An Immune Network Approach for Sensor-Based Diagnosis with Sensor Faults: An Experimental Simulation for Cement Plant *

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Key Words - immune nets; distributed evaluation; sensor network; process diagnosis; sensor faults; self-organization; probabilistic reasoning, distributed AI

Abstract

We deal with the problem of evaluating the system reliability where the probabilistic reasoning cannot apply due to the existence of cyclic structure of probabilistic dependence. The evaluation can be done by multiagents whose reliabilities are evaluated by other agents. The dynamics of the reliabilities will be expressed by a continuous dynamical equation, hence allowing the method applicable to the dynamical environment such as evaluating reliabilities of sensors of process plant, based on the dynamically changing sensor values.

A sensor network for applying the model to the sensor self-diagnosis of process plants, is formalized. The sensor network introduces mutual testing among sensor values by the constraint between sensor values, thus allows locating faulty sensor. The simulation for the firing section of a cement plant is also presented as an example of industrial application. It is demonstrated that the model can diagnose multiple fault and that it can reflect ambiguous situation in the diagnosis. Several modifications on the model, which can be applied to sensor fault diagnosis of process plants,also is proposed.

1 Introduction

Reliability approach has been studied extensively and demonstrated extreme power in design and maintenance of complex engineering systems such as aeronautic systems and atomic power plants. For some situations, however, the reliability approach may become difficult due to the difficulty of aggregating components reliability into system reliability because of the components couple with each other in functionally complex manner. Further, static view of reliabilities computed by statistic way sometimes become the limitation. In other words, the dynamic view of reliability, which determine the components reliability that depends with each other in the system context, rather than one way determination of reliabilities from components to system.

On the one hand, probabilistic reasoning has been extensively studied [2, 3, 4, 5] since the first generation of expert systems [1]. The motivation for the research is also to attain flexible reasoning similar to human reasoning, while avoiding the complex computation of probabilities. For certain topology of the Bayesian network, it has been shown that the

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belief of each event can be calculated in a distributed manner by locally propagating the data through Bayesian network keeping the axiom of the probability satisfied [6, 7]. We focus on the problem where the probabilistic reasoning is difficult to apply due to the existence of cyclic dependence of events and dynamic environment where data of evidence changes dynamically.

On the other hand, as parallel distributed systems become important, the dichotomy of diagnosing parts and being diagnosed parts does not always apply. The dichotomy leads to a logical paradox similar to the self-reproduction paradox.

> In order to make a system reliable, the diagnosis and repair subsystem should be added to the system. Then there arise the possibilities of the fault of the added subsystem. Thus, another subsystem for diagnosis and repair of the added subsystem should be added. In this manner, the diagnosis and repair subsystem should be added infinitely

An engineering treatment of the situation is to add the diagnostic system with higher reliability than that of previously added one, until the reliability of the total system becomes low enough. The other way of dealing with the situation is to add the self-diagnosable diagnostic system.

The main contribution of this paper is the development of the model which allows evaluating the reliabilities even with the cyclic dependence of the events and with the dynamic environment. The model is the continuous dynamical model that can be calculated by the conventional numerical simulation such as Newton-Rapson method. While the reliability measure calculated by this method does not necessarily satisfy the axioms of probability, the measure satisfies the weaker constraints such that the opinions by the reliable agents are reliable, thus reflecting human intuition in evaluating reliabilities.

Section 2 presents multiagent models, which are required in the diagnosis discussed in the following section. Several modifications of the model are also discussed. Section 3 presents the formalization of sensor network and application of the models to sensor self-diagnosis of a process plant. Section 4 compares our approach with the probabilistic reasoning. Section 4 also discusses the merits and problems of applying the models to sensor self-diagnosis, from an engineering viewpoint.

2 Multiagent Network Model

Consider the following problem. Many suspects said that some other suspects are (or aren't) criminal as shown in Figure 1. The problem is to find the criminal based on the testimony. If a suspect is the criminal, he/she may lie. But if a suspect is innocent he/she will tell the truth.

We can find such mutual testing models in fault diagnosis theory [9]. Algorithms for distributed models have been studied, mainly from a viewpoint of attaining fault tolerancy in distributed systems or distributed processings. The multiagents network stated in this section is based on a distributed model. There are many algorithms for this problem [9].

It is already known that if every suspect are tested by more than t other suspects, then the criminals can be identified with the presence of less than t criminals [10].

In general, multiagents network model, consists of autonomous agents which has a capability of testing other agents and being tested by other agents, too.

We first present an algorithm carried out in a parallel distributed manner. Then, in section 3, we also present the algorithm by self-organization.

3 Evaluation by Multiagents

3.1 Agents with complete testing capability

Self-diagnosable system [10] consists of a set of agents $U = \{u_i\} i = 1..n$ each of which has capability of testing other agents and being tested by others as well. e_{ij} indicates the test on the agent u_j done by the agent u_i. Thus, the test outcome T_{ij} of the test e_{ij} is defined:

$$T_{ij} = \begin{cases} -1 & \text{if a testing agent } u_i \text{ is reliable and a tested agent } u_j \text{ is unreliable.} \\ 1 & \text{if both agents } u_i \text{ and } u_j \text{ are reliable.} \\ -1/1 & \text{if a testing agent } u_i \text{ is unreliable.} \\ 0 & \text{if there is no test from agent } u_i \text{ to agent } u_j. \end{cases}$$

The continuous value R_i between 0 and 1, indicating unreliable and reliable of the agent respectively, is assigned to each agent. We call the value R_i calculated by the models the reliability measure, to distinguish it from probabilistic concept of reliability. The diagnostic problem can be formulated as obtaining the reliability measures based on the test outcomes.

