-water pump outlet during a load following operation in which the plant was not in a steady state. By the time of detection, the anomaly had already propagated through various components and affected many sensor outputs although they were still within their allowable ranges except for S9.

After computing the expectation value of S9 using the past observable data (step 1), the suspects computation starts and returns the following components (step 2):

A, B, C, D, E, F, G, H, I, J, K, L, M, N, O, Q, T, S1, S2, S3, S8, S9

Use of the observable data discriminates the suspects to the following seven (step 3):

A, B, C, D, S1, S2, S3

A test is then generated knowing that S3 and S4 are redundant and S3 is in use:

[Switch the selector E to S4 from S3. If the data S1, S2 and S4 are consistent, S3 is faulty. Otherwise, the fault must lie in one of A, B, C, D, S1, S2 and S3.]

In this case, the data are consistent by the assumption, and thus, the test is successful. The faulty component is concluded to be the water level sensor 1.

All of the above diagnosis steps are automated. To improve the efficiency, heuristic knowledge is also employed and used together with the knowledge on system description. An example is a knowledge that it is worth to start resolution from the redundant component in discriminating the suspects using the observable data.

VI CONCLUSION

A method to diagnose a dynamic system with feedback structure is proposed. The method neither require a fault model nor knowledge concerning failure causality. The diagnosis is mainly based on linear input resolution with explicit meta-level control and all of the inference steps are automated.

Application to a BWR feed-water system demonstrates its diagnostic capability although the model is much simplified and the assumed anomaly is hypothetical.

Experience with example recommends combinatory use of heuristic knowledge for efficiency improvement. Employment of frame type representation of the system coupled with criteriality inference capabilty would further improve the efficiency. It is important to distinguish logical inference from simulation.

ACKNOWLEDGEMENTS

This paper is based on the work performed at Teknowledge. Authors are grateful for Profs. M. R. Genesereth and E. H. Shortliffe of Stanford University for their consultation. They extend their thanks to Drs. T. Kiguchi and S. Kobayashi for their critical discussions, and to Drs. S. Yamada and K. Taniguchi for their support of this work.

REFERENCES

[1] Meijer, C. H. and B. Frogner, "On-line Power Plant Alarm and Disturbance Analysis System," EPRI, NP-1379, April (1980)

C2D Nelson, W. R., "REACTOR: An Expert System for Diagnosis and Treatment of Nuclear Reactor Accidents," Proc. of the National Conference on Artificial Intelligence, 296 (1982)

[3] Underwood, W. E., "A CSA Model-Based Nuclear Power Plant Consultant," Proc. of the National Conference on Artificial Intelligence, 302 (1982)

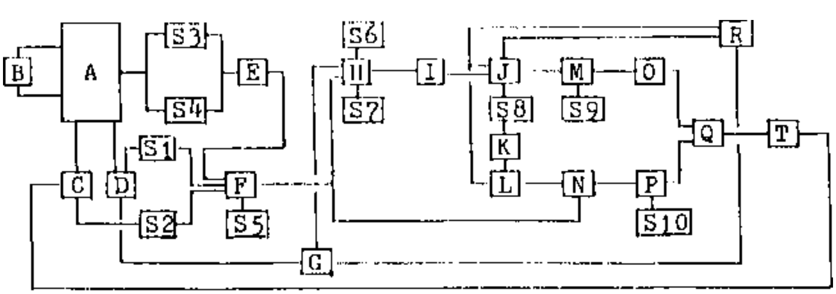
C4D Chandrasekaran, B., D. D. Sharma and D. W. Miller, "The Application of Knowledge-Based Systems to Reactor Operations," Trans. Am. Nucl. Soc, 43, 241 (1982)

[5] Genesereth, M. R., "The Use of Hierarchical Design Models in the Automated Diagnosis of Computer Systems," HPP-81-20, Stanford University Heuristic Programming Project, December (1981)

C63 Genesereth, M. R., "Diagnosis Using Hierarchical Design Models," Proc. of the National Conference on Artificial Intelligence, 278 (1982)

[7] Davis, R., H. Shrobe, W. Hamscher, K. Wieckert, M. Shirley and S. Polit' "Diagnosis Based on Description of Structure and Function," Proc. of the National Conference on Artificial Intelligence, 137 (1982)

[8] Genesereth, M. R., R. Greiner and D. E. Smith, "MRS Mannual," HPP-81-6, Stanford University Heuristic Programming Project, December (1981)



Core	: A
Feed-water controller	: F
Water level selector	: E
Recirculation pump	: B
Feed-water pump	
Turbine-driven (main)	: J
Motor-driven (aug)	: L
Valve	: H, N, O, T
Condensor	: R
Pipe	: C, D, G, I, M, P, Q
Sensor	: S1 - S10
Water level sensor 1	: S3
Water level sensor 2	: S4
Pump outlet flow meter	: S9
Interlock	: K

Fig. 3 Simplified diagram of feed-water system of a BWR