6 Sensor Networks Using the Self-Organizing Network

This chapter[1] presents an application of sensor networks using the immunity-based system (IMBS) discussed in Chap. 5. We propose a concept of *active diagnosis*. As a way of realizing active diagnosis, we apply the immunity-based system. We apply this approach to process diagnosis where agents are defined on a sensor network. Each agent monitoring a sensor or a process constraint evaluates credibility (Sect. 5.3), which corresponds to the active/inactive state of the immune cell, by communicating with other agents. System-level recognition of sensor/process faults can be attained by continuously and mutually monitoring consistency among sensor values and process constraints.

6.1 Introduction

The network uses agents (corresponding to immune cells) that monitor mutually and dynamically. The network approach thereby makes consistency monitoring possible in a dynamic environment where on-line data from sensors arrives continuously.

Diagnosis, in general, is basically considered an *event-driven* task that is triggered by an event of fault; it is also based on information from a pattern of sensor values called a "syndrome." However, as the target system becomes information-intensive, this conventional event-driven approach may not be sufficient.

The immune system is considered the self-defining process that continuously monitors the self, discriminates the nonself from the self, and maintains the identity. This essence of the immune system agrees with *active diagnosis* that extends diagnosis from an event-driven task.

Diagnosis by the IMBS with the self-organizing network may be a way to attain the following requirements of active diagnosis:

- *Temporal requirement*: "Self" monitoring must be carried out all the time, as opposed to only when some fault is detected.
- *Spatial requirement*: Monitoring/diagnosis is done by the agents working in a distributed manner in the sensor network.

[1] Most results in this chapter are presented in [62], [68], and [71].

– *Functional requirement*: It is biased relatively more to monitoring normal condition rather than to detecting abnormal conditions.
– *Consistency requirement*: Consistency among data must be monitored, similarly to an "active data base." But unlike an active data base, not only consistency among the knowledge in a knowledge data base for diagnosis but also consistency among on-line data from sensors and that between on-line data and the knowledge must be monitored.

6.2 Self–Nonself Counterparts in the Sensor Network

In the sensor-based diagnosis task, incoming data to each sensor is time-series data. In the event of sensor faults and process faults, data of some sensors are inconsistent with those of other sensors with respect to the relation and constraint extracted during the normal situation of the target system. Thus, the *nonself* counterpart of the task is sensor and process faults responsible for the inconsistent data. The *receptor* counterpart of the task is the relation between time-series data incoming to related sensors (Table 6.1). In the sensor diagnosis, correspondence between an agent and the time-series data is straightforward: each agent is in charge of one sensor whose fault is monitored by the agent. In the diagnosis extended for process diagnosis, an agent is also in charge of process faults, which amounts to monitoring constraints among several sensor values. Thus, correspondence from agents to sensors is not one-to-one but one-to-many in the process diagnosis.

Sensor faults in particular should not only be identified but "eliminated" in the diagnosis task, since the sensor faults cause confusion in the entire diagnosis task. Thus, the self-organizing network fits the sensor diagnostic task, since it can eliminate the effect from abnormal agents by making them inactive. We first focus on the sensor network for the sensor diagnosis. However, we also show that the sensor network can be extended for a process diagnosis.

Table 6.1. Self–nonself counterparts in sensor networks

Immune system	Sensor network
Self	Normal sensor data (or corresponding agent)
Nonself	Abnormal sensor data (or corresponding agent)
Receptor	Relation between sensor data
Effector (elimination of nonself)	Inactivation of agents corresponding to abnormal sensor data

6.3 Agents on the Sensor Network

This section relates agents to a sensor network for an application to a process diagnosis. For presentation purposes, agents are elaborated gradually as the section proceeds, from a simple one for sensor diagnosis to a sophisticated one for process diagnosis.

In diagnosis, it is often the case that measurements such as temperature, pressure, and flows, which are measured independently, are related. In other words, some measurements are redundant. Using dependency, many relations among sensor values can be identified. In the sensor network, each agent (monitoring a corresponding sensor value) evaluates consistency with other agents using these relations in addition to monitoring sensor values.

These relations between among sensor values have the following form:

$$\text{Sensor Value A} > \text{Sensor Value B.}$$

Or generally, $F(A, B) > 0$.

