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AN EFFICIENT ALGORITHM FOR SIMULTANEOUS MULTIPLE FAULT DETECTION IN IMMUNITY-BASED SYSTEM DIAGNOSIS

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Abstract. *Fault diagnosis using immunity-based systems is well-known for its ability to detect unknown faults in systems composed of multiple sensors. However, it has a limitation in that the algorithm cannot detect faulty sensors when multiple sensors in a local area of the sensor network break down simultaneously. This is because test results obtained using multiple faulty sensors are occasionally inaccurate, and they delay the ability to change the parameters for fault detection. In this paper, we propose an efficient algorithm for this kind of fault detection in an immunity-based system diagnosis. The proposed algorithm identifies a local area in which sensors suspected of having faults exist, and excludes the test results obtained from these sensors from the calculation based on the dynamical model of the parameters for fault detection. The proposed algorithm is advantageous in terms of cost because it does not require any additional redundant sensors. Our experimental results demonstrate that the proposed algorithm can detect fault patterns, which cannot be detected by the conventional algorithm. The fault pattern is represented by multiple faulty sensors that break down simultaneously in a local area of the system.*
Keywords: Simultaneous multiple faults, Diagnosis, Immunity-based system

1. **Introduction.** Fault diagnosis using immunity-based systems is well known for its ability to detect unknown faults [1,2] – without prior learning, which is required for neural networks – and many applications have been proposed for it [3-7]. An application that uses the immunity-based dynamic network architecture for the diagnosis of a system composed of many sensors is shown in [7]. The diagnosis algorithm in [7] detects the faults of not only the sensors but also the components of the system. This feature is very helpful in fault detection in large-scale systems. Therefore, the algorithm should be applied to the diagnosis of an automotive exhaust gas purification system [12,13], which has an increasing scale, to reduce air pollution. Each sensor contained in the system presented in [7] has a parameter for fault detection, called "credibility". A sensor is determined to be normal or faulty depending on credibility, which is calculated using the results of mutual tests with other sensors and their credibility.

The conventional algorithm [7] has two limitations. First, the algorithm needs considerable computation even for typical and known faults. Second, the algorithm cannot detect faulty sensors when multiple sensors in a local area of the sensor network break down simultaneously. Trivial solution to this problem is to add redundant sensors to the network, but it is disadvantageous with cost. To overcome the first problem, we have already proposed an algorithm [8,9].

In this paper, we propose a new algorithm to overcome the second problem, which can efficiently and correctly detect simultaneous multiple sensor faults. Specifically, we improve on the previous analysis of the problem of multiple faults [11], and theoretically demonstrate that the algorithm enables simultaneous multiple fault detection. Furthermore, we experimentally demonstrate that our algorithm is superior to the conventional one [7] in terms of the number of necessary sensors and the number of sampling iterations. To verify the effectiveness of the algorithm, we apply it to the diagnosis of the automotive exhaust gas purification system mentioned above.

Why can immunity-based system diagnosis not detect simultaneous multiple faults without any additional redundant sensors? The reason is that the results of mutual tests among only the faulty sensors may incorrectly be judged as "Normal", i.e., all sensors in the test may be judged as normal even though they are faulty. These misjudgments prevent correct simultaneous multiple fault detection. Therefore, we propose our new algorithm – which identifies a local area in which sensors suspected of having faults exist, and excludes the test results obtained from these sensors from the calculation based on the dynamical model of each sensor's credibility.

We perform two experiments, which show that the proposed algorithm can correctly detect simultaneous multiple faults of the sensors without the requirement of any additional redundant sensors. The first experiment is an example of simultaneous triple fault detection, showing the efficiency of the proposed algorithm. The result shows that the proposed algorithm can detect the fault mode with normal sensors and sampling iterations fewer than those required by the conventional one. The second experiment applies the proposed algorithm to the diagnosis of the automotive exhaust gas purification system mentioned above, as a practical application. The results of this example show that the proposed algorithm can correctly detect a faulty mode that cannot be detected by the conventional algorithm. The experimental results indicate that our proposed algorithm can be applied to many other systems as an efficient diagnosis method.

In Section 2, we show the conventional algorithm in the immunity-based system diagnosis [7]. Then, in Section 3, we explain a problem associated with the conventional algorithm for fault detection if multiple sensors in a local area of the system break down simultaneously. In Section 4, we propose an algorithm that can efficiently detect multiple faulty sensors that break down simultaneously. In Section 5, we present the experimental results. Finally, we conclude the paper in Section 6.

2. **Conventional Algorithm.**

In this section, we explain the conventional algorithm used for the immunity-based system diagnosis [7], which is a base model of our proposed algorithm. Each sensor has a credibility which is used as a parameter for fault assessment. If this parameter is more than 0.5, the sensor corresponding to it is considered to be as "Normal", otherwise, it is considered to be "Faulty". Each parameter used in the conventional algorithm is calculated from the results of the mutual test among other sensors, and the credibilities of the sensors that are used in the mutual tests. Some variations in the dynamical model of the credibility have been proposed in accordance with their purpose [7]. We conducted our study using the dynamical model that allows an ambiguous state of the credibility because in future, we will conduct a further study using the magnitude of the credibility as a measure of the degree of deterioration. Figure 1 shows a control system for a factory that comprises several plants. In the system, the control center summarizes the information from sensors located in each plant. Furthermore, the sensors in the same plant monitor each others' outputs, and the plants and the control center also monitor each other. s_i $(i = 1, \cdots, n)$ is a sensor in the system, and S_k $(k = 1, \cdots, m)$ is a sensor group that includes the sensors whose outputs have a mutual correlation. We define "have a mutual correlation" as a functional relationship, i.e., the relationship in which one variable is determined if other variables are given. Figure 2 shows the relationship between sensors in the system shown in Figure 1. The number marked right side of sensors in Figure 1 corresponds to the sensor number i of s_i in Figure 2. This system has a sensor s_i ($i = 1, \cdots, 7$), and there is a sensor group S_k ($k = 1, \cdots, 9$), where S_k is a set of sensors that has mutual correlations. For example, in the case of $S_1 = \{s_1, s_2\}$, the output value of s_2 is determined uniquely if that of s_1 is given. T_k ($k = 1, \cdots, 9$) is a parameter of test results, and takes either a positive or negative value according to the result of the test, whether or not the sensors included in S_k satisfy the predetermined relationship. $r_i(t)$ is the time function of the credibility of sensor s_i at time t, and its dynamical model is expressed as Equation (1) [8,9,11].

$$\frac{dr_i(t)}{dt} = \sum_{k, s_i \in S_k} \left\{ T_k^+ R_{T_k}(t) \prod_{\substack{j, s_j \in S_k \\ j \neq i}} R_j(t) \right\} - \frac{r_i(t)}{\tau} \tag{1}$$

where $\sum_{k, s_i \in S_k}$ is a sum of index k of sensor group S_k that includes sensor s_i, and $\prod_{\substack{j, s_j \in S_k \\ j \neq i}}$ is a product of the credibility of index j of sensor s_j included in S_k except s_i. In Equation (1), the second term on the right side is added as a time constant τ to that of stated in the cited paper [7] so that the dynamical model does not depend on specifying a unit of time [9]. $R_i(t) \in [0, 1]$ is the credibility calculated by normalizing $r_i(t) \in (-\infty, \infty)$, as in Equation (2).

$$R_i(t) = \frac{1}{1 + \exp(-r_i(t))} \tag{2}$$

The sensor s_i is judged as being "Faulty" if $R_i(t) < 0.5$; otherwise, s_i is considered to be "Normal". T_k is a basic parameter of mutual test results between outputs of sensors in S_k, and it is defined as in Equation (3).

$$T_k \equiv \begin{cases} 1, & \text{if } |f_k(\mathbf{v}_k(t))| \leq \varepsilon_k \\ -1, & \text{otherwise} \end{cases} \tag{3}$$

where $f_k(\mathbf{v}_k(t)) = 0$ is a typical relationship among sensors in S_k, and $\mathbf{v}_k(t)$ is the vector of outputs of sensors included in S_k at time t. A constraint among sensors in S_k is expressed as $|f_k(\mathbf{v}_k(t))| \leq \varepsilon_k$, where ε_k is the allowable error that is predetermined considering the manufacture tolerance and so on. A basic parameter of test result T_k becomes 1 if the constraint is satisfied; otherwise, T_k becomes -1. T_k^+ is a parameter of the mutual test result defined as Equation (4).

$$T_k^+ \equiv h_k(T_k - 1) + \lambda_k \tag{4}$$

where h_k is the number of sensors included in S_k, and λ_k is an adjustment factor for adjusting the range of T_k^+. λ_k is set such that $0 \leq \lambda_k \leq h_k$ [7].

