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ScienceDirect

Procedia Computer Science 154 (2019) 238–248

Procedia Computer Science

www.elsevier.com/locate/procedia

8th International Congress of Information and Communication Technology, ICICT 2019

Intuitionistic Fuzzy Dynamic Bayesian Network and its Application to Terminating Situation Assessment

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Abstract

The period of terminating situation in air combat is time-varying and full of information with uncertainty. In order to process the fuzzy information in time series and assess the situation effectively, Intuitionistic Fuzzy Dynamic Bayesian Network (IFDBN) is built. In this model, intuitionistic fuzzy reasoning engine is embedded into dynamic Bayesian Network as a virtual node. Besides, a new method to convert the intuitionistic fuzzy reasoning output into probability which can be input into dynamic Bayesian Network as virtual evidence is proposed. On these bases, the detailed intuitionistic fuzzy reasoning algorithms are formulated and the dynamic Bayesian Network information transferring mode is analyzed. Finally, a case study for terminating situation assessment in air combat is given to prove the feasibility of the proposed model.

Keywords: Intuitionistic Fuzzy Dynamic Bayesian Network; intuitionistic fuzzy reasoning; terminating situation assessment; Case study;

1. Introduction

Terminating situation assessment aims at determining whether we have fulfilled the conditions for termination of combat, which belongs to the last stage of situation assessment. Traditional situation assessment methods are mainly

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10.1016/j.procs.2019.06.036

based on linear weighting and nonlinear reasoning[1]. At the core of nonlinear reasoning techniques is Bayesian Network (BN), which is widely used because of its information processing system and strong reasoning ability. However, terminating situation has special features and differences from situation in conventional mode. On one hand, the combat in the period of terminating situation is full of fuzzy information and data which always appear in huge volume[2]. On the other hand, terminating situation is in rapid time series, which requires the method to consider the factor of time. Therefore, using the traditional knowledge representation and reasoning ability of BN cannot meet the demand of terminating situation assessment.

In order to describe the situation in time-varying state, the improvement of dynamic Bayesian Network has aroused wide concerns, and many academic achievements have been done. Chai et al. Reference 3 analyze the causal relationship between different elements in Bayesian Network under continuous time slices and incorporates time series factor into BN, which maintains the robust of model. Farnoush. et al. Reference 4 propose a reconfigurable Bayesian Network. They use Maximum Likelihood Estimation to learn the parameters of BN and change the parameters with the pace of data updating in battlefield. Thus, the parameters of Bayesian Network are dynamic in time series. Gao et al.[5] developed a structure varied Bayesian Network, whose network topology is time-varying. This model can adapt to the situation of process mutation. However, most of the dynamic Bayesian network model don't successfully deal with the fuzziness of data, which limits the application of model into battlefield situation assessment.

Some researchers also conduct preliminary attempts to enable BN to express the uncertain information. Mohsen. et al.[6] use a fuzzy quantizer to discretize the observable variables obtained from sensors and output the soft evidence, then employ BN to model the situation. L. P. Perera et al.[7] present a fuzzy-Bayesian decision formulation method, where the decision is formulated by BN's sequential actions. Fuzzy-logic is to reason the parallel decision-making module. Although there are a few literatures concerning dynamic Bayesian Network and fuzzy-Bayesian, respectively, it still need further study to combine these two methods to cope with practical problems.

In view of above-mentioned reasons, this paper proposes a model named Intuitionistic Fuzzy Dynamic Bayesian Network (IFDBN), which consists of two modules. Module 1 is intuitionistic fuzzy reasoning, where the nodes with fuzziness in BN are reasoned by intuitionistic fuzzy engine. Module 2 is using dynamic Bayesian Network to conduct dynamic reasoning in time series. The intuitionistic fuzzy reasoning changes the binary attribute of nodes in BN and combines BN with intuitionistic fuzziness of observation data, which is more suitable to terminating situation assessment.

2. Intuitionistic Fuzzy Reasoning

Intuitionistic fuzzy set (IFS) is put forward by Atanassov in 1986[8], which is an expansion and generalization of Zadeh fuzzy set theory (ZFS). IFS has three indicators, the membership, the non-membership, and the intuitionistic index[9]. The last one is the one more indicator than ZFS. Thus, IFS can not only represent the fuzzy concept of either or, but also neither nor.

