Transformation of Quantitative Measurements into Qualitative Values in Stochastic Qualitative Reasoning for Fault Detection

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Abstract

Fault detection by stochastic qualitative reasoning is an effective way for complex systems such as air conditioning systems. In this framework, the faulty part of a system can be identified by comparing the behavior derived by stochastic qualitative reasoning with the actual measured behavior. The latter is represented as the series of qualitative values that are obtained by classifying quantitative measurements into several qualitative categories based on a definition of the qualitative regions. The fault detection is often ineffective under the inappropriate definitions.

This paper proposes a method that can automatically define the qualitative regions from the measured data. In this system, data are controlled using a certain value and follow a normal distribution. Measurement data must be transformed into stable qualitative values so that its behavior can be distinguished from fault conditions: therefore, the middle of the qualitative region which has the most stable qualitative value is determined as the average value of the data. The width of the most stable qualitative value is determined based on the standard deviation.

This method is applied to an actual air conditioning system. According to the definition of qualitative regions that is determined from the field data, the faults can be identified.

Introduction

Qualitative reasoning can an effectively approximate the behavior of a system (Kuipers and Berleant 1992) (Lackinger and Obreja 1991) (Lackinger and Nejdl 1993). One of its advantages is that its complicated physical mechanisms are expressed simply through a symbolic casual relationship. Fault detection is an important application of qualitative reasoning, in which a part that does not work can be identified by comparing the results of reasoning with the actual measured values.

Stochastic qualitative reasoning for fault detection in air conditioning systems has been studied (Mihara et al. 1994) (Arimoto et al. 1995) (Yumoto et al. 1996a). In this method, the probabilistic process is used for state transitions which are based on the stochastic qualitative model, and several types of behavior are derived as a series of qualitative values. In stochastic qualitative reasoning, since the actual behavior in a target system is compared with the derived behavior in order to estimate how much the derived behavior follows the actual behavior, the former must be considered to be a series of qualitative values. Based on a definition of the qualitative regions, actual quantitative measurement data that are controlled by sensors are classified into several categories. Therefore, one of the most important problems in the above is to define qualitative regions.

This paper proposes a method that can automatically transform quantitative measurements into qualitative values. The qualitative values are defined by using the distribution of the measured data. The middle value of the most stable qualitative region is defined by the average of all measured data, because the qualitative values in the model are controlled at the most stable state. In addition, the width of each qualitative region is defined based on standard deviation σ, because the measured data approximately follows a normal distribution. The width should be determined by 2σ so that the rate of each transformed qualitative value equals the probability of occurrence.

This method is applied to an actual air conditioning system, the VAV system. The faulty parts are identified by using determined qualitative regions. The effectiveness of this method is confirmed using the results from fault detection.

Qualitative Model and Fault Detection

Stochastic Qualitative Model

Figure 1 illustrates an example of a qualitative model of an air conditioning system. The qualitative model is constructed from nodes, directed arcs with propagation rules, and functions.

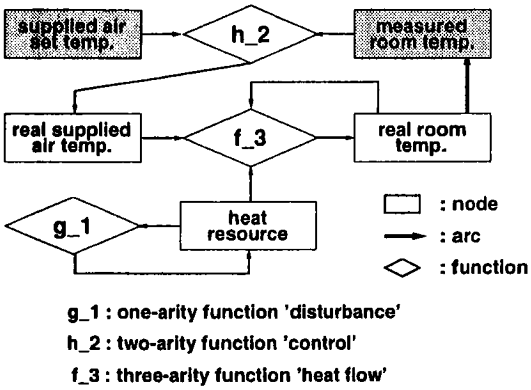

Figure 1: A stochastic qualitative model.

The nodes represent factors that determine the status of a target system, such as the real value of the supplied air temperature, the measured value of the room temperature and heat resources as a disturbance. Each node is characterized with some of the qualitative values, as can be seen in Table 1.

A node representing a component that is measured by a sensor is called a measured node. The nodes with a gray pattern in Figure 1 are measured ones. Their qualitative values must correspond to the measured ones.

Table 1: An interpretation of the qualitative values at different temperatures.

Qualitative value	Interpretation
A	extremely hot
B	hot
C	normal
D	cold
E	extremely cold

An arc connects two nodes. The direction of the arc shows the direction of influence propagation. Propagation rules are attached to an arc. The five types of propagation rules which are shown in Table 2 are defined by the way of the influence. More than one propagation rule is often attached to an arc: therefore, each rule has a choosing probability which indicates its probability.

The following two characteristic parameters have been introduced in order to specify the choosing probability of the rule.

- **Sign** p_s $(-1.0 \leq p_s \leq 1.0)$
  p_s determines the direction of influence from the source node.
- **Delay** p_d $(0.0 \leq p_d \leq 1.0)$
  p_d determines how long the change of the qualitative value in the source node of the arc affects the destination.

According to Table 3, the choosing probability of each type of rule is calculated for an arc by using these two parameters.

Table 2: Types of propagation rules.

