High-Speed Stochastic Qualitative Reasoning by Model Division and States Composition

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Abstract

Stochastic qualitative reasoning is an effective way to grasp approximate behavior of complex systems such as air conditioning systems. The appropriateness of the stochastic qualitative model can be identified by comparing the behavior derived by reasoning that is represented as the transition of states with the actual measured behavior. Since the states are derived based on all conceivable combinations of rule application, the number of derived states exponentially increases with the size of the qualitative model. If the model is large, reasoning cannot be completed in real time.

This paper proposes a method of high-speed stochastic qualitative reasoning. In this method, model division and states composition are introduced. First, the partial models are constructed by dividing the entire model. Next, reasoning is executed in each partial model. Finally, the states in the entire model are generated by composing derived states in each model. By this method, the number of derived states is reduced, and the reasoning time is shorter than for the one by the previous method and reasoning can finish regardless of model size.

This method was applied to an actual air conditioning system. It was confirmed that stochastic qualitative reasoning with model division and states composition derived the same results as the previous method did.

Introduction

Qualitative reasoning can 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 complicated physical mechanisms are expressed simply through a symbolic causal 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 developed (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 (Yumoto et al. 1996b) (Yamasaki et al. 1997).

In stochastic qualitative reasoning, the derived behavior that is represented by a transition of states in the model is compared with the actual behavior of a target system in order to estimate how much the former follows the latter. Because states are derived from all conceivable combinations of rule application, the number of states explosively increases with the size of the qualitative model. The reasoning cannot finish in real time for the large-scale model. Therefore, it is necessary for actual reasoning to execute reasoning at a high speed.

This paper proposes a method of high-speed stochastic qualitative reasoning. In this method, partial models are constructed by dividing the entire target model, the states are derived independently from each one. By composing these derived states, the states of the entire model are generated. By the model division and the state composition, the number of derived states is reduced and reasoning time is shorter than by the previous method.

This method is applied to an actual air conditioning system, the VAV system in the final section. We show the effectiveness of our new method through this application: although the number of derived states on partial models are less than one on entire model, the reasoning gives the same results as the previous method.

Stochastic Qualitative Reasoning

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.

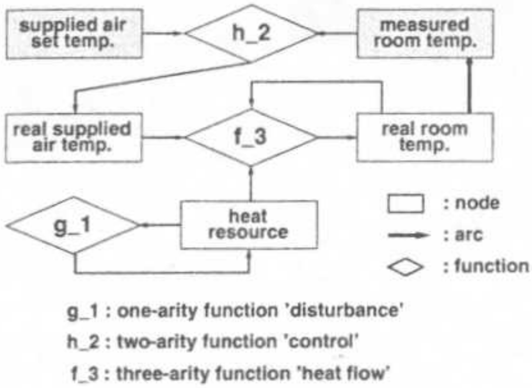

Figure 1: A stochastic qualitative model.

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 by 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 nodes. Their qualitative values must correspond to the measured ones.

Table 1: An interpretation of the qualitative values.

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.

The other type of causal relationship is expressed by a function. A function receives one or more 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 3. A function is represented by probabilities of these types of changes in direction such as in Table 4.

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 will still be unchanged.

Table 3: 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 4: An example of a function.

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

State Transition

Stochastic qualitative reasoning is executed 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 qualitative values of all the nodes in the model. When the qualitative values of nodes 1,2 and 3 in Figure 2 are, respectively, B, B and C, the state of this model is expressed simply as [B, B, C].

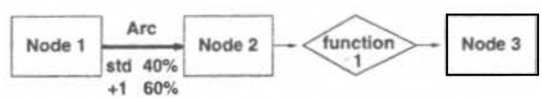

Figure 2: A simple qualitative model.

An example of a state transition of the model in Figure 2 is shown in Figure 3. 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.

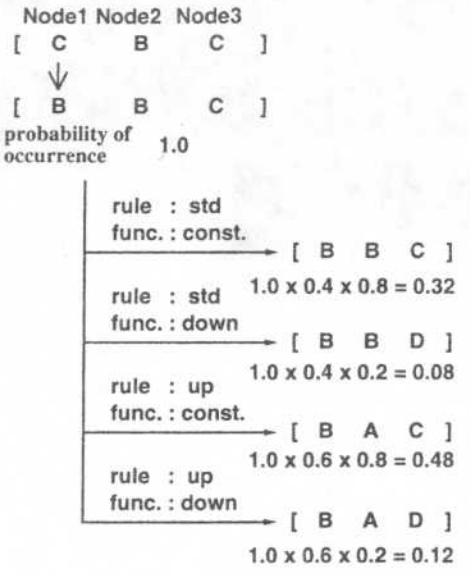

Figure 3: An example of a state transition.

