Diagnosis System of Abnormality in Refuse Incineration Plant using Fuzzy Logic*

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A fuzzy expert system for abnormality diagnosis is developed for all component equipment at a refuse incineration plant. Since fuzzy logic is applied to the reasoning function, diagnosis can be made even in the case of abnormality under unstable conditions of the plant and under transitional conditions, and this system is more flexible than those of the past. At the same time, patterned diagnosis knowledge by membership functions provides a good effect to the human interface, compared with word expression. For example, easy acquisition and modification of the knowledge and easy understanding of the diagnosis process are attained. The results of diagnosis are output audiolly and visually and provide information for removal and correction of the cause of abnormality. This system is in actual operation at several plants.

Key Words: Artificial Intelligence, Expert System, Fuzzy Set, Diagnosis System, Data Base

1. Preface

With recent progress in, for example, modeling technology, control theory, control machinery and equipment, automation and labor savings in the steady operation of plants have produced spectacular results. Furthermore, in refuse incineration plants, in spite of the increase in the requirement of various peripheral machinery and equipment for enhanced pollution prevention and energy-efficient operation, the labor savings in the operation has increased, and now, one-man operation has become feasible.

On the other hand, for the unsteady state at the time of abnormality or failure of component machinery and equipment in plants, human operators were heretofore required for such tasks as detecting the deviation from the steady state using upper and lower limit switches, informing operators of the occurrence of abnormality by sounding alarms, and determining the cause and countermeasures required by referring

to the operation manual and the experience of operators and carrying out the countermeasures.

For the automation of the correction of an unsteady state such as that at the time of abnormality or failure, due to problems such as low frequency of occurrence and low reproducibility, diverse patterns of occurrence, and inapplicability of linear models, the theoretical analysis and development of devices are difficult.

The amount of information increases in proportion to the complexity of the plant. However, there is a limit in the capability of operators; therefore the development of a support system for the occurrence of an unsteady state is important.

Knowledge engineering, which models and applies the human capability of coping with problems, is one of the powerful means for solving ill-defined problems such as this one. These typical expert systems with fuzzy logic are already in practical use in many fields, and their use is expected to expand. Furthermore, in refuse incineration plants, fuzzy logic has already been applied to the automation of the restoration operation upon the occurrence of abnormal combustion in incinerators^{(1),(2)}, and good results have been

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attained. However, problems common to these practical uses are that the quality of knowledge being utilized exerts a large influence on the performance of the system, and that the acquisition of knowledge for the analysis and modification are important.

The feature of the on-line, real-time expert system for plant abnormality diagnosis is that the information to be treated is the numerical data of plants, and the object of diagnosis is the state having an ambiguous border, such as normal/abnormal or steady/unsteady, which is unsuited to numerical treatment. Hereupon, if diagnostic knowledge is expressed only by words as in the conventional method, in order to allow for diagnosis of various cases, much knowledge for classifying states is required, and the total amount of knowledge increases. When numerical information is expressed in words, the objectivity is lost (for example, a problem such as "Which is larger, a large rat or a small elephant?"). Thus, it is difficult to quantitatively determine the effect of diagnostic results, and the work of knowledge modification becomes difficult. On the other hand, in the case of processing everything by numerical treatment, it is difficult to acquire empirical knowledge from skilled operators and other staff, and modification work is difficult since the process of inference and knowledge itself are difficult to express as patterns. Therefore, problems in practical use arise.

Thus, a diagnostic-type expert system, DIANA (diagnosis and navigation system), which enables flexible diagnosis, easy knowledge acquisition and

modification by applying fuzzy logic to process signal treatment and inference was developed and put to practical use as an abnormality diagnosis system for refuse incineration plants.

2. Outline of System

As shown in Fig.1, a refuse incineration plant is divided into 12 systems with the refuse incinerator as the central system. As shown in Fig. 2, the component machinery and equipment of each system are directly connected to the distributed control system (DCS) for plant operation by on-line sensors, and condition monitoring is carried out in real time.

Operators can automatically monitor the change of the machinery and equipment conditions by utilizing the alarm function for the deviation of process signals from the upper and lower limits of the DCS, which is similar to a conventional system (upper and lower limit alarm system); however, the present abnormality diagnosis system (Fig. 3) acts in cooperation with the DCS and further strengthens this system.