From such a relation, agent monitoring the sensor value A and that monitoring the sensor value B can evaluate each other.

Example 6.1 Sensor network of a heat exchanger. Let us consider an example of a condenser-type heat exchanger. Two flows, i.e., the flow of the shell side and the flow of the tube side, exchange heat. Steam enters from an inlet on the shell side, then condenses, and is finally cooled by the flow of the tube side. The flowing object of the tube side then comes out being heated by the flow of the shell side.

Now, we consider inequalities among temperatures of these two flows.

$$T_{\mathrm{hi}} > T_{\mathrm{ho}}, \quad T_{\mathrm{lo}} > T_{\mathrm{li}}, \quad T_{\mathrm{hi}} > T_{\mathrm{li}}, \quad T_{\mathrm{ho}} > T_{\mathrm{lo}},$$

where
T_{hi}: temperature at the inlet of the shell side,
T_{ho}: temperature at the outlet of the shell side,
T_{li}: temperature at the inlet of the tube side, and
T_{ho}: temperature at the outlet of the tube side.

Using these relations among sensors, a sensor network can be constructed. For example, when the relation $T_{\mathrm{hi}} > T_{\mathrm{ho}}$ does not hold, then either sensors T_{hi} or T_{ho} may be faulty. This means that agents corresponding to sensors measuring the values $T_{\mathrm{hi}}, T_{\mathrm{ho}}$ are evaluating each other through this relation. Figure 6.1 shows the sensor network of these four sensors.

Evaluations done by these inequalities are incomplete, for even if the evaluated sensor is faulty it will not be recognized unless the evaluated sensor value fails to satisfy the inequality. Thus, we need the model under incomplete evaluation as presented below.

6.4 Dynamic Interaction Among Agents

In Chap. 5, we assumed that evaluation by a normal agent (i.e., an agent corresponding to a normal sensor value) is always reliable. That is, if $R_i = 1$ then $T_{ij} = 1$ implies $R_j = 1$, and $T_{ij} = -1$ implies $R_j = -1$. In existing systems, however, this is not always the case. As we saw in a sensor network application, evaluations may not be reliable even if done by normal agents due to the sensitivity of the evaluation. Formally, even if $R_i = 1$ and $T_{ij} = 1$, it may be the case that $R_j = 0$ because of incompleteness in evaluation. Evaluation, then, is defined as:

$$T_{ij} = \begin{cases} 1, & \text{if both agent } i \text{ and } j \text{ are normal,} \\ -1/1, & \text{if either agent } i \text{ or } j \text{ is abnormal,} \\ 0, & \text{if there is no evaluation from an agent } i \text{ to } j. \end{cases} \tag{6.1}$$

In that case, the evaluation function $J_i(T, R)$ of the model (5.2) in Chap. 5 should be modified to

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

The contribution from evaluations on agent 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 evaluating agent j is reliable (i.e., $R_j = 1$) and when the agent j evaluates the agent i to be abnormal (i.e., $T_{ji} = -1$). In other cases, there is no contribution from the first term. In the same manner, the contribution from the evaluateed agents comes from the second term, which becomes -2 only when the agent i evaluates the agent j to be abnormal (i.e., $T_{ij} = -1$) while it is actually reliable (i.e., $R_j = 1$).

The solution obtained by the above algorithm is a minimum of the following energy equation:

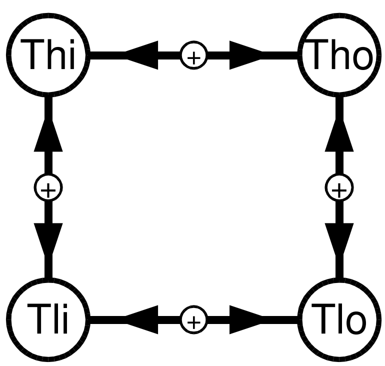

Fig. 6.1. Sensor network for the heat exchanger example [68]. Reprinted by permission of the publisher. ©1996 Complex Systems

$$E = -1/2 \sum \sum_{i \neq j} T^{+}_{ij} R_i R_j,$$

where

$$T^{+}_{ij} = \begin{cases} T_{ij} + T_{ji} - 2, & \text{if both evaluations from } i \text{ to } j \text{ and } j \text{ to } i \text{ exist,} \\ T_{ij} + T_{ji} - 1, & \text{if either evaluation from } i \text{ to } j \text{ or } j \text{ to } i \text{ exists,} \\ 0, & \text{if no evaluation exits between i and j.} \end{cases}$$