+2(−2)	If the source node of the arc changes, the destination node changes in the same (opposite) manner as the source node two time units later.
+1(−1)	If the source node of the arc changes, the destination node changes in the same (opposite) manner as the source node one time unit later.
std	If the source node of the arc changes, the destination node is still unchanged.

Table 3: Choosing rule probabilities.

Type of rule	Choosing probability
+2	$\max(p_s, 0) \times p_d$
+1	$\max(p_s, 0) \times (1 - p_d)$
std	$1 - \lvert p_s \rvert$
−1	$\max(-p_s, 0) \times (1 - p_d)$
−2	$\max(-p_s, 0) \times p_d$

The other type of causal relationship is expressed by a function. A function receives the qualitative values of nodes as input, and gives the change in directions and their probabilities as output. The three types of change in directions on function are shown in Table 4.

The choosing probability of each change in directions in the function is not independently determined, but is determined according to the following three characteristic parameters:

- **Most stable qualitative value**
  f_c $(-5.0 \leq f_c \leq 5.0)$
  f_c is the qualitative value in the destination node that has sustained the most stable amount of change.
- **Vagueness of output**
  f_s $(0.0 \leq f_s \leq 1.0)$
  A function has some choice in regard to its choosing probabilities in connection to the output that corresponds to an input. f_s expresses latitude in output, which expresses the vagueness of the selection.

Table 4: Types of change in directions in a function.

Up	The destination node value increases.
Down	The destination node value decreases.
Const.	The destination node value is unchanged.

Table 5: The choosing probabilities of a function.

Conditions	Return values and Choosing probability
$\frac{f_s}{\lvert f_v\rvert} \le f_c + x$	Up* $= \min(((f_c+x)\lvert f_v\rvert - f_s),\ 0.5) + \min(((f_c+x)\lvert f_v\rvert + f_s),\ 0.5)$ Down* $= 0$ Const. = 1.0 − (Prob. of Up) − (Prob. of Down)
$-\frac{f_s}{\lvert f_v\rvert} \le f_c + x \le \frac{f_s}{\lvert f_v\rvert}$	Up* $= \min(((f_c+x)\lvert f_v\rvert + f_s),\ 0.5)$ Down* $= \min(-((f_c+x)\lvert f_v\rvert - f_s),\ 0.5)$ Const. = 1.0 − (Prob. of Up) − (Prob. of Down)
$f_c + x \le -\frac{f_s}{\lvert f_v\rvert}$	Up* $= 0$ Down* $= \min(-((f_c+x)\lvert f_v\rvert - f_s),\ 0.5) + \min(-((f_c+x)\lvert f_v\rvert + f_s),\ 0.5)$ Const. = 1.0 − (Prob. of Up) − (Prob. of Down)

* If $f_v < 0$, the Up and Down probabilities are reversed.

- **Tendency of output**
  f_v $(-1.0 \le f_v \le 1.0)$

f_v expresses the change rate of the stochastic parameters that corresponds to the input.

According to Table 5, the choosing probabilities of each change in directions can be specified for a function with one argument x by using these three parameters. In this definition, if the value of x is 'A', it is assumed to be '−2'; if the value of x is 'B', it is assumed to be '−1', etc. Figure 2 illustrates the intuitive meaning of the definition. For example, if $(f_s, f_c, f_v) = (0.1, 0.0, 0.1)$, the function is interpreted in Table 6.

A function with n-arity $(n > 1)$ is defined as a linear combination between one-arity functions. If one argument of a two-arity function is fixed, the two-arity function is equivalent to a one-arity function.

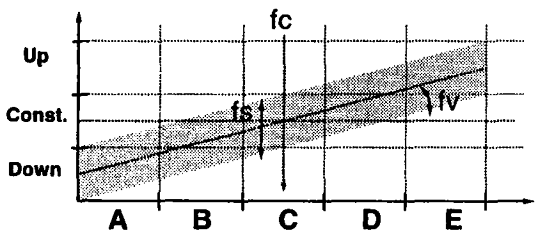

Figure 2: The intuitive meaning of functions with parameters.

Table 6: An example of a function, $(f_s, f_c, f_v) = (0.1, 0.0, 0.1)$.

Input	Output		
Set	Probability(%)		
temp.	Up	Const.	Down
A	0	60	40
B	0	80	20
C	10	80	10
D	20	80	0
E	40	60	0

Stochastic Qualitative Reasoning

Stochastic qualitative reasoning is excused by a series of recursive state transitions in the qualitative model. The state of a system in the qualitative model is defined as one definite set of the qualitative values of all the nodes in the model. When the qualitative values of nodes 1,2 and 3 in Figure 3 are, respectively, B, B and C, the state of this model is expressed as [B, B, C].

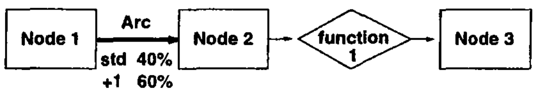

Figure 3: A simple qualitative model.

An example of a state transition of the model in Figure 3 is shown in Figure 4. Each state has a probability of occurrence. The probability of occurrence of each new state is calculated based on the probability of occurrence of the previous state and the choosing probability of the applied rules and functions. The probability of occurrence of the initial state is 1.0. The behavior of the qualitative model is represented by the state transition.