Similarly, the credibility of a constraint is introduced. $R_{T_k}(t)$ is a credibility of constraint $|f_k(\mathbf{v}_k(t))| \leq \varepsilon_k$, and its time function is $r_{T_k}(t) \in (-\infty, 0]$. A dynamical model of $r_{T_k}(t)$ is expressed as Equation (5), and $R_{T_k}(t)$ is expressed as Equation (6).

$$\frac{dr_{T_k}(t)}{dt} = T_k^+ \prod_{i, s_i \in S_k} R_i(t) - \frac{r_{T_k}(t)}{\tau} \tag{5}$$

$$R_{T_k}(t) = \begin{cases} 1, & T_k = 1 \\ 2/\{1 + \exp(-r_{T_k}(t))\}, & \text{otherwise} \end{cases} \tag{6}$$

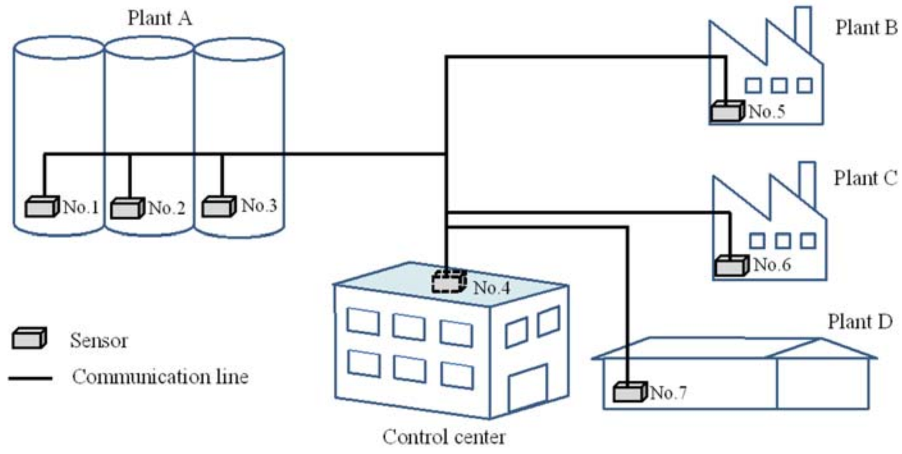


FIGURE 1. Factory control system with 4 plants

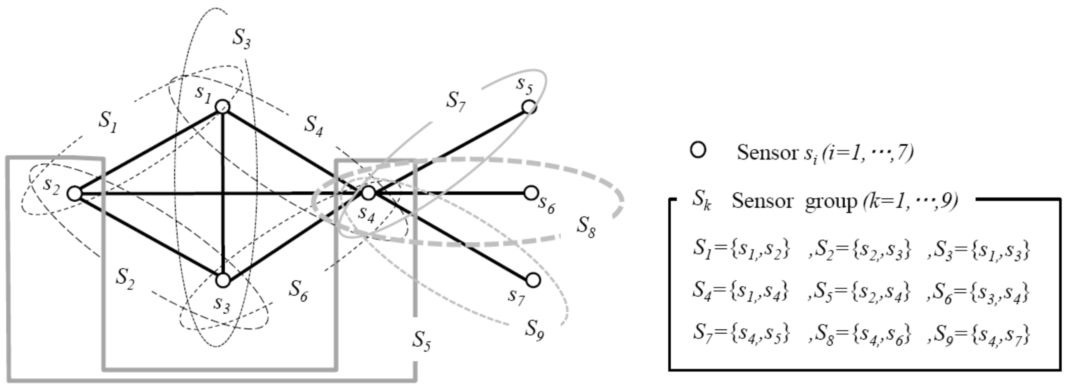


FIGURE 2. Sensor network (with 7 sensors and 9 sensor groups)

3. **Difficulty with Simultaneous Multiple Faults on the Conventional Algorithm.** The occurrence of simultaneous multiple faults is a difficult challenge for immunity-based system diagnosis, because it prevents the credibilities of faulty sensors from decreasing if the fault mode occurs, and the diagnosis may not detect faulty sensors. First, we explain the dynamical model of the credibility of the faulty sensor in the case where a single sensor breaks down. Next, we explain the model for where multiple sensors in a local area of the system break down simultaneously. Considering the case where a single sensor s_g in the system breaks down, all of the constraints of the sensor groups that include s_g are not satisfied, and all results of mutual tests corresponding to the sensor groups become NG (NG: $T_k = -1$). Therefore, we obtain the dynamical model of the time function of the credibility R_g of faulty sensor s_g from Equations (1) and (4) as Equation (7).

$$\begin{aligned}\frac{dr_g(t)}{dt} &= \sum_{k,s_g\in S_k}\left\{T_k^+ R_{T_k}(t)\prod_{\substack{j,s_g\in S_k\\ j\neq s_g}} R_j(t)\right\} - \frac{r_g(t)}{\tau}\\ &= \sum_{k,s_g\in S_k}\left\{(\lambda_k - 2h_k)R_{T_k}(t)\prod_{\substack{j,s_g\in S_k\\ j\neq s_g}} R_j(t)\right\} - \frac{r_g(t)}{\tau}\end{aligned} \tag{7}$$

In this paper, we set adjustment factor λ_k as $\lambda_k = h_k$ so that the absolute values of T_k^+ are same that either constraint $|f_k(\mathbf{v}_k(t))| \leq \varepsilon_k$ satisfies or not. Therefore, we obtain $T_k^+ = \lambda_k - 2h_k < 0$ from Equation (4). Then, the first term on the right side of Equation (7) becomes negative and the credibility of s_g then quickly decreases below the threshold of the fault value; finally, a single faulty sensor is assessed as being faulty.

Next, we explain the case where multiple sensors that have mutual correlation break down simultaneously. The results of the mutual tests among faulty sensors may incorrectly be assessed as being OK (OK: $T_k = 1$). Figure 3 shows the situation where two sensors s_1, s_2 in a local area of the network break down simultaneously. Figure 4 shows the relationship between the output of sensor s_1 and that of s_2, where sensor group $S_1 = \{s_1, s_2\}$, the vector of their output $\mathbf{v}_1 = (v_1, v_2)$, and the constraint $|f_1(\mathbf{v}_1)| = |v_1 - v_2| \leq \varepsilon_1$. Table 1 shows the results of the mutual test between s_1 and s_2, which correspond to the relationship shown in Figure 4. Cases A, B and C in Figure 4 show the situations described below. Case A shows the situation where both v_1 and v_2 are normal. Case B shows the situation where v_1 is abnormal (too small) and v_2 is normal. Case C shows the situation where both v_1 and v_2 are abnormal (too small). The test result of Case C becomes "OK" ($T_1 = 1$) even though both v_1 and v_2 are abnormal, because Case C satisfies the constraint $|f_1(\mathbf{v}_1)| \leq \varepsilon_1$. However, this result is a "Wrong" output. A situation such as that in Case C can be seen where the sensor's parts deteriorate over time, and the output of the sensor decreases more than its original.

