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Blood supply chain operation considering lifetime and transshipment under uncertain environment

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A B S T R A C T

According to the characteristics of blood inventory control problem under the condition of blood shortage, the dynamic decision-making problem of blood supply chain is investigated in this paper. Firstly, based on the recursive equation, the state transition equations of two categories of blood demand under two inventory issue strategies (FIFO and LIFO) are given. The mathematical expressions of key indexes such as blood outdating and blood shortage are obtained. A blood collection decision-making method based on EWA (Estimated Withdrawal & Aging) strategy is proposed. Then, an optimal model of blood transshipment problem is established with the goal of the shortest transshipment time and the maximum freshness of the transported blood. In addition, an allocation planning model with multiple priority requirements and fairness concerns is established to achieve the best fairness and the minimum shortage. Besides, a discrete event system simulation (DESS) framework is designed according to the characteristics of the model. Finally, the effectiveness of the decision-making method and EWA inventory strategy are verified by numerical simulation. The results show that safety stock, target stock level and fluctuation range of demand have significant impacts on the control effect of blood inventory.

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1. Introduction

Blood shortage has become a worldwide thorny problem of clinical blood supply in recent years. The United States, Canada and other countries are facing varying degrees of blood shortage [1]. Blood shortage is more serious in Chinese mainland. From 2010 to 2014, the blood centers in Beijing, Chongqing, Shenzhen, Shanghai and other places appeared in varying degrees of blood shortage. Since 2015, the disaster of blood shortage has affected the whole country. Many blood centers have launched a level-1 early warning system. The continuous blood shortage has reached its peak. The nationwide blood shortage has gradually changed from the periodic and seasonal shortage in past to normal and long-term shortage now, as well as from emergency shortage only to clinical and emergency shortage coexisting. Blood is the fuel for the survival of patients. Blood supply plays a crucial role in ensuring health and saving lives. Therefore, it is of great practical significance to solve the problem of blood shortage and upgrade the level of blood supply to meet the needs of clinical blood demand [2].

Two key measures to solve the problem of blood shortage are to implement the strategy of blood transshipment and coordinate the inventory of blood supply chain. Blood transshipment will benefit local blood collection and inventory, but an effective method of blood supply chain operation considering blood transshipment does not exist. The main difficulties are: ① Blood is a special perishable item with a fixed lifetime. The optimal inventory decision must identify the remaining lifetime (inventory level) of all inventory products. ② Under the condition of blood shortage, the uncertainty of supply and demand information increases the complexity of decision-making. ③ The diversity of

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blood demand also increases the difficulty of inventory level description. Some blood transfusion treatments require higher blood freshness. For example, fresh blood should be used in the treatment of patients with acute blood loss and those with heart, lung, liver and kidney dysfunction [1]. ④ The decisions of blood collection, transshipment and allocation interact in a long period and are dynamic processes [3]. Therefore, the decision-making problem of blood supply chain considering lifetime distribution, transshipment and allocation is an imperative problem to be solved.

There are a lot of researches on blood collection, blood inventory, blood transshipment and other decision-making problems [3], but most of them are based on single-stage static decision-making to solve certain decision-making problems. Single stage static decision-making is insufficient to meet the urgent demand of the state of blood shortage. It is necessary to integrate transshipment and allocation, then establish an integrated dynamic optimization method in the process of blood supply chain dynamic decision-making. Due to the randomness of supply and demand information, the multidimensional nature of inventory level, and the dynamic nature of inventory decision making, the traditional inventory optimization model with minimum system cost, or the inventory model of exponential decay perishable goods cannot be used to carry out effective mathematical analysis for blood inventory. Therefore, it is difficult to apply the optimization method to solve the integrated dynamic decision-making problem of blood supply chain under the condition of blood shortage. So, this paper uses discrete event system simulation (DESS) as a research framework of blood supply chain decision making, especially the inventory decision-making, and introduces the optimization method to solve the blood transshipment and blood allocation decision-making problems into the DESS framework.

In view of this, this paper considers the uncertain supply and demand, blood product lifetime distribution, transshipment, fair allocation and other factors to study the blood supply chain decision-making under the state of blood shortage. A large number of blood shortage events were simulated by the fluctuation characteristics of supply and demand, and the simulation method of blood supply chain decision was established by using DESS, and the optimization model of blood transshipment decision and blood allocation decision were embedded in the simulation process. Finally, a series of sensitivity analysis are carried out for the key parameters, and some valuable management implications are obtained. The theoretical contributions of this paper are as follows: ① By integrating the horizontal and vertical coordination of blood supply chain inventory, the influence of blood transshipment is considered in this paper.② The allocation problem of blood products with different priority demand and fairness concerns in process of inventory decision-making is integrated too. ③ The complexity factors such as supply and demand fluctuation, lifetime distribution, transshipment and freshness constraint are considered in modeling the blood inventory system.

The rest of this paper is organized as follows. The relevant literature is reviewed in Section 2. The decision-making method of blood supply chain considering transshipment and allocation in uncertain environment is presented in Section 3. Simulation experiments and case study are conducted in Section 4, and the conclusions and future work are presented in Section 5.

2. Literature review

The special physiological and security characteristics of blood bring great challenges to inventory management. The physiological characteristics of blood are as follows: ① the scarcity of blood products. The sole supply channel of blood is the human body, which is not easy to obtain. ② Blood products are perishable. Blood products have a fixed shelf time. Depending on different preservation solutions, the shelf time of whole blood and red blood cells is usually 21 days, 35 days or 42 days, and the shelf time of platelets is 5–7 days [4]. ③ Blood products are irreplaceable. Blood serves a single purpose. It directly acts on the human body and cannot be replaced by other materials [5]. The characteristics of blood supply are as follows: ① the consequences caused by blood shortage are extremely serious. ② Excessive discarding of outdated blood also leads to negative social impact [2]. ③ In order to meet diverse blood needs, some blood transfusion treatments require higher blood freshness [6].

In the following, literatures on blood inventory/collection, blood transshipment and blood allocation are classified and reviewed.

(1) Blood inventory/collection and related problems

Under the normal state, the blood collection process is carried out according to the bottom-up information channel (lower: Hospitals; upper: Blood Station). That is to say, medical institutions for blood demand regularly send blood requests to blood banks according to the demand estimation. The blood bank periodically replenishes the inventory for blood reservoirs of hospitals based on the plan reported by hospitals. A daily blood supply chain is similar to a pull supply chain. Millard [7] first introduced the industrial inventory model into the blood inventory management problem. In the 1970s, the study of blood inventory appeared a climax. Nahmias [8], Gregory et al. [9] respectively reviewed the study of this period. In the 1980s and the end of 1990s, there were few studies on blood inventory problem. Goyal et al. [10] summarized the researches in this period. Since the 21st century, the research on blood inventory has entered a new period of development. Beliën et al. [11], Osorio et al. [2], pirab á n et al. [12] reviewed the latest blood supply chain literature.

Most literatures study the blood inventory strategy from the perspective of perishable goods inventory. Kopach [13] applied queuing model to study the optimal strategy of red blood cell inventory management system considering conventional demand and emergency demand, and took a blood bank in Canada as an example. Baron et al. [14] considered the inventory control problem of perishable products based on the (S, s) strategy of continuous inventory inspection with batch mixed Poisson distributed demand, and designed a heuristic algorithm to obtain the satisfactory solution of the problem. Olsson et al. [15] considered the Poisson demand distribution and studied the inventory control problem of single warehouse and single variety perishable items with delayed delivery based on (S-1, S) replenishment strategy. The result proved that (S-1, S) strategy is better than (Q, r) strategy in cost-saving. Hosseinifard and Abbasi [16] studied impacts of centralization in a two-echelon supply chain with perishability and demonstrated that centralization increases the sustainability of the blood supply Chain. Clay et al. [17] used system dynamics to illustrate the response of the blood supply chain to disturbances, and proposed a modification to ameliorate volatility.

