Automatic Model Generation for Stochastic Qualitative Reasoning of Building Air Conditioning Systems

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Abstract

In the stochastic qualitative reasoning, which we have proposed, the probabilistic process is used for state transitions based on the stochastic qualitative model. States with relatively small existence probabilities are eliminated in order to suppress the number of generated states under computable order. The determination of stochastic parameters is the most difficult task in model construction, however, because this model many parameters and therefore the information needed to construct it cannot be obtained.

This paper proposes a automatic model generation method in order to solve this problem. First, propagation rules and functions are formalized with a few characteristic parameters. As a result, the variable elements of the model can be reduced to less than five percent. Next, a reasonable qualitative model will be generated with measured field data by using the characteristic parameter tuning method.

This method will be applied to an actual air conditioning system in a building. A desired qualitative model can be generated in 2.5 hours, it took 8 hours when using the usual method. In addition, institute parameters can be reduced to 25 from 3905.

Introduction

Qualitative reasoning is a key technology for model based fault detection, in which a section in failure can be identified by comparing the results of reasoning with the real measured values(Kuipers & Berleant 1992)(Lackinger & Nejdl 1993)(Lackinger & Obreja 1991). However, the possible behavior patterns of the model tend to increase enormously because of the ambiguity of the qualitative model.

In order to solve this problem we have proposed the stochastic qualitative reasoning(Mihara et al. 1994)(Arimoto et al. 1995). In this method, the probabilistic process is used for state transitions based on the stochastic qualitative model, and states with relatively small existence probabilities are eliminated in order to suppress the number of generated states under computable order. The effectiveness of this method has been shown through simulation experiments for building air conditioning systems(Yumoto at el. 1996a). However, the model generation of a target system is one of the most difficult problem for qualitative reasoning, because a model has many stochastic parameters and, therefore, the information needed to determine these parameters from the target system instrumentation diagram cannot be obtained. In addition, generated models can be only validated by human intuition.

This paper proposes an approach to automatic model generation in order to solve this problem(Yumoto at el. 1996b). First, propagation rules and functions in a model were formalized with several characteristic parameters from the perspective of regular relation among stochastic parameters. Next, a sensitive analysis for the characteristic parameters was performed on an arc and a function for parameter tuning.

Finally, we will propose a scheme for automatic model generation as follows: (1) construct a template of the qualitative model from the target system instrumentation diagram, (2) establish characteristic parameters for the propagation rules on the arc and the functions in the model based on the qualitative knowledge that we have inputted, (3) adjust and determine the values of these parameters based on the measured data by using a steepest ascent based method.

This method was applied to a real air conditioning system in a building. We demonstrated the effectiveness of the automatic model generation of a stochastic qualitative model which expresses the normal condition of the target system.

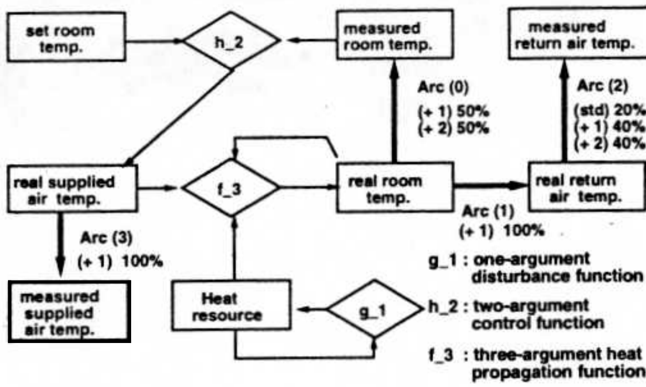


Figure 1: An example of a '1 room' model of an air condition system in a building.

Qualitative model of a building air conditioning system

A building air conditioning system maintains the temperature of a given rooms at a set value by supplying cooled air. The temperature of the air that is supplied is appropriately controlled based on the set value and the measured values at sensors in the room, the duct, etc.

We have introduced a qualitative model with probabilities in order to model a building air conditioning system. The qualitative model is constructed from nodes, directed arcs, propagation rules, and functions. Figure 1 illustrates an example of a qualitative model of an air conditioning system in an building.

The nodes correspond to the elements of a target system such as the real value of the supplied air temperature, the measured value of the supplied air temperature and heat resources as a disturbance, among others. Each node is characterized with some of the qualitative values as seen in Table 1.