Definition 1.

$$A = \{< x, \mu_A(x), \nu_A(x) > | x \in E\} \tag{1}$$

where $\mu_A(x)$: $X \to [0,1]$ and $\nu_A(x)$: $X \to [0,1]$ are respectively the membership and non-membership of x belonging to A. For every x, $0 \le \mu_A(x) + \nu_A(x) \le 1$. Then, A is called the intuitionistic fuzzy set of X.

And $\gamma_A(x) = 1 - \mu_A(x) - \nu_A(x)$ is defined as the hesitancy of x to A.

Compositional algorithm for intuitionistic fuzzy reasoning (IFR) is developed from fuzzy reasoning. The reasoning result depends on the compositional algorithm between Fuzzy Implication Relationship $\tilde{I}$ and IFS. Generally speaking, when a fuzzy system is determined, its fuzzy implication relationship is fixed. What can be changed is the compositional algorithm. We give the compositional algorithms as follows based on Mamdani fuzzy reasoning[10].

Suppose A and A^* are intuitionistic fuzzy propositions of universe of discourse X, B is a intuitionistic fuzzy proposition of universe of discourse Y.

Major Premise (rules): if x is A, then y is B.

Minor Premise (facts): x is A^*

Conclusion: y is $B^*=A^*\circ R(A;B)$

The above IFR process is defined as reasoning rules with single antecedent and single rule. And for the intuitionistic fuzzy logic implication $A \rightarrow B$, the relation matrix is:

$$R_{A\rightarrow B} = (A\times B)\bigcup \quad = \int_{X\times Y} \langle \mu_{A\rightarrow B}(x,y), \gamma_{A\rightarrow B}(x,y)\rangle / (x,y) \tag{2}$$

With A^* known, B^* can be reasoned by compositional algorithm between R and A^*:

$$B^*=A^*\circ R(A;B)=\int_Y \langle \mu_{B^*}(y), \gamma_{B^*}(y)\rangle / y \tag{3}$$

The whole process of intuitionistic fuzzy reasoning (IFR) should firstly build up the attribute functions of intuitionistic fuzzy variables, and then design the reasoning rules. Based on the compositional algorithm and the defuzzification method, the result can be reasoned.

3. Dynamic Bayesian network

As a reasoning model based on Graph Theory and probability transmission, dynamic Bayesian Network (DBN) is in fact a model to transfer the node information in time series. However, owing to the time-variant characteristic of node, the nodes in DBN has a huge volume, which may cause reasoning difficulties. To simplify the structure of DBN and for the sake of reasoning, we introduce the concept of virtual nodes. We use the virtual nodes to replace the local networks composed of intuitionistic fuzzy nodes. The evidence of virtual nodes is calculated by fuzzy engine. Combined with the virtual nodes, DBN completes the reasoning by information transmission. Fig. 1 shows the virtual nodes:

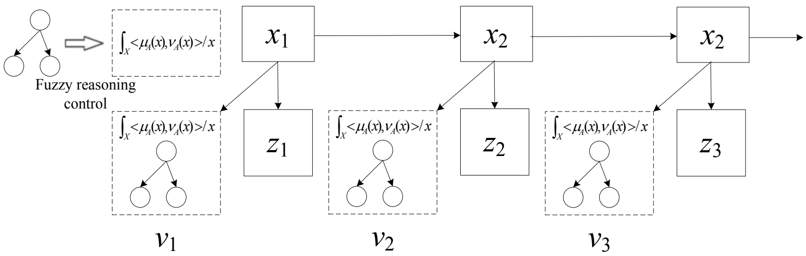


Fig. 1. Virtual nodes in DBN.

The observation nodes are usually replaced by virtual nodes. Especially, when there are many observation nodes in DBN, the effect of network simplification will be better. Reasoning in DBN with virtual nodes is in essence to calculate the posterior probability distribution under the condition of observation nodes and virtual nodes[11]. Suppose that there are s_1 virtual nodes, s_2 hidden nodes, s_3 observation nodes and T time slices, which are marked by $X_{ij}(i=1,\cdots$ $\cdots$, $Y_{ij}(i=1,\cdots$ $\cdots$ and $Z_{ij}(i=1,\cdots$ $\cdots$. Then we can calculate the posterior probability distribution:

$$p(Y_{11},\cdots \quad \cdots \quad \cdots \quad \cdots \quad \cdots \quad \cdots$$
$$\frac{p(Y_{11},\cdots \quad \cdots \quad \cdots \quad \cdots \quad \cdots \quad \cdots}{\sum_{y_{11},\cdots \quad \cdots} p(Y_{11},\cdots \quad \cdots \quad \cdots \quad \cdots \quad \cdots \quad \cdots Z_{Ts_3})} \tag{4}$$

