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Supply Chain Risk Evaluation Based on D-S Evidence Theory

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Abstract. Nowadays, the unexpected consequences of supply chain risk may cause enterprises to suffer huge losses. Reliability and effectiveness of supply chain are limited to the risks due to the fragility of the supply chain system. As such, supply chain risk evaluation is an emerging key subject in supply chain management. This paper proposes a supply chain risk evaluation model based on D-S evidence theory, which is called the D-S evidence discount fusion (D-SDF). By using Shafer discount rule and Dempster combination rule, this evaluation model is able to combine the evaluation results of multiple experts to assess the supply chain risks. In this paper, the feasibility and effectiveness of D-SDF is estimated by simulation. Compared with SAW, it can be concluded that D-SDF can evaluate supply chain risk more steadily and accurately.

Keywords: data fusion, D-S evidence theory, supply chain risk evaluation

1 Introduction

Supply chain management is one critical way with the orientation of market and customer demands. Under the win-win principle, supply chain management was proposed by business and academia for sharing information, cohesion of the core competitiveness of companies, optimization of resource allocation, accelerating market demand response, reducing invalid circulation and cost, improving market share, customer satisfaction and enterprise profit maximization [1]. While the above performance has been improved, it also brings some problems. The rapid development of information technology and the rapid economic integration process had a dramatic impact on the environment of enterprise supply chain operation, comprising product structure, production process, management, organizational structure and decision criteria. Supply chain management shows a tendency to be more complicated, uncertain and more vulnerable to attack at the same time.

In supply chain management, even the smallest problem may cause serious chain reaction. Thus, supply chain risks ought to be taken seriously. Supply chain risks usually be classified as internal and

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external categories. The internal risk is caused by the composition of the interaction between the elements. Including cooperation risk, contract risk, management risk and information risk, internal risk is normally due to lack of information transparency, lack of awareness of deep-level cooperation and incorrect predictions. The external risk is caused by the multiple variables outside the supply chain system. These variables can not be normally limited by the supply chain. External risk includes natural environmental risk, economic risk and market environmental risk [2].

As the premise of the superiority and reliability of supply chain, various supply chain risks need to be fully taken into account to ensure accurate risk evaluation. Aiming to measure the overall risk level and probability of the supply chain, risk evaluation is generally divided into three categories: quantitative models, qualitative models, hybrid models that incorporate qualitative and quantities techniques, among which the systematic method of hybrid models is the most effective [3]. Common risk evaluation includes Subjective Scoring, Analytic Hierarchy Process (AHP)and Fuzzy Comprehensive Evaluation (FCE).

Evidence theory is also one of the effective methods to evaluate supply chain risks. Its original research purpose was to solve the multi-valued mapping problem by using upper and lower probability, and then it developed into D-S evidence theory. By using data fusion technique to model uncertain information, D-S evidence theory is an extension of probability theory [4]. Coming up with the concept of assigning beliefs and possibilities to possible hypotheses of each decision maker, the D-S theory also provides a combination rule to fuse multimodal information. This theory allows each source to incorporate information on different levels of evidence. Hence, the D-S theory can efficiently address both objective uncertainties and subjective uncertainties. This theory provides an effective method to solve the uncertainty and fuse multi-source information. The source could be different expert opinions, multiple data sources, or even multiple individual characteristics of an object.

In this paper, a supply chain risk evaluation method based on evidence theory is proposed, which is called the D-S evidence discount fusion (D-SDF). To analyze the uncertainty of multi-source supply chain risk information, D-S evidence theory is applied to model it. Firstly, transform the evaluation results given by experts from probabilistic data into evidential data. Then normalize these data. The results given by experts are discounted by using Shafer discount rules. Finally, the D-S combination rules are used for data fusion. Then judge the evaluation results which are calculated as a function of safety and insecurity, to evaluate the risk of entire supply chain.

The rest of this paper is organized as follows. Section II reviews related work on supply chain risk evaluation and D-S evidence theory. The D-SDF risk evaluation method is introduced in Section III. Finally, simulation experiments is presented in Section IV. Section V concludes the papers and future works.

2 Related Work

This part introduces the research status of supply chain risk evaluation and basic contents of D-S evidence theory. At the end of this part, the main works of this paper are described.

2.1 Supply Chain Risk Evaluation

This part introduces three frequently-used methods of supply chain risk evaluation, their applications and defects. They are Subjective Scoring, Analytic Hierarchy Process (AHP)and Fuzzy Comprehensive Evaluation (FCE).