We call a reliability measure vector $\mathbf{R} = (R_1, R_2, \ldots, R_n)$ diagnosis. Consistent diagnosis is the reliability measure vector that satisfies the constraint of the T_{ij} for the given set of test outcomes, i.e. if $T_{ij} = 1$ then both R_i and R_j must be 1 or R_i must be 0, and if $T_{ij} = -1$ then $R_i = 1$ and $R_j = 0$, or $R_i = 0$ (see the definition of T_{ij} above). Correct diagnosis is such reliability vector that $R_i = 1$ only when the agent u_i is actually reliable, and that $R_i = 0$ only when the agent u_i is actually unreliable.

We first assign the value between 0 and 1 (the initial value of the reliability measure) to each agent. Then we calculate the reliability measures R_i by the following dynamical model.

$dr_i(t)/dt = \sum_{e_{ji} \in T^i} T_{ji} R_j + \sum_{e_{ij} \in T_i} T_{ij} R_j - \frac{1}{2} \sum_{e_{ij} \in T_i} (T_{ij} + 1) \quad \ldots (1)$

$R_i(t) = \frac{1}{1+\exp(-r_i(t))}$

where T_i is a set of all the tests done by the agent u_i, and T^i is a set of all the tests on the agent u_i.

The right hand side of the equation (1) follows.

$J_i(T, R) = \sum_{e_{ji} \in T^i} T_{ji} R_j + \sum_{e_{ij} \in T_i} T_{ij} R_j - \frac{1}{2} \sum_{e_{ij} \in T_i} (T_{ij} + 1)$

This $J_i(R, T)$ will be positive (negative) if $R_i = 0(1)$ makes inconsistency with the data T_{ij}, T_{ij} and R_j of the adjacent agents. The dynamical model will change to the direction of canceling the inconsistency, i.e. if $J_i(R, T)$ is positive (negative), then r_i hence R_i will increase. The equation ($\mathrm{R}_i(t) = \frac{1}{1+\exp(-r_i(t))}$ is just to map the value r_i into the interval between 0 and 1.

This model is natural one which determines the reliability measure R_i of the agent by summing up the weighted opinions of connected agents.

Focusing the processing of one agent may help to understand the processing of the model. Since the network model is a homogeneous parallel processing model, all the processing done

by each agent are the same. Figure 2 shows the schematic diagram of evaluation to and from one agent. It should be noted that the reliability measure of one agent is evaluated not only from the opinions of other agents testing the agent, but from the opinions of what the agent said to the other tested agents. The former corresponds to the first term of the model (1) and the latter to those of the second and third term. We call the latter *reflection effect*.

The *reflection effect* is somewhat similar to the situation that if you say bad criticism on the highly evaluated person, it affects your own credit not his/her.

There is a *competitive interaction* among agents. When $T_{ij} = -1$ then, $R_i = 1$ inhibits R_j being 1, and *vice versa*. When $T_{ij} = 1$, however, the interaction is not symmetric; $R_i = 1$ activates R_j to be 1, while $R_j = 0$ inactivates R_i to be 0.

This model (1) is known to converge by the following Liapunov function [11] in the same manner as that of Hopfield Net Algorithm. By the analogy of Hopfield's associative memory[8], the diagnosis can be regarded as recalling the memorized facts (the correct diagnosis) by the key (initial setting of $\mathbf{R}$). Since there are several local minimal points in the energy function, it may lead to wrong diagnosis starting from inappropriate $\mathbf{R}$.

$V(t) = -\sum_{i=1}^{n} \int_0^{R_i} \{-\frac{1}{2} \sum_{e_{ij} \in T_i} (T_{ij} + 1)\} R_i'(y_i) dy_i - 1/2 \sum_{i,j=1}^{n} T_{ij}^* R_i R_j$

where

$dV/dt = -\sum_{i=1}^{n} R_i'(r_i) \{-\frac{1}{2} \sum_{e_{ij} \in T_i} (T_{ij} + 1) + \sum_{j=1}^{n} T_{ij}^* R_j\}^2 \leq 0$

where $T_{ij}^* = T_{ij} + T_{ji}$.

In fault diagnosis, minimal diagnosis where the number of $R_i = 0$ is minimal among consistent diagnoses, is often favored. In order to make such diagnosis, the energy function must be modified by adding the energy E_2.

$\mathrm{E} = \mathrm{E}_1 + E_2$

where

E_1 is the same energy function as V(t) defined before, and

$E_2 = -\alpha \sum_{i=1}^{n} R_i$ where $\alpha > 0$. E_1 is added for making the diagnosis consistent with the given test outcomes and E_2 is for making the number of unreliable agents as small as possible in the diagnosis. This new energy modifies the evaluation function J_i of the algorithm as follows:

$J_i(T, R) + \alpha$

For this algorithm using the energy $E = E_1 + E_2$, the local minimal points are biased to those including more 1's as known. If both $R_i = 1$ and $R_i = 0$ are consistent diagnosis, then $R_i = 1$ is always selected in this modified algorithm. The parameter α is chosen so that the minimum point of the total energy $E_1 + E_2$ corresponds to the correct diagnosis, however, the modified algorithm may possibly be trapped in the minimal point, not the minimum one.