The lifetime of blood was not considered in the above literature. In order to improve the performance of inventory management, some scholars considered the inventory level of blood (i.e. the distribution information of the remaining lifetime of all inventory items) in the inventory strategy research. For example, Tekin et al. [18] discussed the influence of an improved batch order control strategy on the remaining lifetime of goods in stock, and established an age-based policy on perishable inventory model considering the loss of market share. Broekmeulen et al. [19] proposed an order strategy based on (R, s, nQ) with inventory lifetime, and proved the cost advantage of the strategy. Civelek et al. [20] divided platelet demand into three categories according to different residual lifetime. They presented that each type of demand can replace each other, but the replacement cost should be considered. On this basis, a replenishment strategy called (S, C) was proposed and compared with NIR strategy [21]. Hamdan et al. [22] presented a two-stage stochastic programming problem for red blood cells that simultaneously considered production, inventory and location decisions. Dillon et al. [23] investigated a two-stage stochastic programming model for optimizing blood inventory replenishment control policies, considering multiple types, perishability, lead time, and a periodic review policy. Chen and Li [24] investigated the benefit of joint decision making regarding whole blood collection and platelet production at a blood center. Zahiri et al. [25] presented a bi-objective mixed-integer model for integrated collection, production/screening, allocation and routing planning of blood products, and sought to simultaneously optimize the total cost and freshness of transported blood products to hospitals. They developed a hybrid multi-objective self-adaptive differential evolution algorithm to solve the model. Rajendran and Ravindran [26] developed a stochastic integer programming model under demand uncertainty to determine ordering policies along the blood supply chain. In the study of blood inventory domain, considering the lifetime and inventory level is helpful to improve the average freshness of the outgoing products and reduce blood shortage and outdating.

There are also some researchers who studied the blood inventory problem based on the background of blood shortage. Wang and Ma [1] studied the problem of blood replenishment strategy with different blood age by considering the emergency transshipment of blood between blood banks. Research shows that inventory transshipment can improve the service level of blood and reduce the overdue rate of blood. Zhou and Ma [2] tried to implement the blood group substitution strategy in the case of severe shortage of blood supply, and established an optimization model of shortage blood collection with service level constraints based on a two-level inventory system (blood center-hospitals). Ma and Zhou [6] studied the dynamic model of emergency blood collection for large-scale emergencies considering the characteristics of emergency blood supply. Luo and Chen [27] investigated the blood order and collection problems with two demand classes and emergency replenishment.

(2) Blood transshipment problem

Blood transshipment is a horizontal coordination strategy among blood banks. Transshipment can make up for the lack of local collection. There are many literatures about the transshipment of regular goods [28] or perishable articles [29], but less about blood transshipment. Lang [30] investigated the transshipment strategy in the inventory control problem of blood banks. Dehghani and Abbasi [31] proposed an age-based lateral-transshipment policy for perishable articles. The results demonstrated that the transshipment policy is effective under various circumstances such as lost sale and backordering. Dehghani et al. [32] developed a new model to make decisions on proactive transshipment and order quantities simultaneously. There are also a small number of studies on blood transshipment for emergency or blood shortage background. Considering the influence of inventory status, the problem of transshipping and transferring overstocked blood in emergency rescue was studied by Wang et al. [33]. Wang and Ma [34] established a multi-stage optimization model to solve the problem of multi-variety emergency blood transshipping with the goal of maximizing the blood freshness delivered within the specified time.

Obviously, blood transshipment is an effective means to relieve blood shortage. Blood transshipment affects collection and inventory decisions of the local blood bank. Based on the consideration of blood transshipping factors, this paper further studies the inventory management strategy of vertical coordination between blood banks and hospitals.

(3) Blood allocation problem

Blood inventory decision often involves the allocation of blood products. In the past, there are many literatures on the allocation of medical supplies [35], but there are few studies on the allocation of blood products. Dumas et al. [36] proposed a double cross matching and substitution strategy in blood allocation to reduce the outdating rate of blood. Sapountzis [37] took the lowest blood outdating rate as the goal, and studied the problem of blood allocation under the condition of determining demand and random demand.

Under the condition of blood shortage, the contradiction of insufficient supply makes the fair allocation of blood products become an urgent concern. At the same time, the blood supply should follow the principles of priority of severe case care and emergency in practice. Therefore, the allocation of blood products with different priority requirements and fairness concerns will also be considered in the inventory operation process.

3. Decision making method of blood supply chain considering transshipment and allocation in uncertain environment

3.1. Problem description

The blood bank is the central node for blood supply chain operation, which is responsible for the whole blood collection, blood product detection and preparation, inventory management, allocation blood products between hospitals and other businesses. China's blood bank system includes blood centers, central blood banks and central blood reserves. Blood centers are generally located in municipalities directly under the central government or provincial capitals. The central blood bank is set up in the city divided into districts, and the central blood reserve is set up in the county-level general hospital which cannot be covered by the central blood bank. In China, blood banks at all levels provide blood products to hospitals within their region. Blood banks at all levels are independent of each other in operation. Under the normal state, the blood inventory system in the region is a two level system with one-to-many structure (the local blood bank-hospitals).

Under the state of blood shortage, the structure and characteristics of blood supply chain have changed. In China, college students are one of the main sources of unpaid blood donation. Chinese universities are usually concentrated in the central city. Due to the return of college students in winter and summer vacation, the central city often has a seasonal blood shortage. Therefore, during the winter and summer vacation, the blood center located in a central city needs to transship blood from other blood banks nearby. At the same time, due to the shortage of blood, it is also necessary to fairly allocate the transshipped and collected blood products, so as to achieve a good blood supply effect. The daily blood collection volume of blood banks is random, which generally obeys normal distribution and can be fitted by historical data. The historical data of blood banks in China's major central cities show that the amount of blood that can be collected will drop sharply once the time enters into winter or summer vacation from normal time. As shown in Fig. 1, under the background of blood shortage, the decisions of blood collection/inventory, transshipment, and allocation should be made in the process of blood supply chain operation. These decisions influence each other and are dynamic processes.

Blood is a kind of perishable articles with a fixed lifetime. Supposing the fixed storage period is M days. The utility of blood products remains unchanged during the storage period. Let the lead time of blood collection be L days. The in-put stored blood from local collection is new blood, that is, the remaining shelf time is M days. So, the inventory level of blood products at

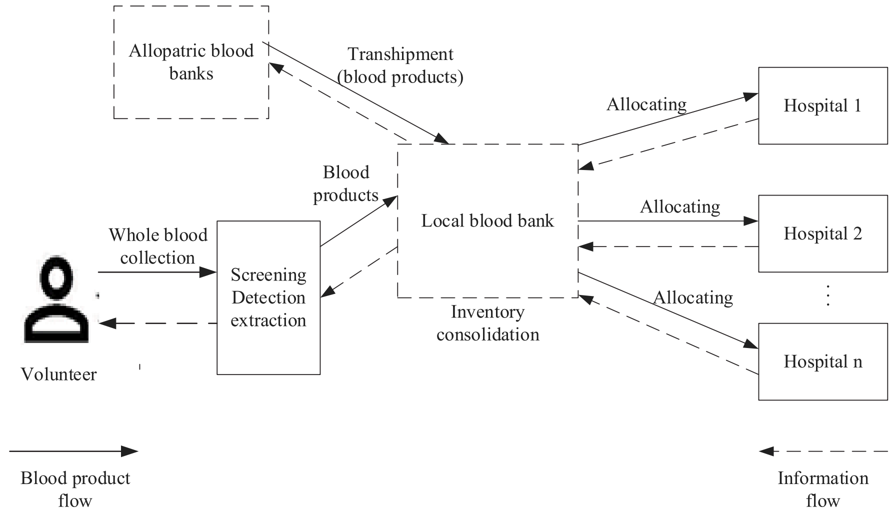

Fig. 1. Chinese blood supply chain under blood shortage.

period t is a vector and can be depicted as $\{x_1(t), x_2(t), \ldots, x_M(t)\}$. The blood inventory level $\{x_1(t), x_2(t), \ldots, x_M(t)\}$ changes dynamically. After entering the period of blood shortage, the blood supply will be greatly reduced. When a new term begins, the blood supply return to normal level. In the clinical blood transfusion treatment, part of the blood demand has to do with blood freshness. That is to say, the old blood is not suitable for some blood demand. The blood with the remaining shelf time longer than r days is required. Therefore, in this paper, the two types of blood demand are considered, and we call the blood demand for any remaining shelf time as Class A, and the demand for fresh blood as Class F respectively [23].

The local blood bank is allowed to carry out transshipment from other blood banks under the condition of blood shortage. In order to minimize blood shortage and give priority to satisfying the demand of blood class F, the two decision targets are selected to maximize the total amount and the freshness of the transshipped blood. Meanwhile, the capacity constraints of other blood banks, the uncertainty of supply and demand are also considered to build the transshipment decision model. The goal of the transshipment decision is to maximize the total amount and the freshness of the delivered blood, so as to ensure the least shortage and the demand priority of blood class F.