The procedures for stochastic qualitative reasoning can be summarized as follows:

Step 1. Predict all possible states from current ones according to the function and propagation rules, and obtain each probability of occurrence.

Step 2. Rank the states in descending order of the probability of occurrence. Add all of these until the sum is more than the threshold. Then eliminate all the remaining ones.

Step 3. Compare the surviving states with the actual measured values. Discard the inconsistent ones.

Step 4. Normalize the probability of occurrence of the surviving states. These states will act as the current states in the next stage. Repeat all steps until there are no surviving states or until all of the stages are finished.

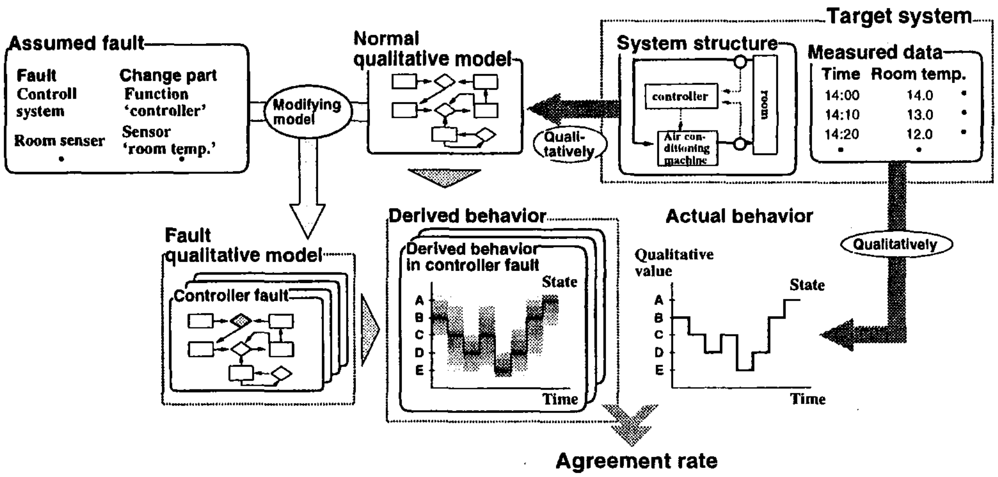

Figure 5: Fault detection by stochastic qualitative reasoning.

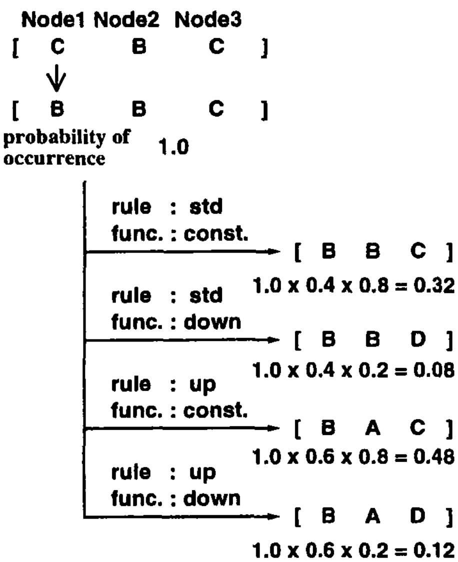

Figure 4: An example of a state transition.

In Step 2, 'threshold', which is a predefined parameter, expresses the maximum sum of the existence probabilities. Eliminating states by using the threshold avoids the need for an enormous amount of time and a large amount of memory in order to generate all possible states. The lower the threshold, the more approximate but the more quickly a simulation can be performed.

In Step 3, the states which are not in agreement with the measurements are discarded. If most of the new states are discarded, the state transition does not accurately reflect the real behavior of the target. On the other hand, if most of the states survive, the state transition is accurate. Here, we have introduced an evaluation parameter that can estimate the degree of agreement of the simulation result with the measured behavior, agreement rate, based on this property.

Agreement rate R_a is formally defined as follows:

$$R_a = \left(\frac{\hat{P}_1}{P_1} \times \frac{\hat{P}_2}{P_2} \cdots \times \frac{\hat{P}_n}{P_n}\right)^{\frac{1}{n}}$$

$$\simeq \frac{(\hat{P}_1 \times \hat{P}_2 \times \cdots \times \hat{P}_n)^{\frac{1}{n}}}{\theta}$$

In this definition, P_i is the sum of the probability of occurrence which is the states after the elimination in Step 2, and $\hat{P}_i$ is the sum of the probability of occurrence of the states that survive in Step 3 at the i-th cycle of the simulation process, n is the number of cycles of the simulation(the simulation time), and θ is the threshold value.

The value for agreement rate R_a is an indicator that shows how consistent a model is with the series of measured values if any state remained until the final step. The higher this value, the higher the possibility of the behavior represented by the simulation model. If there are no state left in a simulation cycle, the value of the agreement rate R_a is calculated as zero and the simulation is terminated.