The energy always decreases as long as the change is made by the algorithm, since the variance of E due to the variance of R_i is

$$\mathrm{d}E = -\mathrm{d}R_i \{ \sum_{j \neq i} T^{+}_{ij} R_j \}.$$

We call the vector of credibility $\mathbf{R} = (R_1, R_2, \ldots, R_n)$ a *diagnosis*. The credibility vector consistent with the pattern of evaluations T_{ij} is called a *consistent diagnosis*. Since the energy measures the consistency between a *diagnosis* and the *evaluation*, a minimum of the energy corresponds to a consistent diagnosis.

For a consistent diagnosis $\mathbf{R}\mathrm{co} = (R\mathrm{co}_1, \ldots, R\mathrm{co}_n)$, $R\mathrm{co}_i = 1(0)$ implies that $\sum_{j \neq i} T^{+}_{ij} R_j \geq 0 (\leq 0)$ by definition. Thus, a consistent diagnosis realizes a local minimum of the energy. With incomplete evaluations, a consistent diagnosis is such that if $R_i = 1$ then R_j must be 0 only when $T_{ij} = -1$.

A consistent diagnosis with incomplete evaluation becomes more difficult to obtain than that with complete evaluation, since less information is obtained from evaluations (i.e., even if we know the evaluating agent i is normal and $T_{ij} = 1$, we cannot say that the evaluated agent j is normal.). Further, with the incomplete case $J_i(T, R) \leq 0$ holds. This means it is impossible to obtain any information from evaluations T_{ij} for believing some agents normal, although information of believing some agents abnormal can be obtained. Thus, the initial value of the credibility 1 is set, otherwise there is no chance for the agent to be evaluated as normal.

The self-organizing model under incomplete evaluation has a simpler form

$$\mathrm{d}r_i(t)/\mathrm{d}t = \sum_j T^{+}_{ji} R_j(t). \tag{6.2}$$

Using the Liapunov function, $V(t) = -1/2 \sum_{i,j=1}^{n} T^{+}_{ij} R_i R_j$, it is known that the solution of the above model converges on a consistent diagnosis, since the time derivative of the Liapunov function is

$$\mathrm{d}V/\mathrm{d}t = -\sum_{i=1}^{n} R'_i(r_i) \{ \sum_{j=1}^{n} T^{+}_{ij} R_j \}^2 \leq 0.$$

Further modification is made on the above model for the sensor diagnosis application. Both models in Eqs. (5.3) and (6.2) are designed to give a clear diagnosis, either abnormal or normal, not an ambiguous state between them. That is, credibility hardly stays around the intermediate values near 0.5. In some circumstances, however, information of ambiguous states is also necessary rather than making them *black or white*. The following system keeps the information of ambiguous states in credibility:

$$\mathrm{d}r_i(t)/\mathrm{d}t = \sum_j T_{ji}^{+} R_j(t) - r_i(t). \tag{6.3}$$

In this model, there are equilibrium points satisfying $r_i(t) = \sum_j T_{ji}^{+} R_j(t)$. 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.

This model in Eq. (6.3) is a modified version of the *black and white model* [61, 63] (Eq. (5.3) for complete evaluation, and Eq. (6.2) for incomplete evaluation), devised to keep information of ambiguous states in credibility. Thus the model in Eq. (6.3) is called a *gray model*.

A reasonable candidate for an initial value of $\mathbf{R}$ is $(1, 1, \ldots, 1)$, since this is always close to a correct *diagnosis* assuming the number of abnormal agents is less than that of normal agents. In numerical simulations of the model (6.3) whose R_i is subject to the sigmoid function in model (5.3), the initial value for R_i can be close to 1 because the initial value of r_i can be set to a large value. In reality, multiple faults do not occur simultaneously. It often happens, however, that a faulty component triggers a chain reaction, leading to multiple faults. Thus, another practical candidate for an initial value of $\mathbf{R}$ is the last value of $\mathbf{R}$ before a new fault occurs. $\mathbf{R}$ may be initiated when the evaluations T_{ij} change, such as when a new fault is added, or when nodes and hence evaluations are added or deleted in the network.