An arc connects two nodes. The direction of an arc shows the direction of the propagation of influence. The propagation rules are attached to an arc. The five types of propagation rules are shown in Table 2. More than one propagation rule is often attached to an arc. In this case, each rule has a choosing probability which indicates the probability of the rule being applied.

In Figure 1, for example, arc (2) has three propagation rules, (std),(+1)and(+2). Their choosing probabilities are 0.2, 0.4, and 0.4, respectively. If the qualitative value of the source node of the arc, in other words, "real return air temp.", changes in this model, the qualitative value of the destination node, "measured return air temp.", does not change for a probability of 0.2 or changes in the same manner as the source node for a probability of 0.4, otherwise, it changes two time units later.

If a qualitative value of a destination node is influenced not by changes in the source node but by the qualitative values, this type of causal relation is expressed with a function. A function receives qualitative values of nodes as inputs, and gives the change directions and their probabilities as output. Three types of change directions on a function are shown in Table 3. Table 4 shows an example of a definition of a function. Each change direction of the source node is determined according to the table.

Table 1: Qualitative value of temperature.

Qualitative value	Interpretation	Definition
A	extremely hot	24°C ~
B	hot	23°C ~ 24°C
C	normal	22°C ~ 23°C
D	cold	21°C ~ 22°C
E	extremely cold	~ 21°C

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 of 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: Types of change direction in a function.

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

Table 4: An example of a definition of a function.

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

Characteristic Parameters

Concept

Table 6 shows the number of stochastic parameters, choosing probabilities, on a propagation rule and a function. The total number of stochastic parameters on the qualitative model as shown in Figure 1 is 535. Since a qualitative model has an extreme number of parameters, it is difficult to create the model according to a target system.

In reality, however, stochastic parameters in a propagation rule or a function are not determined at random but with great regularity. By corresponding to these kinds of regulations, i.e. the representation of the propagation rules and functions with a few parameters, which are called characteristic parameters, contribute to ease in handling the models.

Table 5: 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	$max(-p_s, 0) \times p_d$

(1) Propagation rule

Two properties, the sign of influence and the delay, can formalize a propagation rule on an arc. We will here introduce the following two parameters in order to specify the choosing probability of the rule in question.

- **Sign** p_s $(-1.0 \leq p_s \leq 1.0)$

  p_s determines the destination of influence from the source node. If $p_s = 1$, the destination node value always increases when the value of the source node increases. If $p_s = -1$, the value of the destination node always decreases when the value of the source node increases. If $p_s = 0$, the value of the destination node is never changed irrespective of the value of 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. If $p_d = 0$, the change in the value always occurs after one time unit. If $p_d = 0.5$, the change occurs after one time unit at a probability of 0.5 and two time units at the other probability of 0.5.

The choosing probability of each type of rules is calculated for each arc using these two parameters, according to Table 5. Figure 2 shows examples of formalized propagation rules.

Table 6: The number of stochastic parameters in a propagation rule and functions

component	number of parameters
propagation rule	5
1 argument function	$3 \times 5 = 15$
2 argument function	$3 \times 5^2 = 125$
3 argument function	$3 \times 5^3 = 375$

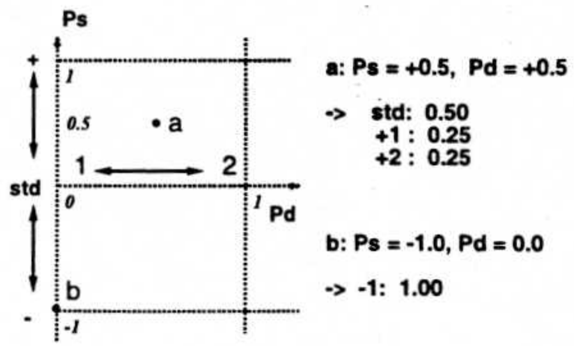


Figure 2: Examples of formalized propagation rules.

(2) One-argument function

A function expresses the causal relation among the nodes in a model. The stochastic probabilities of the function are not independently determined but are determined according to the following three factors:

- **latitude in output**

  A function does not always have only an output for a input. Generally, a function has some choices with their choosing probabilities as for the output that corresponds to an input. In Table 4, for example, $(Up, Const, Down) = (0.2, 0.8, 0.2)$ for input 'C'. The latitude in output, which expresses the vagueness of the selection in the output, has a fixed size in a function.

