Studies for Hierarchy DDBN and Its Inference Algorithm

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Abstract

In order to solve the problem of modeling and inference for a vast complicated system, a new concept of Hierarchy DDBN was proposed here through the layer analysis method, and worked out the inference algorithm of the Hierarchy DDBN based on the strict probability theory. In order to test the validity of the inference algorithm, a series of simulation were conducted. The result showed that the Hierarchy DDBN could model the complicated system in a proper way, and it ccould simplify the modeling process, speed up the inference. Also the result was totally in accord with the human decision.
Keyword: Discrete Dynamic Bayesian network, Inference, Algorithm.

I. Introduction

Since Discrete Dynamic Bayesian Network (DDBN) inferences and predicts system state through the observations acquired in the past and at present, it can make the observations compensate to each other, and can tolerate the uncertainty and missing of the observations. Thus, DDBN has become an important tool for modeling and inferring a dynamic system. The studies for DDBN are quite active in the world. Refs. [1,2] introduced DSBN (Discrete Static Bayesian Network) and its junction tree inference algorithm in details. Refs. [3] described DDBN and its inference algorithm in more details. DSBN or DDBN has been widely used in image identification [5], target identification [6], combating situation assessment [7] and tracking [8]. The more studies for inference and learning of DSBN or DDBN are on going [8-12].

Because there are a large number of observation variables, the medium variables and system variables in a complicated system or in a distributed system, using traditional DDBN will result in a high complexity in modeling and in variables, which slowdowns its inference speed. Especially as for the distributed systems consisted of a large number of entities, the observations must come from every entity, so a large number of observations must be transmitted, and this will depend on a high quality communication system. In order to solve this problem, we proposed the concept of Hierarchy DDBN and its inference algorithm based on the theory of complicated system. The new type of DDBN can be used to rid of the hardship of applying the traditional DDBN to complicated systems.

II. Hierarchy DDBN and Its Inference Algorithm

A. The Definition of Hierarchy DDBN

A DDBN is composed of a series of DSBN corresponding to different time chips. A node in a DSBN will be a group of nodes in the corresponding DDBN. We assume, $DDBN_1$、$DDBN_2$….. $DDBN_n$， if a hidden node of $DDBN_i$ is an observation node of another DDBN, $DDBN_{i-1,}$ then the *n* numbers of DDBNs compose a Hierarchy DDBN. Basically, a Hierarchy DDBN is a group of DDBNs with some relations. For example, the distribution of a node in $DDBN_2$ which comes from the inference is the input of an observation node of $DDBN_1$.

B. Inference Algorithm of Hierarchy DDBN

In [2], the author introduced the characters and the conditional independency property of the DSBN. To a DSBN which contains *n* numbers of hidden nodes and *m* numbers of observation nodes, we can summarize the essence of its inference as the formulation below:

$$p(x_1, x_2, \ldots x_n | y_1, y_2, \ldots y_m) = \frac{\prod_j p(y_j | pa(y_j)) \prod_i p(x_i | pa(x_i))}{\sum_{x_1 x_2 \cdots x_n} \prod_j p(y_j | pa(y_j)) \prod_i p(x_i | pa(x_i))}$$
$$i \ni [1, n], j \in [1, m] \qquad (1)$$

Where the x_i is a state of variable X_i. y_i is a state of variable Y_i. $pa(y_i)$ is the parents set of variable Y_i.

If the DSBN develops *T* time chips along with the time, the *T* numbers of DSBN and their predecessor-successor relations between each other will form a DDBN. Because every observation variables has only one state, so the joined distribution of all hidden variables is

$$p(x_{11}, x_{12}, \ldots x_{1n}, \ldots\ldots x_{T1}, x_{T2}, \ldots x_{Tn} | y_{11}, y_{12}, \ldots y_{1m}, \ldots\ldots y_{T1}, y_{T2}, \ldots y_{Tm})$$
$$= \frac{\prod_{i,j} p(y_{ij} | pa(y_{ij})) \prod_{i,k} p(x_{ik} | pa(x_{ik}))}{\sum_{x_{11} x_{21} \ldots x_{T1} \ldots x_{Tn}} \prod_{i,j} p(y_{ij} | pa(y_{ij})) \prod_{i,k} p(x_{ik} | pa(x_{ik}))} \quad i \ni [1, T], j \in [1, m], K \in [1, n] \qquad (2)$$

Where x_{ij} is a state of variable X_{ij}, the first subscript stands for the number of the time chip which the variable belongs to, the second subscript stands for the number of the hidden variable in set $(x_1, x_2, \ldots x_n)$. The same as the variable of y_{ij}. $pa(y_{ij})$ is the parents set of variable y_{ij}.