Figure 6.2 shows a simulation of Example 5.3 by the models in Eqs. (6.2) and (6.3). The initial values for $r_i(t)$ are set to be 5 to compare features in transition between these two models.

6.5 Extension of the Sensor Network

6.5.1 Agents for Process Diagnosis

This section extends the sensor network using the fact that the knowledge of a normal process is embedded in the constraint among the sensor values. Thus, when process faults such as *flow leak* or *stuck* (as opposed to sensor faults) occur, it causes a violation of constraints. In fact, when a process fault occurs, credibilities for many sensors related to the constraint become low simultaneously, while only a few agents corresponding to faulty sensors show low credibility when only sensors are faulty. In other words, when sensor

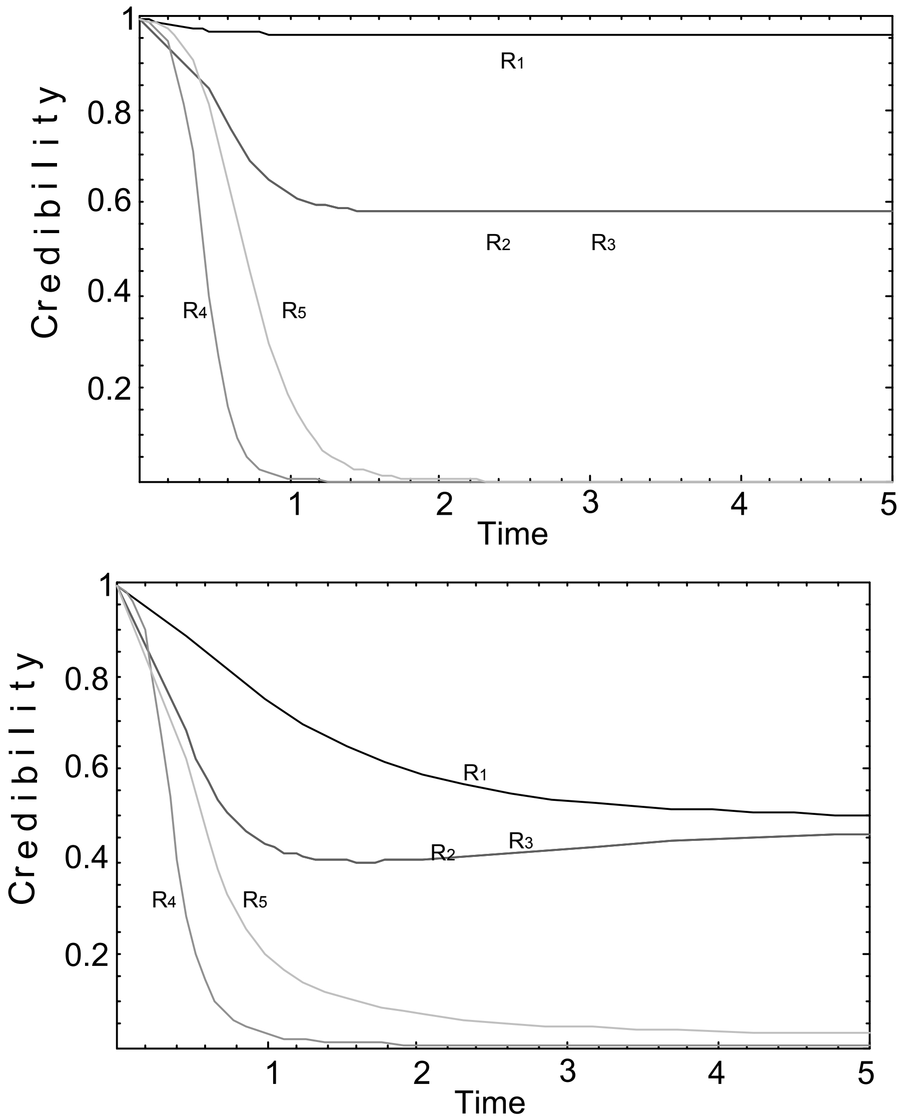

Fig. 6.2. Simulation for the evaluation in Fig. 5.5 by the models (6.2) *above* and (6.3) *below*. The initial values for $r_i(t)$ are set to be 5

values do not satisfy the constraint among these values, then it implies that sensors or process corresponding to the constraint may be faulty. Figure 6.3 illustrates the situation when a process fault corresponding to the constraint between the sensor i and j occurs.