3.2 Agents with incomplete testing capability

So far, we have assumed that the test done by reliable agent is always reliable. That is, if $R_i = 1$ then $T_{ij} = 1$ implies that $R_j = 1$ and that $T_{ij} = -1$ implies that $R_j = -1$. In existing systems, however, this is not always the case. As will be seen in the sensor diagnosis application, test may not be reliable even if it is done by reliable agent due to the sensitivity of test. Formally said, even if $R_i = 1$ and $T_{ij} = 1$, it may be the case that $R_j = 0$ because of the incompleteness of test. The test outcome, then, is defined as:

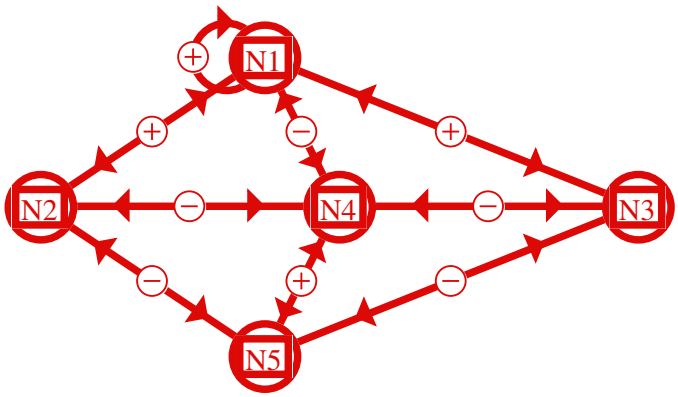

Figure 1: Testimony among suspects. +/- indicates that the suspect said the other suspect is/isn't criminal.

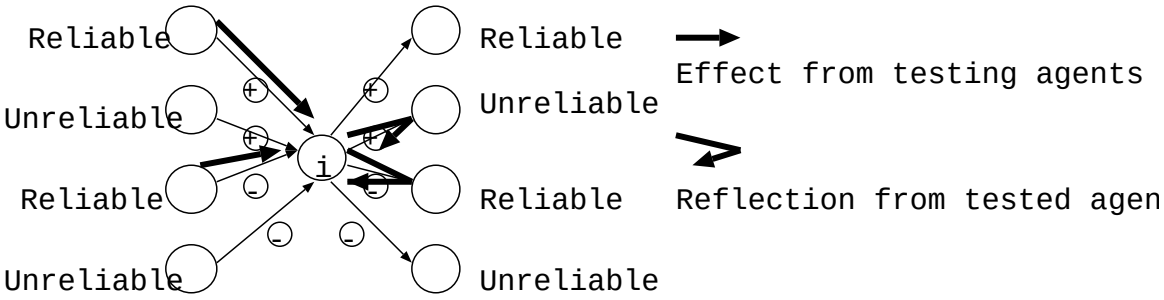

Figure 2: Function of an Agent

$$T_{ij} = \begin{cases} 1 & \text{if both a testing agent } u_i \text{ and a tested agent } u_j \text{ is reliable.} \\ -1/1 & \text{if either a testing agent } u_i \text{ or a tested agent } u_j \text{ is unreliable .} \\ 0 & \text{if there is no test from agent } u_i \text{ to agent } u_j. \end{cases}$$

In that case, the evaluation function $J_i(T, R)$ of the above model should be modified to:
$dr_i(t)/dt = \sum_{e_{ji} \in T^i}(T_{ji} - 1)R_j(t) + \sum_{e_{ij} \in T_i}(T_{ij} - 1)R_j(t) \quad \ldots(2)$
$R_i(t) = \frac{1}{1+\exp(-r_i(t))}$
Using the Liapunov function:
$V(t) = -1/2 \sum_{i,j=1}^{n} T_{ij}^{+} R_i R_j$
where

$$T_{ij}^{+} = \begin{cases} T_{ij} + T_{ji} - 2 & \text{if both tests } e_{ij} \text{ and } e_{ji} \text{ exist.} \\ T_{ij} + T_{ji} - 1 & \text{if one of } e_{ij} \text{ or } e_{ji} \text{ exists.} \\ 0 & \text{if neither } e_{ij} \text{ nor } e_{ji} \text{ exists.} \end{cases}$$

It is known the solution of the above model converges on the consistent diagnosis, since the time derivative of the Liapunov function is as follows:
$dV/dt = -\sum_{i=1}^{n} R_i'(r_i)\{\sum_{j=1}^{n} T_{ij}^{+} R_j\}^2 \leq 0$
The right hand side of the equation (2) follows.
$J_i(T, R) = \sum_{e_{ji} \in T^i}(T_{ji} - 1)R_j + \sum_{e_{ij} \in T_i}(T_{ij} - 1)R_j$
The contribution from the opinions of the agent testing agent u_i comes from the first term of $J_i(T, R)$. The first term $\sum_{e_{ji} \in T^i}(T_{ji} - 1)R_j$ becomes -2 only when the testing agent u_j is reliable (i.e.$R_j = 1$) and that agent is saying that the agent u_i is unreliable (i.e. $T_{ji} = -1$). In other cases, there is no contribution from the first term. In the same manner, the contribution from the tested agents comes from the second term, which becomes -2 only when the agent u_i is saying that the tested agent u_j is unreliable (i.e. $T_{ij} = -1$) while it is actually reliable (i.e. $R_j = 1$).

With the incomplete tests, consistent diagnosis is such reliability measure vector that if $R_i = 1$ then R_j must be 0 only when $T_{ij} = -1$. For a consistent diagnosis $\mathbf{R}co = (Rco_1, \ldots, Rco_n)$, $Rco_i = 1(0)$ implies that $\sum_{j \neq i} T_{ij}^{+} R_j \geq 0 (\leq 0)$ by the definition of consistent diagnosis.