As to a hierarchy DDBN, because it contains more DDBN and the inference of high level depends on the inference of the low level, so the inference of the Hierarchy DDBN must begin at the lowest level, and upwards one after another.

At first, we deduce the inference algorithm of a two levels Hierarchy DDBN, and generalize it to common situations. Assume that the first level DDBN is the high level and that it contains T time chips and n_1 numbers of hidden variables and m_1 numbers of observation nodes in each chip. Note these variables as x_{1jk} $(1 \le j \le T \quad 1 \le k \le n_1)$ and y_{1pq} $(1 \le p \le T \quad 1 \le q \le m_1)$ respectively, where x_{1jk} $(1 \le j \le T \quad 1 \le k \le n_1)$ stands for the number k hidden node in chip j of the level one DDBN, same as the variable of x_{1jk} $(1 \le j \le T \quad 1 \le k \le n_1)$. But in the level one, variables $y_{1_{p_1 q_1}}$ $(1 \le p_1 \le T)$ can not be observed directly. Their status must come from the inference of the second level.

The second level DDBN contains T time chips too. In each chip, there are n_2 numbers of hidden variables and m_2 numbers of observation variables. Note them as x_{2jk} $(1\le j\le T \quad 1\le k\le n_2)$ and y_{2pq} $(1\le p\le T \quad 1\le q\le m_2)$ respectively. According to the definition of Hierarchy DDBNs, assume that the observation variables $y_{1p_1q_1}$ $(1\le p_1\le T)$ in level one is equal to the hidden variables $x_{2j_1k_1}$ $(1\le j_1\le T)$ in level two, so the inference results of variables $x_{2j_1k_1}$ $(1\le j_1\le T)$ are the observations of variables $y_{1p_1q_1}$ $(1\le p_1\le T)$.

Assume that every observation variables in level one can be observed and only be observed in one state, then the joint distribution of all hidden variables is below

$$p(x_{111},x_{112},\cdots x_{11n_1},\cdots\cdots x_{1T1},x_{1T2},\cdots x_{1Tn_1}\mid y_{111},y_{112},\cdots y_{11m_1},\cdots\cdots y_{1T1},y_{1T2},\cdots y_{1Tm_1})$$
$$=\frac{\prod_{p,q}p(y_{1pq}\mid pa(y_{1pq}))\prod_{i,k}p(x_{1ik}\mid pa(x_{1ik}))}{\sum_{x_{111}x_{112}\cdots x_{1T1}\cdots x_{1Tn_1}}\prod_{p,q}p(y_{1pq}\mid pa(y_{1pq}))\prod_{i,k}p(x_{1ik}\mid pa(x_{1ik}))}\quad i\ni[1,T],\ p\in[1,T],\ K\in[1,n_1],\ q\in[1,m_1] \tag{3}$$

where $(y_{111},y_{112},\cdots y_{11m_1},\cdots\cdots y_{1T1},y_{1T2},\cdots y_{1Tm_1})$ is the only state vector of all observation variables.