Next, we explain the influence of the "Wrong" result of the mutual test on the dynamical model of the credibilities. Let the sensor groups that include a faulty sensor s_g, where the mutual test results are NG be Ξ^{NG}, and let the sensor groups that include s_g, where the mutual test results for faulty sensors are incorrectly "OK" be Ξ^{OK}. We obtain the dynamical model of credibility of s_g from Equation (1) as Equation (8), where $T_k^+ = h_k$,

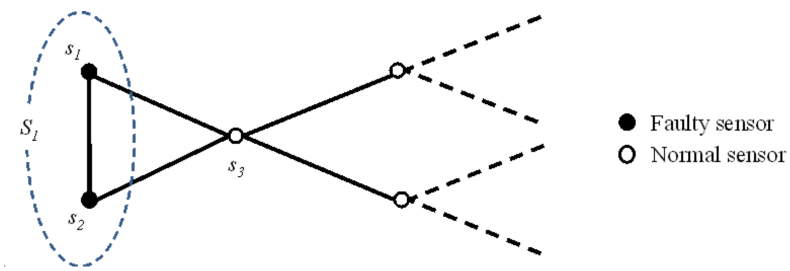


FIGURE 3. Example of multiple faults (2 faulty sensors)

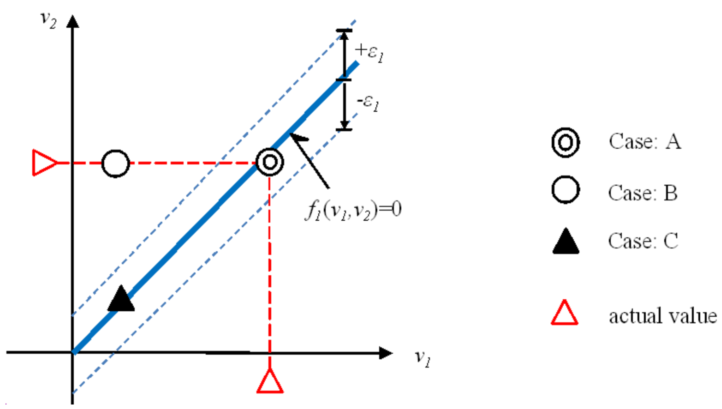


FIGURE 4. Relationship showing output of two sensors

TABLE 1. Test result corresponding to Figure 4

Case	Output of sensor		$\lvert f_1(v_1, v_2)\rvert$	Test result
	v_1	v_2		
A	Normal	Normal	$< \varepsilon_1$	OK
B	Faulty	Normal	$> \varepsilon_1$	NG
C	Faulty	Faulty	$< \varepsilon_1$	OK(Wrong)

$R_{T_k}(t) = 1$, if $S_k \in \Xi^{OK}$ and $T_k^+ = -h_k$, if $S_k \in \Xi^{NG}$ from Equation (6).

$$\begin{aligned}\frac{dr_g(t)}{dt} &= \sum_{k, s_g \in S_k, S_k \in \Xi^{OK}} \left\{ T_k^+ R_{T_k}(t) \prod_{\substack{j, s_g \in S_k, S_k \in \Xi^{OK} \\ j \neq g}} R_j(t) \right\} \\ &+ \sum_{k, s_g \in S_k, S_k \in \Xi^{NG}} \left\{ T_k^+ R_{T_k}(t) \prod_{\substack{l, s_g \in S_k, S_k \in \Xi^{NG} \\ l \neq g}} R_l(t) \right\} - \frac{r_g(t)}{\tau} \\ &= \sum_{k, s_g \in S_k, S_k \in \Xi^{OK}} \left\{ h_k \prod_{\substack{j, s_g \in S_k, S_k \in \Xi^{OK} \\ j \neq g}} R_j(t) \right\} \\ &+ \sum_{k, s_g \in S_k, S_k \in \Xi^{NG}} \left\{ -h_k R_{T_k}(t) \prod_{\substack{l, s_g \in S_k, S_k \in \Xi^{NG} \\ l \neq g}} R_l(t) \right\} - \frac{r_g(t)}{\tau}\end{aligned} \tag{8}$$

The first term on the right side of Equation (8) is positive, so the decreasing speed of the credibility of s_g becomes slower than that of s_g, which was calculated by Equation (7). Therefore, the "wrong" result of the mutual test delays the timing with which the fault is determined. Furthermore, if $R_g(t) \geq 0.5$ ($r_g(t) \geq 0$), and the magnitude relation on the right side of Equation (8) becomes as in Equation (9), then the dynamical model of R_g remains above the fault threshold value, i.e., the diagnosis cannot judge sensor s_g as being faulty.

$$\begin{aligned}&\sum_{k, s_g \in S_k, S_k \in \Xi^{OK}} \left\{ h_k \prod_{\substack{j, s_g \in S_k, S_k \in \Xi^{OK} \\ j \neq g}} R_j(t) \right\} \\ \geq &\sum_{k, s_g \in S_k, S_k \in \Xi^{NG}} \left\{ h_k R_{T_k}(t) \prod_{\substack{l, s_g \in S_k, S_k \in \Xi^{NG} \\ l \neq g}} R_l(t) \right\} + \frac{r_g(t)}{\tau}\end{aligned} \tag{9}$$

Assuming that the number of sensors included in S_k is all same as shown in Figure 2, that is, h_k are all same, and that $\prod R_j(t)$ is equal to $\prod R_l(t)$ because all credibilities are same normal value at just after simultaneous multiple faults occurrence. Taking $R_{T_k} \in [0, 1]$ into consideration, it is likely that Equation (9) will be satisfied if the magnitude relation of the number of sensor groups Ξ^{OK} and Ξ^{NG} becomes $|\Xi^{NG}| < |\Xi^{OK}|$. Generally, the outputs of sensors in a local area of the system have high correlation. Therefore, there are high density connections among sensors in this area. Inappropriate results of mutual tests among faulty sensors may occur if multiple sensors break down simultaneously in such an area. Increasing the number of sensor groups $|\Xi^{NG}|$ is an effective method of suppressing the satisfaction of the magnitude relation of Equation (9), even though there are inaccurate results of mutual tests. The method is the same as adding redundant sensors and increasing sensor groups for which the mutual test results are NG. However, this method is disadvantageous with respect to cost.