- **reference input**

  A reference input is the one in which the qualitative value in the destination node sustained the most stable amount of change. For example, the reference input is 'C' in Table 4.

- **change rate**

  This rate shows the change rate of the stochastic parameters that corresponds to the input. If this rate is zero, the stochastic parameters do not change according to the input in question. If this rate has a certain value, the parameters of $(Up, Const, Down)$ will be determined as in Table 4.

Based on these three factors, the following three characteristic parameters are introduced here in order to specify the stochastic parameters of the one-argument function.

- **Sensitivity** f_s $(0.0 \leq f_s \leq 1.0)$

  f_s expresses latitude in output. If $f_s = 0$, there is no latitude and the stochastic parameters have the probability of 1.0 in an output. For example, if $f_s = 0$ occurred under conditions in which both f_c and argument x are zero, the probability of 'Const' is only '100%'.

- **Center** f_c $(-2.0 \leq f_c \leq 2.0)$

  f_c expresses the reference input where the qualitative value in the destination node sustained the most stable amount of change. If $f_c = 2$, for example, input qualitative value 'A' provides the most stationary amount of change.

- **Variance** f_v $(-1.0 \leq f_v \leq 1.0)$

  f_v expresses the change rate of the stochastic parameters that correspond to input. If $f_v = 0$, output has no change. If $f_v < 0$, the probability of 'Up' increases when the input value increases, and, if $f_v > 0$, the probability of 'Down' increases. If volume $|f_v|$ is large, the rate of change is high in the function.

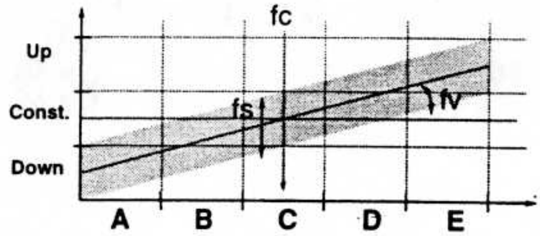
For a function with one-argument x, the choosing probability of each change direction can be specified by using these three parameters according to Table 7.

In this definition, if the value of x is 'A', it is treated as '-2', if the value of x is 'B', it is treated as '-1', etc. Figure 3 illustrates the intuitive meaning of the definition and examples of functions that are defined by these parameters. The function shown in Table 4 can be simply redefined as $(f_s, f_c, f_v) = (0.1, 0.0, 0.1)$.

Table 7: Choosing probabilities of function return values.

Return value	Choosing probability
Up^*	$= min(((f_c + x)\|f_v\| - f_s), 0.5)$ $+min(((f_c + x)\|f_v\| + f_s), 0.5)$ $(\frac{f_s}{\|f_v\|} \leq f_d + x)$
	$= min(((f_c + x)\|f_v\| + f_s), 0.5)$ $(-\frac{f_s}{\|f_v\|} \leq f_d + x \leq \frac{f_s}{\|f_v\|})$
	$= 0 \quad (f_d + x \leq -\frac{f_s}{\|f_v\|})$
$Down^*$	$= 0 \quad (\frac{f_s}{\|f_v\|} \leq f_d + x)$
	$= min(-((f_c + x)\|f_v\| - f_s), 0.5)$ $(-\frac{f_s}{\|f_v\|} \leq f_d + x \leq \frac{f_s}{\|f_v\|})$
	$= min(-((f_c + x)\|f_v\| - f_s), 0.5)$ $+min(-((f_c + x)\|f_v\| + f_s), 0.5)$ $(f_d + x \leq -\frac{f_s}{\|f_v\|})$
$Const$	$= 1.0-$ (Prob. of Up) $-$ (Prob. of Down)

* If $f_v < 0$, the up and down probabilities swap.



(fs, fc, fv) = (0.0, 0.0, 0.0)

	A	B	C	D	E
Up					
Const.	1.0	1.0	1.0	1.0	1.0
Down					

(fs, fc, fv) = (0.1, 0.0, 0.2)

	A	B	C	D	E
Up			0.1	0.4	0.8
Const.	0.2	0.6	0.8	0.6	0.2
Down	0.8	0.4	0.1		

Figure 3: Examples of functions with parameters.

(3) More than one argument function

A function with more than one argument is defined as a linear combination between one-argument functions. Each one-argument function is the function of each of the arguments of the two-argument function. Figure 4 illustrates the construction of a two-argument function in which the arguments in question are 'set room temp.' and 'measured room temp.'