Owing to the Conditional independence hypothesis in BN, the joint probability distribution of all nodes is[12]:

$$\begin{aligned} & p(Y_{11},\cdots \quad \cdots \quad \cdots \quad \cdots \quad \cdots \quad \cdots \\ & \prod_{ij} p(Y_{ij} = y_{ij} \mid pa(Y_{ij} = y_{ij})) \times \prod_{kl} p(X_{kl} = x_{kl} \mid pa(X_{kl} = x_{kl})) \\ & \times \prod_{mn} p(Z_{mn} = z_{mn} \mid pa(Z_{mn} = z_{mn})) \end{aligned} \tag{5}$$

where $i,k,m = 1,\cdots \quad \cdots \quad \cdots \quad \cdots$. Now Equation 5 can be represented as:

$$p(Y_{11},\cdots \quad \cdots \quad \cdots \quad \cdots \quad \cdots \quad \cdots$$
$$\frac{\prod_{ij} p(Y_{ij} \mid pa(Y_{ij})) \times \prod_{kl} p(X_{kl} \mid pa(X_{kl})) \times \prod_{mn} p(Z_{mn} \mid pa(Z_{mn}))}{\sum_{y_{11},\cdots \quad \cdots} \prod p(Y_{ij} \mid pa(Y_{ij})) \times \prod_{kl} p(X_{kl} \mid pa(X_{kl})) \times \prod_{mn} p(Z_{mn} \mid pa(Z_{mn}))} \tag{6}$$

What should be note is that Equation 6 is the joint probability distribution of hidden nodes. We can calculate the marginal probability distribution of any hidden variable based on Bayesian formula of holohedral probability.

4. Intuitionistic Fuzzy Dynamic Bayesian Network

In this section we will illustrate the modelling of Intuitionistic Fuzzy Dynamic Bayesian Network (IFDBN). IFDBN is inspired by fuzzy dynamic Bayesian Network, which developed the fuzziness representation in DBN. DBN combined with intuitionistic fuzzy reasoning engine has a stronger ability to process the fuzziness of nodes. Because IFDBN method takes the intuitionistic characteristic of nodes, that is, the hesitancy degree of observations into account, it can incorporate the fuzziness of evidence into Bayesian reasoning, which helps the reasoning result more consistent with human cognition13.

The IFDBN modelling process can be illustrated as follows. Firstly, the influential factors are extracted, which are necessary to build the BN. Then we need to find the intuitionistic fuzzy nodes which are mainly distributed in the observation nodes. Secondly, we use virtual nodes to replace the local network composed of nodes with intuitionistic fuzziness. Besides, fuzzy reasoning engine is employed to calculate the evidence of virtual nodes. Finally, the result is generated based on probability reasoning of BN. The whole process is shown in Fig. 2.

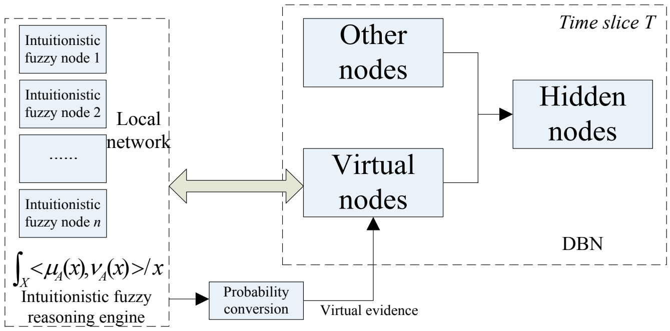


Fig. 2. IFDBN model.

4.1. Intuitionistic fuzzy reasoning engine of virtual nodes

Intuitionistic fuzzy reasoning engine (IFRE) is introduced in this paper to conduct the reasoning in virtual nodes. IFRE makes the fuzziness preserved and transmitted in BN, which contributes to the easier cognition. We use the module in MATLAB to build fuzzy reasoning engine. Fig. 3 shows an engine in MATLAB. In this engine, we can design the membership and non-membership for the variables, and input the corresponding reasoning rules, conduct the reasoning process by Mamdani compositional algorithm[14].