In clinical practice, the blood demand in hospitals is divided into 3 priorities, such as emergency demand, severe case demand, and common demand. Among them, the emergency demand refers to the very urgent demand for blood transfusion, the severe case demand refers to the demand with serious disease but slightly lower emergency, and the common demand refer to the demand beyond the emergency and severe case demand. The transfusion of emergency blood and severe case blood is usually reserved blood, and their demand is determined. The common demand is uncertain. Its probability distribution can be fitted in accordance with the historical data of hospital blood demand. Therefore, blood allocation needs to consider the fairness concerns and different priority demand of patients. An allocation optimization model with objectives to search the best fairness and the least blood shortage rate is established Considering the uncertainty of supply and demand.

As previously mentioned, it is difficult to model and calculate blood collection decisions with optimization methods due to the complexity of blood inventory systems. We use indicators of blood shortage, outdating and fairness to measure the effect of inventory management, and establish a DESS framework to study the dynamic decision of blood supply chain operation. The DESS framework of this paper is shown in Fig. 2.

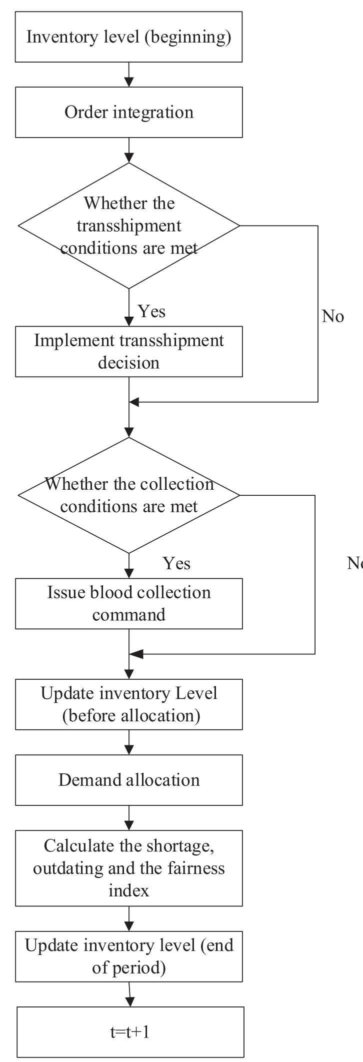

Fig. 2. Dynamic decision process of blood supply chain.

In the long-term process of blood supply chain decision-making, the main decision-making objectives are to ensure blood supply, improve the fairness of blood allocation, and reduce the amount of blood outdating. The question to be solved is as follows. When to collect the blood? How much blood should be collected? How to make the decision of blood transshipment? How to make blood allocation decision? How to simulate and optimize inventory control parameters?

3.2. Description of blood inventory level

In the process of blood collection planning, it is necessary to calculate the amount of issued blood, the amount of outdated blood, and the amount of collected blood with different remaining shelf time every day, and update the inventory level according to the calculation results each day.

A recursive equation can be used to establish the relationship between the parameters and calculate the variables in the inventory review cycle and lead time. The transfer equation of inventory level from period t to period $t+1$ depends on the planning period t, blood collection volume S, inventory level variables x, two types of blood demand (class A and F) and issue strategy R (FIFO and LIFO), in which FIFO is a first-in-first-out strategy and LIFO is a last-in-last-out strategy. It can be described as:

$$x(t+1) = x_R(x(t), A, F, S) \tag{1}$$

Considering the two kinds of blood demand of class A and F, the inventory level transition equation is also divided into two categories, and the state transition of class A and F relates to each other. In clinical practice, the blood demand for class F is usually reserved for surgery, and it is usually given priority when it is delivered out of the warehouse on the same day. Therefore, it is assumed that the blood demand for class F is guaranteed first, and then blood demand for class A is supplied according to the remaining inventory level.

The state transition equation of blood class F based on FIFO strategy can be expressed as follows:

$$\begin{cases} x_m(t+1) = [x_{m+1}(t) - (D_o^F(t) - \sum_{j=r}^{m} x_j(t))^+]^+, r \le m \le M-1 \\ x_M(t+1) = S(t+1-L) \end{cases} \tag{2}$$

In Eq. (2), r is the minimum remaining shelf time required for blood class F. $D_o^F(t)$ is the demand of blood center o for class F at period t. Where:

$$D_o^F(t) = d_{oe}^F(t) + d_{os}^F(t) + d_{og}^F(t) = \sum_{h\in H}[d_{he}^F(t) + d_{hs}^F(t) + d_{hg}^F(t)] \tag{3}$$

$d_{he}^F(t), d_{hs}^F(t), d_{hg}^F(t)$ are respectively the emergency demand, severe case demand and common demand for class F in hospital h at period t.

The state transition equation of blood class A based on FIFO strategy is as follows:

$$\begin{cases} x_m(t+1) = [x_{m+1}(t) - (D_o^A(t) - \sum_{j=1}^{m} x_j(t))^+]^+, 1 \le m \le M-1 \\ x_M(t+1) = S(t+1-L) \end{cases} \tag{4}$$

In expression (4), $D_o^A(t)$ is the demand of type A in blood center o at period t. Where,

$$D_o^A(t) = d_{oe}^{kA}(t) + d_{os}^A(t) + d_{og}^A(t) = \sum_{h\in H}[d_{he}^A(t) + d_{hs}^A(t) + d_{hg}^A(t)] \tag{5}$$

$d_{he}^A(t), d_{hs}^A(t), d_{hg}^A(t)$ are respectively the emergency demand, severe case demand and common demand of class A in hospital h at period t respectively.

The state transition equation of blood class F based on LIFO strategy can be expressed as follows:

$$\begin{cases} x_m(t+1) = [x_{m+1}(t) - (D_o^F(t) - \sum_{j=m+2}^{M} x_j(t))^+]^+, r \le m \le M-2 \\ x_{M-1}(t+1) = (x_M(t) - D_o^F(t))^+ \\ x_M(t+1) = S(t+1-L) \end{cases} \tag{6}$$

The state transition equation of blood class A based on LIFO strategy can be expressed as follows:

$$\begin{cases} x_m(t+1) = [x_{m+1}(t) - (D_o^A(t) - \sum_{j=m+2}^{M} x_j(t))^+]^+, 1 \le m \le M-2 \\ x_{M-1}(t+1) = (x_M(t) - D_o^F(t))^+ \\ x_M(t+1) = S(t+1-L) \end{cases} \tag{7}$$

3.3. Decision making method of blood collection

The EWA replenishment strategy proposed in reference [6] is adopted in blood collection decision-making. EWA strategy uses the method of estimating the expected outdated quantity in the decision-making process of blood collection. This inventory strategy takes the possible outdating amount into account in the process of inventory replenishment, which can deal with the dynamic decision-making process of blood inventory replenishment, and minimize the outdating amount.

Firstly, an expected final stock level (EFS) is defined as:

$$EFS = \text{total current inventory} - \text{expected demand} - \text{expected outdating}$$

Based on the historical data of hospitals served by the blood center, the expected total demand of hospitals is taken as the expected demand of the blood center. That is to say, the expected blood demand for class F in the blood center is:

$$FD_o^F(t) = \sum_{h\in H}[\bar{d}_{he}^F(t) + \bar{d}_{hs}^F(t) + \bar{d}_{hg}^F(t)] \tag{8}$$

In formula (8), $\bar{d}_{he}^F(t), \bar{d}_{hs}^F(t), \bar{d}_{hg}^F(t)$ are the average blood demand for class F in hospital h at period t.

The expected blood demand for class A in blood center $FD_o^A(t)$ is as follows:

$$FD_o^A(t) = \sum_{h\in H}[\bar{d}_{he}^A(t) + \bar{d}_{hs}^A(t) + \bar{d}_{hg}^A(t)] \tag{9}$$

In formula (9), $\bar{d}_{he}^A(t), \bar{d}_{hs}^A(t), \bar{d}_{hg}^A(t)$ are the average blood demand for class A in hospital h at period t.

The expected outdating (aging) is predicted based on the expected demand. Under FIFO strategy, the expected aging for class F at period t, $FQ_o^F(t)$ is as follows:

$$FQ_o^F(t) = [x_r(t) - FD_o^F(t)]^+ \tag{10}$$

That is, the expected aging is the blood stock with the remaining shelf time of r minus the expected demand.

The expected outdating for class A at period t, $FQ_o^A(t)$ is as follows:

$$FQ_o^A(t) = [x_1(t) - FD_o^A(t)]^+ \tag{11}$$

That is to say, the outdating is the blood inventory with the remaining shelf time of 1 day minus the expected demand.