It should be noted that the diagnosis with this incomplete test becomes more difficult than that with complete test, since the information obtained from test results is less (i.e. even if we know the testing agent u_i is reliable and test $T_{ij} = 1$, we cannot say that the tested agent u_j is reliable.). Further, with incomplete case $J_i(T, R) \leq 0$ holds. This means, it is not possible to get any evidence from the test results T_{ij} for believing some agents reliable, although the evidence of believing some agents unreliable can be obtained. Thus, the initial value of the reliability measure 1 is to be set, otherwise there is no chance for the agent to be evaluated as reliable.

Further modification is made on the above models for the sensor diagnosis application. Both models of (1) and (2) are designed to give clear diagnosis, unreliable or reliable not in ambiguous state between them. That is, the reliability measure hardly stay around the intermediate values near 0.5. In some situations, however, the information of ambiguous state is also necessary rather than making them black or white. The following system keeps the information of ambiguous state of sensor reliability measure.
$dr_i(t)/dt = \sum_j T_{ji}^{+} R_j(t) - r_i(t) \quad \ldots(3)$

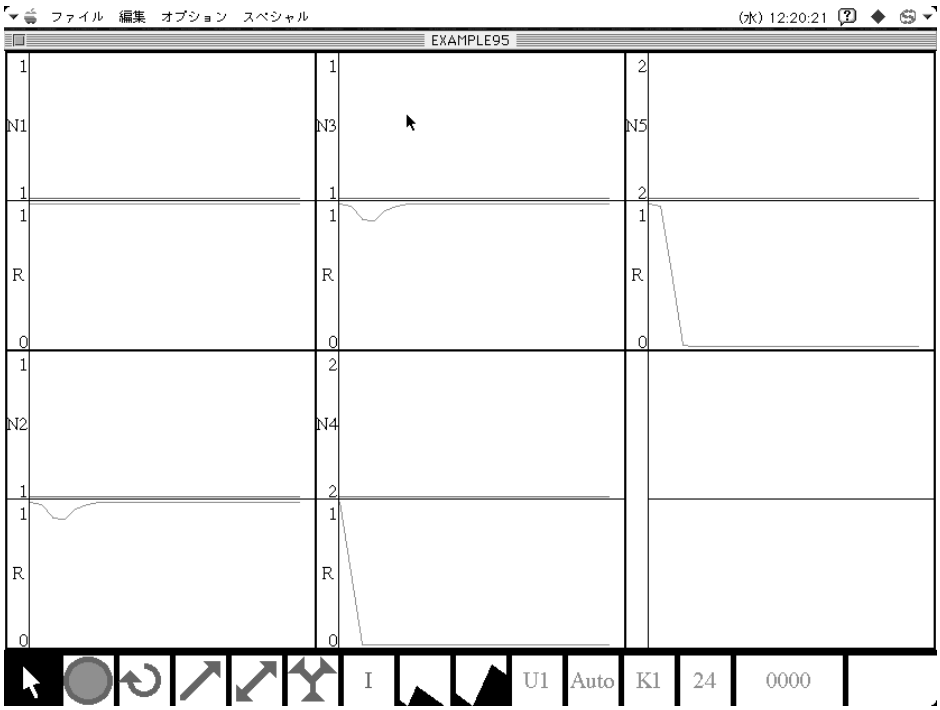

Figure 3: Simulation result of Figure 1 by the model with complete test(1)

In this system, there are equilibrium points satisfying that $r_i(t) = \sum_j T_{ji}^+ R_j(t)$. Thus, R_i monotonically reflects the value of $\sum_j T_{ji}^+ R_j(t)$. If $\sum_j T_{ji}^+ R_j(t)$ is close to 0, then R_i is close to 0.5.

We call the models the model with complete test, the model with incomplete test, the modified model, respectively by the systems (1), (2) and (3). We have noted that the reasonable candidate for the initial value of $\mathbf{R}$ is $(1, \ldots 1)$, since this is always near to the correct diagnosis assuming the number of unreliable agents are less than that of reliable agents. In reality, multiple fault does not occur at the same time. It often happens that after one agent falls into abnormal then another agent become unreliable and so on. Thus, another practical way to determine the initial value $\mathbf{R}$ is to use the last value of $\mathbf{R}$ before new fault occurs. Figures 3, 4 and 5 show the evolution of reliabilities of agents in the example shown in Figure 1 done by the model (1), (2) and (3) respectively. N4 and N5 are unreliable agents (criminals). It can be seen that both the model (1) and (2) give the clear separation of reliable agents whose reliabilities converged on one from unreliable agents whose reliabilities converged on zero. Since the model (2) is more skeptical than (1), even reliable agents N2 and N3 were dragged a little towards zero. Although the reliabilities of the reliable agents N1, N2, and N3 eventually converges on one in the models (1) and (2), those in model (3) remain ambiguous states between zero and one.