But for the Hierarchy DDBN mentioned above, because the variables $y_{1p_1q_1}$ $(1\le p_1\le T)$ can not be observed in level one DDBN, their distributions can only be acquired after the inference of second level DDBN is finished, so every variables of $y_{1p_1q_1}$ $(1\le p_1\le T)$ has more than one state, their state is a distribution. so the joint distribution of all hidden variables is the weight sum of their joint distribution under each distribution of $y_{1p_1q_1}$ $(1\le p_1\le T)$. We deduce the inference algorithm as below:

$y_{1p_1q_1}$ $(1\le p_1\le T)$ in the second level DDBN are hidden nodes, and they are noted as $x_{2j_1k_1}$ $(1\le j_1\le T)$, so we must determine the joint distribution of $x_{2j_1k_1}$ $(1\le j_1\le T)$ according to (3) and the probability theory. The joint distribution of variables $x_{2j_1k_1}$ $(1\le j_1\le T)$ can be determined as below.

$$p(x_{21k_1},x_{22k_1},\cdots x_{2Tk_1}\mid y_{211},y_{212},\cdots y_{21m_2},\cdots\cdots y_{2T1},y_{2T2},\cdots y_{2Tm_2})=$$
$$\sum_{x_{211},x_{212},\cdots x_{21n_2},\cdots\cdots x_{2T1},x_{2T2},\cdots x_{2Tn_2}\setminus x_{21k_1}\cdots\cdots x_{2Tk_2}} p(x_{211},x_{212},\cdots x_{21n_2},\cdots\cdots x_{2T1},x_{2T2},\cdots x_{2Tn_2}\mid y_{211},y_{212},\cdots y_{21m_2},\cdots\cdots y_{2T1},y_{2T2},\cdots y_{2Tm_2})$$
$$=\sum_{x_{211},x_{212},\cdots x_{21n_2},\cdots\cdots x_{2T1},x_{2T2},\cdots x_{2Tn_2}\setminus x_{21k_1}\cdots\cdots x_{2Tk_2}}\frac{\prod_{p,q}p(y_{2pq}\mid pa(y_{2pq}))\prod_{i,k}p(x_{2ik}\mid pa(x_{2ik}))}{\sum_{x_{211}x_{221}\cdots x_{2T1}\cdots x_{2Tn_2}}\prod_{p,q}p(y_{2pq}\mid pa(y_{2pq}))\prod_{i,k}p(x_{2ik}\mid pa(x_{2ik}))} \tag{4}$$

where $i\ni[1,T],p\in[1,T],K\in[1,n_2],q\in[1,m_2]$ When there is only one group of observation variables, get their status from the second level DDBN, the joint distribution of all the hidden variables of level one DDBN is below:

$$p(x_{111},x_{112},\cdots x_{11n_1},\cdots\cdots x_{1T1},x_{1T2},\cdots x_{1Tn_1}\mid y_{111},y_{112},\cdots y_{11m_1},\cdots\cdots y_{1T1},y_{1T2},\cdots y_{1Tm_1})$$
$$=\sum_{x_{21k_1}\cdots\cdots x_{2Tk_1}}\left[\frac{\prod_{p,q}p(y_{1pq}\mid pa(y_{1pq}))\prod_{i,k}p(x_{1ik}\mid pa(x_{1ik}))}{\sum_{x_{111}x_{121}\cdots x_{1T1}\cdots x_{1Tm_1}}\prod_{p,q}p(y_{1pq}\mid pa(y_{1pq}))\prod_{i,k}p(x_{1ik}\mid pa(x_{1ik}))}\times\right.$$

$$p(x_{21k_1},x_{22k_1},\cdots x_{2Tk_1}\mid y_{211},y_{212},\cdots y_{21m_2},\cdots\cdots y_{2T1},y_{2T2},\cdots y_{2Tm_2})\,]$$

$$=\sum_{x_{21k_1}\cdots\cdots x_{2Tk_1}}\left[\frac{\prod_{p,q} p(y_{1pq}\mid pa(y_{1pq}))\prod_{i,k} p(x_{1ik}\mid pa(x_{1ik}))}{\sum_{x_{111}x_{121}\cdots x_{1T1}\cdots x_{1Tn_1}}\prod_{p,q} p(y_{1pq}\mid pa(y_{1pq}))\prod_{i,k} p(x_{1ik}\mid pa(x_{1ik}))}\times\right.$$