Fault Detection by Stochastic Qualitative Reasoning

A fault detection framework is shown in Figure 5. First, in fault detection, a normal qualitative model is constructed from the structure of the target system (Yumoto et al. 1996b). It is a model of a system under normal conditions. Its parameters can be tuned with the measured data using the steepest ascent based method (Yamasaki et al. 1997).

Next, the assumed faults in the target system are considered. Several fault models are constructed by modifying the functions or the arc propagation rules that correspond to each assumed malfunctioning part. The behaviors are derived in each fault model through stochastic qualitative reasoning.

On the other hand, the quantitative measured data are transformed into a series of qualitative values which are based on the definition of qualitative regions. A series of transformed qualitative values qualitatively shows the actual behavior of the target system.

By comparing the derived behavior and the actual behavior, an agreement rate can be calculated. If the agreement rate for the reasoning of a fault model is the highest in all the models, a faulty part in this fault model is the cause.

Transformation of Quantitative Measurements into Qualitative Values

Theoretical Background

In order to use stochastic qualitative reasoning on a practical basis, quantitative measurements must be transformed into qualitative values. This transformation can be done based on the definition of qualitative regions such as that found in Table 7.

Table 7: Definition of the qualitative regions at room temperature.

Qualitative value	Definition
A	28°C ~
B	26°C ~ 28°C
C	24°C ~ 26°C
D	22°C ~ 24°C
E	~ 22°C

In stochastic qualitative reasoning, one of the most important problems is how to define qualitative regions. The landmark values that serve as a precise boundary for those regions to date have been defined by human intuition based on measured data. It is difficult, however, to define qualitative regions. If they are defined by regions that are too strict, the robustness of the qualitative value is lost and the results are weakened by noise. On the other hand, if the qualitative values are defined by regions that are too vague, it is impossible to represent the actual behavior by the fluctuations in qualitative values.

In order to solve this problem, we have proposed a method in which qualitative regions are automatically defined for all measurement data, respectively. In actual air conditioning systems, the measured data approximately follows a normal distribution. By using this feature, one can use a method by which a definition of qualitative regions can be determined according to the probability of occurrence of the latter.

Probability of Occurrence of Qualitative Values

In air conditioning systems, the measured values are controlled so that they are stable; therefore, a qualitative model is generated so that the qualitative values of each node can become stable at qualitative value C.

In the qualitative model of the target system, however, the qualitative value of the nodes are respectively controlled by each function. For example, in the model that has tight control, the qualitative values on the model are immediately controlled to C even if it is A or E, ant it is hard to change the qualitative values except for C. On the other hand, in the model in which control is loose, the qualitative value cannot be controlled to C immediately, and the qualitative values became unstable.

For the sake of simplicity, the behavior is derived from a simple model such as in Figure 6. This model has only one node and one function. In this model, therefore, the state is represented by the one qualitative value of the node. The qualitative value one unit time later is determined based on the current qualitative value and the choosing probability of 'f_1'. In the stationary state, the probability of occurrence of each state is determined by 'f_1'.

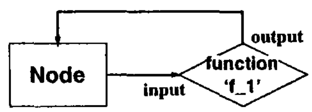

Figure 6: An example of a qualitative model.

- The example with loose control

  In the model which has a function such as in Table 8, the qualitative value is loosely controlled to C. For example, if the qualitative value of the node is A, the probability that the qualitative value becomes B one unit time later is only 60%. The probability of occurrence of each of the stationary states is the following:

A	B	C	D	E
2.0%	25.1%	45.8%	25.1%	2.0%

  The width of the qualitative regions is defined by approximately 1.2σ so that the measured data can be transformed into qualitative values at the above rate.

- The example with normal control

  If the function in Figure 6 is defined as Table 9, the probability of occurrence is the following. In this function, the qualitative value is ordinarily controlled to C. The probability of occurrence of each of the stationary states is the following:

A	B	C	D	E
0.0%	16.7%	66.6%	16.7%	0.0%

  If the width of the qualitative regions is defined by approximately 1.9σ, each qualitative value is parted in the above rate by the transformation measured data that is based on this definition.

- The example with tight control

  The function which is defined in Table 10 is a typical example that the qualitative value is immediately controlled to C, which is a stable qualitative value. In this function, the qualitative value is closely controlled to C. For example, if the qualitative value is A, the probability that the qualitative value will become B one unit time later is 100%, and, if the qualitative value is C, the probability that the qualitative value will become stable is 90%. The probability of occurrence of each of the stationary states is the following:

A	B	C	D	E
0.0%	7.2%	85.6%	7.2%	0.0%

  The qualitative values are transformed based on the definition that states that the width of the qualitative regions is defined by about 2.9σ and almost follows the above rate.

The middle value of qualitative region C is defined as the average of all measured data. The width of each qualitative region, which is the interval between two neighborhood landmarks, is defined based on standard deviation σ. The optimal width of qualitative regions is different for each function. In the above examples which involve very extreme examples, the width of qualitative value C is confirmed within the range of $1.2\sigma \sim 2.9\sigma$. Because the qualitative value is not controlled so closely in air conditioning systems, the width should be determined by 2σ.