Figure 4 (a), (b) shows the one-argument function for 'set room temp.' and 'measured room temp.' respectively. The two-argument function in Figure 4 (c) has the stochastic parameters of these two one-argument functions. The function in Figure 4 (c) can be constructed by shifting the parameters f_c of the one-argument function in Figure 4 (b).

The following parameter will be introduced in order to express this phenomenon.

Set room temp.	Up	Const	Down
A	100	0	0
B	60	40	0
C	10	80	10
D	0	40	60
E	0	0	100

(a) One-argument function 'set room temp.'

Combination

Measured room temp.	Up	Const	Down
A	0	0	100
B	0	40	60
C	10	80	10
D	60	40	0
E	100	0	0

(b) One-argument function 'measured room temp.'

Set	Measured	Up	Const	Down
A	A	10	80	10
A	B	60	40	0
A	C	100	0	0
A	D	100	0	0
A	E	100	0	0
B	A	0	40	60
B	B	10	80	10
B	C	60	40	0
B	D	100	0	0
B	E	100	0	0
C	A	0	0	100
C	B	0	40	60
C	C	10	80	10
C	D	60	40	0
C	E	100	0	0
D	A	0	0	100
D	B	0	0	100
D	C	0	40	60
D	D	10	80	10
D	E	60	40	0
E	A	0	0	100
E	B	0	0	100
E	C	0	0	100
E	D	0	40	60
E	E	10	80	10

(a)
(b)

(c) Two-argument function

Figure 4: Construction of a two-argument function.

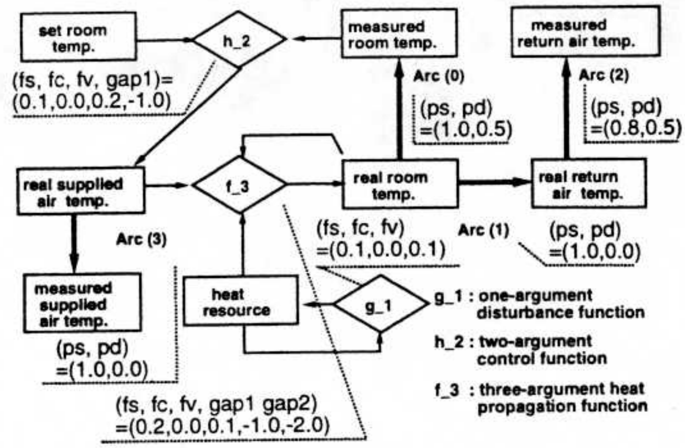


Figure 5: An example of a model representation with characteristic parameters.

Set room temp.	Measured room temp.	Up	Const	Down	Characteristic parameters of one argument function for 'measured room temp.' (fs, fc, fv)
	A	10	80	10	
	B	40	60	0	
A	C	60	40	0	(0.1, 2.0, 0.2)
	D	80	20	0	
	E	100	0	0	
	A	0	60	40	
	B	10	80	10	
B	C	40	60	0	(0.1, 1.0, 0.2)
	D	60	40	0	
	E	80	20	0	
	A	0	40	60	
	B	0	60	40	
C	C	10	80	10	(0.1, 0.0, 0.2)
	D	40	60	0	
	E	60	40	0	
					gap1= -1.0
	A	0	20	80	
	B	0	40	60	
D	C	0	60	40	(0.1, -1.0, 0.2)
	D	10	80	10	
	E	40	60	0	
	A	0	0	100	
	B	0	20	80	
E	C	0	40	60	(0.1, -2.0, 0.2)
	D	0	60	40	
	E	10	80	10	

Figure 6: Two-argument function 'control'.

- **Gap for correlation** $gap1$ ($-5.0 \leq gap1 \leq 5.0$)
  $gap1$ express the correlation between arguments 1 and 2. If $gap1 = 0$, the f_c is not changed according to argument 2. If $gap2 = 1$, the f_c is changed according to argument 2 in the same way as the change for argument 1.

The left side of Figure 6 defines the two-argument function 'control' in Figure 1. In this definition, $f_s = 0.1, f_c = 0.0, f_v = 0.2$ and $gap = -1.0$. The right side of Figure 6 illustrates the change for (f_s, f_c, f_v), which are established in the one-argument function in Figure 4 (b). From this figure, $gap1$ changes these three parameters according to argument 2. $gap2, gap3$ are defined in a similar situation in a three or four argument function.