Therefore, the expressions of EFS for class F and class A under FIFO strategy are as follows:

$$EFS^F = \sum_{m=r}^{M} x_m(t) - FD_o^F(t) - [x_r(t) - FD_o^F(t)]^+ \tag{12}$$

$$EFS^A = \sum_{m=1}^{M} x_m(t) - FD_o^A(t) - [x_1(t) - FD_o^A(t)]^+ \tag{13}$$

Similarly, under LIFO strategy, the expected aging of class F at period t, $FQ_o^{kF}(t)$ is as follows.

$$FQ_o^F(t) = \left[x_r(t) - \left(FD_o^F(t) - \sum_{m=r+1}^{M} x_m(t) \right)^+ \right]^+ \tag{14}$$

Under LIFO strategy, the expected outdating for class A at period t, $FQ_o^{kA}(t)$ is as follows:

$$FQ_o^A(t) = \left[x_1(t) - \left(FD_o^A(t) - \sum_{m=2}^{M} x_m(t) \right)^+ \right]^+ \tag{15}$$

Therefore, the expressions of EFS for the two blood classes under LIFO strategy are obtained as follows:

$$EFS^F = \sum_{m=r}^{M} x_m(t) - FD_o^F(t) - \left[x_r(t) - \left(FD_o^F(t) - \sum_{m=r+1}^{M} x_m(t) \right)^+ \right]^+ \tag{16}$$

$$EFS^A = \sum_{m=1}^{M} x_m(t) - FD_o^A(t) - \left[x_1(t) - \left(FD_o^A(t) - \sum_{m=2}^{M} x_m(t) \right)^+ \right]^+ \tag{17}$$

Let $SS(t)$ be the safety stock at period t, λ the guarantee level of blood, $\sigma_{og}^F(t)$ the standard deviation of common demand for class F at period t, and $\sigma_{og}^A(t)$ the standard deviation of common demand for class A at period t. $SS(t)$ can be expressed by (18).

$$SS(t) = \lambda\sqrt{L((\sigma_{og}^F(t))^2 + (\sigma_{og}^A(t))^2)} \tag{18}$$

The decision rule of blood collection under EWA strategy is as following.

If $EFS \geq SS$, the blood collection operation is not performed;

if $EFS < SS$, then, perform the blood collection operation.

The collection quantity $S(t)$ at period t is as follows:

$$S(t) = min[TSL - EFS, \bar{S}(t)] \tag{19}$$

In expression (19), TSL is the target inventory level of blood products, and $\bar{S}(t)$ is the maximum collection capacity.

3.4. Decision making method of blood transshipment

When the blood supply is insufficient, the local blood center needs to request for blood transshipment from blood banks outside local region. If the outside blood banks have surplus inventory after meeting their own demand, they can transfer out blood products of different quantities with different ages. The goal of the transshipment decision is to maximize the total amount and the freshness of the delivered blood, so as to ensure the least shortage and the demand priority of blood class F. The transshipment decision process is shown in Fig. 3. The parameters involved in the transshipment decision model are as follows.

o: Label of the blood center

B: Label of other blood banks, $b = \{1, 2, \ldots, n\}$

H: Set of hospitals served by the blood center, $h \in H$

M: The maximum shelf time of blood products

m: The remaining shelf time of blood products, $0 \leq m \leq M$

L: The lead time of blood collection

λ: The guarantee level of blood products

A: Notation of blood demand for class A.

F: Notation of blood demand for class F.

X_{om}: The inventory of blood products with remaining shelf time m in blood center

D_o: The total blood demand in blood centers

d_h: The blood demand in hospital h

fd_h: The reservation demand in hospital h

rd_h: The random demand in hospital h

d_{he}^F: The emergency demand for class F in hospital h

d_{he}^A: The emergency demand for class A in hospital h

d_{hs}^F: The severe case demand for class F in hospital h

d_{hs}^A: The severe case demand for class A in hospital h

d_{hg}^F: The common demand for class F in hospital h

d_{hg}^A: The common demand for class A in hospital h

IP_o: The inventory position in blood center

n_{bm}: The available amount of blood products with remaining shelf time m at blood bank b

Decision variables are as follows.

β_{bm}: If tranship blood from blood bank b to blood center, it is 1, otherwise, it is 0

B_{bm}:The amount of transshipment blood with remaining shelf time m from blood bank b

According to the above transshipment principles, the transshipment decision model P1 is constructed as following.

Model P1

$$\max\ f_1 = \sum_b \sum_m \beta_{bm} B_{bm} \tag{20}$$

$$\max\ f_2 = \frac{\sum_b \sum_m (B_{bm} * m)}{\sum_b \sum_m B_{bm}} \tag{21}$$

$s.t.$

$$\sum_b \sum_m B_{bm} \leq \lambda(D_o - IP_o), \quad 1 \leq m \leq M, 1 \leq \lambda \leq 2 \tag{22}$$

$$B_{b1} = 0, \forall b \in B \tag{23}$$

$$B_{bm} \leq n_{bm}, \forall 1 \leq m \leq M, b \tag{24}$$

$$B_{bm} = \beta_{bm} B_{bm}, \forall 1 \leq m \leq M, b \in B \tag{25}$$

$$\beta_{bm} \in \{0, 1\}, \forall 1 \leq m \leq M, b \in B \tag{26}$$

$$B_{bm} \geq 0, \forall 1 \leq m \leq M, b \in B \tag{27}$$

The objective function (20) represents the maximum amount of blood transshipment. The objective function (21) indicates that the freshness of the transhipped blood is the best. Constraint (22) is the total amount limit of blood transshipping. Formula (23) indicates that blood with remaining shelf time of 1 day is not allowed to be transshipped. Formula (24) is the available amount limit of blood products with residual shelf time m. Formula (25), (26) and (27) are the range constraints of decision variables.

Let $f_1^{\max}$ and $f_1^{\min}$ be the maximum and minimum values of f_1, and $f_2^{\max}$ and $f_2^{\min}$ be the maximum and minimum values of f_2 respectively. By nondimensionalizing the two objectives, the multi-objective optimization problem can be transformed into

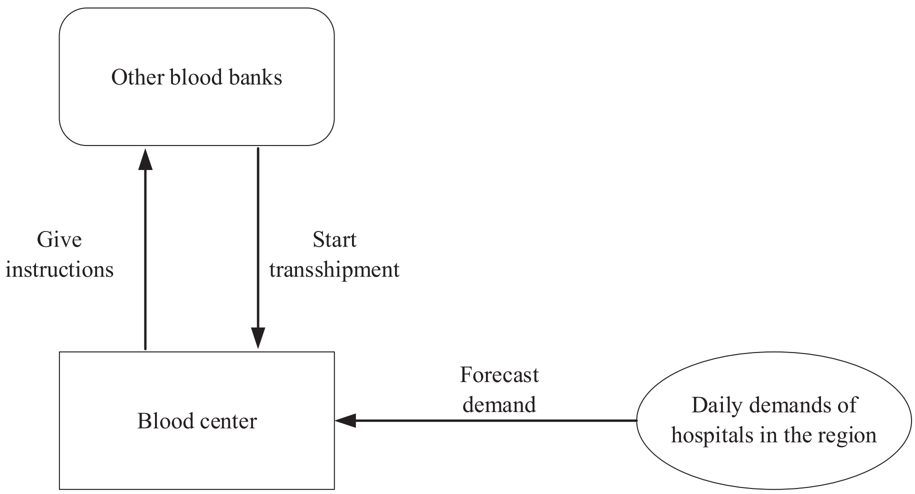

Fig. 3. Transshipping process of a blood center.

the single objective optimization problem shown in Eq. (28) [38, 39].

$$\max F = \omega_1 \left[\frac{f_1}{f_1{}^{\max}}\right] + (1-\omega_1)\left[\frac{f_2}{f_2{}^{\max}}\right] \quad 0 \le \omega \le 1 \tag{28}$$

The chance constrained programming is used to deal with uncertain demand. Then, constraint (22) can be rewritten as Eq. (29). The proved process of equivalency can be seen Appendix.

$$\sum_b \sum_m B_{bm} \le \lambda\Big(\sum_{h\in H} d_{he}^A + \sum_{h\in H} d_{hs}^A + \sum_{h\in H} d_{he}^F + \sum_{h\in H} d_{hs}^F + \sum_{h\in H} \overline{d}_{hg}^F + \sum_{h\in H} \overline{d}_{hg}^A - IP_o\Big) - \lambda \Phi^{-1}(\alpha)\sqrt{\sum_{h\in H}(\sigma_{hg}^F)^2 + \sum_{h\in H}(\sigma_{hg}^A)^2} \tag{29}$$

By replacing constraint (22) with constraint (29), a new equivalent model of blood transshipment decision can be obtained. The model is a mixed integer programming model. The existence of a solution to this model is obvious. Because as long as there is a feasible solution to the problem, there must be at least one optimal solution. Relevant research on solving methods for similar problems can be roughly divided into two categories: design heuristic algorithm or exact algorithm according to specific characteristics of the problem, or use existing mathematical programming software, such as LPSOLVE, CPLEX, MOSEK, etc. In this paper, the free software, LPSOLVE, is used to solve the model. In practice, blood transshipment or allocation decision-making problems have a small or medium scale (the number of nodes is generally less than 30), so the application of LPSOLVE can quickly obtain the optimal solution.