4.2. Probability conversion

The output of intuitionistic fuzzy reasoning engine is a fuzzy control value, which cannot be input into Bayesian Network directly. We have to convert it into probability and extract it as virtual evidence. In short, probability conversion is using the membership of variable to deal with the fuzzy control value. We input the fuzzy control value into membership functions and calculate the membership degrees of the fuzzy control value belonging to different fuzzy sets. Then the membership degrees are normalized and input into BN as virtual evidence. Suppose that η_1 is a fuzzy control value, R_i is the corresponding membership functions. The following formula shows how to realize probability conversion[15]:

$$E_i = \frac{R_i(\eta)}{\sum_i R_i(\eta)} \tag{7}$$

where E_i is the virtual evidence.

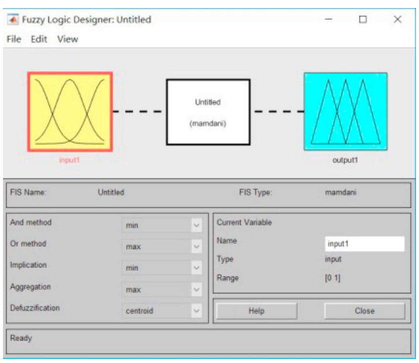


Fig. 3. Fuzzy reasoning engine.

5. Case study

According to the threat and situation analysis[16] proposed by Steinberg, we select intention and command constraint as influential factors of terminating situation. Intention is mainly judged by the enemy behaviors and command constraint depends on damage degree and endurance. Thus, we build the terminating situation assessment network as Fig. 4:

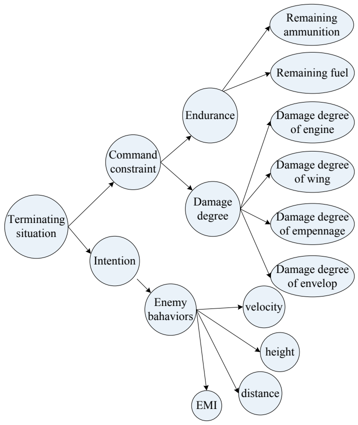


Fig. 4. Terminating situation assessment network.

In Fig. 4, there are several nodes with fuzziness. People's cognition to Damage degree and endurance are usually uncertain. These two nodes and their child nodes can be considered as intuitionistic fuzzy nodes. Therefore, we can use two virtual nodes to replace above intuitionistic fuzzy ones. Fig. 5 shows this replacement process.

The fuzzy variables corresponding to fuzzy nodes in terminating situation is damage degree (damage degree of engine, damage degree of empennage, damage degree of wing and damage degree of envelop) and endurance (remaining ammunition and remaining fuel). We mark them as D, R, respectively. Thus we can design the membership of these two variables and its child variables17.

There are four input variables in damage degree reasoning engine, each of them has four states, Therefore, we should make 256 rules for this reasoning engine. In fact, according to the reality, if any of the main part of an aircraft is scrapped, the overall damage situation should be judged as scrapped. Then, we can reduce some rules and the ultimate number of rules that we need to input into reasoning engine is $(4-1)\times(4-1)\times(4-1)\times(4\text{-}1)+4=85$. The rules for endurance reasoning engine are made in the same way, whose number is 9. Fig. 6 is the rules input into the fuzzy engine in MATLAB.

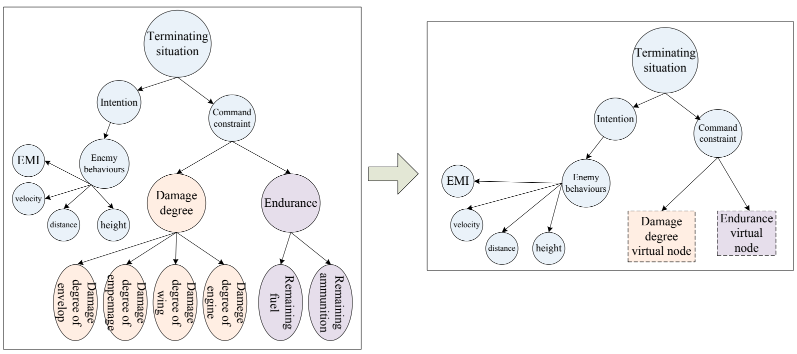


Fig. 5. Virtual nodes replacement process.