As for the system configuration, the inference function and the management of the knowledge base are performed by a minicomputer, and the man-machine interface functions, such as audio output and video display of diagnostic results, and knowledge management are performed by the workstation. Process data are input on-line in real time from the DCS through a local area network (LAN), and are utilized for the diagnosis. Since the LAN can transmit and receive communication, it can accommodate the

Fig. 1 Diagnosis objects of plant system

Fig. 2 Schematic system diagram

Fig. 3 Photograph of system

automation of the restoration measures at the occurrence of abnormality of future full-scale abnormality diagnosis systems.

The knowledge base and the history of abnormality data are managed by the object-oriented data base management system, and the system configuration which can accommodate remote management through public telephone networks has been adopted (Fig. 2).

3. Actuality of Abnormality Diagnosis

3.1 Level of abnormality diagnosis and diagnostic method

To determine the level of the abnormality diagnosis that the present system requires, the early detec-

tion of abnormality and the postulated cause after its appearance are considered. Accordingly, this is different from the so-called "abnormality prediction" in which detection is carried out before an abnormality arises.

As shown in Fig.1, in the systems of a plant, the degree of risk is divided according to the direction and speed of spread of the abnormality. For an incinerator or steam system, for example, the effect of abnormality is large; therefore, in this system, by carrying out "symptom detection" for detecting an abnormality earlier than the upper and lower limit alarm system executed by the DCS, and "symptom analysis" for inferring the cause of the abnormality, the efficacy is strengthened. As shown in Fig. 4, this method compares the calculated theoretical value and that presumed from the steady process model of this system, and the related measured process data always with the measured data for symptom detection. When the deviation exceeds a certain value, the system judges that an abnormal symptom has arisen, and then attempts to determine the cause.

When the abnormality advances further, process signals deviate from the steady values to such a degree that the ordinary upper and lower limit alarm system can detect them, and the diagnostic system shifts to the second mode, "alarm analysis."

Table 1 Diagnosis method

	Symptom analysis	Alarm analysis	Fuzzy combustion control
Diagnosis trigger	Model reference error detection	Detection of deviation from upper and lower limits	Reasoning by fuzzy logic (always)
Detection level	Following type (fuzzy value)	Fixed type (fuzzy value)	Fixed type (fuzzy value)
Cause identification	Pattern match (CDM-S)	Pattern match (CDM-A)	Pattern match (CDM-F)
Form of knowledge	Process model formula, membership function, rule	Membership function, rule	Membership function, rule
Source of knowledge	Quantitative and qualitative model of plant	Qualitative model of plant	Operator's rule of thumb
Utilized data	Time series	Snapshot	Snapshot
Diagnosis object	Furnace, boiler, steam, air, exhaust gas systems	Whole plant	Combustion system

Fig. 4 Fault level and diagnosis item

As for the method of abnormality diagnosis, “fuzzy combustion control”, which is automatically carried out up to the restoration countermeasures by limiting the object to the incinerator, is also incorporated in this system, and these features are summarized in Table 1. A detailed discussion of alarm analysis follows, and symptom analysis and fuzzy

combustion control will be reported separately.

3.2 Fuzzy inference

In Fig. 5, the alarm analysis procedure is shown. When an abnormality is detected by the upper and lower limit alarm system of the DCS, a diagnosis trigger signal is sent out, and this system carries out a series of procedures: acquisition of related process

data, fuzzy inference of all possible causes, determination of the cause with maximum degree of certainty, output of the diagnostic results, and revision of the data base.

All possible causes which are conceivable in every abnormal event are registered beforehand in the abnormal event cause matrix (cause diagnosis matrix: CDM), and the possible causes are related with the process data which are effective for arranging the causes in matrix form utilizing the knowledge data base, in which the strength of interrelation, called "weight," is conventionally expressed by real numerical values in the range of $-1 \sim 1$. Instead of the weight, some systems assign linguistic truth values, classified into seven steps, to the membership values between $0 \sim 1^{(3)}$; however, in this system, consideration was given so that humans can easily coordinate incorporated knowledge and diagnostic results by using the same set of membership values for the degree of certainty, as the measure of diagnostic results.

Moreover, process data are not treated with the crisp set determined by a single slice level such as large/small or normal/abnormal. By treating them with the membership values according to a fuzzy set, the method by which some results of inference can be obtained even in the transient case, in which the process condition after the occurrence of an abnormality is not yet sufficiently established, was adopted. Furthermore, in the case of using a crisp set, there

Fig. 5 Procedure of alarm analysis

was a disadvantage in that the sensitivity of diagnostic results to the slice level was strong, and the modification work was hard to converge, but in the present system the convergence was improved.