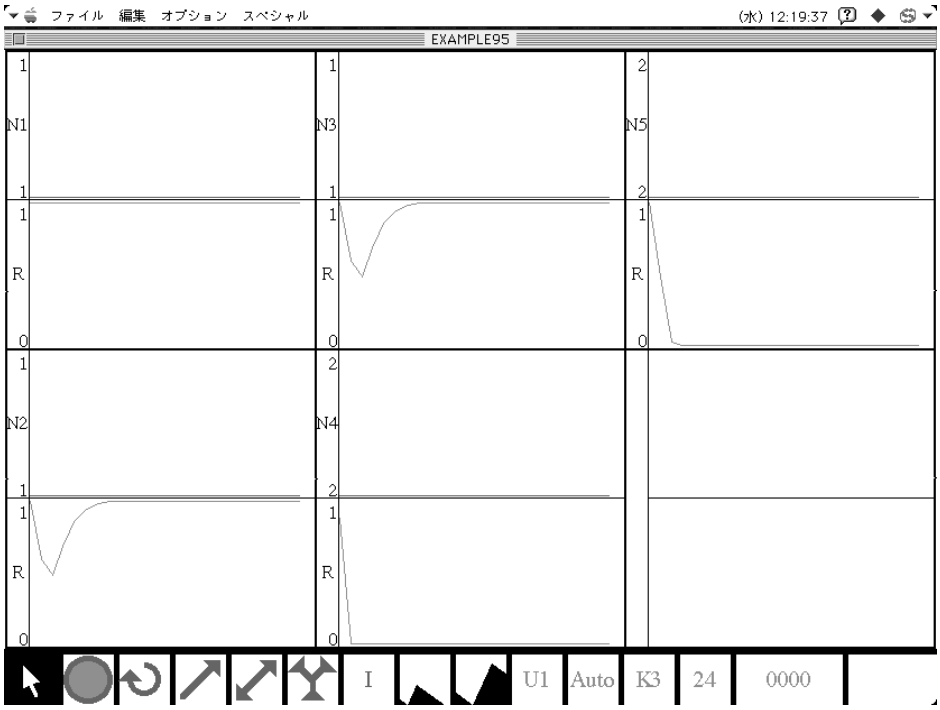

Figure 4: Simulation result of Figure 1 by the model with incomplete test(2)

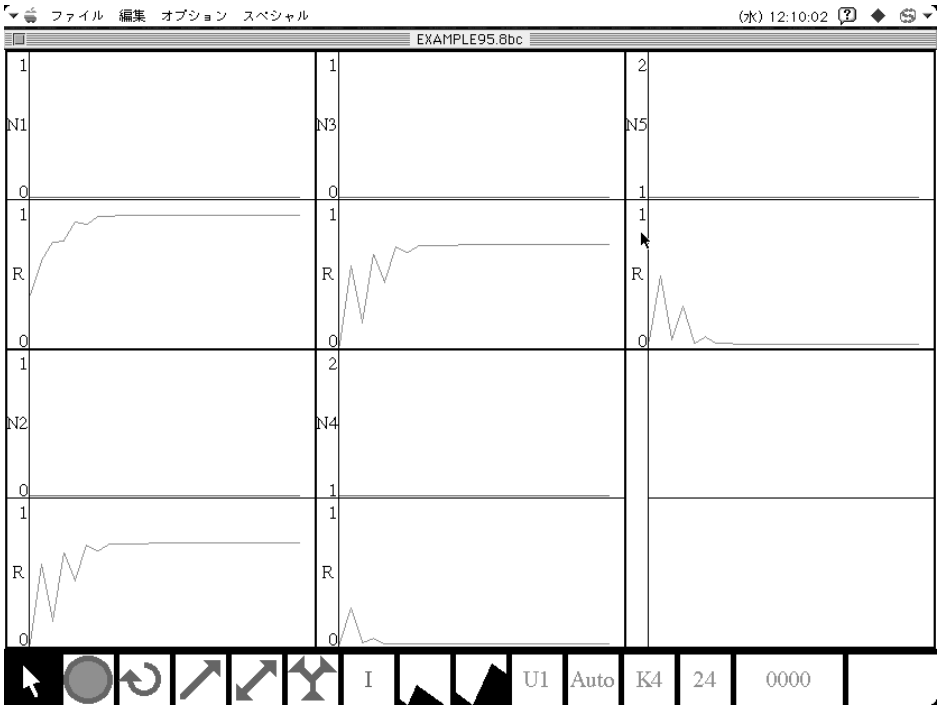

Figure 5: Simulation result of Figure 1 by the modified model (3)

4 Multiagents Network Model Applied to Sensor Fault Diagnosis

4.1 Formalization of sensor network

In this section, network for process instrumentation systems in detail. First, we formalize the sensor network.

In process diagnosis, it is often the case that measurements such as temperature, pressure, flows, which are independently measured have relation with each other. In other words, some of these measurements are redundant. Using the dependencies, many tests among sensors can be constructed. In the sensor network proposed in this section, each sensors test other sensors using these relation, rather than just measuring the process values.

If the process value calculated from other process value is not pinpoint, and only plausible interval is obtained, then we must say that the test here is incomplete. In that case, the model with incomplete test should be adopted. As we will see in the next example, we must also adopt the model with incomplete test in the case when test is done by inequality.

Although we focus on the example of the application to a cement process, the similar approach may be possible in many other process plants. In many cement plants, sensors are used in a severe environment with dust. Process diagnosis including sensor fault is needed. The model allows the process diagnosis including sensor fault by taking consistency among many sensor values into account.

Figure 6 shows the schematic diagram of the firing section of the cement process. The raw materials are introduced at the top of the preheating tower. These raw materials fall down and meet the warm gases coming from the kiln. After passing through each cyclone, they go into the kiln, where a reaction called clinkerization is held. Finally, the product of the reaction, the clinker, is cooled. Cement is then obtained from clinker after grinding. This process has the heat flow structure that hot gas introduced at the bottom are being cooled by relatively cold materials as they proceed to the upper part. The cold material, on the other hand, being warmed by the gas as they go down.