Model representation

Figure 5 illustrates an example of the application of characteristic parameters to the qualitative model representation in Figure 1. This representation contributes to the easy handling of qualitative models.

Table 8: The effectiveness of characteristic parameters on the qualitative model in Figure 1.

component	stochastic parameters	characteristic parameters
propagation rule	20	8
1 argument function	15	3
2 argument function	125	4
3 argument function	375	5

Table 8 shows the effectiveness of the representation of the characteristic parameters on the qualitative model in Figure 1. The number of stochastic parameters is 535. In a representation with characteristic parameters, the number of parameters can be reduced to 22. Through research until now, we demonstrated that the variable elements of the models can be reduced to less than five percent.

Sensitivity Analysis

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.

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

Step 1. Generation of the states

Step 2. Elimination of states with the small existence probability

Step 3. Discarding of the states that is not in agreement with the measured values

Step 4. Normalization of existence probability

In reasoning 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 does accurately reflects the real behavior. We have introduced an evaluation parameter that can estimate the degree of agreement of the simulation result with the measured behavior, the agreement rate, based on this idea(Yumoto at el. 1996a).

It is important to analyze the sensitivity of the agreement rate for the fluctuation of parameters, in order to develop a model generation based on an automatic parameter tuning.

Analysis of an arc

The model that was used for sensitivity analysis was the same one shown in Figure 1.

Figure 7 indicates the value of the agreement rate for the parameter p_d in the rule with the arc (0), when p_s is fixed. This diagram shows that the agreement rate values changed smoothly. In addition, these curves formed convex forms when p_d was fixed. When $p_s = 1.0$, the agreement rate changed at the highest order because the propagation rule had no probability in '*std*'. Then this phenomenon is proper under normal conditions because the propagation of influence was completely performed.

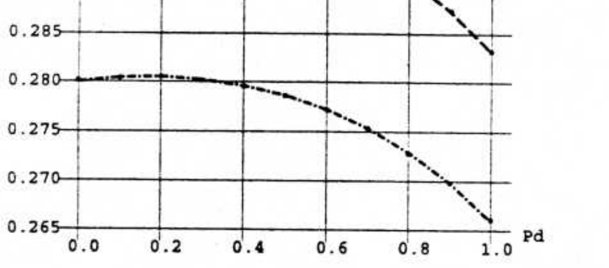


Figure 7: Result of sensitivity analysis for the parameters of the propagation rule on the arc (0) in Figure 1.

Analysis of a function

Figure 8 sketches a counter map of the agreement rate when parameters f_s and f_v of function 'control' in Figure 1 were changed and f_c = -1.0, 0.0, 1.0, and 2.0. In this figure, the agreement rate values changed smoothly.

However, the rate is zero when $f_v < 0.0$ at $f_c = -1.0, 0.0$. In addition, the shapes of the contour lines at $f_c = -1.0, 1.0$ are different from the ones at $f_c = 1.0, 2.0$. The highest agreement rate could not be obtained by adjusting the parameters unless we gave initial values at f_c and the sign of f_v.

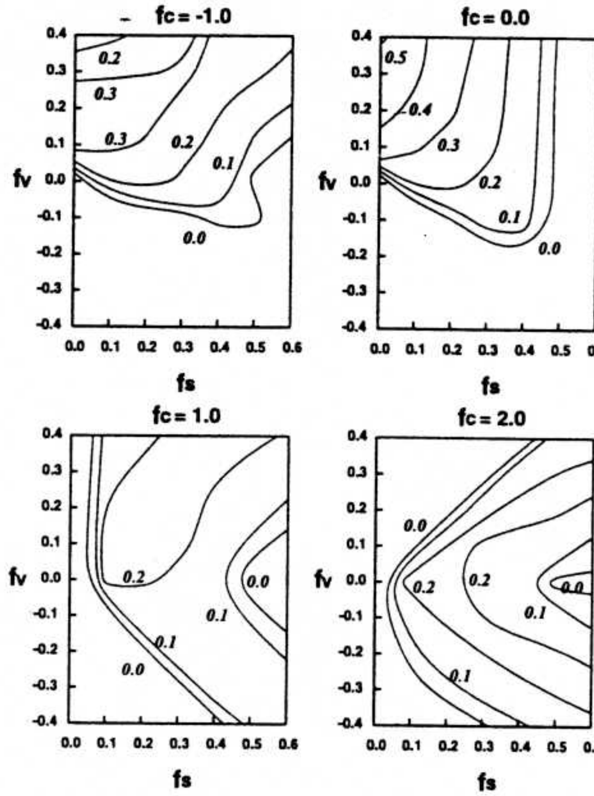


Figure 8: Result of sensitivity analysis for the function 'control' parameters in Figure 1 (f_c is fixed).