In the CDM in Fig. 6, the i -th process datum is denoted by X_i , its "condition" fuzzy set by A_i , the weight with which the j -th possible cause and the i -th process data are related by Y_{ij} , and the probability that the j -th possible cause has Y_{ij} as the median value of the basic set of membership functions is expressed as the amount of the i -th process condition by the concluding fuzzy set B_{ij} . The fuzzy inference is as follows.

$$\text{if } X_i \text{ is } A_i \text{ then } Y_{ij} \text{ is } B_{ij} \quad (1)$$

If the multiplying calculation of a membership function is given as shown in Fig. 7, the result of inference for the actual value x_0 of a process datum is given by the following equation which uses the "bounded product⁽⁴⁾".

$$\mu_{B'ij}(y) = \mu_{A_i}(x_0) \odot \mu_{B_{ij}}(y) \quad (2)$$

Process value	Cause Condition	Cause Cause number			
		#1	... #j ...	#n	
X_1	A_1	B_{11}			
$\vdots$	$\vdots$		$\ddots$		
X_i	A_i		B_{ij}		
$\vdots$	$\vdots$				
X_m	A_m				B_{mn}
Certainty factor		Y_{01}	$\cdots Y_{0j} \cdots$		Y_{0n}

Fig. 6 Abnormal event-cause matrix

Fig. 7 Method of fuzzy inference

To decrease knowledge data and increase computation speed, when the conclusion membership functions are formed into similar isosceles triangles, the positions of the centers of gravity of individual membership functions are on the central lines; therefore, for the method of determining the final conclusion, the treatment equivalent to the "drastic product⁽⁴⁾" or the "simplified method⁽⁴⁾" becomes feasible, and by using the consistency h , it can be simplified as follows.

$$h_{ij} = A_i(x_o) \quad (3)$$

$$y_{oj} = \frac{(y_{1j}h_{1j} + y_{2j}h_{2j} + \dots + y_{mj}h_{mj})}{(h_{1j} + h_{2j} + \dots + h_{mj})} \quad (4)$$

However, y_{oj} is the final output of fuzzy inference, and is the degree of certainty, as shown in Fig. 6.

By this method, the result of inference is the same as that of the simplified method, except that concluding part is a real number instead of a fuzzy set.

Fig. 8 Situation of artificial abnormality

However, as shown in Fig. 7, since the size of membership functions is convenient for converting knowledge or the inference process to visual patterns, this method was adopted.

4. Performance Confirmation Test

This system was installed at an actual plant, and the evaluation test for the quality of the diagnostic performance and knowledge modification was carried out. Using the testing method, as shown in Fig. 8, the results of the system response were examined when the load of a furnace was artificially lowered; that is, the initial target value of the quantity of steam in a waste heat boiler, which is the quantity detected in the feedback control of combustion, was decreased, and the gas temperature at the furnace exit was lowered to below the lower limit.

Figure 9 shows the output image of the results of alarm analysis at that time. Among eight possible causes, in the fifth, "the set-up value of steam quantity is low," the degree of certainty was maximum at 0.3; thus, the result of diagnosis agreed with the real cause. However, the certainties of the fourth and seventh possible causes were close to this since both were 0.2; therefore, it is necessary to increase the certainty of the fifth cause by knowledge modification. Below, such a procedure is shown in detail.

Figure 10 shows the CDM expressing the breakdown of the diagnostic results; process data and their