Table 8: Function 'f_1' in a example with loose control $(f_s, f_c, f_v) = (0.2, 0.0, 0.15)$.

Qualitative value	Output Probability(%)		
	Up	Const.	Down
A	0	40	60
B	5	60	35
C	20	60	20
D	35	60	5
E	60	40	0

Table 9: Function 'f_1' in a example with normal control $(f_s, f_c, f_v) = (0.1, 0.0, 0.2)$.

Qualitative value	Output Probability(%)		
	Up	Const.	Down
A	0	20	80
B	0	60	40
C	10	80	10
D	40	60	0
E	80	20	0

Table 10: Function 'f_1' in a example with tight control $(f_s, f_c, f_v) = (0.05, 0.0, 0.3)$.

Qualitative value	Output Probability(%)		
	Up	Const.	Down
A	0	0	100
B	0	40	60
C	5	90	5
D	60	40	0
E	100	0	0

An Example of a Definition of Qualitative Regions

Figure 7 shows the daily measured data for actual room temperature in a air conditioning system and the definition of qualitative regions. The middle of qualitative region C is 27.48°C, which is the average of the measurement data. In addition, the width of the qualitative regions is 0.38°C, because each width is defined as 2σ.

Using this definition, most of the measured data are included in qualitative region C. On the other hand, there is no measured data that is transformed into qualitative value A or E. This transformation is suitable because this data was measured when the target system was stable.

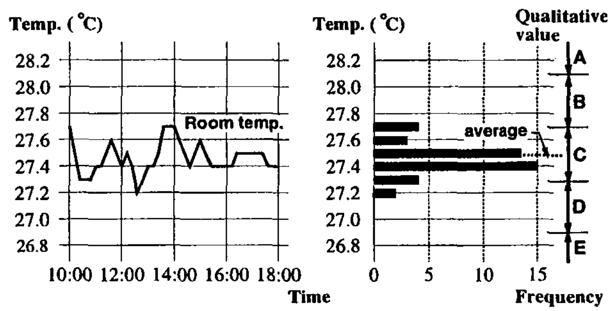

Figure 7: An example of the definition of qualitative regions.

Application to VAV Systems

Experiments to define the qualitative regions are done in regard to the VAV (Variable Air Volume) system of a building in Tokyo.

A Stochastic Qualitative Model of a VAV System

Figure 8 shows a diagram of a VAV system. It consists of one fan, one refrigerator, and eight VAV valves and sensors. The room temperature is controlled, respectively. This system controls the room temperature by controlling the supplied air temperature and the room air volume. At the fan and refrigerator, the air that is supplied is generated from the outside, and is separated in order to send it to each VAV valve. At each valve, the room air volume is controlled according to the gap in the room temperature between the preset value and the measured one. The volume of air in the room controls the temperature of air. Figure 9 illustrates a qualitative model for a VAV system in Figure 8. This qualitative model can be constructed with eight blocks which correspond to each VAV valve, because the VAV valves are independent of each other.

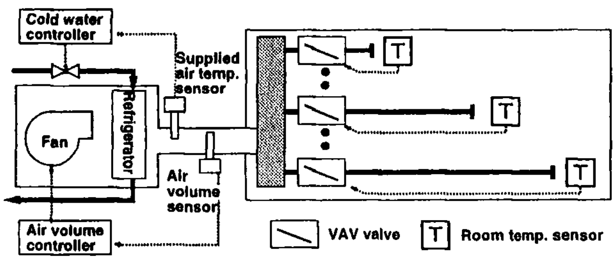

Figure 8: VAV system instrumentation diagram.

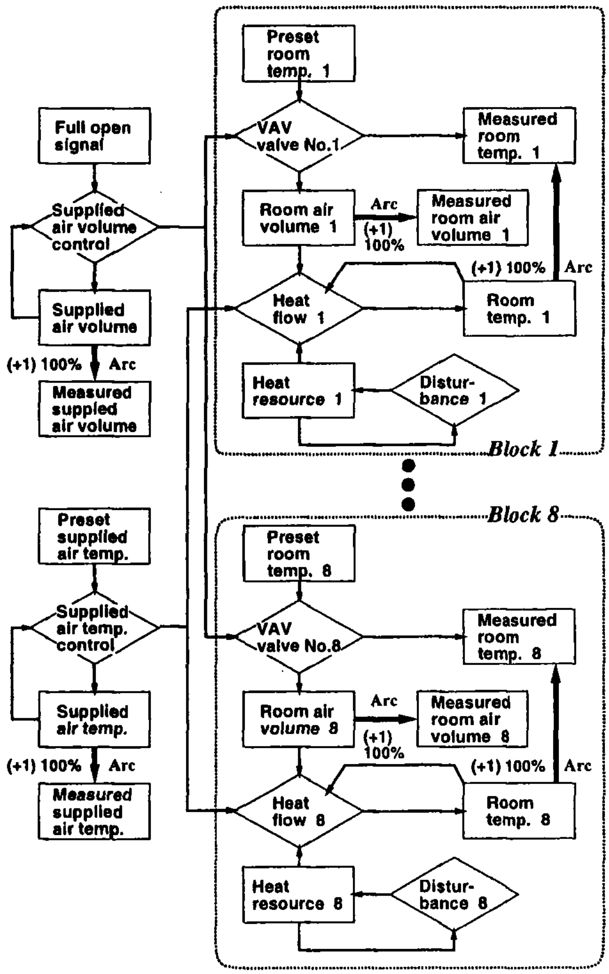

Figure 9: A qualitative model for the VAV system.