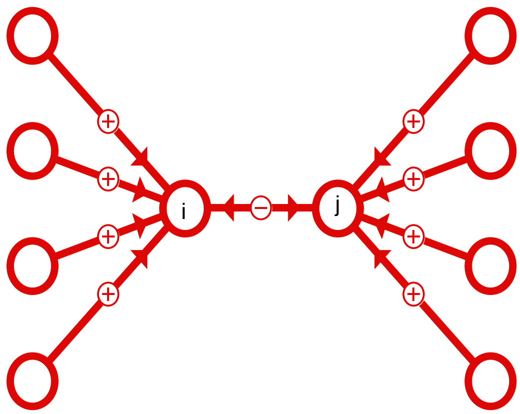

Fig. 6.3. Situation when a process fault occurs [68]. Reprinted by permission of the publisher. ©1996 Complex Systems

Therefore, a natural way of detecting process faults by sensor networks is to introduce credibility for the relations. Let $R_{T_{ji}}$ denote the credibility of evaluation T_{ji}. Then the dynamical model Eq. (6.3) becomes

$$\mathrm{d}r_i(t)/\mathrm{d}t = \sum_j T^{+}_{ji} R_j(t) R_{T_{ji}} - r_i(t), \tag{6.4}$$

$$\mathrm{d}r_{T_{ji}}(t)/\mathrm{d}t = T^{+}_{ji} R_j(t) R_i(t) - r_{T_{ji}}(t). \tag{6.5}$$

Equation (6.4) results from considering the effect of credibility of evaluation T_{ji}. The change rate of agent i, $\mathrm{d}r_i(t)/\mathrm{d}t$ should reflect all evaluations from other agents weighted not only with credibility of these evaluating agents but with credibility of their evaluations. Equation (6.5) comes from the fact that the evaluation is considered unreliable only when $T_{ji}, R_j(t)$, and $R_i(t)$ are contradictory: $T_{ji} = -1, R_j(t) = 1$ and $R_i(t) = 1$.

6.5.2 Process Diagnosis by Evaluating Consistency Among Data from Sensors

Agents monitoring a process fault do not correspond to a physical sensor device. In this sense, agents monitoring process faults are considered *virtual* monitoring sensors. Other virtual sensors attained by agents and useful for process fault diagnosis are *combined* sensors. These sensors monitor a combined pattern of multiple sensor values, since a combined pattern of sensor values, rather than values of a single sensor, are often necessary for process diagnosis. Credibility of a *combined* sensor is defined by how consistent these sensors are with each other. In other words, if some members of a *combined* sensor are internally contradictory then the *combined* sensor as a whole is considered faulty. Let I_{ij} be a measure of inconsistency between two sensors s_i and s_j. The following for $I_{ij} \in [0,2]$ is a candidate when the symmetric evaluation in Eq. (6.1) is assumed for T_{ij}:

$$I_{ij} = -T_{ij}R_i\left[R_j - 1/2(T_{ij}+1)\right] - T_{ij}R_j\left[R_i - 1/2(T_{ij}+1)\right].$$

This I_{ij} is reasonable since it can be rewritten as

$$\begin{cases} 2R_iR_j, & \text{if } T_{ij} = -1, \\ R_i(1-R_j) + R_j(1-R_i), & \text{if } T_{ij} = 1, \\ 0, & \text{if } T_{ij} = 0. \end{cases}$$

The highest inconsistency, $I_{ij} = 2$, is obtained when the agent i with credibility $R_i = 1$ evaluates the agent j with credibility $R_j = 1$ as abnormal ($T_{ij} = -1$). When $T_{ij} = 1$, both cases: $R_i = R_j = 1$ and $R_i = R_j = 0$ do not cause inconsistency, hence $I_{ij} = 0$. Both cases $R_i = 1, R_j = 0$ and $R_i = 0, R_j = 1$ do not cause inconsistency with respect to Eq. (6.1), nevertheless $I_{ij} = 1$ is set, since either incomplete evaluation by a normal agent or evaluation by an abnormal agent has occurred.