In plants which contain a preheating tower like this example, problems often occur within the cyclones. Consequently, one puts some thermometers in order to forecast or analyze such problems. These sensors are not very safe, especially because they are often stopped up by the materials. Then, since their data are used in various ways by process software, it becomes important to detect automatically what are the faulty ones. Unfortunately, this is not easy. For instance, a technic like verifying if the values of thermometers are between two reference values doesn't work since the whole profile of temperature can move depending on the process running.

Since there are a lot of such sensors, they don't go wrong at the same time. Therefore, an interesting idea is to use the whole information provided by the sensors, and deduces which is (are) the faulty one(s) using the sensor network approach.

Many kinds of sensors are used in cement process, but in this study, we considered only the thermometers mentioned above. In our example, the agents of the network are naturally the sensors, and the testing relations are obtained from simple process knowledge. These relations between the values of the sensors have the following form:

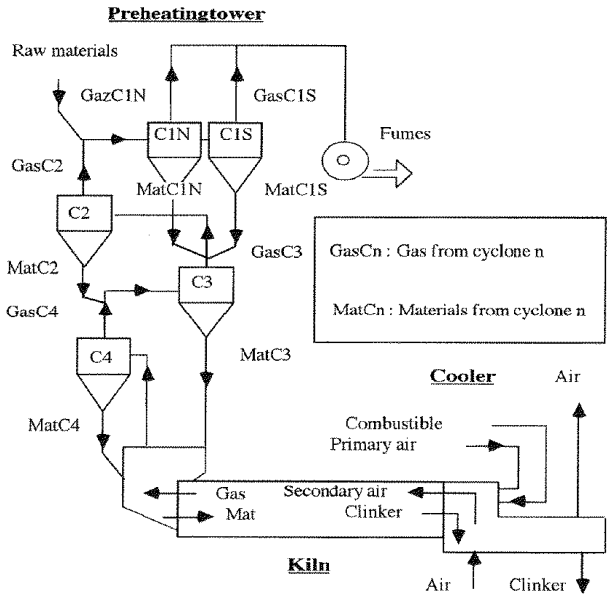

Figure 6: Schematic Diagram of the Firing Section of a Cement Plant

`Temperature of gas in cyclone n > temperature of materials in cyclone n.`

From such a relation, we can build a link between the thermometer of the gas of the cyclone n and the thermometer of the materials of the same cyclone, and say that the previous sensor can performed a diagnosis about the latter. If the relation is satisfied, the test of the $T_{Gas_{Cn}}$ sensor on the $T_{Mat_{Cn}}$ sensor to be fault-free, and faulty otherwise. The tests done by these inequalities are incomplete, for even if the tested sensor is faulty it will not be recognized unless the tested sensor value fails to satisfy the inequality. Thus, the model under incomplete test should be used for this case.

Of course, if the $T_{Gas_{Cn}}$ sensor is faulty, this diagnosis could be wrong. However, this fact can be discovered, if we take into account information provided by other sensors.

For the plant shown in Figure 6, the following set of relations (4) to (9) could be used:

- $AlphaMin_{Gas_n} < T_{GasC_n} - T_{GasC_{n+1}} < AlphaMax_{Gas_n} n = 1N, 1S, 2, 3 \ldots (4)$
- $AlphaMin_{Mat_n} < T_{MatC_{n+1}} - T_{MatC_n} < AlphaMax_{Mat_n} n = 1N, 1S, 2, 3 \ldots (5)$
- $T_{GasC_n} > T_{MatC_n}, n = 1N, 1S, 2, 3, 4 \ldots (6)$
- $T_{GasC_n} < T_{MatC_n} + Delta_n, n = 1N, 1S, 2, 3, 4 \ldots (7)$
- $|T_{GasC_0} - T_{GasC_1}| < Beta_{Gas} \ldots (8)$

- $|T_{MatC_0} - T_{MatC_1}| < Beta_{Mat} \ldots (9)$

where $MatC_n$ indicates the temperature of the material at cyclone C_n, and T_{GasC_n} indicates that of the gas.

$AlphaMin_{Gas_n}$, $AlphaMin_{Gas_n}$, $AlphaMin_{Mat_n}$, $AlphaMax_{Mat_n}$, $Beta_{Gas}$, $Beta_{Mat}$, and $Delta_n$ are parameters which can be adjusted if necessary, in order to make the relations more precise. In our example, we initialized these parameters as follow:

$$AlphaMin_{Gas_n} = 125, AlphaMin_{Gas_n} = 275,$$
$$AlphaMin_{Mat_n} = 125, AlphaMax_{Mat_n} = 275,$$
$$Beta_{Gas} = 30, Beta_{Mat} = 30, and Delta_n = 10.$$

The relation (6) is typically a relation from physical theories. The relations (4) and (5) could also be considered as relations from physical theories. However, the estimation of the parameters comes under an experimental approach. The others relations are typically from an experimental approach.

Figure 7 shows the sensor network of these twenty-two sensors. Sensors connected by bi-directional arc have mutually testing via above relations.