Reasoning Process

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.

In Step 2, 'threshold', which is a predefined parameter, expresses the maximum sum of the probability of occurrence. 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 dash but the more quickly a simulation can be performed.

For further details of the algorithm, see the reference(Arimoto et al. 1995). Figure 4 shows a sample of simulation practice. First, ten states are generated based on the initial state S0 in Step 1. The sum of those states' probability of occurrence is 1.0. In Step 2, the states are sorted in order of their probability of occurrence. After the sum of probabilities reached 0.7, which is a predefined threshold, remaining states, namely, S1, S4, S7, S9 and S10, are eliminated. S6 and S2, which disagree with the real measured values pattern, are discarded in Step 3. Since S3 and S5 are the same states, they are unified into one state S3' and their probabilities of occurrence are added. In Step 4, probabilities of occurrence of survived states S3' and S8 are divided by the sum of them, namely, 0.42. Then those states become the next current states, and simulation is continued.

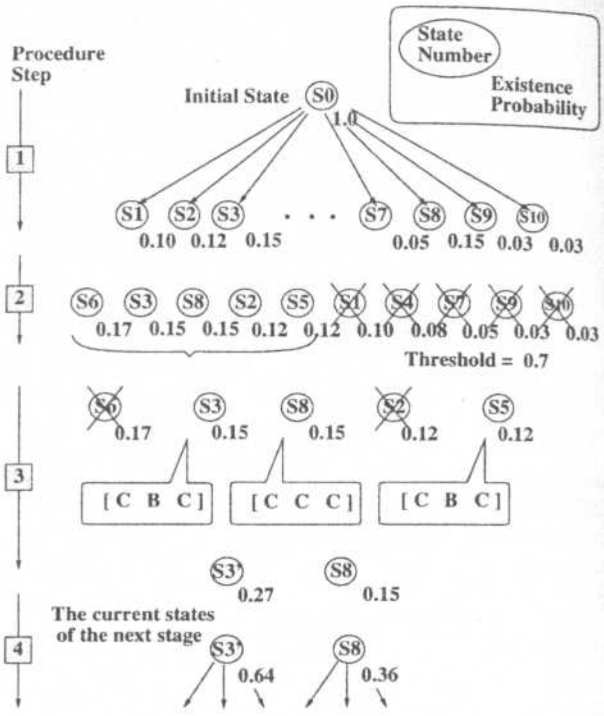

Figure 4: Simulation processes.

In Step 3, the state 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. 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 immediately.

High-Speed Stochastic Qualitative Reasoning

Background

In stochastic qualitative reasoning, state transition is performed whether the derived states agree or disagree with real behavior on the target system. Since states are generated from all conceivable combinations among elements, the number of derived states exponentially increases with the size of the qualitative model. Table 5 shows a rough relationship between the model scale to the number of derived states and its reasoning time. If the number of nodes is more than about 40, the reasoning is impossible because of memory size.

Table 5: Rough relationship between model scale to the number of derived states and reasoning time.

Number of modes	Number of derived states	Reasoning time
5	500	1 min.
10	1000	5 min.
15	3000	10 min.
20	5000	20 min.
25	10000	50 min.
30	25000	120 min.
35	40000	400 min.
40	reasoning impossible	

In order to solve this problem, we introduce model division and states composition techniques. Increase of the number of derived states is prevented by using divided qualitative models. The states of the entire model are generated by composing each survived state on divided models.

Model Division

In the model division phase, partial qualitative models called *blocks* are constructed by dividing the entire model. The closely connected elements (nodes or functions) are included in the same partial model.

One node, called a *common node*, is owned jointly between adjoining blocks in order to keep consistency between partial models and a whole model. This is because the common nodes must have the same qualitative values at any time. A method of propagating qualitative values between common nodes is introduced here.