3.5. Decision making method of blood allocation

Allocation decision refers to the allocation of blood inventory from the blood center to hospitals in local region (Fig. 4). Different from general supplies, in addition to ensure the minimum shortage, the fairness concerns of patients must be fully considered in blood allocation decision. In clinical practice, blood transfusion must meet the allocation principles of emergency priority, severe case care priority, and emergency superior to severe case care.

The related parameters of the blood allocation decision model are described as follows:

$|H|$: Number of hospitals served by the blood center

d_h^F: Blood demand for class F in hospital h

d_h^A: Blood demand for class A in hospital h

d_{he}^F: Emergency demand for class F in hospital h

d_{he}^A: Emergency demand for class A in hospital h

d_{hs}^F: Severe case demand for class F in hospital h

d_{hs}^A: Severe case demand for class A in hospital h

d_{hg}^F: Common demand for class F in hospital h

$\overline{d}_{hg}^F$: Average common demand for class F in hospital h

d_{hg}^A: Common demand for class A in hospital h

$\overline{d}_{hg}^A$: Average common demand for class A in hospital h

σ_{hg}^A: Standard deviation of common demand for class A in hospital h

ω_2: Weight of objectives

Decision variables:

Q_h^F:Allocation amount of blood class F to hospital h

Q_h^A: Allocation amount of blood class A to hospital h

Q_{he}^F: Allocation amount of blood class F for emergency demand to hospital h

Q_{he}^A: Allocation amount of blood class A for emergency demand to hospital h

Q_{hs}^F: Allocation amount of blood class F for severe case demand to hospital h

Q_{hs}^A: Allocation amount of blood class A for severe case demand to hospital h

Q_{hg}^F: Allocation amount of blood class F for common demand to hospital h

Q_{hg}^A: Allocation amount of blood class A for common demand to hospital h

In order to measure the fairness of blood allocation, Gini coefficient, an evaluation index of economic income fairness, is introduced as the objective function of blood allocation optimization model.

The commonly used Gini index in China is as follows:

$$f = \frac{1}{2n^2\overline{u}} \sum_i \sum_j \left|u_i - u_j\right|, i \ne j \tag{30}$$

In expression (30), $\overline{u}$ is the average income of all industries. u_i, u_j are the average income of the i and j industries. n is the number of types of industries.

Let $\overline{u} = \frac{\sum_{h\in H} Q_h}{\sum_{h\in H} d_h}$ be the average satisfaction rate of the allocated blood products at hospital h, then $u_i = \frac{Q_i}{d_i}, i \in H$ and

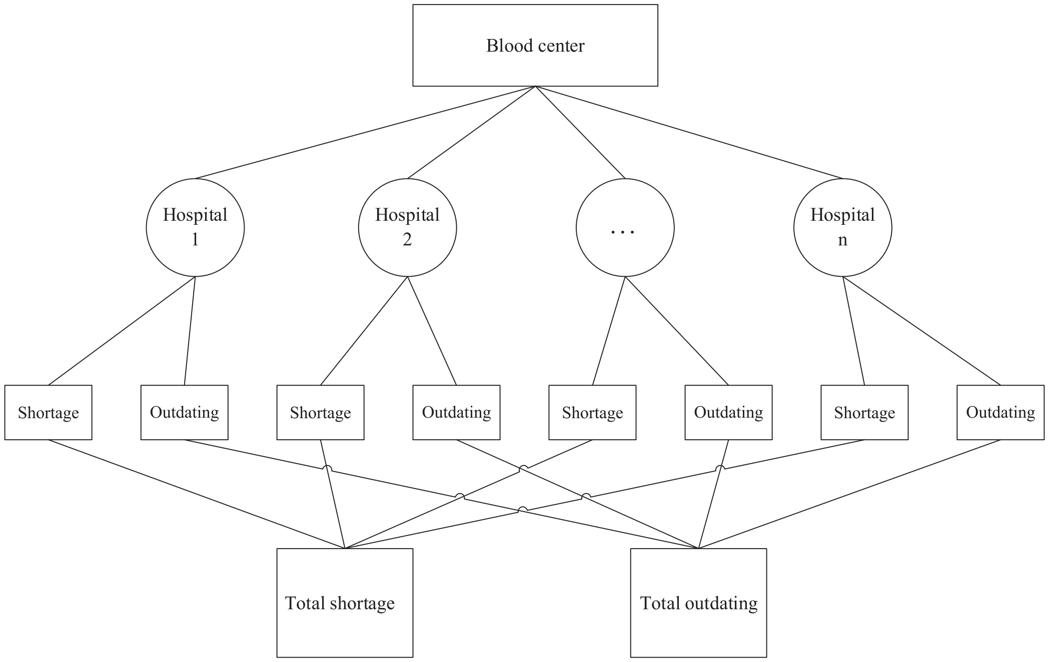

Fig. 4. Allocation decision process of the blood center.

$u_j = \frac{Q_j}{d_j}, j \in H$ are the satisfaction rates of hospital i and hospital j respectively. It can be concluded that the fairness index of blood allocation based on Gini coefficient is as expression (31).

$$G = \frac{1}{2\left|H\right|^2 \frac{\sum_{h\in H} Q_h}{\sum_{h\in H} d_h}} \sum_i \sum_j \left| \frac{Q_i}{d_i} - \frac{Q_j}{d_j} \right|, \quad i \neq j \tag{31}$$

So far, the allocation decision-making model for blood class F is established, as shown in P2.

Model P2

$$\begin{aligned} \min f_3 = \omega_2 & \frac{1}{2\left|H\right|^2 \frac{\sum_{h\in H} Q_h}{\sum_{h\in H} d_h}} \sum_i \sum_j \left| \frac{Q_i^F}{d_i^F} - \frac{Q_j^F}{d_j^F} \right| \\ & +(1-\omega_2)\left(\frac{\sum_{h\in H}(d_h^F - Q_h^F)}{\sum_{h\in H} d_h^F} \right), \quad i \neq j \end{aligned} \tag{32}$$

s.t.

$$\left(d_{ie}^F - d_{je}^F\right)\left(\frac{Q_{ie}^F}{d_{ie}^F} - \frac{Q_{je}^F}{d_{je}^F} \right) \geq 0, i \neq j, \forall i,j = 1,2,\ldots,n \tag{33}$$

$$\left(d_{is}^F - d_{js}^F\right)\left(\frac{Q_{is}^F}{d_{is}^F} - \frac{Q_{js}^F}{d_{js}^F} \right) \geq 0, i \neq j, \forall i,j = 1,2,\ldots,n \tag{34}$$

$$\left(d_{ig}^F - d_{jg}^F\right)\left(\frac{Q_{ig}^F}{d_{ig}^F} - \frac{Q_{jg}^F}{d_{jg}^F} \right) \geq 0, \quad i \neq j, \forall i,j = 1,2,\ldots,n \tag{35}$$

$$\begin{cases} Q_{ie}^F = d_{ie}^F & \text{if } \sum_i d_{ie}^F \leq IP_o^F \leq \sum_i d_{ie}^F + \sum_i d_{is}^F, i = 1,2,\ldots,n \\ Q_{ie}^F + Q_{is}^F = d_{ie}^F + d_{is}^F & \text{if } IP_o^F \geq \sum_i d_{ie}^F + \sum_i d_{is}^F, i = 1,2,\ldots,n \end{cases} \tag{36}$$

$$\frac{Q_{ie}^F}{d_{ie}^F} \geq \frac{Q_{is}^F}{d_{is}^F} \geq \frac{Q_{ig}^F}{d_{ig}^F} \quad, \forall i = 1,2,\ldots,n \tag{37}$$

$$0 \leq \frac{Q_{ie}^F}{d_{ie}^F}, \frac{Q_{is}^F}{d_{is}^F}, \frac{Q_{ig}^F}{d_{ig}^F} \leq 1 \quad, \forall i = 1,2,\ldots,n \tag{38}$$

$$Q_i^F = Q_{ie}^F + Q_{is}^F + Q_{ig}^F, \forall i = 1,2,\ldots,n \tag{39}$$

$$\begin{cases} d_h^F = d_{he}^F + d_{hs}^F + d_{hg}^F, \forall h = 1,2,\ldots,n \\ d_{hg}^F \sim N(\overline{d}_{hg}^F, \sigma_{hg}^{F2}), \forall h = 1,2,\ldots,n \end{cases} \tag{40}$$

$$0 \leq \sum_{h\in H} Q_h^F \leq \left(IP_o^F + \sum_{b\in B} \sum_{m=r}^{M} B_{bm} \right) \tag{41}$$