The subjective scoring method directly judges each single risk of the supply chain and assigns corresponding weights based on tacit knowledge such as experts' experience. One of the simplest methods is the subjective scoring method based on simple additive weighting (SAW). It has the advantages of intuitive and concise structure, but the obvious problem is that it is too subjective to give empirical theory a credible theoretical support. Hence, this method is usually used in combination with other methods. Mona Jaberidoost raised a pharmaceutical supply chain risk evaluation in Iran by using analytic hierarchy process and simple additive weighting (SAW) methods [5]. The author used literature review and expert interviews to identify risks, and conducted risk analysis through a questionnaire and consultation with experts using group analytic hierarchy process (AHP) method and rating scale (RS) and risk evaluation of simple additive weighting (SAW) method. Through this evaluation the risks of the pharmaceutical supply chain were classified, and financial management was identified as a major consideration of supply chain risk. In this paper, SAW were only used as a pretreatment for expert evaluation results, and the classification of specific risks was still based on AHP method. The comprehensive evaluation method simplified the pretreatment of risk sources on the premise of relative accuracy.

Analytic Hierarchy Process (AHP) deals with complex decision-making problems based on evaluation element selection and data analysis. In the case of determining factors that affect the decisions and degrees of influences, it selects the optimal one by comparing various combinations of evaluation factors. Guan divided the hierarchical structure of food supply chain risk factors with F-AHP [6]. This paper divided the hierarchical structure of food supply chain risk factors with F-AHP, and built a food supply chain risk factor identification system and risk fuzzy comprehensive evaluation model on the basis of definition of food supply chain. Conclusion is that this F-AHP method can reasonably identification and evaluate the risk on supply chain. Li and Hu Risk assessed agricultural supply chain risks based on AHP-FCS in Eastern Area of Hunan Province [7]. This model was based on the AHP-FCS method to deal with the qualitative to quantitative analysis about risk management of agricultural product supply chain. And the purpose was to make the risk identification and risk assessment process of agricultural supply chain more reliable. Through these two papers, it can be found that the current usage of AHP is mostly combined with the fuzzy algorithm framework. Due to choosing from the alternatives, AHP does not provide a new solution to decision-making. It also uses less quantitative data than the qualitative component so that the evaluation results lack credibility.

Based on fuzzy mathematics and the principle of fuzzy relation synthesis, Fuzzy Comprehensive Evaluation has an ability of quantifying fuzzy and ambiguous factors by constructing membership degree. The evaluation results are given in vector form. Liu raised a supply chain risk evaluation based on AHP and fuzzy comprehensive evaluation. In this essay, author used the AHP to estimate the weights of risk factors are the results in the previous article, and used fuzzy comprehensive evaluation to estimate the total risk of the supply chain. Liu proposed a supply chain finance business risk evaluation scheme based on fuzzy theory [8]. In this paper, risk factors are integrated and classified, then the author established hierarchical model of secondary risk evaluation. The fuzzy comprehensive evaluation method was used to set up risk evaluation system of supply chain finance business. Aqlan came up with a fuzzy-based integrated framework for supply chain risk evaluation [9]. The framework consisted of three main components: survey, Bow-Tie analysis, and fuzzy inference system (FIS). The author used Bow-Tie, which was a diagram that displays the links between potential causes, preventative and mitigative controls and consequences of a risk, to calculate the aggregated likelihood and impact of the risk. FIS was then used to calculate the total risk score considering the risk management parameters and risk predictability. Through the above three papers, it is found that a FCE system was usually developed to identify the scores of the risks considering risk factors and risk management factors. However, in the process of quantification, the determination of weight vector of qualitative indicators is highly subjective due to lack of theoretical basis. It is impossible to distinguish whose membership degree is higher under the circumstances of large scale of index sets. Beyond that the Fuzzy Comprehensive Evaluation is complex to calculate.

2.2 The Content of D-S Evidence Theory

The D-S theory of evidence, initiated by Dempster, and then, mathematically formalized by Shafer, is a general framework which can model and reason with epistemic uncertainty. This framework allows us to fuss evidence of various sources, such as predictions from different people and data from different sensors, to achieve a comprehensive degree of belief in different assumptions. Its essence is an extension of probability theory. Comparing with the Bayesian model, the D-S theory is a combined approach to addressing uncertainty and inaccuracy with a theoretically attractive evidential reasoning framework. The D-S theory provides a method for processing uncertain and inaccurate information from multiple information sources [10-11].

The D-S theory contains three main concepts: (1) assigning appropriate beliefs and possibilities to possible hypotheses; (2) using the D-S rule of combination to fusing independent evidence items; and (3) making the final decision on the choice of optimal hypothesis flexibly and rationally.