Fig. 9 Visual output of diagnosis

Process name: 1号炉出口ガス温度L Cause #5 日付: 91/04/17 23:17

Process condition: Fuzzy value

プロセス名	状態	原因1	原因2	原因3	原因4	原因5	原因6	原因7	原因8	原因9	原因10
X_1 炉出口ガス温度L	A_1 1	0.6	0.6	0.4	0.8	0.8	0.3	0.3	0.3		
X_2 No.2コンパネトメント圧力	正常 A_2 4	-1	0	-0.3	0.4	0	0	-0.5	0		
No.2コンパネトメント圧力	小 8	1	0	0	0	0.4	0	-0.5	0		
No.2コンパネトメント圧力	大 6	-1	0	0	0	0	0	0.5	0		
燃焼ガス温度	正常 9	0	-1	0	0	0	0	0	0		
燃焼ガス温度	高 0	0	1	0	0	0	0	0	0		
燃焼ガス温度	低 0	0	0	1	0	0.4	0	0	0		
主燃ガス温度	正常 A_9 1	0.6	0	0	-0.6	-0.3	-0.6	0	0		
主燃ガス温度	小 8	0.6	0	0	0.6	0.3	-0.6	0	0		
X_{11} 燃焼ガス温度	正常 A_{11} 2	-0.4	0	0	0	-1	0	0	0		
X_{12} 燃焼ガス温度	小 A_{12} 8	0.4	0	-0.4	0.3	1	0	0	0		
ボイラ出口ガス温度	正常 8	-0.6	0	0	-0.3	-0.6	1	-0.6	0		
炉温制御水開閉	大 0	0	0	0	0	0	0	0	0.6		
炉温制御水開閉	小 1	0	0	0	0	0	0	0	-0.6		
燃焼度		0.2	-0.2	-0.3	0.2	0.3	-0.2	0.1	-0.2		
対策		ファン速度増大	燃焼温度上昇	燃焼温度減少	燃焼温度上昇	燃焼温度増大	燃焼温度増大	ファン速度増大	ファン速度増大	ファン速度増大	

Fig. 10 CDM image

conditions are indicated in the longitudinal direction of the matrix, and possible causes in the lateral direction. The F -values in the figure are the process data converted into the condition membership functions. When F -values are other than zero, and the weight of respective possible causes corresponding with those lines are also other than zero, the conclusion membership functions corresponding with the intersections of the matrix are assigned, while the others are not used for the inference. Namely, if a possible cause has a weight of zero, even if the process data are other than zero, it does not contribute to the results of inference.

Figure 11 shows the fuzzy inference process for cause 5 in Fig. 10, and the state under which the degree of certainty of 0.3 was calculated is shown. Here, only the treatment of the gas temperature at the furnace exit gives a crisp set. This is because it is recognized by the DCS as the trigger for diagnosis; therefore its value was always either zero or one.

When the distribution of the conclusion membership functions are observed, one of the reasons for the small degree of certainty may be because the membership functions A_{11} and A_{12} did not become the proper basic sets for the process condition; hence h_{11} and h_{12} were unbalanced. Both membership functions were shifted rightward, countermeasures were taken, and the results are shown in Fig. 12. As a result, the degree of certainty was improved to 0.5.

Next, the adjustment of the weight for the conclusion membership functions corresponding to A_9 is examined. The condition membership functions for A_9 itself represent the deviation of the initial value of

Fig. 11 Knowledge modification (1)

Fig. 12 Knowledge modification (2)

steam quantity, and the form also conformed with the actual state; therefore, further adjustment was not carried out, and in order to shift the conclusion membership functions to the true side, the weight was amended, and the results are shown in Fig. 13. As a result of this, the degree of certainty was improved to 0.6, and a satisfactory result was attained.

As shown by the above procedure of modification,

Fig. 13 Knowledge modification (3)

even if the amendment of knowledge is carried out by observing the CDM in Fig. 10 only, the rate of contribution and the overall balance of individual knowledge data are difficult to recognize using the patterns, and the modification is not efficient. However, this method, which can carry out modification while referring to actual process data, is an effective method in an actual expert system.

5. Conclusions

By utilizing the flexibility that is one of the features of fuzzy logic, the improvement of expert systems was attempted, and they were put to practical use as an abnormality diagnosis system for refuse incineration plants. Two systems are already in operation in actual plants, and the extension of application to other plants is planned. The points discussed in this report are summarized as follows.

(1) A large-scale abnormality diagnosis system which takes the entire system of a plant as the object was developed.

(2) By setting up the level of abnormality diagnosis, three concrete methods were devised, and among them, alarm analysis was discussed in detail.

(3) As a result of applying fuzzy logic to the

pretreatment of process data required for on-line, real-time diagnosis-type expert systems, the improvement of functions was possible. For example, setting up of the slice level for classifying conditions was facilitated, and even at the initial stage of the advance of an abnormality, diagnosis can be initiated.

(4) By utilizing fuzzy inference, the degree of the contribution of diagnostic knowledge to the result and the process of inference were expressed as visual patterns, and flexibility was provided to the human interface at the time of acquiring and compiling knowledge.

(5) An artificial abnormality was induced in an actual plant, and a performance test of the system was carried out.

(6) The concrete procedure of knowledge modification for coordinating the diagnostic results and the true cause was shown, and the merit of applying fuzzy logic was confirmed.

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