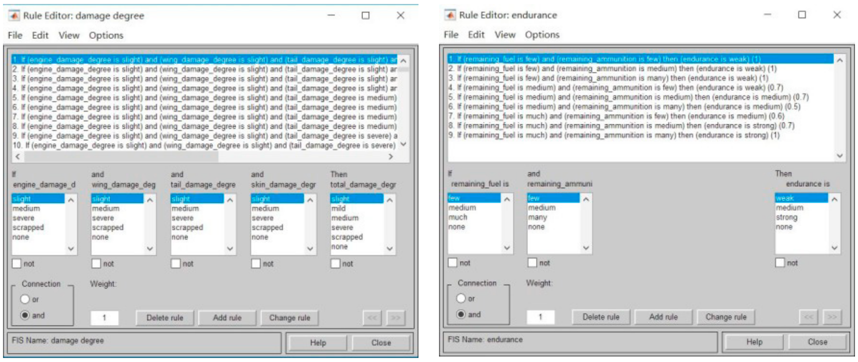
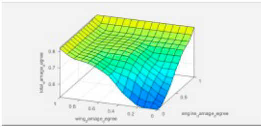
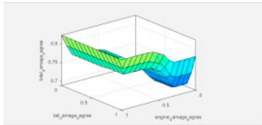


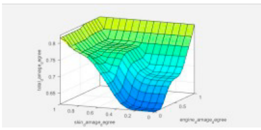
Fig. 6. Reasoning rules in fuzzy engine.



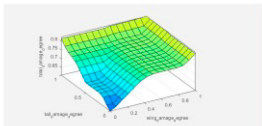
(a) D_E – D_W – D surface



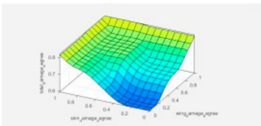
(b) D_E – D_T – D surface



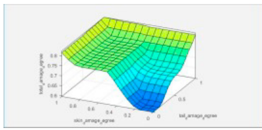
(c) D_E – D_S - D surface



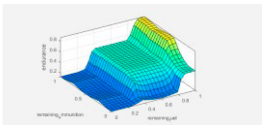
(d) D_T – D_W - D surface



(e) D_S – D_W - D surface



(f) D_T – D_S - D surface



(g) R_A – R_f - R surface

Fig. 7. Output surface.

Fig. 7 is the output surface, which shows the relationship between variables. It can be seen that the combination of the attribute functions in different state variables are smooth. Therefore, the reasoning rules in Fig. 6 are reasonable and can be applied into reasoning process.

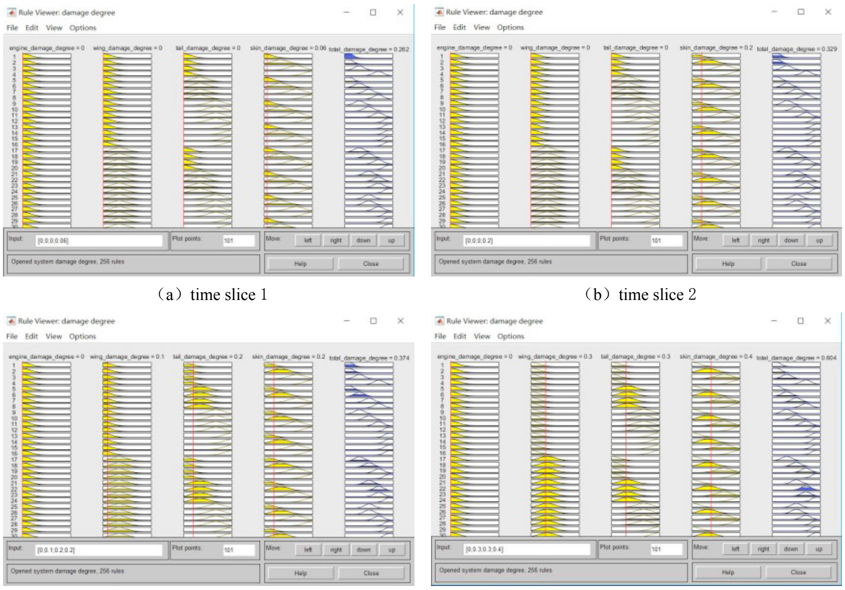
The terminating situation assessment can be done after above preparations. This paper chooses air defense combat as the assessing context, and we extract some observations from the data set in air defense combat. The observations in time slice 0 to 3 are collected in Table 1.