Assumed Faults

Qualitative models that represent every assumed fault are built by modifying the normal model, as is shown in Figure 9. The qualitative model is separated into eight blocks because the room temperatures are controlled independently. The assumed faults are as follows:

VAV valve full opened fault

- *Phenomenon* : The room air volume increases to an extremely high level. As a result, the room temperature decreases.
- *Cause* : VAV valve is fixed at full open.
- *Modification point*: The function 'VAV valve', which represents the volume control for the air in the room, is modified so that the room temperature decreases.

VAV valve full closed fault

- *Phenomenon* : The room air volume decreases to an extremely low level. As a result, the room temperature increases.
- *Cause* : VAV valve is fixed at full close.
- *Modification point*: The function 'VAV valve' is modified so that the room temperature increases.

Supplied air volume dropped fault

- *Phenomenon* : The supplied air volume has dropped to an extremely low level. As a result, the room temperature increases.
- *Cause* : Supplied air volume control.
- *Modification point* : The function 'Supplied air volume control' is modified so that the volume of air that is supplied already decreases.

Cold water volume dropped fault

- *Phenomenon* : The volume of the cold water dropped to an extremely low level. As a result, the room temperature increases because the supplied air temperature increases.
- *Cause* : Cold water valve is closed.
- *Modification point* : The function 'Supplied air temperature control' is modified so that the temperature of the supplied air is already low.

The Results of Fault Detection

In the qualitative model which has a block of VAV valve No.5, No.6 and No.7 in Figure 9 model, the qualitative values are defined based on actual measured data. The middle value of qualitative region C is defined by the average of all measured data, and the width of each qualitative region is defined as 2σ.

Tables 11 and 12 show some of the respective definitions of qualitative regions for measured data for August and November in the target VAV system. These definitions are determined by the respective monthly data in a normal controlled system.

Based on the definitions in Tables 11 and 12, the characteristic parameters of the qualitative model are

Table 11: The definition of the qualitative regions in the model used in August.

qualitative value	temperature of supplied air	room temperature 6
A	13.42 ~	27.98 ~
B	11.18 ~ 13.42	27.62 ~ 27.98
C	8.94 ~ 11.18	27.27 ~ 27.62
D	6.69 ~ 8.94	26.91 ~ 27.27
E	~ 6.69	~ 26.91

qualitative value	volume of supplied air	room air volume 6
A	9008 ~	1285 ~
B	6300 ~ 9008	919 ~ 1285
C	3591 ~ 6300	552 ~ 919
D	882 ~ 3591	185 ~ 552
E	~ 882	~ 185

Table 12: The definition of the qualitative regions in the model used in November.

qualitative value	supplied air temperature	room temperature 6
A	19.49 ~	27.27 ~
B	15.92 ~ 19.49	26.76 ~ 27.27
C	12.35 ~ 15.92	26.25 ~ 26.76
D	8.78 ~ 12.35	25.74 ~ 26.25
E	~ 8.78	~ 25.74

qualitative value	supplied air volume	room air volume 6
A	5985 ~	1885 ~
B	4066 ~ 5985	1271 ~ 1885
C	2146 ~ 4066	657 ~ 1271
D	227 ~ 2146	43 ~ 657
E	~ 227	~ 43

tuned by measured data under the normal conditions (Yamasaki et al. 1997). This model is a normal qualitative ones. Fault models can be created by modifying components.

In the VAV valve No.6 of the target VAV system, the experiment on assumed fault was performed on August 7th and November 12th, 1996. Table 13 shows the fault state and the time occurred fault state on each day. Figure 10 shows the measured data for the room temperature and the supplied air temperature for VAV valve No.5, 6 and 7 on August 7th. Figure 11 shows the measured data of the room air volume and the supplied air volume on the same day.

Fault detection for each model whose qualitative regions are defined with measured data is performed. Table 14 shows the results.

In a similar fashion, the measured data on November 12th are transformed into qualitative values based on

Table 13: The time that fault states occurred.

fault content	August 7th	November 12th
VAV valve full opened	10:15 ~ 10:45	10:00 ~ 10:40
VAV valve full closed	11:30 ~ 12:10	11:20 ~ 12:20
Supplied air volume dropped	14:05 ~ 14:40	13:35 ~ 14:20
Cold water volume dropped	15:25 ~ 17:00	15:35 ~ 16:40

the definition from Table 12. Table 15 shows the results of fault detection on November 12th.

From the results in Table 14 and Table 15, the faulty parts can be identified because the agreement rate for the model on assumed fault is the highest for each fault state.