Propagation of Qualitative Value

Figure 5 shows the relationship between adjoining blocks. The common node of one block supplies the same common node of the others with qualitative values. The former block is called an *output block*. The latter block is called an *input block*. The arc is accompanied with the propagation of qualitative values and the probabilities of occurrence between the common nodes. In one block, the other blocks are regarded as black boxes, and the predicted states are derived from the received qualitative values.

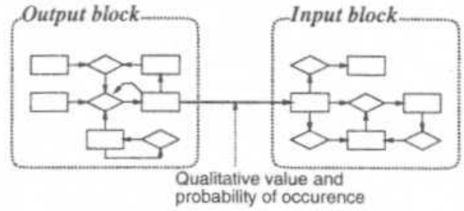

Figure 5: The relationship between blocks

In the stochastic qualitative reasoning, qualitative values are propagated through a function or an arc between nodes. The basic idea is unchangeable between common nodes.

In the reasoning process, the qualitative value of nodes (except for the measured node) are not fixed as a unique value, these have probabilities of occurrence. For example, the probability of 'C' is 12.5%, one of 'D' is 75%, and one of 'E' is 12.5% at reasoning unit time 1 in Table 6. These values must be exactly alike on each common node. Therefore, for every reasoning unit time, the probabilities of occurrence are calculated and then transfered between each common node.

Table 6: Example of probabilities of occurrence.

==0==	==1==	==2==	==3==
A 0.000	A 0.000	A 0.000	A .....
B 0.000	B 0.000	B 0.000	B .....
C 0.000	C 0.125	C 0.123	C .....
D 1.000	D 0.750	D 0.753	D .....
E 0.000	E 0.125	E 0.123	E .....

States Composition

An increase in the number of the derived states can be prevented by reasoning in partial models. However, the state of the entire model is needed in order to grasp the behavior of the target system, and to compare derived behavior with the real behavior. The state of the entire model can be generated by composing each state of partial models. As mentioned above, the common nodes must indicate the same qualitative value. Therefore, the entire states are generated by composing each derived partial state whose qualitative values on the common node are the same. This states composition method guarantees that the composed states can be the same states by using the previous method. As space is limited, the proof is excluded.

Condition for Model Division

It is not comparatively important how to divide a target model by the mentioned states composition method. However, in order to execute reasoning efficiently, some limitations must be added for the actual model division process:

1. Each block includes only directly connected nodes and functions.
2. At least one measured node is included in each block.
3. The nodes that are connected by an arc must not be separated.

Because the propagation of the influence happens between connected elements, the 1st condition is to be considered. In the reasoning process, unlikely reasoning states where the qualitative value of a measured node differs from the real measured value are eliminated. By the 2nd condition, these unlikely states are eliminated in each block. The 3rd condition means that the division on the node whose qualitative values are uniquely determined is useless.

Application to VAV Systems

A Stochastic Qualitative Model of a VAV System

Experiments have been done in regard to the VAV (Variable Air Volume) system of a building in Tokyo.

Figure 6 shows a diagram of a VAV system. It consists of one fan, one refrigerator, and three VAV valves and sensors. This system controls the room temperature by controlling the supplied air temperature and the room air volume.

The air is absorbed from the outside by a fan. The supplied air is generated by a refrigerator and is separated in order to send it to each VAV valve. The room air volume is controlled by each valve according to the gap in room temperature between the preset value and the measured one. The volume of supplied air controls the room temperature. Figure 7 illustrates a qualitative model of the VAV system in Figure 6. This qualitative model can be constructed with three parts which correspond to each VAV valve, because the VAV valves are independent of each other.

In Figure 7, the entire model is divided into five blocks: supplied air volume, supplied air temperature, VAV1, VAV2, and VAV3. The common nodes are "Supply air volume" between supplied air volume block and VAV1, 2, 3 block and "Supply air temperature" between the supplied air temperature block and VAV1, 2, 3 block.

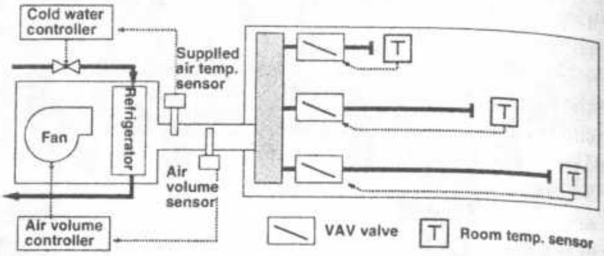

Figure 6: VAV system instrumentation diagram.