Following is the advantage of D-S evidence theory. The priory data is more easily to get. This theory does not need to meet the addition of probability. It has ability of expressing the uncertainty directly, and these information is showed in the mass function and is to keep during the process of evidence fusion.

Next is several basic concepts in the evidence theory. Identification of uncertainty. It is the range of the event need to be judged. Basic Probability Assignment which is also called BPA, is the probability of each event in the basic framework of each person or each sensor. And the sum of the probability of all of the people or sensors is 1. This probability is called the mass function. Belief function. The belief function of an event is the sum of all the probability of the event's subsets, showing the degree of trust in the event. Plausibility function. The plausibility function of an event is the sum of all the probability of the condition that is intersected with it, and it is used to show the degree of trust in not denying the event.

2.3 Main Works

In the context of supply chain, this paper uses D-S evidence theory to model the uncertainty of various risks of supply chain. The availability, advantages and disadvantages of the method are analyzed by simulation. Experts give probabilistic evaluation data of the security of the supply chain, and we first convert it into evidentiary data. In order to make sure that the sum of evidential data is 1, the evidential data need to be normalized, and we obtain the Basic Probability Assignment (BPA). Because different experts have different degrees of influence on the evaluation, it is necessary to discount the results given by the experts. In this paper, BPA is discounted according to the degree of trust in experts by using the traditional Shafer discount rule. The next step is fusion of evidence. By using Dempster combination rule, two pieces of evidence are fused to form a new evidence at a time. The new evidence and the next evidence are fused in an iterative manner. After (n-1) times of iteration, we get the final calculation result, which is represented by two belief functions. Judge these two belief functions according to the preset threshold, to decide whether it is safe or not.

In the end, this paper will estimate the feasibility and effectiveness of the D-SDF by simulation.

3 System Model

This part raised the D-S evidence discount fusion (D-SDF) supply chain risk evaluation. Firstly, the basic concepts and principles of D-S evidence theory are explained. Then it described the application of D-SDF evaluation model.

3.1 Basic Concepts and Principles of D-S Evidence Theory

The D-S theory of evidence, as a general theory for reasoning under uncertainty, it based on the notion of belief function. Its principal characteristics and concepts are described as follows.

Let Θ be the set of all possible states, $\Theta = \{A_i; i = 1, 2, \cdots, N\}$, of a system, which is named the frame of discernment in the D-S framework.

$$\Theta = \{A_1, A_2, \cdots, A_N\} \quad \textbf{(1)}$$

The set Θ consists of N exhaustive and exclusive hypotheses. Information sources can distribute mass values on the power set of the frame of discernment, denoted by 2^Θ. There are 2^N mutex subsets in a collection which has N elements.

$$2^\Theta = \{\varnothing, \{A_1\}, \{A_2\}, \cdots, \{A_N\}, \{A_1, A_2\}, \cdots, \{A_1, A_2, \cdots, A_N\}\} \quad \textbf{(2)}$$

In (2), $\varnothing$ mains the empty set. Each subset of Θ may represent a proposition about the actual state of the system.

A Basic Probability Assignment (BPA) is defined over the power set 2^Θ. It is a mapping m : $2^\Theta \rightarrow [1,0]$. A BPA then is a function $\mathrm{m}(\cdot)$ from 2^Θ to $[1,0]$, which satisfies the following constraints:

$$\begin{cases} \sum_{A \in 2^\Theta} m(A) = 1 \\ m(\varnothing) = 0 \end{cases} \quad \textbf{(3)}$$

The set A such that $m(A)>0$ is called a focal element of m. The BPA function is also called the mass function. If all focal elements are singletons elements of the frame of discernment, then it is a Bayesian BPA [12].

Then recommend Dempster's combination rule of mass functions. If M_1 and M_2 are two evidences in the same frame of discernment, and their mass functions are m_1 and m_2. The focal elements are $B_1,B_2,\cdots,B_k$ and $C_1,C_2,\cdots,C_n$. Dempster's combination rule of mass functions, which is denoted as $m=m_1\oplus m_2$, integrates the two BPAs, m_1 and m_2, to yield a combined BPA as followings:

$$m_1\oplus m_2(A)=\frac{1}{1-K}\sum_{B\cap C=A}m_1(B)m_2(C) \tag{4}$$

$$\mathrm{K}=\sum_{B\cap C=\varnothing}m_1(B)m_2(C) \tag{5}$$

Where all $\mathrm{A,B,C}\subseteq 2^{\Theta}, A\neq\varnothing, m_1\oplus m_2(\varnothing)=0$. K is a normalization parameter which makes the sum of $m(A)$ vulnerable to become 1 in the D-S theory.