$$\left.\sum_{x_{211},x_{212},\cdots x_{21n_2},\cdots\cdots x_{2T1},x_{2T2},\cdots x_{2Tn_2}\backslash x_{21k_1}\cdots\cdots x_{2Tk_2}}\frac{\prod_{p,q} p(y_{2pq}\mid pa(y_{2pq}))\prod_{i,k} p(x_{2ik}\mid pa(x_{2ik}))}{\sum_{x_{211}x_{221}\cdots x_{2T1}\cdots x_{2Tn_2}}\prod_{p,q} p(y_{2pq}\mid pa(y_{2pq}))\prod_{i,k} p(x_{2ik}\mid pa(x_{2ik}))}\right] \quad (5)$$

where $i\ni[1,T], p\in[1,T], K\in[1,n_1], q\in[1,m_1]$ 或 $i\ni[1,T], p\in[1,T], K\in[1,n_2], q\in[1,m_2]$.

If there are more than one group of observation variables which get their status from the inference results of the lower level DDBN, let us say there are z groups of this kind of observation variables, we note them as:

$y_{1p_1q_1}$ $(1\le p_1\le T)$, $y_{1p_1q_2}$ $(1\le p_1\le T)$, …… , $y_{1p_1q_z}$ $(1\le p_1\le T)$

They are hidden variables in the second level DDBN(maybe more than one DDBN in level two), and then the joint distribution of all hidden variables in level one DDBN is below.

$$p(x_{111},x_{112},\cdots x_{11m_1},\cdots\cdots x_{1T1},x_{1T2},\cdots x_{1Tn_1}\mid y_{111},y_{112},\cdots y_{11m_1},\cdots\cdots y_{1T1},y_{1T2},\cdots y_{1Tm_1})$$

$$=\sum_{x_{2_z1k_z}\cdots\cdots x_{2_zTk_z}}\Bigg(\cdots\cdots\sum_{x_{2_21k_2}\cdots\cdots x_{2_2Tk_2}}\Bigg(\sum_{x_{2_11k_1}\cdots\cdots x_{2_1Tk_1}}\Bigg(\frac{\prod_{p,q} p(y_{1pq}\mid pa(y_{1pq}))\prod_{i,k} p(x_{1ik}\mid pa(x_{1ik}))}{\sum_{x_{111}x_{121}\cdots x_{1T1}\cdots x_{1Tn_1}}\prod_{p,q} p(y_{1pq}\mid pa(y_{1pq}))\prod_{i,k} p(x_{1ik}\mid pa(x_{1ik}))}\times$$

$$\sum_{x_{2_111},x_{2_112},\cdots x_{2_11n_{2_1}},\cdots\cdots x_{2_1T1},x_{2_1T2},\cdots x_{2_1Tn_{2_1}}\backslash x_{2_11k_1}\cdots\cdots x_{2_1Tk_1}}\frac{\prod_{p,q} p(y_{2_1pq}\mid pa(y_{2_1pq}))\prod_{i,k} p(x_{2_1ik}\mid pa(x_{2_1ik}))}{\sum_{x_{2_111}x_{2_112}\cdots x_{2_1T1}\cdots x_{2_1Tn_{2_1}}}\prod_{p,q} p(y_{2_1pq}\mid pa(y_{2_1pq}))\prod_{i,k} p(x_{2_1ik}\mid pa(x_{2_1ik}))}\Bigg)\times$$

$$\cdots\times$$

$$\sum_{x_{2_z11},x_{2_z12},\cdots x_{2_z1n_{2_z}},\cdots\cdots x_{2_zT1},x_{2_zT2},\cdots x_{2_zTn_{2_z}}\backslash x_{2_z1k_z}\cdots\cdots x_{2_zTk_z}}\frac{\prod_{p,q} p(y_{2_zpq}\mid pa(y_{2_zpq}))\prod_{i,k} p(x_{2_zik}\mid pa(x_{2_zik}))}{\sum_{x_{2_z11}x_{2_z12}\cdots x_{2_zT1}\cdots x_{2_zTn_{2_z}}}\prod_{p,q} p(y_{2_zpq}\mid pa(y_{2_zpq}))\prod_{i,k} p(x_{2_zik}\mid pa(x_{2_zik}))}\Bigg)$$

$$i\ni[1,T], p\in[1,T], K\in[1,n_1], q\in[1,m_1] \text{ or } i\ni[1,T], p\in[1,T], K\in[1,n_{2_l}], q\in[1,m_{2_l}]. \quad (6)$$

If a hierarchy DDBN contains *H* levels of DDBN, and there are z_i observation variables in the *ith* level which their status must come from the inference results of the level *i+1*, then the inference of this Hierarchy DDBN will be the generalization of the two levels Hierarchy DDBN mentioned above. It is below:

1 At first, we must start from the level *H*, and calculate the joint distribution of all hidden variables in level *H* according to formula 3.