When this inconsistency I_{ij} is evaluated high, a process fault identified by the combined pattern of two sensors s_i and s_j is suspected.

Example 6.2 Sensor network for process diagnosis. As an illustrative example, consider a tank whose level is controlled as shown in Fig. 6.4.

Figure 6.5 shows the extended sensor network using agents corresponding to process fault with simulation results for the following two events: (1) fault of the sensor indicating the valve V1 pattern, which is characterized by the sensor pattern $(F1, F2, V1, L1) = (N, N, O, N)$; and (2) process fault of flow lost between F2 and V1, which is characterized by the sensor pattern $(F1, F2, V1, L1) = (H, H, N, N)$ where H, N, O respectively stands for "too high," "normal," and "open." Square nodes indicate agents corresponding to *virtual* sensors monitoring process faults. The credibility of agent calculated by Eq. (6.3) with initial value set to 1 is shown at each node, where a circle node is an agent corresponding to a sensor and a square node corresponds to a *virtual* sensor. Credibilities of agents corresponding to case (1) (the dark circle node in the upper figure) and that corresponding to case (2) (the dark square node in the lower figure) are shown to be quite low in a simulation by the model in Eq. (6.3).

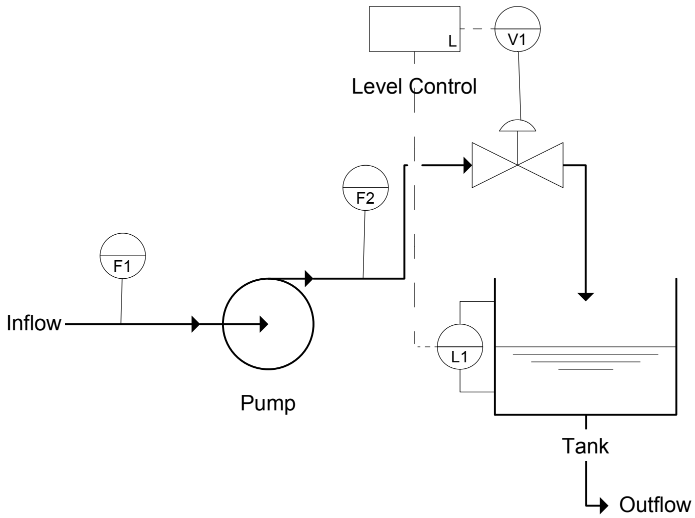

Fig. 6.4. Example of a tank with level control

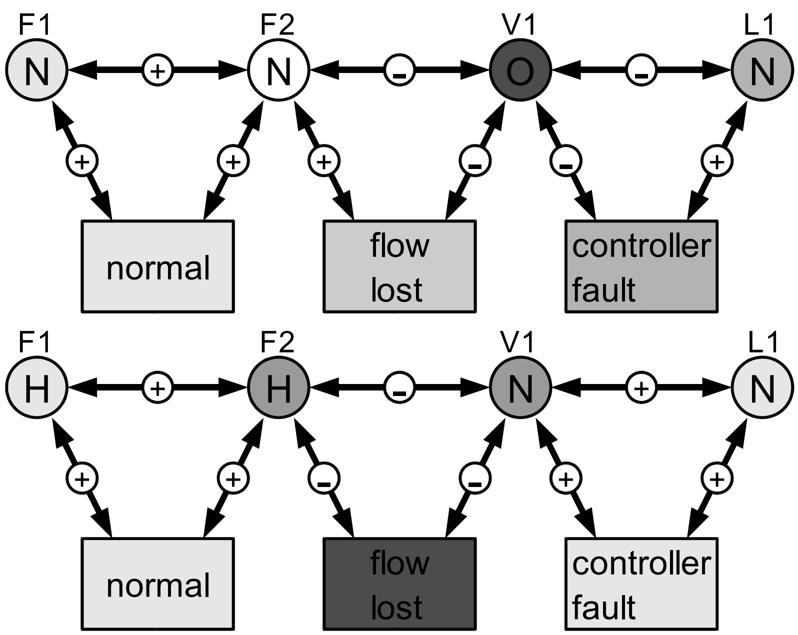

Fig. 6.5. Extended sensor network using agents of *virtual* sensor monitoring process fault when the sensor for valve V1 becomes faulty (*above*) and flow lost between F2 and V1 occurs (*below*). *Gray level* of nodes reflects the credibility: a *dark node* corresponds to low credibility and a *white node* corresponds to high credibility

6.6 Related Works and Discussions

Diagnosis based on qualitative constraints [50] expressed by a graph (e.g., [60]) or a predicate logic [124] have been studied extensively. In dynamical systems (such as processing plants), abnormal states propagate rapidly through many parts, hence a pattern (normal/high/low, oscillation, stick, etc.) of a large number of sensors (syndrome) results. It is critical to filter out unimportant sensor patterns and to focus on the key sensors.

"Data reconciliation" studied in the control theory community also focuses on finding a consistent interpretation among data from sensors. Data reconciliation filters out noise in the measurement by state estimate methods [88, 149]. However, when there are gross errors such as process/sensor faults, the technique does not apply, since the constraints used for estimation change because of these gross errors. Modifications have been made for the data reconciliation so that it will work even when gross errors may exist [107, 108, 149]. We extend the sensor network so that it will work even with measurement error by incorporating the data reconciliation [67], but this is omitted here since it may be difficult to implement the method by agents in a distributed manner.

The strong point of the sensor network is that processing is done in a fully distributed and autonomous manner at each agent. This is made possible by providing each agent with information processing capability, in addition to monitoring capability.