We show the difficulty associated with multiple fault detection using a simulation. The simulation conditions were as follows. The target network architecture of the simulation has 7 sensors, as shown in Figure 2. The arrangement of faulty sensors in this network is shown in Figure 5, and the number of faulty sensors is 3, which is nearly half of the sensors in the network. Furthermore, the connections of the 3 faulty sensors form a complete graph. This formation is an important condition of fault detection, because faulty sensors have many connections with other faulty sensors; there are likely to be inaccurate mutual test results that may prevent the detection of faulty sensors. For simplicity, the output values of all sensors are the same and are time-invariant. Furthermore, we set the condition of the output value of faulty sensors so that the results of mutual tests among the faulty sensors are all "OK(Wrong)". Details of the simulation condition are shown in Table 2. Figure 6(a) shows the behavior of the credibility of each faulty sensor in the case where they alternately break down, i.e., one sensor breaks down after a fault assessment of another faulty sensor. In this case, the fault detection for each faulty sensor is correct. The reason is that the influence of the "OK(Wrong)" on the dynamical model of the credibility of a faulty sensor (expressed as Equation (8)) decreases because the credibilities of other faulty sensors have already become small after assessments of their faults. However, all of the credibilities of faulty sensors increase over the fault judgment value after identifying a third faulty sensor, i.e., the diagnosis algorithm cannot continue to assess faults for three faulty sensors. The reason is that the results of mutual tests T_1, T_2 and T_3 become "OK(Wrong)" after the third faulty sensor judgment, then the dynamical model of the

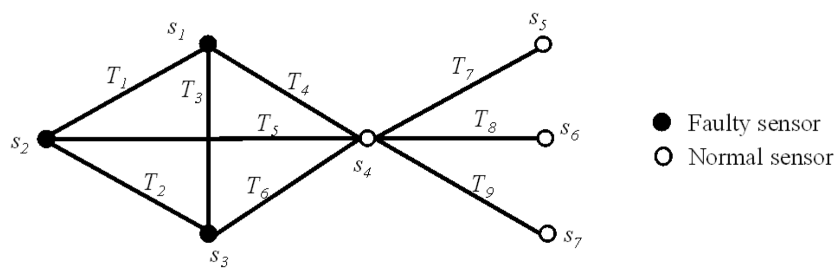
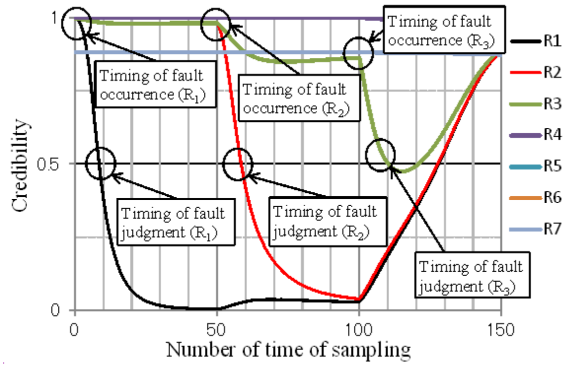


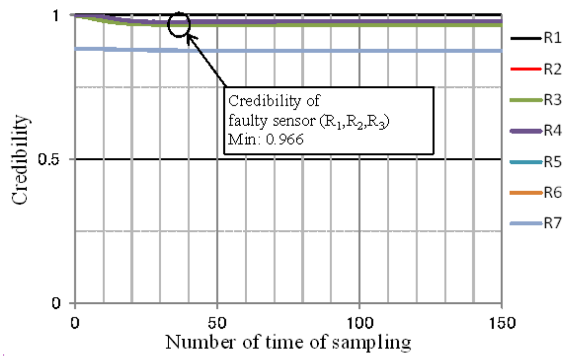
FIGURE 5. Simulation model (with 3 faulty sensors and 4 normal sensors)

TABLE 2. Simulation conditions

Parameters		Value
Output of sensor	Normal	1 (constant)
	Faulty	0 (constant)
Allowable error (ε_k; k=1,$\cdots$,9)		0.5
Adjustment factor (h_k; k=1,$\cdots$,9)		2
Time constant (τ)		1.0
Step size (μ)		0.1



(a) In case of breaking down one by one



(b) In case of simultaneous breaking down

FIGURE 6. Simulation results for the detection of 3 faulty sensors using the conventional algorithm (behavior of the credibilities)

credibilities of s_1, s_2, s_3 has two "OK(Wrong)" test results and one NG test result, and they become positive. Figure 6(b) shows the behavior of the credibility of each faulty sensor in the case where they break down simultaneously. Slight changes in the credibilities can be seen just after faults occur, but no credibilities decrease below the fault judgment value.

As a result, the conventional algorithm cannot detect three faulty sensors that break down simultaneously in a local area of the system.

4. **Proposed Algorithm.** In the previous section, we explain that the credibilities of faulty sensors in the immunity-based system diagnosis may be prevented from decreasing due to inaccurate test results. Then, its fault detection timing is either delayed [11] or it cannot detect faulty sensors if simultaneous multiple faults occur.

To overcome this problem, we proposed a new algorithm for simultaneous multiple-fault detection. The feature of the proposed algorithm is identifying a local area in which the "suspected faulty" sensors exist, and excluding the mutual test among sensors suspected of having faults based on calculations of the dynamical model of the credibility of each sensor.

The proposed algorithm is composed of three parts as follows:

[Step 1] Assessment of the presence/absence of application of excluding the inaccurate mutual test result.

[Step 2] Identifying a local area in which the "suspected faulty" sensors exist, and detecting these sensors.

[Step 3] Excluding inaccurate mutual test results among "suspected faulty" sensors.

A detailed explanation of this algorithm is given below:

[Step 1] The presence/absence of application of excluding the inappropriate mutual test result is assessed by the possibility that multiple faulty sensors exist. The algorithm determines the possibility of multiple faulty sensors, and applies the excluded inaccurate test results if there are more than two test results that are "NG" in the system.

[Step 2] Count the number of results of mutual tests that include s_i $(i = 1, \cdots, n)$ of "NG" and that of "OK" for each s_i. The set of sensor groups that includes s_i is Ξ_i $(i = 1, \cdots, n)$, i.e., $\Xi_i = \{S_k | s_i \in S_k\}$. The set of sensor groups that includes s_i and whose test result is "NG" is Ξ_i^{NG} $(i = 1, \cdots, n)$, i.e., $\Xi_i^{NG} = \{S_k | s_i \in S_k, T_k = -1\}$. In a similar way, the set of sensor groups that includes s_i and whose test result is "OK" is Ξ_i^{OK} $(i = 1, \cdots, n)$, i.e., $\Xi_i^{OK} = \{S_k | s_i \in S_k, T_k = 1\}$. The numbers of elements of set Ξ_i^{NG} and Ξ_i^{OK} are N_i $(i = 1, \cdots, n)$ and O_i $(i = 1, \cdots, n)$, respectively, i.e., $N_i = |\Xi_i^{NG}|$,

$O_i = |\Xi_i^{OK}|$. If $2 \leq N_i \leq O_i$ and O_i is the largest in the all sensors, then let the elements included in Ξ_i^{NG} except s_i be a set of "suspected faulty" sensors D_i.

$$D_i = \bigcup_{u, S_u \in \Xi_i^{NG}} (S_u - \{s_i\}) \tag{10}$$

In Equation (10) $S_u - \{s_i\}$ is defended as $S_u - \{s_i\} = \{s_k | s_k \in S_u, k \neq i\}$. The condition $2 \leq N_i \leq O_i$ and Equation (10) are based on the following consideration: sensor s_i, which has more "OK" results than that of "NG" is regarded as a "normal sensor", and s_i is assumed to be on the boundary line between the region in which the multiple "suspected faulty" sensors exist and that where the "possibly normal" sensors exist if s_i satisfies $2 \leq N_i \leq O_i$, as shown in Figure 7. The sensors whose mutual test results with s_i are "NG," are regarded as "suspected faulty" sensors.