Automatic Model Generation

In regards to the qualitative model generation of an air conditioning system in a building we can make use of the following information:

- target system instrumentation diagram

  This diagram shows how the temperature is controlled, where sensors are set up, and so on.

- measurement data

  This data is collected from sensors at the target system. In air conditioning systems in buildings, we can measure room temp., supplid air temp., air volume, water volume, as well as other factors.

Figure 9 shows a framework of the method to generate qualitative models.

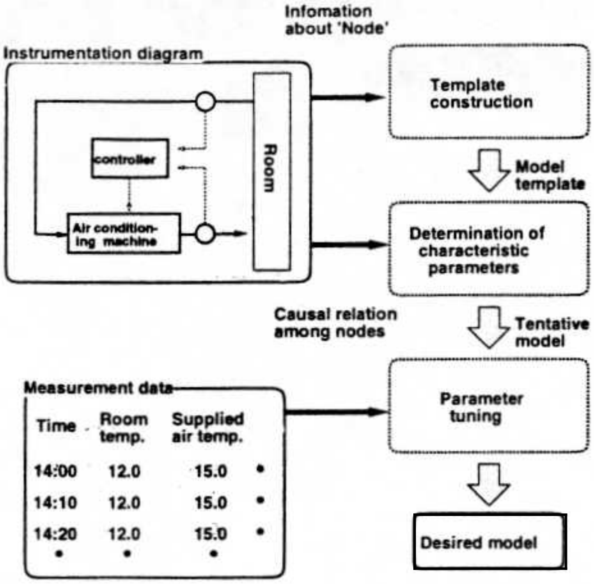


Figure 9: A framework of a method that can generate qualitative models.

(1) Template construction

The component that is related to the behavior of the target system is extracted as the 'node' of the qualitative model from a target system instrumentation diagram. In an air conditioning system, for example, these components are 'set room temp.', 'measured supplid air temp.' as well as other factors. Next, the relation amongst the nodes is defined as 'arc' or 'function' according to the type of influence propagation. In an air conditioning system, the sensor is defined as an 'arc', and 'control', and 'heat propagation' and 'disturbance' are defined as functions.

By using the above procedures, a template of a qualitative model was constructed.

(2) Determination of characteristic parameters

From sensibility analysis results, it is necessary to give initial values at the f_c and the sign of f_v in order to obtain the highest agreement rate in regards to characteristic parameter tuning. These initial values can be defined as qualitative knowledge to obtain from the target system instrumentation diagram.

Tables 9 and 10 show the qualitative knowledge needed to define the propagation rule on an arc and a one-argument function. The qualitative knowledge for the propagation rule is 'sign' and 'delay', and for the one-argument function it is 'stable input' and 'change direction'. Each item has more than one input which corresponds to a characteristic parameter.

Qualitative knowledge for a more than two argument function can be expressed by a linear combination of the knowledge of the one-argument functions for each argument.

(3) Parameter tuning

This tentative model does not completely represent the target air conditioning system because qualitative knowledge can only inexactly determines the stochastic parameters. Next, we will propose an automatic parameter tuning method with measured data.

Figure 10 conceptually illustrates these processes. The basic procedures of parameter tuning are as follows: ① establish an initial set of parameters from qualitative knowledge, ② calculate the agreement rates at the initial set and the surrounding ones, ③ decide the change direction of the parameters if the gap between the agreement rates is over a predefined value by calculating $\tan\theta$, ④ change the parameters along the direction, and select the next initial set of parameters where the agreement rate is the highest. In ③, if the gap between the agreement rates is under a predefined value, the reference set of parameters is the desired set and the procedure is finished.