$$\sum_{A\in 2^{\Theta}}m(A)=1 \tag{6}$$

And $(1-\mathrm{K})$ is the conflict coefficient between m_1 and m_2, indicating the degree of contradiction of the combined evidence. It is the sum of products $m_1(B)m_2(C)$ for all focal elements B in m_1 and C in m_2, where $B\cap C$ is not null. The lager $(1-\mathrm{K})$ is, the more the conflict between the two evidences are there. If $1-\mathrm{K}=1$, these two pieces of evidence are in complete logical conflict.

It can be observed from the above that the associativity and commutativity support the combinatorial rule. Therefore, the aggregation order does not matter the combination of BPA. When the number of information sources is n, the total Dempster combination rule of mass functions is defined as:

$$(m_1\oplus m_2\oplus\cdots\oplus m_n)(A)=\frac{1}{K}\sum_{A_1\cap\cdots\cap A_n=A}m_1(A_1)\times m_2(A_2)\times\cdots\times m_n(A_n) \tag{7}$$

$$\begin{aligned}K&=\sum_{A_1\cap A_2\cap\cdots\cap A_n\neq\varnothing}m_1(A_1)\times m_2(A_2)\times\cdots\times m_n(A_n)\\&=1-\sum_{A_1\cap A_2\cap\cdots\cap A_n=\varnothing}m_1(A_1)\times m_2(A_2)\times\cdots\times m_n(A_n)\end{aligned} \tag{8}$$

After the fusion of every evidence, the following is the judgement rule. Here, both A_1 and A_2 are the subsets of U, and the result meets:

$$\begin{cases}m(A_1)=\max\{m(A_i), A_i\subset U\}\\ m(A_2)=\max\{m(A_i), A_i\subset U \text{且} A_i\neq A_1\}\end{cases} \tag{9}$$

If

$$\begin{cases}m(A_1)-m(A_2)>\varepsilon_1\\ m(\Theta)<\varepsilon_2\\ m(A_1)>m(\Theta)\end{cases} \tag{10}$$

Then A_1 is judged as the result. Among the formula, ε_1, ε_2 is the threshold, and Θ is the uncertain set [13-14]. This equation means that the lager $m(A)$ determines the security of the system.

3.2 Application of Supply Chain Risk Evaluation Model

There are n experts in the system to evaluate supply chain risks. Suppose the probability that the i-th expert evaluates the supply chain as safe is P_i, and the probability of supply chain insecurity is $1-P_i$. Hence, the evaluation of supply chain risk given by the i-th expert is $\left[P_i, 1-P_i\right]$.

Next process results from these experts. In order to use the D-S evidence theory, probabilistic data is supposed to be transformed to evidential data. Besides of two probability, an unknown part was added to the evidential data. The equation that calculate the unknown part of the evidence is usually shown as following:

$$m(\Theta)=\left[1-\mathrm{m}(A_1)\right]\times\left[1-\mathrm{m}(A_2)\right]\times\cdots\times\left[1-\mathrm{m}(A_n)\right] \tag{11}$$

Therefore, the evaluation result of expert I can be obtained from formula (11) that the unknown part in the evidence is:

$$\begin{aligned} m(\Theta)&=(1-P_i)\times\left[1-(1-P_i)\right] \\ &=(1-P_i)\times P_i \end{aligned} \tag{12}$$

Hence, evidential data of the evaluation result can be described as:

$$\left[P_i, 1-P_i, P_i\times(1-P_i)\right] \tag{13}$$

Then normalize the data and get the normalized evidence as follows:

$$\left[\frac{P_i}{1+P_i\times(1-P_i)}, \frac{1-P_i}{1+P_i\times(1-P_i)}, \frac{P_i\times(1-P_i)}{1+P_i\times(1-P_i)}\right] \tag{14}$$

The above formula (14) is the Basic Probability Assignment (BPA).