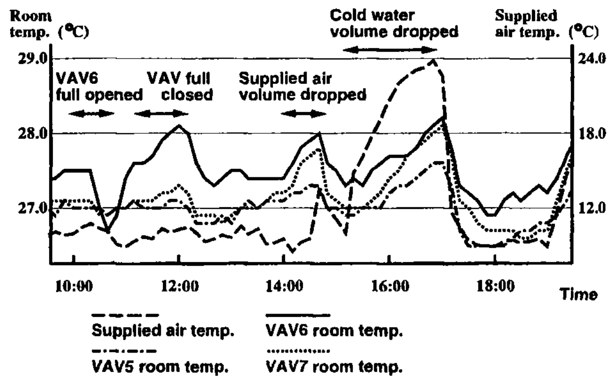

Figure 10: Room temperature and supplied air temperature on August 7th.

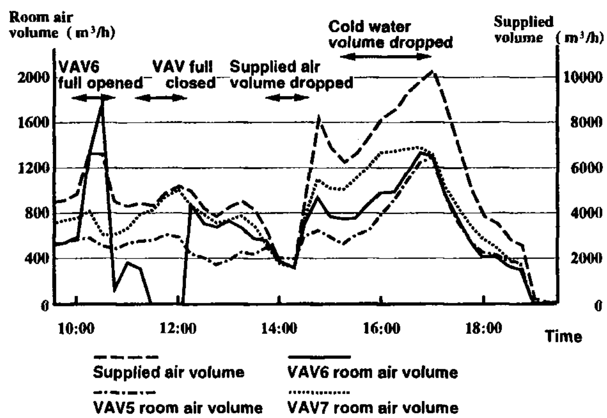

Figure 11: Room air volume and supplied air volume on August 7th.

Table 14: The results of fault detection on August 7th.

fault model	fault state				
	normal	VAV opened	VAV closed	air volume dropped	water volume dropped
normal	**0.225**	0.000	0.128	0.076	0.081
VAV valve full opened	0.108	**0.106**	0.000	0.026	0.006
VAV valve full closed	0.000	0.000	**0.310**	0.000	0.000
supplied air volume dropped	0.091	0.000	0.082	**0.252**	0.000
cold water volume dropped	0.073	0.000	0.077	0.091	**0.178**

Table 15: The results of fault detection on November 12th.

fault model	fault state				
	normal	VAV opened	VAV closed	air volume dropped	water volume dropped
normal	**0.225**	0.000	0.128	0.076	0.081
VAV valve full opened	0.108	**0.106**	0.000	0.026	0.006
VAV valve full closed	0.000	0.000	**0.310**	0.000	0.000
supplied air volume dropped	0.091	0.000	0.082	**0.252**	0.000
cold water volume dropped	0.073	0.000	0.077	0.091	**0.178**

Sensitivity Analysis for Width of Each Qualitative Region

In the previous example, the width of qualitative regions is defined as 2σ. In this section, it is confirmed whether the fault part can be identified if the width of qualitative regions is changed.

The method of definition is applied to the same qualitative model which has the block of VAV valve No.5, No.6 and No.7. Table 16 shows the definitions at the room temperature when the width of qualitative regions is changed. Fault detection is done by using these definitions.

Figure 12 ~ 16 shows the agreement rates of the series of qualitative values for each condition, which is transformed based on the definitions in Table 16, for normal and fault models. In Figure 12 ~ 16, the faulty part was identified exactly if the width of the qualitative regions is suitable. Table 17 is a summary of the fault detection.

For the VAV systems, the width of the qualitative regions should be about 2σ. If the qualitative width determined as more than 2σ, in the VAV full closed case, which shows in Figure 14, the agreement rate for the VAV closed model is zero, and the agreement rate for the normal model is highest, so that the fault detection is incorrect. That is to say, for spreading width of qualitative region, if measured data is large varied, the data are transformed into no variable series of qualitative value. On the other hand, if the qualitative width determined as less than 2σ, for example, in the VAV full opened case, which shows in Figure 13, the fault state cannot distinguish. That is to say, by narrowing width, the real behavior disagrees the derived behaviors because the series of transformed qualitative values show large transition.

Table 16: The definitions of the qualitative regions at room temperature (°C).

qualitative value	the width of the regions	
	0.5σ	1.0σ
A	27.58 ~	27.71 ~
B	27.49 ~ 27.58	27.54 ~ 27.71
C	27.40 ~ 27.49	27.36 ~ 27.54
D	27.31 ~ 27.40	27.18 ~ 27.36
E	~ 27.31	~ 27.18
qualitative value	the width of the regions	
	1.5σ	2.0σ
A	27.85 ~	27.98 ~
B	27.58 ~ 27.85	27.62 ~ 27.98
C	27.31 ~ 27.58	27.27 ~ 27.62
D	27.05 ~ 27.31	26.91 ~ 27.27
E	~ 27.05	~ 26.91
qualitative value	the width of the regions	
	2.5σ	3.0σ
A	28.11 ~	28.25 ~
B	27.67 ~ 28.11	27.71 ~ 28.25
C	27.22 ~ 27.67	27.18 ~ 27.71
D	26.78 ~ 27.22	26.65 ~ 27.18
E	~ 26.78	~ 26.65
qualitative value	the width of the regions	
	3.5σ	4.0σ
A	28.38 ~	28.51 ~
B	27.76 ~ 28.38	27.80 ~ 28.51
C	27.13 ~ 27.76	27.09 ~ 27.80
D	26.51 ~ 27.13	26.28 ~ 27.09
E	~ 26.51	~ 26.28