Objective function (32) indicates to search the best fairness and the least blood shortage rate. Constraint (33) indicates the priority for emergency patients, that is, hospitals with more urgent demand have higher emergency demand satisfaction rate. Constraint (34) indicates priority for severe case. Constraint (35) represents fair allocation of common demand. Constraint (36) indicates that if the blood supply meets the emergency demand, but cannot meet the severe case demand and common demand, then give priority to emergency demand, second priority to severe case demand, and finally the common demand. Constraint (37) indicates that the satisfaction rate of emergency demand is higher than severe case demand, and severe case demand is greater than common demand. Constraint (38) indicates that the demand satisfaction rate of blood class F is greater than 0 and less than or equal to 1. Eq. (39) indicates that the total allocation amount of emergency, severe case and common demand. Eq. (40) shows that the blood demand is the sum of emergency demand, severe case demand and common demand, in which the common demand follows a normal distribution. Constraint (41) indicates that the blood allocation is less than the current inventory position.

Constraint (35) can be transformed into expression (42) based on chance constrained programming.

$$\Phi^{-1}(\alpha)\left(\frac{\sigma_{ig}^F}{\sigma_{jg}^F} Q_{jg}^F - \frac{\sigma_{jg}^F}{\sigma_{ig}^F} Q_{ig}^F \right) \leq \frac{\overline{d}_{jg}^F}{\overline{d}_{ig}^F} Q_{ig}^{kF} + \frac{\overline{d}_{ig}^F}{\overline{d}_{jg}^F} - Q_{jg}^F Q_{ig}^F - Q_{jg}^F \tag{42}$$

Similarly, constraints (37) and (38) can be transformed into expressions (43) and (44) respectively based on chance constrained programming.

$$\frac{Q_{ie}^F}{d_{ie}^F} \geq \frac{Q_{is}^F}{d_{is}^F} \geq \frac{Q_{ig}^F}{\overline{d}_{ig}^F} + \Phi^{-1}(\alpha)\frac{Q_{ig}^F}{\sigma_{ig}^F} \tag{43}$$

$$0 \leq \frac{Q_{ig}^F}{\overline{d}_{ig}^F} + \Phi^{-1}(\alpha)\frac{Q_{ig}^F}{\sigma_{ig}^F} \leq 1 \tag{44}$$

By replacing the relevant constraints, a new equivalent Decision making model of blood allocation can be obtained. The proof process is similar to Appendix.

The allocation model for blood class *A* is similar as model P2. It is just need to update the inventory level before the allocation decision for blood class *A*.

3.6. Discrete event simulation system

Discrete event system is a system driven and interacted by discrete events according to certain operation rules, resulting in dynamic state changes. The process of modeling and analyzing discrete event system is DESS. This method simulates the behavior of the discrete system to be studied, records the important parameters, and analyzes the performance of the system, so as to guide the actual operation activities in real life. In view of the complexity of blood products, such as perishability, randomness of demand, characteristics of multi-product and multi-stage, a large number of researchers use DESS to optimize inventory system [40,41]. Considering the fluctuation of blood supply and demand, the multi-dimensional of inventory level, the dynamic and complexity of decision-making such as collection, transshipment and allocation, this paper uses DESS to study the decision-making problem of blood supply chain operation. Through the operation of the system, the important parameters such as blood shortage, outdating and freshness are recorded, and the effect of inventory management is analyzed. At the same time, through the simulation experiments, the sensitivity analysis of some important parameters is carried out, and some beneficial management implications are obtained to guide the blood center to optimize the operation of inventory management. Blood supply chain management is a dynamic process, and its basic process can be described as Fig. 2. The specific operation process is described as follows.

Step 1: Record the beginning inventory level.

Let t_0 denote the beginning time, and the inventory level $\{x_1(t_0), x_2(t_0), \ldots, x_M(t_0)\}$ should be recorded first to make the inventory decision.

Step 2: Integrate the demand orders of all hospitals.

The integration of demand orders of all hospitals is the demand of blood center *o*.

The demand of blood center *o* for class *F* at period *t*, $D_o^F(t)$, can be integrated by expression (3). The demand of blood center *o* for class *A* at period *t*, $D_o^A(t)$, can be integrated by expression (5).

Step 3: Judge whether the transshipment conditions are met by the following method.

For each blood class, If the inventory position of the blood center $IP_o(t)$ is greater than or equal to the total demand, no transhipment is needed. Otherwise, the transshipment should be implemented. That is to say, if $IP_o(t) < \left\{D_o^F(t) \vee D_o^A(t)\right\}$, the transshipment should be implemented, then step into Step 4.

Step 4: make a transshipment decision.

The transshipment model P1 built in Section 3.4 should be applied to make a transshipment decision. The model can be solved by the solver *LPSOLVE. LPSOLVE* can be invoked in the process of DESS based on MATLAB [42,43].

Step 5: make a blood collection decision.

Use the method given in Section 3.3 to make blood collection decision. The collection quantity $S(t)$at period t should be calculated according to expression (8)∼(19) in this step.

Step 6: Update the inventory level after collected blood arrived.

Update the inventory level based on the state transition equation (2), (4) , (6) and (7).

Step 7: Make a blood allocation decision.

Use the model P2 proposed in Section 3.5 to make blood allocation decision. Model P2 is also solved by *LPSOLVE* invoked in the process of DESS. The allocation decision of blood class *F* should be first made. Then update the inventory level as Step 6. The allocation decision for blood class *A* can be made as the same method as blood class *F* .

Step 8: Calculate the Blood shortage, outdating and the fairness index.

Step 9: Update inventory level $\{x_1(t+1), x_2(t+1), \ldots, x_M(t+1)\}$ at the end of the period.

Step 10: Step into the next day.

4. Numerical simulation

4.1. Blood supply chain decision

The research data of red blood cell products in a city in western China are used for numerical simulation. There are 20 hospitals in the region, and their demand information is shown in Tables 1–2. There are four different blood banks nearby the blood center. The daily available blood inventory level of each blood bank can be used for transshipment is transmitted to the blood center through the information system every day. The initial inventory level of the blood center is shown in Table 3. The maximum collectable volume information of blood center is shown in Tables 4 and 5. The maximum shelf time of blood products *M* is 21 days, the lead time is $L = 1$ day, and the threshold of residual shelf time for blood class *F* r is 15 days. According to the clinical experience of blood transfusion in Chinese hospitals, the proportion of blood class *F* demand is 30%, and the rest is blood class *A* demand. Summer vacation was chosen as the research period. Summer vacation in Chinese universities is about 42 days. In order to accurately cover the seasonal blood shortage period, 42 days before and after summer vacation were included in the simulation period. That is, the simulation period is 126 days.

Using EWA strategy, the sensitivity analysis of inventory parameter combination is carried out according to the process shown in Fig. 5. A large number of numerical simulations show that it is reasonable to take $1.8 \times \sum_{h \in H} fd_h$ as *SS* and 2000U as *TSL* [6]. Under the optimal control parameters, 20 random events are simulated, and each event is run for 126 days randomly. Averaging the results, the operation results are shown in Table 6. The results show that FIFO strategy can reduce the amount of shortage and blood transshipping.

4.2. Comparison of major inventory strategies

The decision-making effect of different inventory strategies is analyzed in this section. As shown in Fig. 6, eight inventory strategies are input in DESS, including EWA (FIFO), EWA(LIFO), (s, S) (FIFO), (s, S) (FIFO), (s, Q) (FIFO), (s, Q) (LIFO), (t, s) (FIFO), (t, S) (LIFO). Similarly, 20 random events were simulated, and each event ran for 126 days to obtain the indexes of shortage, outdating and fairness. By comparing these indexes, the best inventory strategy is finally selected.