2 Start with the result of 1, extract out the distribution of hidden variables, which are the observation variables in level *H*-1 using formula 4. Now, all status of the observation nodes in level *H-1* are known.

3 Let control C=H-1.

4 Calculate the joint distribution of all hidden variables in level *C* DDBN using formula 6。

5 If C>1, because the joint distribution of all hidden variables in level *C* DDBN are known, we can extract out the distribution of hidden variables which are the observation variables in level *C*-1 using formula 4, now, all status of the observation nodes in level *C-1* are known, Let C=C-1, go to 4; else The process of the inference is over.

III. Samples and Simulation

Now, we can see the application and advance of the hierarchy DDBN. The sample is the emergency helicopter schedule problem. Assume that we have some helicopters for the use of disaster saving. The command center directs all the helicopters and allocate task for them according to the position of the disaster, the emergency of the disaster and the capacity of these helicopters. However, the status and capacity of every helicopter change dynamically according to the position between the disaster and the helicopter, and the emergency of the disaster are change dynamically too. Thus, the helicopter dispatch should be modeled using dynamic Bayesian network, otherwise, the status and capacities of the helicopters can not be acquired by the command center directly. If we model the helicopter dispatch problem by a single DDBN, the inference can only be executed in the command center and every helicopter must transfer a large number of data to the command center. The data transfers will cost much time, and data transfers are jammed easily. The best method is that the capacity and status are calculated by every helicopter itself using inference, and transfer the concise results of their inference to the command center. This process is just a hierarchy work and the hierarchy DDBN is the right way to model the process.

A. The Helicopter Schedule Model

The function of the command center is to evaluate the preponderant relationship between the helicopter and the disaster, and allocate helicopters for the disasters by their emergency order. The method of the command center is dispatching the most preponderant and the most capable one to saving a disaster. To make it simple, assume that the command has the power to command two helicopters, and now, a disaster in some place occurred. Then we can model the helicopter schedule as fig 1.

Each helicopter must calculate its capacity by inference and take its own motor state, saving equipment state, detection equipment state and screw capacity in to account. The inference DDBN model is shown in fig 2. In this model(fig 2), All the status can be acquired form transducers and database. To make it simple, we assume that the two helicopters have the same flying quality and have the same equipment. They are installed remote saving system and short range saving system, remote detector and short range detector. The saving system contains electrical equipment and mechanical equipment. So the capacity of a helicopter can be classified to 4 stages, super, comparative, common and inferior.

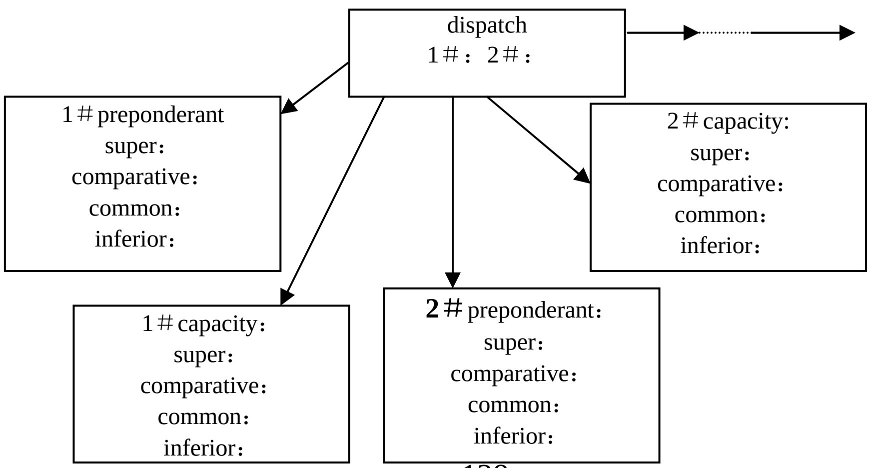

Fig 1. The helicopter schedule model (level 1)