Because different experts have different degrees of influence on the evaluation, it is necessary to discount these results which are given by the experts. The traditional Shafer discount rule in formula (15) is adopted here to discount the evidence. α is the discount factor which represents the credible degree of the expert evaluation results.

$$\begin{cases} m(A)_\alpha=\alpha\bullet m(A) \\ m(\Theta)_\alpha=\alpha\bullet m(\Theta)+(1-\alpha) \end{cases} \tag{15}$$

Suppose that the credible degree of the evaluation results of the i-th expert is α_i. The BPA is discounted according to Shafer discount rule in formula (15). The evidence obtained after discount is:

$$\left[\frac{\alpha_i\times P_i}{1+P_i\times(1-P_i)}, \frac{\alpha_i\times(1-P_i)}{1+P_i\times(1-P_i)}, \frac{\alpha_i\times P_i\times(1-P_i)}{1+P_i\times(1-P_i)}+(1-\alpha_i)\right] \tag{16}$$

The next step is the evidence fusion. Due to the associative property of Dempster's combination rule, two evidences can be fused successively at one time. First, the results of the first two experts were fused. The fusion result is regarded as a new evidence, And the new evidence and a next evidence are fused by using a iterative theory.

According to formula (8), the normalization parameter K is calculated as following:

$$\begin{aligned} K_{12}&=1-\sum_{A_1\cap A_2=\varnothing} m_1(A_1)\times m_2(A_2) \\ &=1-\sum_{A_1\cap A_2=\varnothing}\left(m_1(A_1)\times m_2(A_2)+m_1(A_2)\times m_2(A_1)\right) \\ &=1-\left[\begin{array}{l} \dfrac{\alpha_1\times P_1}{\left[1+P_1\times(1-P_1)\right]}\times\dfrac{\alpha_2\times(1-P_2)}{\left[1+P_2\times(1-P_2)\right]} \\ +\dfrac{\alpha_1\times(1-P_1)}{\left[1+P_1\times(1-P_1)\right]}\times\dfrac{\alpha_2\times P_2}{\left[1+P_2\times(1-P_2)\right]} \end{array}\right] \end{aligned}$$

$$=1-\frac{\alpha_1\times\alpha_2\times\left[P_1\times\left(1-P_2\right)+P_2\times\left(1-P_1\right)\right]}{\left[1+P_1\times\left(1-P_1\right)\right]\times\left[1+P_2\times\left(1-P_2\right)\right]} \tag{17}$$

According to formula (7) and the Dempster's combination rule, mass functions $m_{12}(A_1)$ and $m_{12}(A_2)$, which mean safe and unsafe evaluation results, were respectively calculated and obtained as:

$$\begin{aligned}
m_{12}\left(A_1\right)&=m_1\oplus m_2\left(A_1\right)\\
&=\frac{1}{K_{12}}\sum m_1(A_1)\times m_2(A_1)+m_1(A_1)\times m_2(\Theta)+m_1(\Theta)\times m_2(A_1)+m_1(\Theta)\times m_2(\Theta)\\
&=\frac{1}{K_{12}}\times\left\{\begin{aligned}&\frac{\alpha_1\times P_1}{\left[1+P_1\times\left(1-P_1\right)\right]}\times\frac{\alpha_2\times P_2}{\left[1+P_2\times\left(1-P_2\right)\right]}\\
&+\frac{\alpha_1\times P_1}{\left[1+P_1\times\left(1-P_1\right)\right]}\times\left[\frac{\alpha_2\times P_2\times\left(1-P_2\right)}{\left[1+P_2\times\left(1-P_2\right)\right]}+\left(1-\alpha_2\right)\right]\\
&+\left[\frac{\alpha_1\times P_1\times\left(1-P_1\right)}{\left[1+P_1\times\left(1-P_1\right)\right]}+\left(1-\alpha_1\right)\right]\times\frac{\alpha_2\times P_2}{\left[1+P_2\times\left(1-P_2\right)\right]}\\
&+\left[\frac{\alpha_1\times P_1\times\left(1-P_1\right)}{\left[1+P_1\times\left(1-P_1\right)\right]}+\left(1-\alpha_1\right)\right]\times\left[\frac{\alpha_2\times P_2\times\left(1-P_2\right)}{\left[1+P_2\times\left(1-P_2\right)\right]}+\left(1-\alpha_2\right)\right]\end{aligned}\right\}\\
&=\frac{1}{K_{12}}\left\{\begin{aligned}&\left(1-\alpha_1\right)\times\left(1-\alpha_2\right)+\frac{\alpha_1\times\alpha_2\times P_1\times P_2\times\left[4\text{-}2\left(P_1+P_2\right)+P_1\times P_2\right]}{\left[1+P_1\times\left(1-P_1\right)\right]\times\left[1+P_2\times\left(1-P_2\right)\right]}\\
&+\left(1-\alpha_2\right)\times\frac{\alpha_1\times P_1\times\left(2-P_1\right)}{\left[1+P_1\times\left(1-P_1\right)\right]}+\left(1-\alpha_1\right)\times\frac{\alpha_2\times P_2\times\left(2-P_2\right)}{\left[1+P_2\times\left(1-P_2\right)\right]}\end{aligned}\right\}
\end{aligned} \tag{18}$$