Table 1
Blood demand for emergency and severe cases in hospitals.

h. num	MON		TUE		WED		THU		FRI		SAT		SUN	
	ED	SD	ED	SD	ED	SD	ED	SD	ED	SD	ED	SD	ED	SD
1	18.3	27.45	12.68	19.03	12.65	18.98	11.73	17.59	14.13	21.19	3.1	4.65	3.19	4.79
2	14.24	21.35	9.87	14.8	9.84	14.76	9.12	13.68	10.99	16.48	2.41	3.62	2.48	3.73
3	21.73	32.6	15.06	22.6	15.02	22.54	13.92	20.89	16.78	25.16	3.68	5.52	3.79	5.69
4	12.22	18.32	8.47	12.7	8.44	12.67	7.83	11.74	9.43	14.15	2.07	3.1	2.13	3.2
5	16.84	25.27	11.67	17.51	11.64	17.46	10.79	16.19	13	19.5	2.85	4.28	2.94	4.41
6	6.13	9.2	4.25	6.38	4.24	6.36	3.93	5.89	4.73	7.1	1.04	1.56	1.07	1.61
7	3.83	5.75	2.65	3.98	2.65	3.97	2.45	3.68	2.96	4.43	0.65	0.97	0.67	1
8	8.82	13.23	6.11	9.17	6.1	9.15	5.65	8.48	6.81	10.21	1.49	2.24	1.54	2.31
9	10.40	15.6	7.21	10.81	7.19	10.78	6.66	9.99	8.03	12.04	1.76	2.64	1.81	2.72
10	10.53	15.79	7.3	10.95	7.28	10.92	6.75	10.12	8.13	12.19	1.78	2.67	1.84	2.76
11	6.38	9.57	4.42	6.64	4.41	6.62	4.09	6.14	4.93	7.39	1.08	1.62	1.11	1.67
12	0.76	1.14	0.53	0.79	0.52	0.79	0.49	0.73	0.59	0.88	0.13	0.19	0.13	0.2
13	11.8	17.71	8.18	12.27	8.16	12.24	7.56	11.34	9.11	13.67	2	3	2.06	3.09
14	6.12	9.18	4.24	6.36	4.23	6.35	3.92	5.88	4.72	7.09	1.04	1.55	1.07	1.6
15	13.73	20.6	9.52	14.27	9.49	14.24	8.8	13.19	10.6	15.9	2.32	3.49	2.4	3.59
16	6.51	9.77	4.51	6.77	4.5	6.75	4.17	6.26	5.03	7.54	1.10	1.65	1.14	1.7
17	5.29	7.94	3.67	5.5	3.66	5.48	3.39	5.09	4.08	6.13	0.9	1.34	0.92	1.39
18	3.27	4.9	2.26	3.4	2.26	3.39	2.09	3.14	2.52	3.78	0.55	0.83	0.57	0.86
19	5.92	8.87	4.1	6.15	4.09	6.14	3.79	5.69	4.57	6.85	1	1.5	1.03	1.55
20	0.97	1.45	0.67	1.01	0.67	1.01	0.62	0.93	0.75	1.12	0.16	0.25	0.17	0.25

Note: emergency demand (ED), severe case demand (SD).

Table 2
Common demand information in hospitals.

h.num	MON		TUE		WED		THU		FRI		SAT		SUN	
	avg	var	avg	var	avg	var	avg	var	avg	var	avg	var	avg	var
1	45.76	20.34^2	31.71	11.26^2	31.63	12.04^2	29.32	10.28^2	35.32	11.16^2	7.75	2.75^2	7.99	3.16^2
2	35.59	16.94^2	24.67	10.58^2	24.6	11.26^2	22.8	9.95^2	27.47	10.14^2	6.03	2.66^2	6.21	2.55^2
3	54.34	22.17^2	37.66	15.54^2	37.56	16.39^2	34.81	12.29^2	41.94	18.7^2	9.2	3.52^2	9.48	4.63^2
4	30.54	14.62^2	21.17	11.05^2	21.11	10.29^2	19.57	9.22^2	23.58	10.02^2	5.17	2.39^2	5.33	2.22^2
5	42.11	19.52^2	29.19	13.68^2	29.11	14.43^2	26.98	10.82^2	32.5	13.46^2	7.13	2.98^2	7.35	3.65^2
6	15.33	6.77^2	10.63	4.25^2	10.6	4.7^2	9.82	4.53^2	11.83	4.93^2	2.6	1.1^2	2.68	1.29^2
7	9.58	4.31^2	6.64	2.52^2	6.62	2.18^2	6.14	2.16^2	7.39	3.85^2	1.62	0.66^2	1.67	0.66^2
8	22.06	10.12^2	15.29	6.90^2	15.25	7.44^2	14.13	6.83^2	17.02	6.91^2	3.74	1.28^2	3.85	1.38^2
9	26	12.34^2	18.02	8.05^2	17.97	7.34^2	16.66	7.5^2	20.07	9.94^2	4.4	1.73^2	4.54	1.89^2
10	26.32	5.43^2	18.25	8.09^2	18.2	7.41^2	16.87	7.56^2	20.32	9.02^2	4.46	1.75^2	4.6	1.82^2
11	15.96	7.01^2	11.06	4.42^2	11.03	4.88^2	10.23	4.66^2	12.32	5.13^2	2.7	1.25^2	2.79	1.25^2
12	1.9	0.46^2	1.315	0.6^2	1.31	0.61^2	1.22	0.58^2	1.47	0.39^2	0.32	0.14^2	0.33	0.13^2
13	29.51	11.34^2	20.45	10.45^2	20.4	9.08^2	18.91	7.06^2	22.78	8.78^2	4.99	1.33^2	5.15	2.15^2
14	15.3	5.77^2	10.605	5.25^2	10.58	4.7^2	9.805	4.52^2	11.81	4.92^2	2.59	1.2^2	2.67	1.3^2
15	34.33	13.62^2	23.79	11.35^2	23.73	10.03^2	21.99	9.77^2	26.5	12.86^2	5.81	2.59^2	5.99	2.47^2
16	16.28	6.13^2	11.28	5.5^2	11.25	4.97^2	10.43	4.73^2	12.57	5.24^2	2.76	1.27^2	2.84	1.4^2
17	13.23	5.94^2	9.165	4.67^2	9.14	4.09^2	8.48	3.07^2	10.21	4.23^2	2.24	1.13^2	2.31	1.31^2
18	8.17	3.09^2	5.66	2.02^2	5.65	2.35^2	5.23	2.07^2	6.3	2.25^2	1.38	0.45^2	1.43	0.62^2
19	14.79	4.57^2	10.25	4.11^2	10.23	5.05^2	9.48	3.41^2	11.42	5.06^2	2.51	1.06^2	2.58	1.16^2
20	2.42	1.08^2	1.675	0.68^2	1.68	0.66^2	1.55	0.69^2	1.87	0.75^2	0.41	0.15^2	0.42	0.15^2

Table 3
Initial inventory level of blood center.

Remaining shelf time	Inventory	Remaining shelf time	Inventory	Remaining shelf time	Inventory	Remaining shelf time	Inventory
1	16.8	7	20.72	13	19.6	19	39.2
2	16.8	8	19.6	14	19.6	20	27.16
3	16.8	9	19.6	15	18.2	21	26.88
4	16.8	10	19.6	16	18.2	Sum	448.84
5	19.6	11	19.6	17	16.8	–	–
6	21.28	12	19.6	18	36.4	–	–

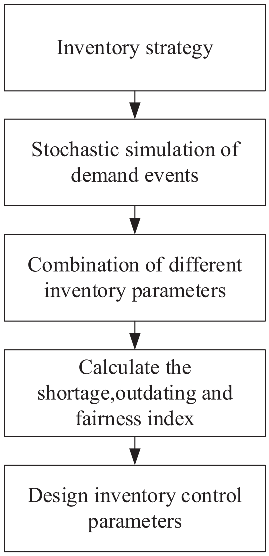

Fig. 5. Sensitivity analysis process.