Table 9: Qualitative knowledge choices that is necessary to define the propagation rule on an arc.

item	sign	delay
relational characteristic parameter	p_s	p_d
option for input	direct, inverse	short, normal, long
corresponding value of parameter	$+,-$	$0.0, 0.5, 1.0$

Table 10: The qualitative knowledge that is necessary to define one-argument function.

item	stability point	change direction
relational characteristic parameter	f_c	f_v sign
option for input	high, normal, low	direct, inverse
corresponding parameter value	$2, 0, -2$	$+,-$

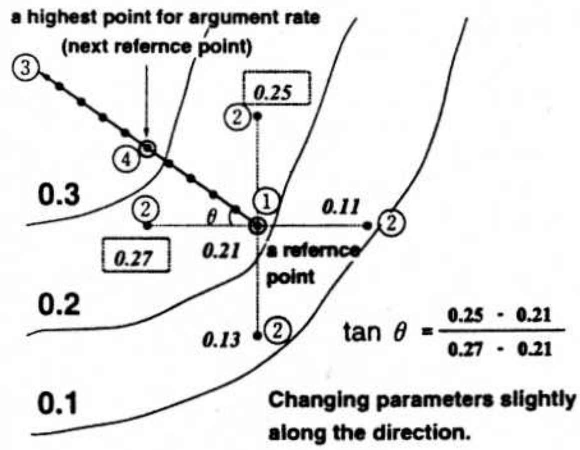


Figure 10: Parameter tuning by the steepest ascent based method.

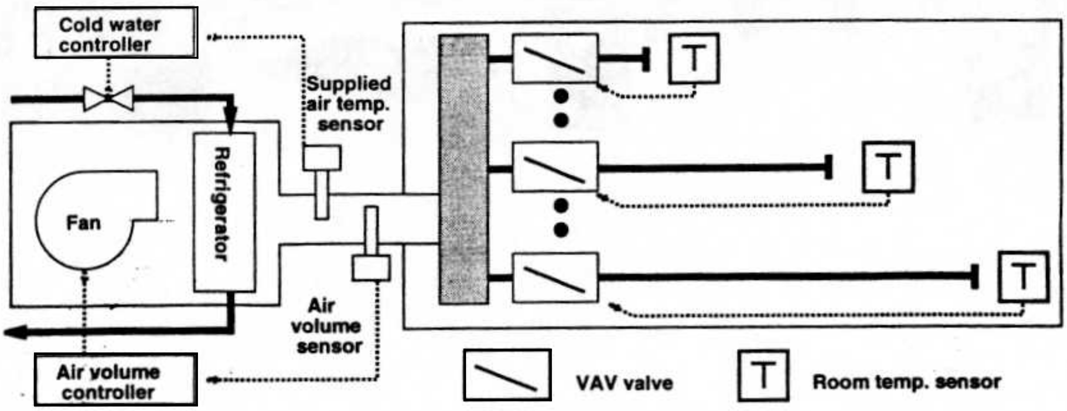


Figure 11: VAV system instrumentation diagram.

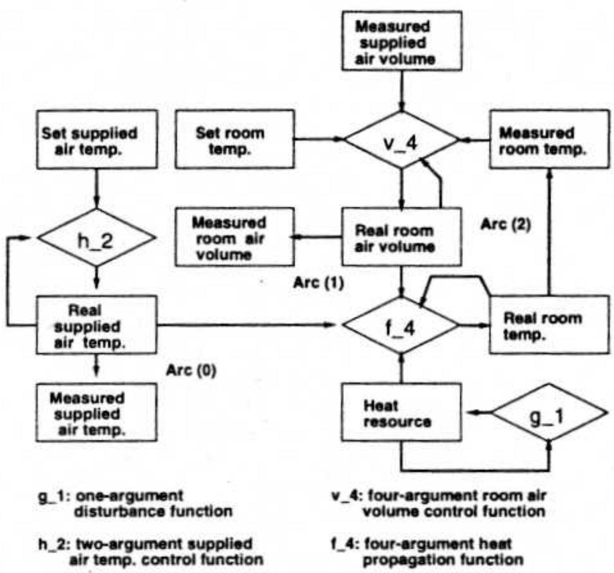


Figure 12: The template of a qualitative model for the VAV system.

Practical application of model generation

We performed an experiment in regards to the model generation of an air conditioning system, the VAV (Variable Air Volume) system. Figure 11 shows the diagram of the VAV system, which controls the temperature and the volume of the supplied air in the refrigerator and in the VAV valves for the air conditioning. The components and their relations to model construction can be observed from this figure. Figure 12 illustrates a template of the qualitative model for the VAV system.