$$\begin{aligned}
m_{12}\left(A_2\right)&=m_1\oplus m_2\left(A_2\right)\\
&=\frac{1}{K_{12}}\sum m_1(A_2)\times m_2(A_2)+m_1(A_2)\times m_2(\Theta)+m_1(\Theta)\times m_2(A_2)+m_1(\Theta)\times m_2(\Theta)\\
&=\frac{1}{K_{12}}\times\left\{\begin{aligned}&\frac{\alpha_1\times\left(1-P_1\right)}{\left[1+P_1\times\left(1-P_1\right)\right]}\times\frac{\alpha_2\times\left(1-P_2\right)}{\left[1+P_2\times\left(1-P_2\right)\right]}\\
&+\frac{\alpha_1\times\left(1\text{-}P_1\right)}{\left[1+P_1\times\left(1-P_1\right)\right]}\times\left[\frac{\alpha_2\times P_2\times\left(1-P_2\right)}{\left[1+P_2\times\left(1-P_2\right)\right]}+\left(1-\alpha_2\right)\right]\\
&+\left[\frac{\alpha_1\times P_1\times\left(1-P_1\right)}{\left[1+P_1\times\left(1-P_1\right)\right]}+\left(1-\alpha_1\right)\right]\times\frac{\alpha_2\times\left(1\text{-}P_2\right)}{\left[1+P_2\times\left(1-P_2\right)\right]}\\
&+\left[\frac{\alpha_1\times P_1\times\left(1-P_1\right)}{\left[1+P_1\times\left(1-P_1\right)\right]}+\left(1-\alpha_1\right)\right]\times\left[\frac{\alpha_2\times P_2\times\left(1-P_2\right)}{\left[1+P_2\times\left(1-P_2\right)\right]}+\left(1-\alpha_2\right)\right]\end{aligned}\right\}\\
&=\frac{1}{K_{12}}\times\left\{\begin{aligned}&\left(1-\alpha_1\right)\times\left(1-\alpha_2\right)+\frac{\alpha_1\times\alpha_2\times\left(1\text{-}P_1\right)\times\left(1\text{-}P_2\right)\times\left[1+\left(P_1+P_2\right)+P_1\times P_2\right]}{\left[1+P_1\times\left(1-P_1\right)\right]\times\left[1+P_2\times\left(1-P_2\right)\right]}\\
&+\frac{\left(1-\alpha_2\right)\times\alpha_1\times P_1\times\left(1-P_1\right)}{\left[1+P_1\times\left(1-P_1\right)\right]}+\frac{\left(1-\alpha_1\right)\times\alpha_2\times P_2\times\left(1-P_2\right)}{\left[1+P_2\times\left(1-P_2\right)\right]}\end{aligned}\right\}
\end{aligned} \tag{19}$$

The evidence is further iterated according to the results of formula (18) and (19).The iterative normalization parameter K is:

$$K_{123} = 1 - \sum_{A_1 \cap A_2 = \varnothing} m_{12}(A_1) \times m_3(A_2) \\ = 1 - \sum_{A_1 \cap A_2 = \varnothing} \left(m_{12}(A_1) \times m_3(A_2) + m_{12}(A_2) \times m_3(A_1) \right) \tag{20}$$

$$m_{123}(A_1) = m_{12} \oplus m_3(A_1) \\ = \frac{1}{K_{123}} \sum \begin{bmatrix} m_{12}(A_1) \times m_3(A_1) + m_{12}(A_1) \times m_3(\Theta) \\ + m_{12}(\Theta) \times m_3(A_1) + m_{12}(\Theta) \times m_3(\Theta) \end{bmatrix} \tag{21}$$

$$m_{123}(A_2) = m_{12} \oplus m_3(A_2) \\ = \frac{1}{K_{12}} \sum \begin{bmatrix} m_{12}(A_2) \times m_3(A_2) + m_{12}(A_2) \times m_3(\Theta) \\ + m_{12}(\Theta) \times m_3(A_2) + m_{12}(\Theta) \times m_3(\Theta) \end{bmatrix} \tag{22}$$