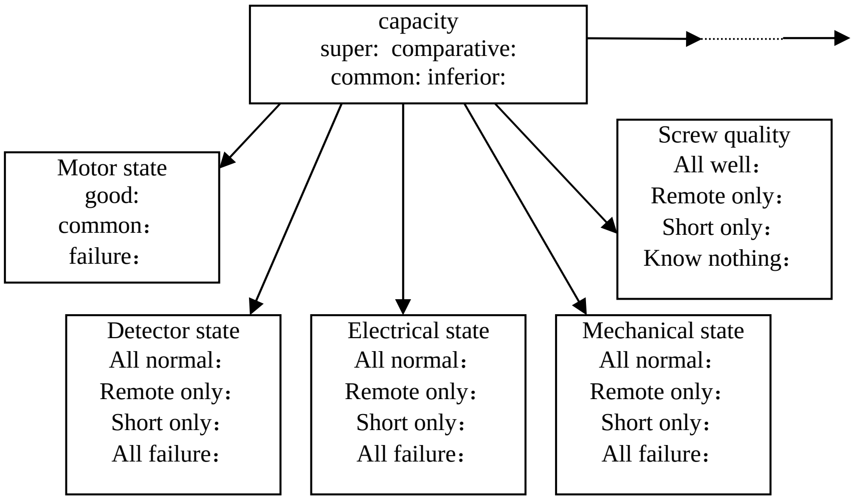

Fig 2. The capacity decision model for a helicopter （level 2）

In order to execute the inference, we also need to set the conditional probability table for each level of the DDBN. This table should be determined by experts. According to some experts, we set the conditional probability table as table 1 and table 2.

Table 1. The conditional probability table of the helicopter schedule model (level 1)

	1#	2#		1#	2#
1# preponderant	0.7	0.05	1# capacity	0.7	0.1
	0.2	0.2		0.15	0.25
	0.05	0.1		0.1	0.25
	0.05	0.65		0.05	0.4
2# preponderant	0.1	0.7	2# capacity	0.1	0.7
	0.25	0.2		0.25	0.15
	0.25	0.05		0.25	0.1
	0.4	0.05		0.4	0.05

Table 2. The conditional probability table of the capacity decision model (level 2)

	super	comparative	common	inferior
Motor state	0.5	0.5	0.5	0.1
	0.5	0.5	0.5	0.1
	0	0	0	0.8
Electrical state	0.4	0.4	0.2	0.1
	0.35	0.4	0.2	0.1
	0.2	0.1	0.5	0.1
	0.05	0.1	0.1	0.7
Screw quality	0.75	0.2	0.1	0.1
	0.1	0.5	0.1	0.1
	0.05	0.2	0.7	0.1
	0.1	0.1	0.1	0.7
Detector state	0.45	0.3	0.1	0.1
	0.25	0.5	0.3	0.1
	0.2	0.1	0.5	0.1
	0.1	0.1	0.1	0.7
Mechanical	0.4	0.4	0.2	0.1

state	0.35	0.4	0.2	0.1
	0.2	0.1	0.5	0.1
	0.05	0.1	0.1	0.7
Next time	0.7	0.1	0.1	0.1
	0.1	0.7	0.1	0.1
	0.1	0.1	0.7	0.1
	0.1	0.1	0.1	0.7

Assume that a disaster occurred in some place, and the distances between each helicopter and the disaster are the same. This means, no.1 helicopter has the same preponderant as the no.2 helicopter. The command center must dispatch a helicopter to go to the place to save the disaster. Assume we observed the situation and the helicopters 4 times, and have 4 groups of observations. All the observations are shown in table 3 and table 4.