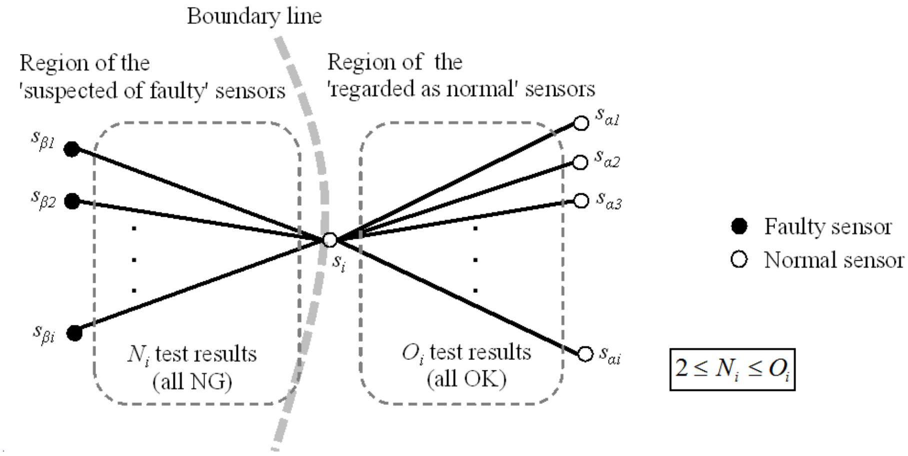


FIGURE 7. Concept of identifying local area in which the suspected faulty sensors exist

The set of "suspected faulty" sensors in the entire system F is a sum of D_i, which is expressed as Equation (11).

$$F = \bigcup_{i=1}^{n} D_i \tag{11}$$

[Step 3] Exclude the results of the mutual test among only the "suspected faulty" sensors from the calculation of the dynamical model of the credibility of each sensor. To exclude the test results, we expanded the parameters of test result T_k^+ in the conventional algorithm that is expressed as Equation (3) and Equation (4). The expanded parameter of test result T_k^* is defined in Equation (12).

$$T_k^* \equiv \begin{cases} 0, & \text{if } S_k \in P(F) \\ T_k^+, & \text{otherwise} \end{cases} \tag{12}$$

where $P(F)$ is a power set of set F. $P(F)$ is the set of sensor groups which includes only "suspected faulty" sensors. The dynamical model of the credibility, which is expressed as Equation (1), is modified as Equation (13) using the expanded test result T_k^*.

$$\frac{dr_i(t)}{dt} = \sum_{k, s_i \in S_k} \left\{ T_k^* R_{T_k}(t) \prod_{\substack{j, s_j \in S_k \\ j \neq i}} R_j(t) \right\} - \frac{r_i(t)}{\tau} \tag{13}$$

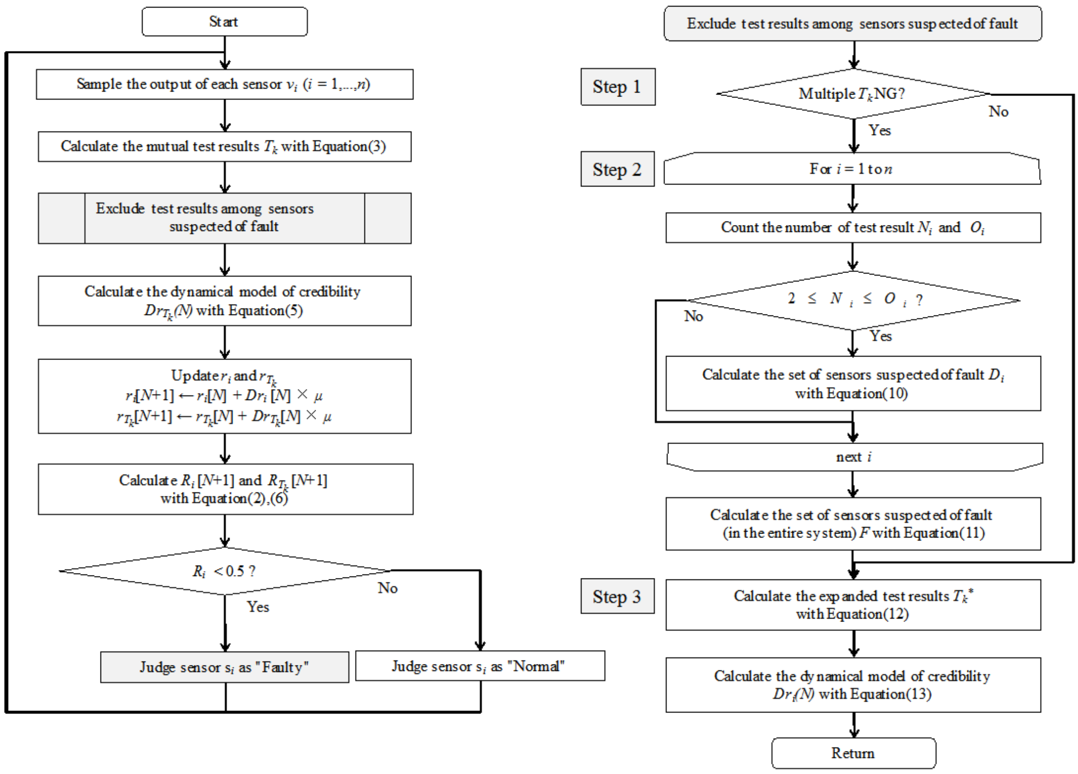


FIGURE 8. Flowchart of the proposed algorithm

The parameter of the results of mutual test T_k^* among only "suspected faulty" sensors in $S_k \in P(F)$ is calculated as 0 using Equation (12). Therefore, the inaccurate mutual test result is excluded from the first term on the right side of Equation (13). The flowchart of the proposed algorithm is shown in Figure 8.

5. Experiments.

In this section, we demonstrate that our algorithm is superior to the conventional one [7] in terms of the number of necessary sensors and the number of sampling iterations by performing computer simulations.

5.1. Simultaneous triple fault detection.

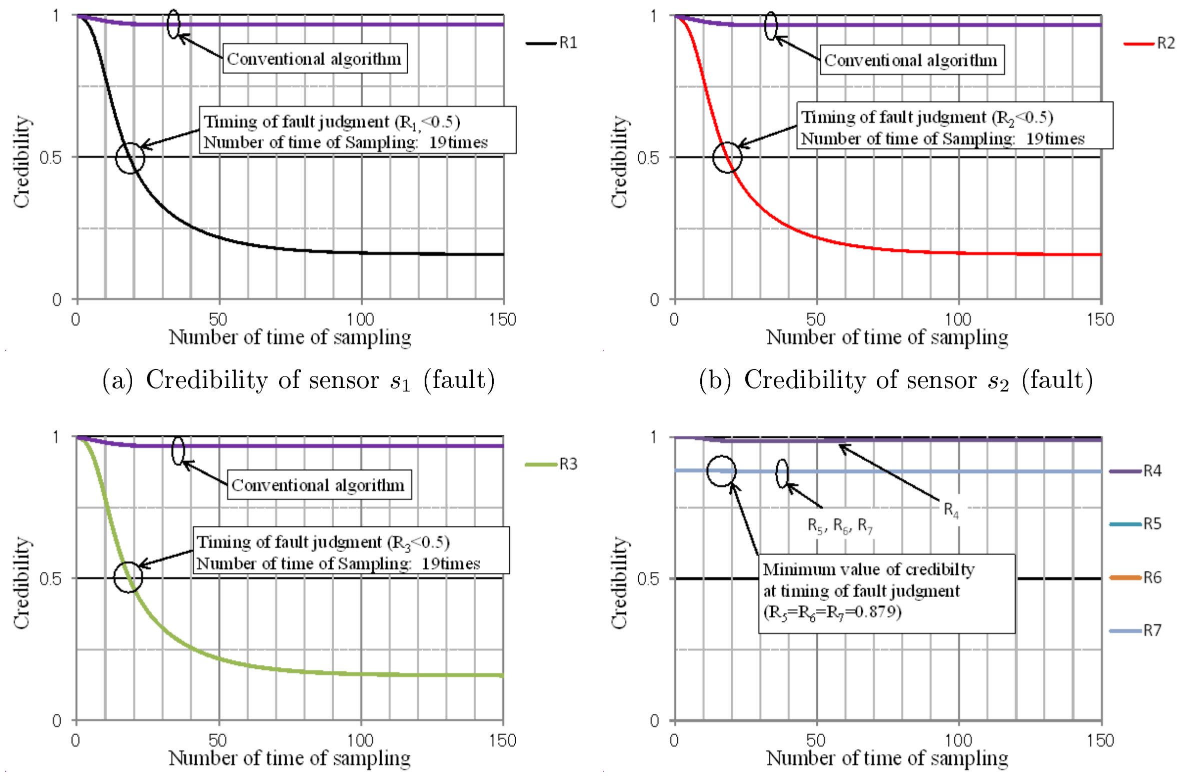
We show two kinds of results of the simultaneous triple fault detection in this section. The first is the result performed under the condition where the number of faulty sensors is one less than that of normal sensors. This condition is the most difficult for the diagnosis using immunity-based system to detect faulty sensors, because the diagnosis uses a mutual test together with other sensors, so it is impossible in principle to detect faulty sensors which are greater in number than normal sensors. The second is the comparison of the minimum number of necessary normal sensors between the proposed algorithm and the conventional one.