The above algorithm is merged for $(n-1)$ times to get the final calculation result:

$$m(A_1) = m_{1\ldots i+1}(A_1) = m_{1\ldots i} \oplus m_{i+1}(A_1) \\ = \frac{1}{K_{1\ldots i+1}} \sum \begin{bmatrix} m_{1\ldots i}(A_1) \times m_{i+1}(A_1) + m_{1\ldots i}(A_1) \times m_{i+1}(\Theta) \\ + m_{1\ldots i}(\Theta) \times m_{i+1}(A_1) + m_{1\ldots i}(\Theta) \times m_{i+1}(\Theta) \end{bmatrix} \tag{23}$$

$$m(A_2) = m_{1\ldots i+1}(A_2) = m_{1\ldots i} \oplus m_{i+1}(A_2) \\ = \frac{1}{K_{1\ldots i+1}} \sum \begin{bmatrix} m_{1\ldots i}(A_2) \times m_{i+1}(A_2) + m_{1\ldots i}(A_2) \times m_{i+1}(\Theta) \\ + m_{1\ldots i}(\Theta) \times m_{i+1}(A_2) + m_{1\ldots i}(\Theta) \times m_{i+1}(\Theta) \end{bmatrix} \tag{24}$$

The last step is judging the iteration results according to formula (10). If

$$\begin{cases} m(A_1) - m(A_2) > \varepsilon_1 \\ m(\Theta) < \varepsilon_2 \\ m(A) > m(\Theta) \end{cases} \tag{25}$$

Then the supply chain is safe, otherwise the supply chain is unsafe. In the above equation, ε_1 and ε_2 are preset thresholds, and Θ is the set of all possible states.

The complete process algorithm is shown in Table 1.

Table 1. Algorithm process

```
Input Pi,α;
Calculate the unknown part of the evidence m(Ω).
Transform probabilistic datas to evidential datas[Pi,1- Pi, Pi *(1-Pi)].
Normalize the evidence.
Calculate the evidence after discount.
Calculate in an iterative method:
for i=1:1:n-1
      m1,2...i+1(A1)=m1,2...i⊕mi+1(Ai+1);
      m1,2...i+1(A2)=m1,2...i⊕mi+1(Ai+1);
Get the result of m(A1) and m(A2).
Judge m(A1) and m(A2).
if
      m(A1)- m(A2)>ε1 and m(Θ)<ε1 and m(A)> m(Θ);
then
      output m(A1);
```

4 The Simulation Results

In this section, the examples are given to evaluate the model from three aspects.

Under the premise that the supply chain system is safe, there are 100 experts on this experiment. Some of them judge the supply chain system as safe with a higher probability of 0.7. The other experts judge the system as safe with a probability of 0.3, meaning that they have low credibility and give poor results. The availability of the model is validated in Fig. 1.

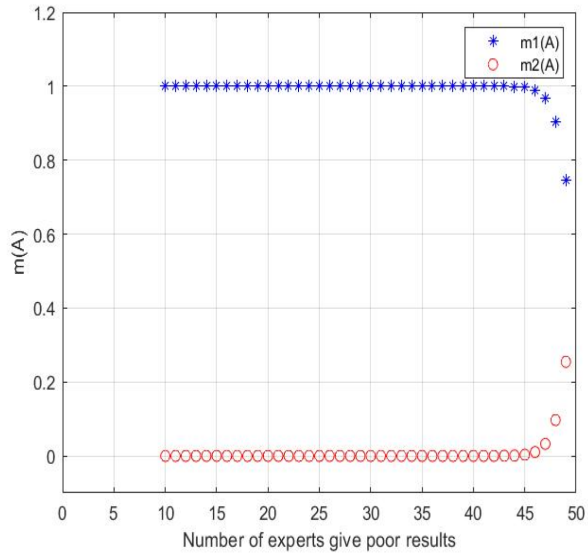

Fig. 1. Graph of number of low-credibility experts and mass function

The x-coordinate represents the number of experts out of 100 that give poor results, with a range of 10 to 50. The y-coordinate represents the size of the mass function, where $m_1(A)$ means the mass function of security and $m_2(A)$ means the insecurity, the larger of which determines the security of the system. As can be seen in the Fig. 1, $m_1(A)$ is always greater than $m_2(A)$ as the number of low-credibility experts increases. This means that the system is judged to be safe and the D-S evidence fusion model is reliable. When the number of experts that give poor results increases to 50, the values of $m_1(A)$ and $m_2(A)$ fluctuate greatly. This is due to a large data conflict, which may lead the evaluation results to be inaccurate.

Fig. 2 illustrates the role of evidence discount in risk evaluation. In the first test, the evidence discount was calculated with a discount factor of 0.8 for the results from high-credibility experts, and the discount factor of the expert results with low credibility was 0.4. Evaluate the security of supply chain system according to the model proposed in this paper. The value of the mass function $m_1(A)$ is 0.9999. In the second test, the evidence discount is not used during the evaluation process, and the value of $m_1(A)$ is 0.47922. By comparing these two tests, it can be concluded that the evidence discount operation can enhance the reliability of the evaluation results.