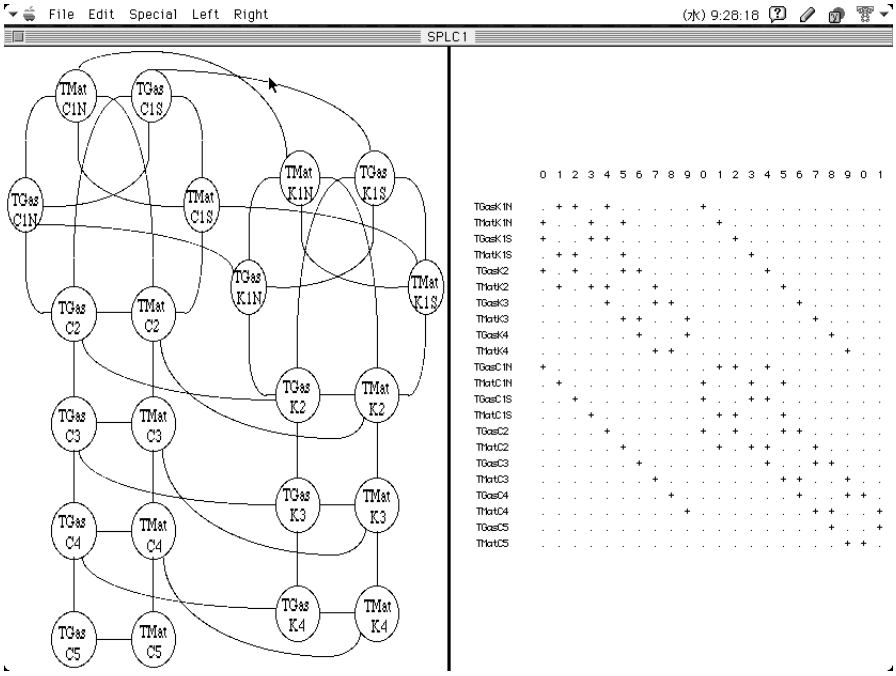

Figure 7: Sensor Network of the Cement Plant with Test Matrix

4.2 Building complex sensor network

We have applied the above approach to industrial processing plants such as a process including firing section of a cement process and a blast furnace of a steel process. In applying the

techniques to these complex industrial processes, we found it necessary to have a software facilitated to design a sensor net efficiently. We have implemented a tool (called Sensor Net Generator) which allows process engineers to design complex sensor network with several different types of mutual testings as well as with several models so far discussed.

Four types of testing are available in Sensor Net Generator: simple link (one way link), self link (test of one node comparing its value with some reference value) and multiple link (test of more than three nodes). Default tests for them are $|a_i x_i - b_j x_j - c_{ij}| < \epsilon_{ij}, |a_i x_i - c_i| < \epsilon_i$,and$|\sum a_i x_i - c| < \epsilon$ respectively where x_i represents process values, $c_{ij}, c_i$and c represents reference values, $\epsilon_{ij}, \epsilon_iand\epsilon$ some error constant. The parameters $a_i, b_i, c_{ij}, c_i, c, \epsilon_{ij}, \epsilon_i$ and ϵ are assigned values in defining each test. Other than these default linear functions for simple, self, and multiple links, user can define any non-linear functions, which are actually needed in expressing the process knowledge in a complex process.

The main characteristic of the mutual evaluation approach to process diagnosis is that this method admits relative relation between process values, hence does not suffer from the shifting of all the process values (which occurs depending on the load to the process or the change of environment such as seasonal change). However, it is possible for the sensor net to involve the heuristics which refer to absolute values of the process values by the self link of the Sensor Net Generator. Further, more than two variables are often involved in the process constraints such as balance equations like $Fi_1 + F_i 2 = F_o$. Then, we need the multiple link facilitated in Sensor Net Generator.

Figure 8 shows a sensor diagnosis system for the preheating process of a cement plant. Twenty-two sensors (thermometers) are involved. In constructing the sensor net, not only process knowledge but the experimental knowledge among sensor values is used to obtain enough relations for diagnosis.

5 Discussions

5.1 Comparison with the reasoning on Bayesian network

The main difference of the method from the probabilistic reasoning is that the method is for evaluating the reliability of the multi-agent system where each agent is capable of evaluating other agents, as opposed to evaluating simple event. It is possible to describe the event dependency of the multi-agent system by Bayesian network, however, the network would be cyclic hence preventing the usual probabilistic approach. Since the model can be simulated by a continuous differential equation, the method fits in the dynamic environment such as processing plants where the target system can be described by a differential equation. One demerit of our method is that we not consider the axioms of probability. In fact, dynamics of reliability of each agent depends on the reliabilities of other adjacent agents, and unreliability does not appear in the dynamics. The dynamics of both reliability and unreliability of agents satisfying the constraint that their sum must be one would be a complicated differential equation. Another interesting problem for future is to recast the probabilistic reasoning on Bayesian network to the continuous differential equations, which would make simulation as well as stability analysis easier.

The significant feature of the proposed models is that it uses the energy defined on the