First, we set the simulation conditions to be the same as what was explained in Section 3, i.e., where the conventional algorithm cannot correctly detect faulty sensors.

In terms of the simulation conditions, the network architecture and arrangement of faulty sensors and normal sensors are shown in Figure 5, and the setting of each parameter is shown in Table 2. Table 3 shows the result of each parameter corresponding to all sensors s_i in the system, as calculated by the proposed algorithm. Only s_4 satisfies the condition of detecting "suspected faulty" sensors, and $2 \leq N_4 \leq O_4$. The set of "suspected faulty" sensors corresponding to s_4, D_4 is calculated as $D_4 =$

TABLE 3. Simulation results of the proposed algorithm (results of detecting "suspected faulty" sensors and excluding inaccurate test results)

i	Ξ_i	Ξ_i^{NG}	Ξ_i^{OK}	N_i	O_i	D_i	F	$S_k \in P(F)$	*Excluded test results*
1	$\{S_1,S_3,S_4\}$	$\{S_4\}$	$\{S_1,S_3\}$	1	2	$\{\phi\}$			
2	$\{S_1,S_2,S_5\}$	$\{S_5\}$	$\{S_1,S_2\}$	1	2	$\{\phi\}$			
3	$\{S_2,S_3,S_6\}$	$\{S_6\}$	$\{S_2,S_3\}$	1	2	$\{\phi\}$			
4	$\{S_4,S_5,S_6,S_7,S_8,S_9\}$	$\{S_4,S_5,S_6\}$	$\{S_7,S_8,S_9\}$	3	3	$\{s_1,s_2,s_3\}$	$\{s_1,s_2,s_3\}$	S_1,S_2,S_3	T_1,T_2,T_3
5	$\{S_7\}$	$\{\phi\}$	$\{S_7\}$	0	1	$\{\phi\}$			
6	$\{S_8\}$	$\{\phi\}$	$\{S_8\}$	0	1	$\{\phi\}$			
7	$\{S_9\}$	$\{\phi\}$	$\{S_9\}$	0	1	$\{\phi\}$			



(a) Credibility of sensor s_1 (fault)

(b) Credibility of sensor s_2 (fault)

(c) Credibility of sensor s_3 (fault)

(d) Credibilities of sensor s_4, s_5, s_6 and s_7 (normal)

FIGURE 9. Simulation results for the proposed algorithm (behavior of the credibilities)

$\bigcup_{u, S_u \in \Xi_4^{NG}} (S_u - \{s_4\}) = \{s_1, s_2, s_3\}$ using Equation (10). The set of "suspected faulty" sensors of the entire system F is calculated as $F = D_4 = \{s_1, s_2, s_3\}$ using Equation (11). Then, $P(F) = \{\phi, \{s_1\}, \{s_2\}, \{s_3\}, \{s_1, s_2\}, \{s_2, s_3\}, \{s_1, s_3\}, \{s_1, s_2, s_3\}\}$. The sensor groups that satisfy $S_k \in P(F)$ are S_1, S_2 and S_3. Therefore, the results of the mutual tests that were excluded from each calculation of the dynamical model of the credibilities are T_1, T_2 and T_3; the expanded test results corresponding to T_1, T_2 and T_3 are calculated as $T_1^* = T_2^* = T_3^* = 0$ using Equation (12).

Finally, the dynamical model of the credibility of each sensor is calculated from Equation (13). Figure 9 shows the behavior of the credibilities of each sensor. Figures 9(a)-9(c) show the credibilities R_1, R_2 and R_3 of faulty sensors s_1, s_2 and s_3, respectively; they show that all of the credibilities decrease below the fault judgment value at 19 sampling time intervals after the occurrence of faults of s_1, s_2 and s_3. On the other hand, Figure 9(d) shows the credibilities of normal sensors s_4, s_5, s_6 and s_7, and they stay in the normal judgment region (over the fault judgment value).

Next, we show the second result. Table 4 shows the comparison of the minimum number of necessary normal sensors. The proposed algorithm needs four normal sensors to detect the fault mode, i.e., it can detect faulty sensors which number is one less than that of normal sensors, that is, no redundant sensors, as demonstrated in the first result. On the other hand, the conventional algorithm needs six normal sensors, i.e., it requires two redundant sensors. Moreover, the proposed algorithm needs less number of sampling iterations than the conventional one.

As a result, we demonstrated that the simultaneous break down of three faulty sensors in a local area of the network is efficiently detected by the proposed algorithm.

5.2. **Application to the automotive exhaust gas purification system.** In this section, we apply the proposed algorithm to the diagnosis of the automotive exhaust gas purification system shown in Figure 10 [12], as a practical application. This system purifies exhaust gas including hazardous substances such as hydrocarbons (HCs), carbon monoxide (CO), and nitrogen oxide (NOx), using a three-way catalytic converter (TWC), thus reducing air pollution. TWC converts these hazardous substances into harmless components such as water vapor (H_2O), carbon dioxide (CO_2), and nitrogen (N_2). Optimal conversion efficiency is attained if the mass ratio of air and fuel supplied to the automotive engine is about 14.6, as shown in Figure 11 [13]. Therefore, an important task of the system is to precisely supply fuel to the engine according to the amount of engine intake air. To precisely supply fuel to the engine, the amount of supplied fuel is compensated by the feedback control, which has a primary feedback loop with the linear air-fuel ratio sensor and a secondary feedback loop with the oxygen sensor [14]. These sensors are arranged on the exhaust section of the engine, where temperature is very high. Therefore, these sensors may break down simultaneously because of abnormally high temperature, if abnormal combustion occurs because of use of inferior fuel. Considering such a situation, we set the simulation conditions.