Table 1. Observations in time series.

Observations	Velocity（km/h）	Height（km）	Distance（km）	EMI	Damage degree of skin
Time 0	1200	4.2	180	F	6
Time 1	1400	4.2	150	F	20
Time 2	1500	1	100	F	20
Time 3	1200	4	120	F	40
Observations	Damage degree of	Damage degree of	Damage degree of	Remaining	Remaining

	empennage	wing	engine	fuel	ammunition
Time 0	0	0	0	4050	5217
Time 1	0	0	0	3480	4164
Time 2	20	10	0	2790	2967
Time 3	30	30	0	1549	1847

The observation data which belong to the fuzzy nodes are input into fuzzy engine and the other data are input into BN directly. We firstly complete the intuitionistic fuzzy reasoning in fuzzy engine. Fig. 8 and Fig. 9 show the reasoning process and results, respectively.



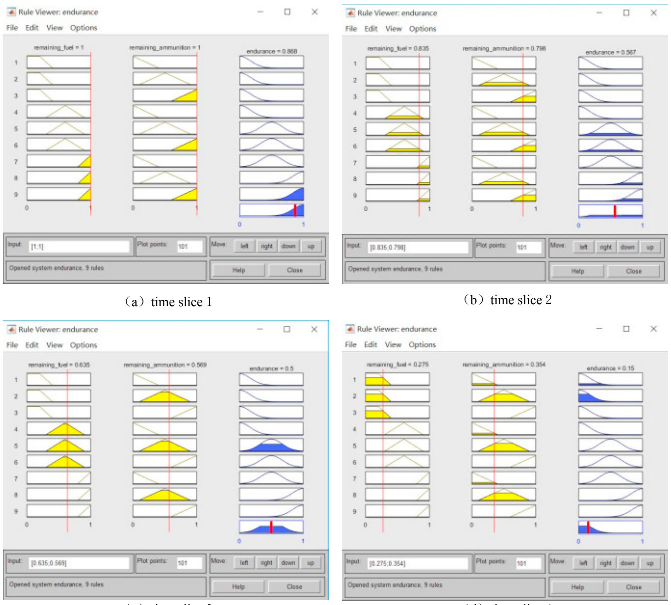
(a) time slice 1 (b) time slice 2

(c) time slice 3 (d) time slice 4

Fig. 8. Reasoning results of damage degree.

After obtaining the fuzzy reasoning result, we can convert it into probability by Equation 7. Table 2 and Table 3 show the probability of damage degree and endurance, respectively.

The intuitionistic fuzzy output proves that the reasoning process of fuzzy engine is non-linear. Besides, the reasoning rules have the ability to reflect the preference of the subject. It can be concluded that the result accords with human cognition. Now we can input all the probabilities into DBN as virtual evidence. The reasoning process of DBN is shown in Fig. 10 and the assessing result is shown in Fig. 11.



(a) time slice 1 (b) time slice 2

(c) time slice 3 (d) time slice 4

Fig. 9. Reasoning results of endurance.

Table 2. Probability conversion of damage degree.

Intuitionistic fuzzy output		Probability				
Time slice	Output control value	Slight	Mild	Medium	Severe	Scrapped
0	0.262	0.1586	0.7955	0.0456	4.78e-05	3.32e-04
1	0.329	0.0387	0.7730	0.1869	8.27e-04	5.65e-04
2	0.374	0.0184	0.6126	0.3642	0.0040	8.56e-04
3	0.653	6.63e-04	0.0016	0.2494	0.7199	0.0284

Table 3. Probability conversion of endurance.

Intuitionistic fuzzy output		Probability		
Time slice	Output control value	Weak	Medium	Strong
0	0.868	2.573e-06	0.1147	0.8853
1	0.567	0.00393	0.9559	0.0402
2	0.5	0.0128	0.9743	0.0128
3	0.15	0.8497	0.1503	4.6076e-06

From the assessing result we can learn that:

(1) From time slice 0 to time slice 1, the behavior of enemy aircraft is judged as air cruise in medium altitude according to its velocity, distance, height and other characteristics. The intention of enemy is inference or evacuation, which have about the same probability. In this moment, the endurance ability of aircraft is strong and the damage degree is mild. Therefore, the overall situation is to continue the air combat.