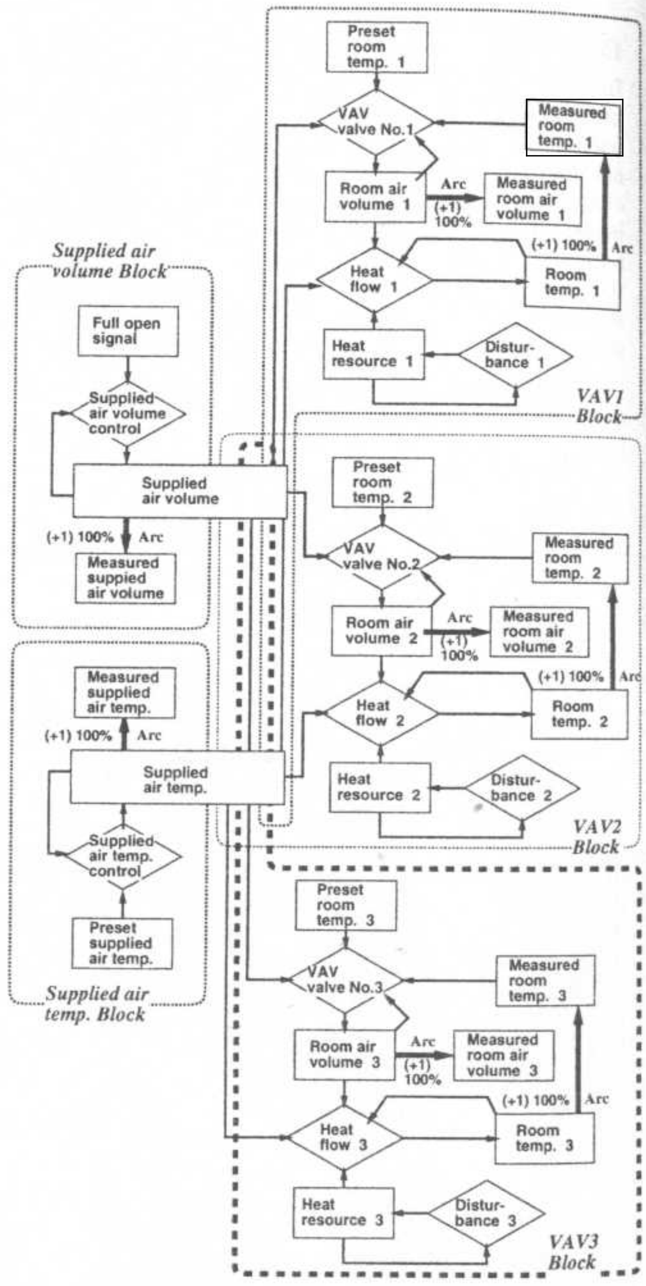

Figure 7: A qualitative model for the VAV system.

The Results

In the entire qualitative model in Figure 7 and the partial models (the nodes with a gray pattern are common nodes), stochastic qualitative reasoning was executed. The reasoning time was six unit times (one unit time is 15 minutes), and threshold value is 1.0. Table 7 shows the number of derived states and execution time for each VAV model.

Table 7: Number of derived states and execution time.

unit time	entire model	air vol.	air temp.	VAV1	VAV2	VAV3
0	125	1	1	5	5	5
1	575	5	4	20	32	82
2	1030	5	4	120	140	129
3	4559	15	10	272	510	321
4	22197	15	12	1021	715	301
5	22197	15	12	1021	715	518
6	22197	15	12	1021	715	518
time	95min.	1min.	1min.	4min.	7min.	5min.
rate	0.231	0.231				

In this table, the sum of the derived states number in partial models is drastically less than the one in the entire model. Also, the reasoning time is shorter, but the agreement rate has the same value. From the results, the stochastic qualitative reasoning is executed efficiently by the method of model division and states composition.

Conclusion

This paper presents a method for model division and states composition within stochastic qualitative reasoning, that has the following features:

- In the application to VAV system, it is confirmed that the reasoning time is shortened to one-fifth by the proposed method.
- By states composition, the derived states can reappear as the same ones for the entire model. This reasoning can produce the same results as the previous method.
- The parallel reasoning for divided blocks using multiple processors will help for much more high-speed reasoning.

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