The characteristic of the approach to process diagnosis is that it admits relative relations between process values other than values themselves. One merit is that the approach does not suffer from shifting of all the process values, which occurs due to the change of load to the process or a change of environment such as seasonal changes, since the method can deal with consistency among sensor values and the process knowledge. Further, the change of some knowledge embodied by interactions among the agents does not propagate to other parts since the relations among process values are rather independent of each other, although the values are dependent on each other. When the model is implemented in a distributed processing environment with agents, evaluation of credibility can be done in a fully distributed and autonomous manner in the sensor network.

The difficulty of the approach in this chapter is to find enough relations between agents. Generally, such relations can be obtained from physical relations such as mass or heat balances, thermodynamical principles, etc., or by mathematical ones such as the value of a flow, which is always a positive value, ratios between 0 and 1, and so on, or by experimentation. With increasing numbers of redundant sensors values, more relations are obtained. Performance in diagnosis depends on the quality of the relations involved: the ability to make a diagnosis depends on the number of distinct relations, and the reliability of the diagnosis in turn depends on the quality of relations involved.

Sensor networks with wireless network technology and ad hoc routing are also becoming important, where many nodes must coordinate and operate in a dynamic and task-dependent environment [33]. “Exception-free” operation has been the focus for such sensor networks. This exception-free character seems to agree with the IMBS perspective, since the survivability (that is, keeping the system operational) of the system is a major concern of IMBS.

6.7 Summary and Conclusion

The sensor network is extended to deal with dynamical systems such as processing plants as a target for diagnosis. As an immunity-based system, on-line sensor-based diagnosis for process plants was discussed by defining and extending agents on the sensor network.

An important characteristic inspired by the immune network is cooperative and mutual monitoring by interacting agents, which leads to an emergent recognition capability (i.e., system-level diagnosis). We developed several algorithms for agents. The sensor network is extended so that it can diagnose not only sensor faults by evaluating the credibility of data from sensors but also process faults by evaluating inconsistencies among data. The sensor network dynamically reacts the online data from sensors. It identifies the faulty sensor and violated constraint, by moving from an equilibrium to another equilibrium, reacting to the change in data and hence to the change in relations among data.

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Immunity-Based Systems
A Design Perspective
Ishida, Y.
2004, XII, 177 p., Hardcover
ISBN: 978-3-540-00896-5