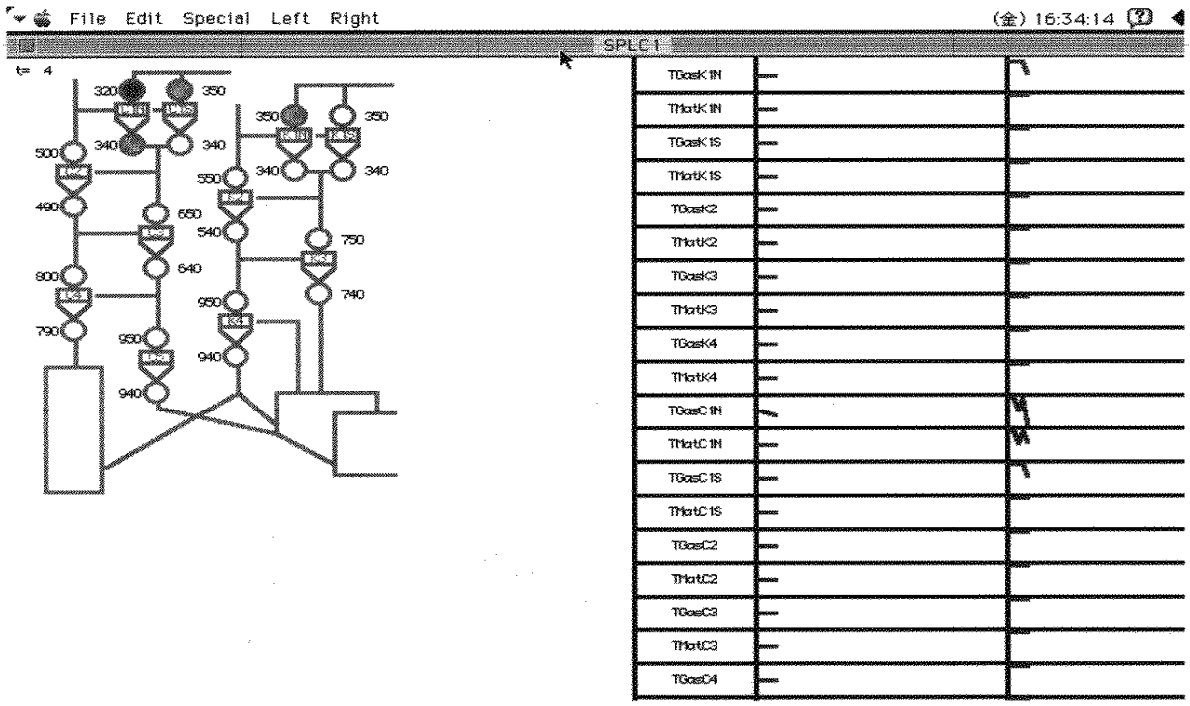

Figure 8: Sensor Diagnosis System of the Cement Plant

network. The introduction of the energy in models have the following impacts:

- Associating consistent diagnosis with minimal point of the energy. This association will lead several interesting points such as a proof technique of correctness of the model by the energy convergence.
- Regarding the model as an associative memory. The associative memory can *recall* the correct diagnosis if the key (the initial diagnosis, i.e., the initial value of $\mathbf{R}$.) is appropriately given. This raises another important, but not much discussed engineering issue of selecting an appropriate initial diagnosis.

Another important merit of introducing energy is its flexibility; the model can be modified so that it can apply to continuous values of test outcomes, it can produce continuous values of reliability measures, and it allows to design diagnosis by modifying the energy function as discussed in section 2.1.

5.2 Application to diagnostic problems

The main characteristic of the approach to process diagnosis is that this method admits only relative relation between agents without referring to the absolute value of th e process values. One of the merits is that the approach does not suffer from the shifting of all the process values (which occurs depending on the load to the process or the change of environment

such as seasonal change), since the method only focuses the relative relation of the process values.

Further, the change of some parts of the network does not propagate to the other parts, since the relation among process values are rather independent from each other. The knowledge acquisition is not very hard, since the uniformity of the knowledge required (That is the relative constraints among process values).

When the model is implemented in a distributed processing environment, the evaluation of the reliability measure can be done in a fully distributed and autonomous manner in each sensor before the information of sensors are collected and entering central processing of these sensor information. Thus, a hybrid system combining the approach and the knowledge-based system may be needed for sophisticated diagnosis. It may be good strategy to filter out unreliable sensor values before sending the process values to knowledge-based diagnosis system. Then, the knowledge-based diagnostic systems can diagnose more efficiently and its knowledge becomes much simpler than directly feeding the process values to the knowledge-based systems.

The main difficulty of the approach discussed in this paper is to find enough relations between the sensors values. Generally speaking, such relations could be obtained from physical theories (mass or heat balances, thermodynamical principles, etc.), mathematics (the value of a flow is always a positive value, a ratio is comprised between 0 and 1, ...), or by experimentations. More the sensors values are redundant, more there are testing relations. The performance of the diagnosis depends on the quality of the relations involved; the diagnosability depends on the number of distinct tests, and the reliability of the diagnosis depends on the reliability of the tests involved.

We are currently investigating a more elaborate sensor network that works for process faults as well as sensor faults. Process faults may fall under two types: abnormal events where some process values exceed pre-specified thresholds while satisfying flow balances, and faults that violate the flow balance, such as a leak of some flows. In the latter faults, consistency among sensor values are violated, which lead to the difficulty of identifying the abnormal sensors in the current approach. An elaborate sensor network involving the virtual node corresponding to the process fault would identify such process faults that violate the consistency among sensor values while no sensor is actually faulty.

6 Conclusion

We proposed the model which allows evaluating the reliabilities even with the cyclic dependence of the events and with the dynamic environment. The model is the continuous dynamical model that can be simulated by the conventional numerical method such as Newton-Rapson method. While the reliability measure calculated by this method does not necessarily satisfy the axioms of probability, the measure satisfies the weaker constraints such that the opinions by the reliable agents are reliable, thus reflecting human intuition in evaluating reliabilities.

We formalized the concept of sensor network by which the method discussed here can be applied to sensor diagnosis of processing plants.

By applying the method to the real cement plant, we have demonstrated the applicability

of the method in large-scale and dynamical environments where large amount of data must be evaluated continuously.

We also presented several modifications to apply the model for sensor network in the instrumentation of process plants. Further, we developed an elaborate tool with sensor net composing component facilitated with simple link, auto link, and multiple link as well as an on-line diagnostic component facilitated with several models discussed in this paper.

Modifying the method so that the reliability measures satisfy the stronger constraint such as the axioms of probability if left for the future research.

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