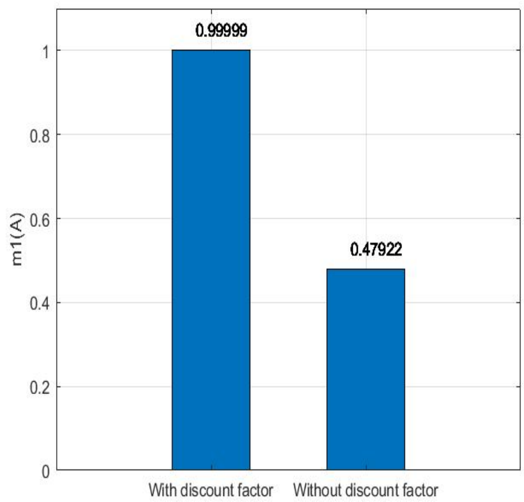

Fig. 2. Graph of discount factor and mass function

In Fig. 3, the evaluation effects of the simple probability additive weighting method and the evidence theory method are compared. The parameter settings here are the same as in the experiment in Fig. 1. It can be observed that the mass function value of evidence theory method is basically stable at 1. While the mass function value of the simple probability additive weighting method is in the range of 0.4 to 0.7, and it always declines by the increase in the number of experts that give poor results. Obviously, it can be concluded that the evidence theory method is more reliable and stable than the simple probability additive weighting method, by comparing the value of mass function. The judgment result of D-SDF is generally better than SAW, which is due to the advantages of the evidence theory method and the advantage of the discount theory. Discount can correct some sources of low credibility and weaken the results of conflicts.

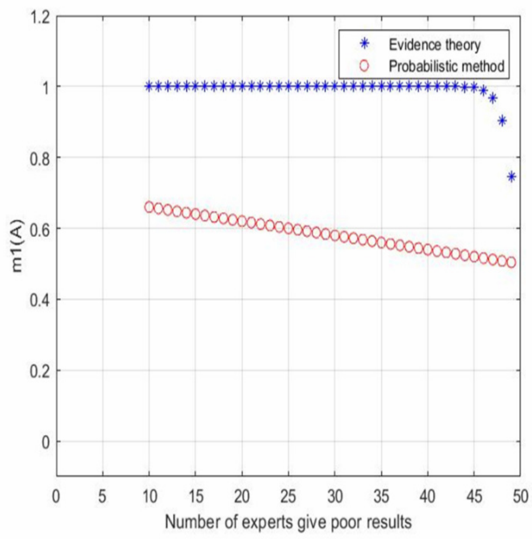

Fig. 3. Graph of two evaluation methods and mass function

5 Conclusion and Future Work

Supply chain risk is a potential threats. It exploits weaknesses of the supply chain system to destroy the supply chain. Since each part of the supply chain is interdependent and interactional, any of them goes wrong may spread to the rest. Moreover the whole supply chain functions will be affected [15]. Through the literature review, it is found that many scholars have started research on supply chain risk evaluation in recent years, and a number of evaluation methods have been proposed. One of the common methods is to obtain the final evaluation results from the opinions of several experts. However, since there are individual variation in evaluation among experts, in order to improve fusion of evaluation results, this paper proposes a D-S evidence discount fusion (D-SDF) supply chain risk evaluation model. Simulation is conducted to estimate the feasibility of this model.

From the result of the simulation, the method of supply chain risk evaluation in this paper is credible. The model in this paper is based on the D-S evidence theory, and it fuses the results of supply chain risk evaluation given by experts. Through the probability given by experts to evaluate whether the supply chain is safe or not, the mass functions of safe and unsafe are counted separately. This model makes supply chain risk evaluation result vulnerable to be more reliable.

For the D-SDF evaluation model, the prospect of future research is as follows. First point is about the data conflict. It is found that the result becomes inaccurate when there are many experts with low credibility taking part in evaluation. The reason for this problem is the large data conflicts. To improve this problem, it is one approach to improve the model from the perspective of evidence combination. Another point is about the discount factor. In this paper, α is determined according to the credibility of the evidence source. In order to make the evidence after discount calculation more reliable, it is effective to improve the discount factor by quantitative method. Therefore, a more optimized and improved evidence fusion mode is needed to meet a more accurate result in the scenario of supply chain risk evaluation.

Acknowledgements

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