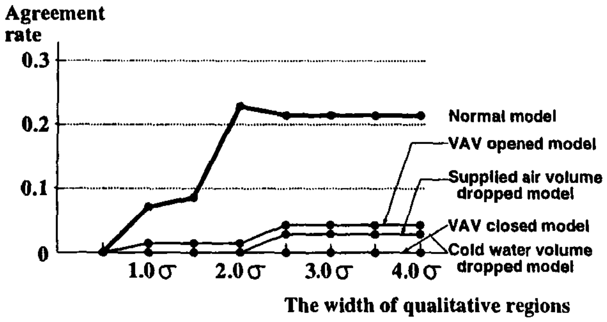

Figure 12: The agreement rate for each fault model under normal condition.

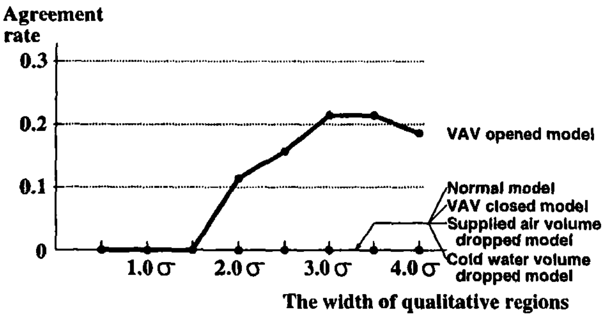

Figure 13: The agreement rate for each fault model in the VAV full opened fault.

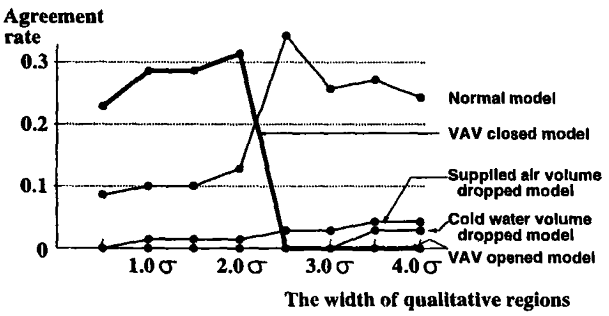

Figure 14: The agreement rate for each fault model in the VAV full closed fault.

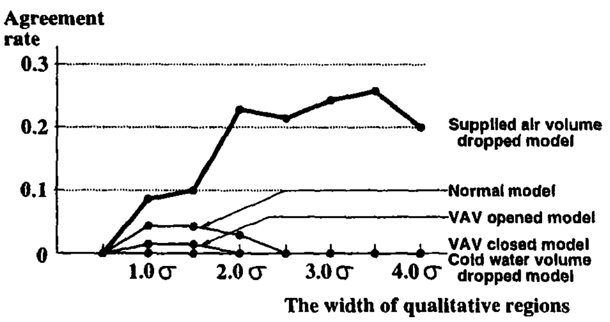

Figure 15: The agreement rate for each fault model in supplied air volume dropped fault.

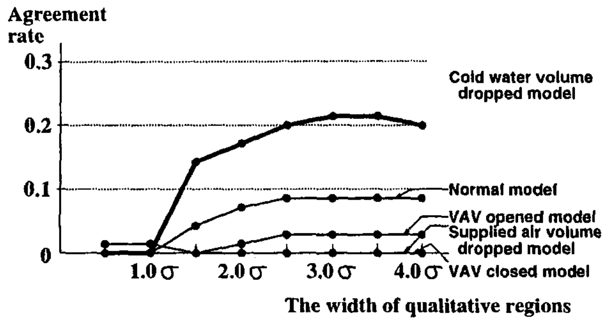

Figure 16: The agreement rate for each fault model in cold water volume dropped fault.

Table 17: Summary of the fault detection.

Faulty state	successful width
Normal	$1.0\sigma \sim$
VAV full opened	$2.0\sigma \sim$
VAV full closed	$\sim 2.0\sigma$
Supplied air dropped	$1.0\sigma \sim$
Cold water dropped	$1.5\sigma \sim$

Conclusion

This paper presented a method for transforming quantitative measurements into qualitative values in stochastic qualitative reasoning for fault detection. It was concluded that:

- The qualitative regions were defined by using the distribution of measurement data.
- The qualitative regions were defined so that the rate of each qualitative value transformed was equal to the probability of occurrence.
- This method was applied to an actual air conditioning system, the VAV system, and the faulty parts were identified by using determined qualitative regions.
- It was confirmed that the width of qualitative regions using this method is suitable.

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