(2) From time slice 1 to time slice 2, enemy aircraft changes its behavior from air cruise to speed-up cruise in low altitude. The intention is lingering or making contact with us. The endurance ability of aircraft is medium. And the damage degree is mild. the overall situation is still to continue the air combat.

(3) From time slice 2 to time slice 3, the behavior of enemy aircraft is still speed-up cruise in low altitude, but its intention turns into making contact with us or evacuation. And in this period, the damage degree is medium while

the endurance ability is medium, too. The overall situation has about the same probability between continuing combat and terminating combat. This is because the intention of enemy is turning into evacuation, and the contribution of command constraint due to the aircraft performance is crucial.

(4) From time slice 3 to time slice 4, the enemy behavior turns into lingering in medium altitude and its intention is judged as lingering or evacuation. At this time the damage degree is medium and the endurance ability is weak. Thus, the command constraint is terminating, which contributes to the overall situation. In this time slice, the overall situation changes significantly. Under the condition that the enemy intention does not pose a threat, the command constraint is the main influential factor. Furthermore, owing to the weakness of endurance ability, the overall situation is judged as terminating.

From above analysis, we can conclude that based on IFDBN, the situation can be assessed in a reasonable way. The assessing result is consistent with the reality in air combat. Therefore, it can be proved that IFDBN can be used as a situation assessment method effectively and support the decision-making of commanders.

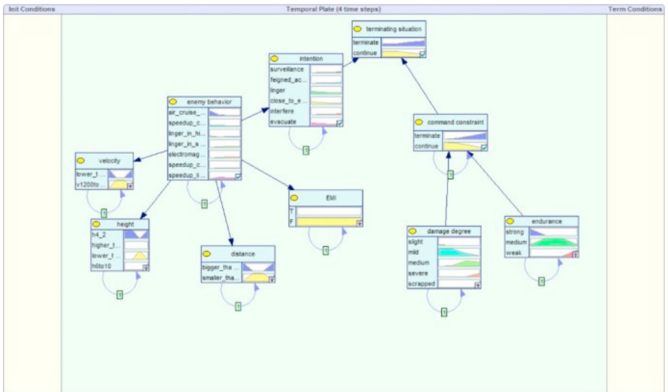


Fig. 10. Reasoning process of DBN.

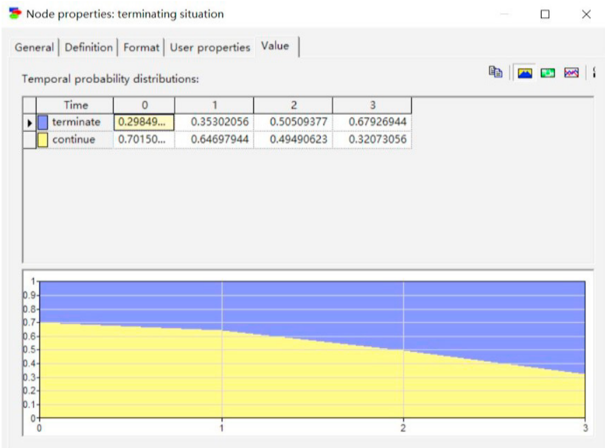


Fig. 11. Assessing result.

6. Conclusions

Owing to a large number of information and data with uncertainty in terminating situation period of an air combat, it is urgent to propose a dynamic method which can deal with the fuzzy information effectively. This paper embeds intuitionistic fuzzy reasoning engine in dynamic Bayesian Network, and proposes a model named IFDBN, which greatly improves the performance of DBN. Main conclusions are as follows:

(1) The intuitionistic fuzzy reasoning engine in DBN is a way to represent the uncertain information. This solves the problem that traditional Bayesian Network cannot judge the fuzzy states of situation precisely, which contributes to a clearer and more accurate assessment of terminating situation.

(2) The dynamic Bayesian Network has the ability to describe the situation in time series. Taking advantage of the probability reasoning capability of DBN, the terminating situation can be assessed in a more robust way, which is more in line with the reality of battlefield.

(3) Terminating situation is a dynamic process with fuzziness, the combination of intuitionistic fuzzy reasoning engine and DBN will give commanders an effective method to assess terminating situation and assist their decision-making.

Acknowledgement

This paper was funded by National Natural Science Foundation of China (No.61472441) and Aviation Science Foundation (201651U7001).

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