Let v_i $(i = 1, \dots, 9)$ be the outputs of the sensors s_i $(i = 1, \dots, 9)$. The sensor groups and their constraints are expressed as follows. In the exhaust section, the sensor groups are $S_1 = \{s_1, s_2\}$, $S_2 = \{s_1, s_3, s_4, s_8\}$ and $S_3 = \{s_2, s_3, s_4, s_8\}$. Their constraints are $|v_1 - G_1(v_2)| \leq \varepsilon_1$, $|v_1 - G_2(v_3, v_4, v_8)| \leq \varepsilon_2$, $|v_2 - G_3(v_3, v_4, v_8)| \leq \varepsilon_3$, respectively, where $v_1' = G_1(v_2)$, $v_1' = G_2(v_3, v_4, v_8)$, $v_2' = G_3(v_3, v_4, v_8)$, v_1' is the estimated value of v_1, and v_2' is the estimated value of v_2. In the intake air mass measurement section, the sensor groups are $S_4 = \{s_3, s_5, s_6\}$ and $S_5 = \{s_3, s_5, s_7\}$. Their constraints are $|v_3 - G_4(v_5, v_6)| \leq \varepsilon_4$ and $|v_3 - G_5(v_5, v_7)| \leq \varepsilon_5$, respectively, where $v_3' = G_4(v_5, v_6)$, $v_3' = G_5(v_5, v_7)$, and v_3'

TABLE 4. Comparison of the minimum number of necessary normal sensors

Condition					Results	
Number of sensors				Algorithm	Fault detection (○: detect correctly)	Number of sampling [times]
Overall	Normal	Faulty	Redundant			
9	6	3	2	Conventional	○	110
				Proposed	○	14
8	5	3	1	Conventional	×	-
				Proposed	○	16
7	4	3	0	Conventional	×	-
				Proposed	○	19

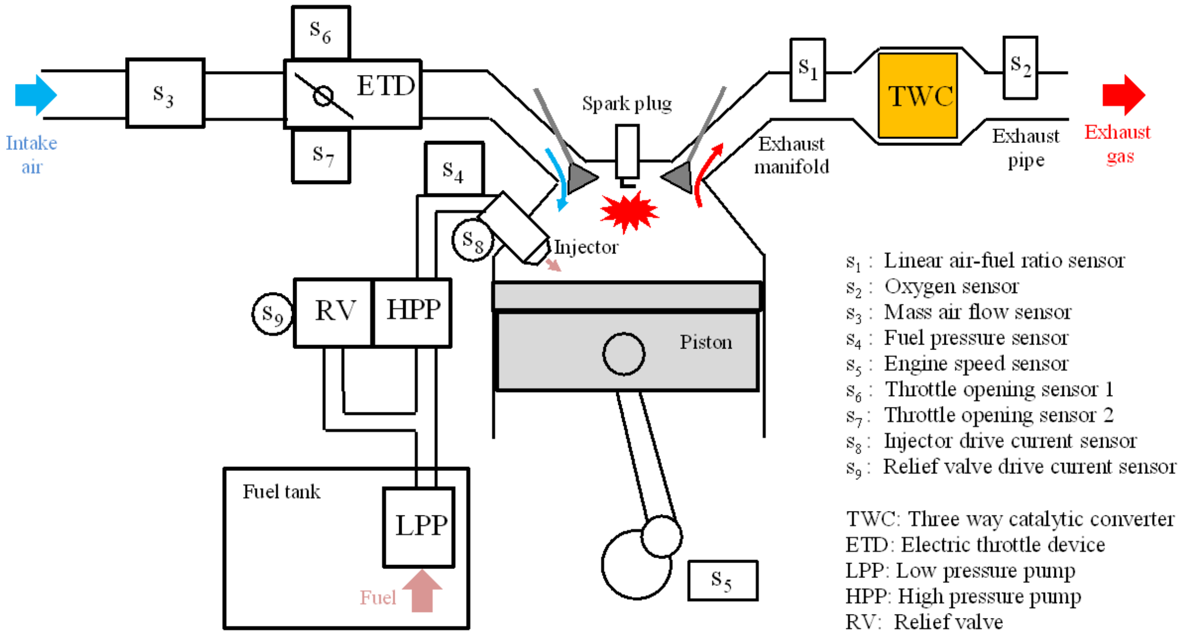


FIGURE 10. Automotive exhaust gas purification system

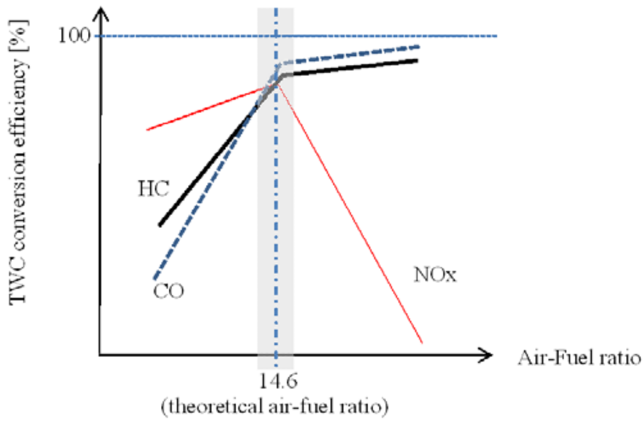


FIGURE 11. Conversion efficiency of the three way catalytic converter

is the estimated value of v_3. In the intake air mass control section, the sensor group is $S_6 = \{s_6, s_7\}$, and its constraint is $|v_6 - v_7| \leq \varepsilon_6$. In the fuel supply control section, the sensor group is $S_7 = \{s_4, s_5, s_8, s_9\}$, and its constraint is $|G_{71}(v_4, v_8) - G_{72}(v_5, v_9)| \leq \varepsilon_7$, where $G_{71}(v_4, v_8)$ is the estimated amount of the fuel supplied from the injector, and $G_{72}(v_5, v_9)$ is that supplied from the high pressure pump.

Let the faulty sensors be the linear air–fuel ratio sensor (s_1) and the oxygen sensor (s_2). Therefore, we set the simulation conditions in terms of the constraints of these faulty sensors as $|v_1 - G_1(v_2)| \leq \varepsilon_1$, $|v_1 - G_2(v_3, v_4, v_8)| > \varepsilon_2$, and $|v_2 - G_3(v_3, v_4, v_8)| > \varepsilon_3$.

The sensor network of this simulation model is shown in Figure 12. Table 5 shows the result of the parameters corresponding to all sensors s_i in the system, as calculated by the proposed algorithm. Only s_3 satisfies the condition of detecting "suspected faulty" sensors, and $2 \leq N_3 \leq O_3$. Therefore, the result of the mutual test that was excluded from each calculation of the dynamical model of the credibilities is T_1. Figure 13(a) shows the behavior of the credibilities of the sensors by using the conventional algorithm, and Figure 13(b) shows those obtained using the proposed algorithm. The credibilities of s_1