Table 3. The 4 time slots observations of no.1 helicopter

	Time slot 1	Time slot 2	Time slot 3	Time slot 4
preponderant	comparative	comparative	comparative	comparative
motor	good	good	good	good
detector state	all normal	all normal	all normal	all normal
electrical state	all normal	all normal	all normal	all normal
mechanical	all normal	all normal	all normal	all normal
screw quality	all well	all well	all well	all well

Table 4. The 4 time slots observations of no.2 helicopter

	Time slot 1	Time slot 2	Time slot 3	Time slot 4
preponderant	comparative	comparative	comparative	comparative
motor	good	good	good	good
detector state	short only	all normal	short only	all normal
electrical state	short only	short only	short only	short only
mechanical	all normal	all normal	all normal	all normal
screw quality	short only	short only	short only	short only

From table 2 and table 4, we can know that the two helicopters has the same preponderant at four times, and the equipments of no.1 helicopter are all normal. But the equipments of no.2 helicopter are not all normal, further more; the screw of no.1 helicopter has high quality than the screw of the no2 helicopter. So we can conclude that the capacity of no.1 helicopter is more better than no.2 helicopter. The command center should dispatch no.1 helicopter to undertake the saving task.

B. Results of the simulation

Using the inference algorithm, we take a simulation for the helicopter schedule problem, the results are shown in table 5, table 6 and table 7.

Table 5. The capacity inference results for no.1 helicopter

Time slot 1	Time slot 2	Time slot 3	Time slot 4
0.9684 0.0305 0.0011 0.0001	0.9889 0.0109 0.0002 0.0000	0.9889 0.0109 0.0002 0.0000	0.9684 0.0305 0.0011 0.0001

Table 6. The capacity inference results for no.2 helicopter

Time slot 1	Time slot 2	Time slot 3	Time slot 4
0.0182 0.0421 0.9395 0.0002	0.0057 0.0188 0.9755 0.0000	0.0057 0.0188 0.9755 0.0000	0.0182 0.0421 0.9395 0.0002

Table 7. The helicopter schedule inference results

Time slot 1	Time slot 2	Time slot 3	Time slot 4
0.9906 0.0094	0.9974 0.0026	0.9878 0.0122	0.9868 0.0132

From the inference results mentioned above we can conclude that the inference results are totally in accord with the judgment of human beings. The inference program is running by a P-III-900 CPU. The capacity decision inference takes 0.6 seconds. The helicopter schedule inference takes 0.5 seconds. The total time cost is 1.1 seconds. We also integrated the two levels model to form a single big DDBN, and took an inference on the big one, the results of the four time slots are （0.9757 0.0243）、（0.9852 0.0148）、（0.9570 0.0430）、（0.9601 0.0399））, it takes 1 second. So on this condition, the time consumption of the two types DDBN is the same. Using the hierarchy DDBN can save more time for data communications, so inference in the hierarchy DDBN are fast. Further more, when the numbers of the dynamic Bayesian networks in level two are more than 2, because the second level inference are executed in parallel by more than one computers, the inference in hierarchy DDBN will more fast. In addition, there is a slight difference between the inference results of the hierarchy DDBN and the integrated. The reason is that the inference result is influenced by the priority probabilities. In a hierarchy DDBN, there will be more priority probabilities, and there is only one priority probability in a single level DDBN. The slight difference, for qualitative inference, can be omitted.

VI. Conclusions

The basic idea of the hierarchy DDBN comes from the actual requirement for modeling and inference the complicated system. The model of the hierarchy DDBN is the abstract of the relationship between the actual physical system, and the inference algorithm comes from the basic theories of Bayesian network and from the probability theory, so we can trust the truth of this. From the simulation, we can conclude that the hierarchy DDBN can make the modeling and inference for the complicated system easy. The inference formulations (1.3~1.6) seems more complicated. But it is more easy for programming, and it is faster than the big single level DDBN which is the integration of the all levels of DDBN。 The reasons are two main points: one is that the inference of the hierarchy DDBN was executed by more computers and in a parallel manner; another one is that the hierarchy DDBN can save more time for data communications in the distributed system; in addition, it can be implemented locally and in parallel manner without sacrificing accuracy.

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