The qualitative knowledge needed to establish the initial values of the characteristic parameters for the model is shown in Table 11. By using the knowledge and the templates we can construct a tentative model which can inexactly express the behavior of the VAV system.

Table 11: Qualitative knowledge for characteristic parameters.

function	input	stability point	change direction
g_1	heat resource	normal	inverse
v_4	set supplied air temp.	normal	inverse
	measured supplied air temp.	normal	direct
v_4	set room temp.	normal	inverse
	supplied air volume	normal	direct
	measured room temp.	normal	direct
	room air volume	normal	inverse
f_4	heat resource	normal	direct
	supplied air temp.	normal	direct
	room air volume	normal	inverse
	room temp.	normal	inverse

Based on the above model, the desired qualitative model can be generated by using measured field data with characteristic parameter tuning. Table 12 summarizes the transition of characteristic parameters in parameter tuning.

Evaluation

In Table 13, the automatically generated model is evaluated by comparing it with model generation by means of human intuition. In our proposed method, it is necessary to determine only 25 characteristic pa-

Table 12: Transition of characteristic parameters.

function	characteristic parameter	tentative parameter	definite parameter
g_1	f_s	0.20	0.18
	f_c	0.00	0.09
	f_v	0.20	0.21
h_2	f_s	0.20	0.10
	f_c	0.00	0.00
	f_v	0.20	0.27
	$gap1$	-1.00	-1.00
v_4	f_s	0.20	0.03
	f_c	0.00	0.00
	f_v	0.20	0.20
	$gap1$	1.00	1.00
	$gap1$	-1.00	-1.00
	$gap1$	-1.00	-1.00
f_4	f_s	0.20	0.01
	f_c	0.00	0.87
	f_v	0.20	0.01
	$gap1$	-1.00	0.14
	$gap1$	-1.00	0.07
	$gap1$	1.00	1.87

Table 13: Evaluation of automatic model generation.

method		human intuition	automatic model generation
parameter	kind	stochastic	characteristic
	number	3905	25
generation time (calculation time)		8 hours (3hours)	2.5 hours 2hours
agreement rate		0.52	0.49
confirmation of objectivity		-	parameter tuning

rameters, and the agreement rate is as high that for the normal method and can be determined in a shorter time and by using fewer parameters. The above demonstrates the effectiveness of automatic model generation.

Conclusion

In this paper, we proposed a method for generating qualitative models that is based on automatic parameter tuning. A tentative model was constructed with characteristic parameters and qualitative knowledge and then these parameters were optimized by automatic parameter tuning that used the steepest ascent method.

This method will be applied to an actual building air conditioning system. A desired qualitative model can be generated in 2.5 hours, it took 8 hours when using the usual method. In addition, institute parameters can be reduced to 25 from 3905.

References

Kuipers, B., and Berleant, D. 1992. Qualitative-numeric simulation with Q3. *Recent Advances in Qualitative Physics, The MIT Press.*: 3–16

Lackinger, F., and Nejdl, W. 1993. Diamon: A model-based troubleshooter based on qualitative reasoning. *IEEE Expert, vol.8, no.1*:33–40

Lackinger, F., Obreja, I. 1991. Model-based troubleshooting of complex technical systems using integrated qualitative techniques. In Proc. of AI, Simulation and Planning in High Autonomy System:122–129

Mihara, K., Aono, Y., Ohkawa, T., Komoda, N., Miyasaka, F. 1994 Stochastic qualitative reasoning and its application to diagnosis of air conditioning system. In Proc. of the IEEE Industrial Conference on Industrial Electronics, Control and Instrumentation '94: 1401–1406

Arimoto, S., Mihara, K., Ohkawa, T., Komoda, N., Miyasaka, F. 1995. Real-time stochastic qualitative simulation of large scale air conditioning system. In Proc. of IEEE International Symposium on Industrial Electronics '95: 902–907

Yumoto, M., Ohkawa, T., Komoda, N., Miyasaka, F. 1996a. Practical Application of Stochastic Qualitative Reasoning to Fault Detection of Building Air Conditioning Systems. In Proc. of Tenth International Workshop on Qualitative Reasoning: 283–291

Yumoto, M., Ohkawa, T., Komoda, N., Miyasaka, F. 1996b. An Approach to Automatic Model Generation for Stochastic Qualitative Simulation of Building Air Conditioning Systems. In Proc. of IEEE International Symposium on Industrial Electronics '96: 1037–1042