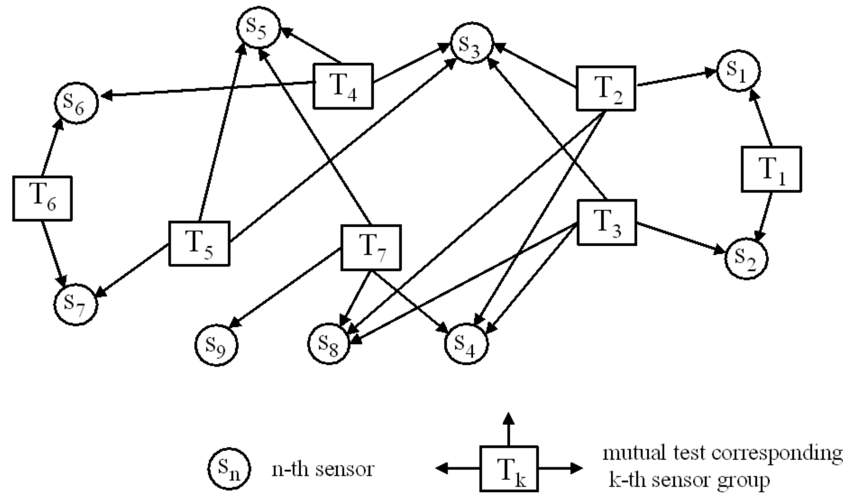


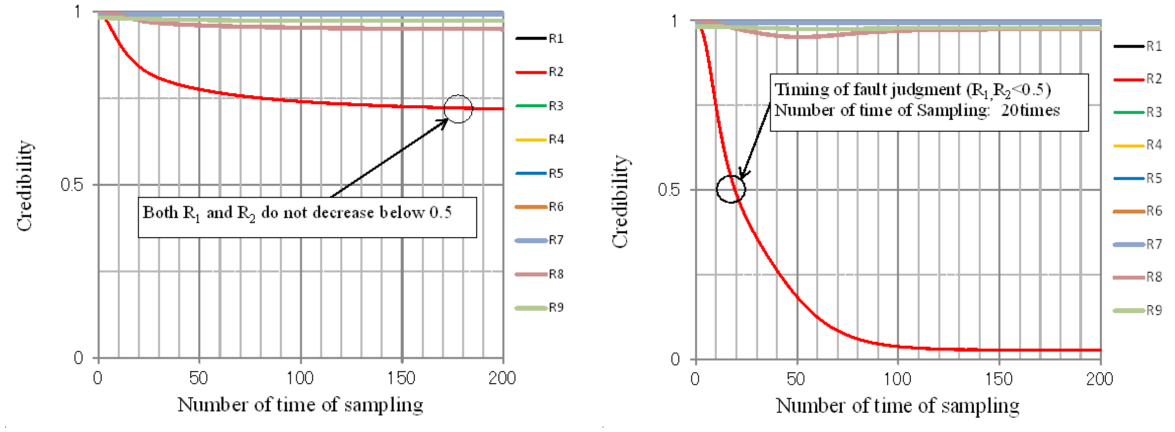
FIGURE 12. Sensor network corresponding to the exhaust gas purification system

TABLE 5. Simulation results of the proposed algorithm (results of detecting "suspected faulty" sensors and excluding inaccurate test results)

i	Ξ_i	Ξ_i^{NG}	Ξ_i^{OK}	N_i	O_i	D_i	F	$S_k \in P(F)$	*Excluded test results*
1	$\{S_1, S_2\}$	$\{S_2\}$	$\{S_1\}$	1	1	$\{\phi\}$			
2	$\{S_1, S_3\}$	$\{S_3\}$	$\{S_1\}$	1	1	$\{\phi\}$			
3	$\{S_2, S_3, S_4, S_5\}$	$\{S_2, S_3\}$	$\{S_4, S_5\}$	2	2	$\{s_1, s_2, s_4, s_8\}$			
4	$\{S_2, S_3, S_7\}$	$\{S_2, S_3\}$	$\{S_7\}$	2	1	$\{\phi\}$			
5	$\{S_4, S_5, S_7\}$	$\{\phi\}$	$\{S_4, S_5, S_7\}$	0	3	$\{\phi\}$	$\{s_1, s_2, s_4, s_8\}$	S_1	T_1
6	$\{S_4, S_6\}$	$\{\phi\}$	$\{S_4, S_6\}$	0	2	$\{\phi\}$			
7	$\{S_5, S_6\}$	$\{\phi\}$	$\{S_5, S_6\}$	0	2	$\{\phi\}$			
8	$\{S_2, S_3, S_7\}$	$\{S_2, S_3\}$	$\{S_7\}$	2	1	$\{\phi\}$			
9	$\{S_7\}$	$\{\phi\}$	$\{S_7\}$	0	1	$\{\phi\}$			

and s_2 in Figure 13(a) slightly change just after faults occur, but do not decrease below the fault judgment value. On the other hand, those in Figure 13(b) decrease below the fault judgment value after only 20 sampling iterations, i.e., the proposed algorithm can correctly detect the faults of both s_1 and s_2 without addition of redundant sensors.

6. **Conclusion.** In this paper, we discussed the reason for which the immunity-based system diagnosis cannot detect faulty sensors, or its fault detection timing is delayed using the conventional algorithm if multiple sensors break down simultaneously. Next we proposed a new algorithm that efficiently detects multiple sensors in a local area of the network break down simultaneously. The proposed algorithm identifies a local area in which sensors suspected of having faults exist, and excludes the test results obtained from these sensors from the calculation based on the dynamical model of each sensor's credibility. Because the algorithm for fault detection involving immunity-based system diagnosis uses a mutual test together with other sensors, it is impossible in principle for the diagnosis to detect faulty sensors which are greater in number than normal sensors. In the first experiment, we set the simulation condition to be that the number of faulty sensors should be one less than that of normal sensors. In the second experiment, we applied the proposed algorithm to the diagnosis of the automotive exhaust gas purification system as a



(a) Conventional algorithm (b) Proposed algorithm

FIGURE 13. Simulation results for the proposed algorithm (behavior of the credibilities)

practical application. Both experimental results demonstrate that the proposed algorithm can correctly detect faulty sensors without the requirement of any additional redundant sensors under these conditions where the conventional algorithm cannot correctly detect them. We therefore conclude that the proposed algorithm is more efficient than the conventional one.

It is hoped that sensor networks for diagnoses that do not require any redundant sensors and that are advantageous from a cost perspective can be realized using our proposed algorithm. Especially, it is hoped that the proposed algorithm is applied to diagnosis of the systems which have possibility of occurrence of multiple sensor faults due to being used under severe conditions, for example, automotive engines, steelworks and power stations.

REFERENCES

[1] D. Dasgupta, Advances in artificial immune systems, *IEEE Computational Intelligence Magazine*, pp.40-49, 2006.

[2] X. Gao, H. Xu, X. Wang and K. Zenger, A study of negative selection algorithm-based fault detection and diagnosis, *International Journal of Innovative Computing, Information and Control*, vol.9, no.2, pp.875-901, 2013.

[3] X. Yue, D. Wen, H. Ma and J. Zhang, Fault detection based on real-value negative selection algorithm of artificial immune system, *International Conference on Intelligent Computing and Cognitive Informatics*, pp.234-246, 2010.

[4] G. R. Halligan, B. T. Thumati and S. Jagannathan, Artificial immune system-based diagnostics and prognostics scheme and its experimental verification, *IEEE International Conference on Control Applications*, pp.958-963, 2011.

[5] Y. Ishida, Active diagnosis by immunity-based agent approach, *Proc. of the 7th International Workshop on Principles of Diagnosis*, Val-Morin, Canada, pp.106-114, 1996.

[6] H. Shida, T. Okamoto and Y. Ishida, Immunity-based diagnosis for a motherboard, *Sensors*, vol.11, no.3, pp.4462-4473, 2011.

[7] Y. Ishida, An immune network approach to sensor-based diagnosis by self-organization, *Complex Systems*, vol.10, pp.73-90, 1996.

[8] K. Wada, T. Toriu and H. Hama, Fault diagnosis by immunity-based agent network using degree of similarity with specific fault mode, *ICIC Express Letters*, vol.7, no.6, pp.1761-1766, 2013.

[9] K. Wada, T. Toriu and H. Hama, Improving the efficiency of known fault mode detection for immunity-based diagnosis, *Transactions of the Institute of Systems, Control and Information Engineers*, vol.27, no.2, 2014.

[10] Y. Ishida and F. Mizessyn, Sensor diagnosis of process plants by an immune-based model, *Transactions of the Institute of Systems, Control and Information Engineers*, vol.7, no.1, pp.1-8, 1994.

[11] K. Wada, T. Toriu and H. Hama, Improving the performance of detection of simultaneous double faults on immunity-based system diagnosis, *ICIC Express Letters, Part B: Applications*, vol.5, no.1, pp.83-88, 2014.
[12] BOSCH, *Automotive Handbook*, 8th Edition, SAE Society of Automotive Engineers, 2011.
[13] M. J. Anderson, A feedback A/F control system for low emission vehicle, *SAE Technical Paper, No.930388*, 1993.
[14] H. Kitagawa, T. Mibe, K. Okamatsu and Y. Yasui, L4-engine development for a super ultra low emissions vehicle, *SAE Technical Paper, No.2000-01-0887*, 2000.