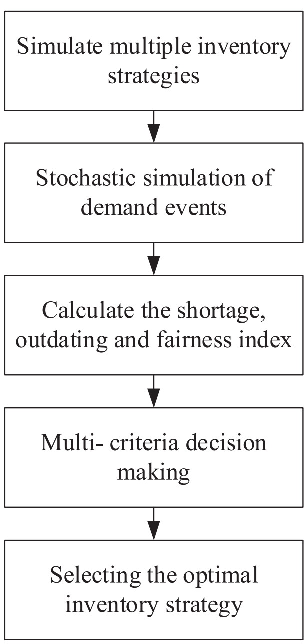

Fig. 6. Selection process of the optimal inventory strategy.

The decision indexes of different inventory strategies during vocation are shown in Table 7. In order to evaluate the optimal inventory strategy, two classical multi-attribute decision-making methods, the TOPSIS method and gray relational analysis (GRA) method are used to evaluate the optimal inventory strategy [44]. The comprehensive evaluation results based on TOPSIS are shown in Table 8 and Fig. 7. The evaluation results based on the TOPSIS method show that the EWA (FIFO) strategy is the most reasonable inventory strategy, while the (t, S) (LIFO) strategy are the most infeasible strategy.

Table 4
Daily collectable volume information of blood products.

Time	Statistical distribution	Characteristic parameter
Monday	Normal	$N \sim N(738.75, 370.06^2)$
Tuesday	Normal	$N \sim N(668.24, 320.35^2)$
Wednesday	Normal	$N \sim N(613.43, 307.36^2)$
Thursday	Normal	$N \sim N(754.77, 315.17^2)$
Friday	Normal	$N \sim N(725.28, 311.17^2)$
Saturday	Normal	$N \sim N(484.76, 225.38^2)$
Sunday	Normal	$N \sim N(465.83, 210.59^2)$

Table 5
Collectable volume information of blood products during winter and summer vacation.

Time	Statistical distribution	Characteristic parameter
Monday	Normal	$N \sim N(147.75, 69^2)$
Tuesday	Normal	$N \sim N(133.65, 65.08^2)$
Wednesday	Normal	$N \sim N(122.69, 62.45^2)$
Thursday	Normal	$N \sim N(150.95, 55.06^2)$
Friday	Normal	$N \sim N(145.06, 67.72^2)$
Saturday	Normal	$N \sim N(96.95, 34.46^2)$
Sunday	Normal	$N \sim N(93.17, 36.2^2)$

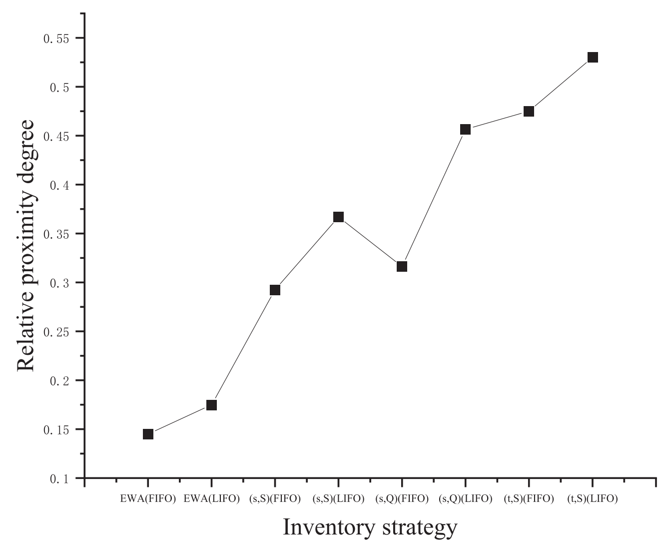

Fig. 7. Ranking of relative proximity based on TOPSIS method.

The results of comprehensive evaluation based on GRA are shown in Table 9 and Fig. 8. The results show that the EWA (FIFO) strategy is the most reasonable inventory strategy, while the (t, S) (LIFO) strategy are less effective. The conclusion is almost consistent with the TOPSIS method. Therefore, the presented EWA inventory strategy is effective.

4.3. Sensitivity analysis of key parameters

4.3.1. Sensitivity analysis of SS

Let $TSL = 2000$, the sensitivity analysis of SS was carried out. The results show that (see Table 10), the setting of SS has a significant impact on the decision-making effect. If the SS is set large, the shortage situation will be slowed down; otherwise, the

Table 6
Results under EWA strategy.

Inventory strategy	Shortage		Average fairness index		Total transshipment		Total collection		Total outdating
	Shortage days	Total shortage	Class F	Class A	Class F	Class A	Class F	Class A	
FIFO(non- vacation)	0	0	0	0	870.42	7790	3169.55	16 629.38	0
FIFO(vacation)	28	8568.36	0.02	0.41	1536.03	6222.28	3886.95	811.05	0
LIFO(non- vacation)	0	0	0	0	1177.63	10 725.71	3620.49	32 436.97	6186.26
LIFO(vacation)	30	9872.64	0.02	0.42	1894.44	5556.69	3250.73	2019.28	0

Table 7
Indexes of different inventory strategies.

Strategy	TSF	TSA	TO	TTF	TTA	TCF	TCA	AFI
EWA(FIFO)	227.28	8341.08	0	1536.03	6222.28	3886.95	811.05	0.43
EWA(LIFO)	491.63	9381	0	1894.44	5556.69	3250.73	2019.28	0.44
(s, S)(FIFO)	147.3	8536	0	921.62	1804.25	1952.65	3465.35	0.49
(s, S)(LIFO)	245.49	13 066.17	26.41	1228.83	0	1818.55	4110.86	0.51
(s, Q)(FIFO)	196.4	9789.42	0	921.62	541.27	3244	2466	0.49
(s, Q)(LIFO)	245.49	1228.83	247	1228.83	0	4185	1965	0.51
(t, S)(FIFO)	2005.69	15 916.14	0	1484.83	0	2636.8	453.2	0.53
(t, S)(LIFO)	2375.59	17 917.78	0	1689.64	0	3625.42	2524.58	0.49

Note: Total blood shortage for class F (TSF), Total blood shortage for class A (TSA), Total outdating (TO), Total transshipment of blood class F (TTF), Total transshipment of blood class A (TTA), Total blood collection amount of blood class F (TCF), Total blood collection amount of blood class F (TCA), Average fairness index (AFI).

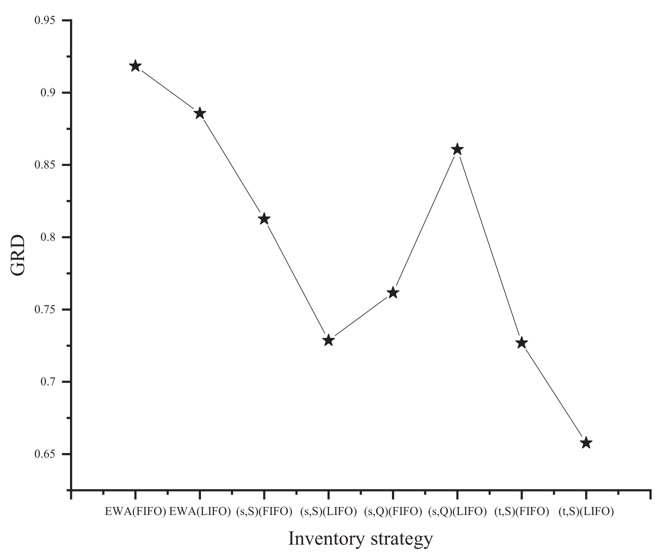

Fig. 8. Evaluation results based on GRA.

Table 8
Evaluation results based on TOPSIS method.

Inventory strategy	D_i^+	D_i^-	C_i	Sort
EWA(FIFO)	1.967	0.3337	0.1450	1
EWA(LIFO)	1.8522	0.3924	0.1748	2
(s, S)(FIFO)	1.81	0.7482	0.2925	3
(s, S)(LIFO)	1.6994	0.9851	0.367	5
(s, Q)(FIFO)	1.7793	0.8232	0.3163	4
(s, Q)(LIFO)	1.5361	1.2905	0.4565	6
(t, S)(FIFO)	1.1555	1.0465	0.4752	7
(t, S)(LIFO)	1.0524	1.187	0.5300	8

Note: D_i^+ is the distance from the positive ideal scheme, D_i^- is the distance from the negative ideal scheme, and C_i is the relative proximity degree.

shortage will be more serious. Due to the priority of meeting the demand of blood class *F*, the shortage degree of blood demand for class *F* is far lower than class *A*. The change of *SS* also has an impact on the collection quantity. The higher the *SS*, the greater the collection quantity is required.

4.3.2. Sensitivity analysis of TSL

Let $SS = 1.8 \times \sum_{h\in H} fd_h$, the sensitivity analysis of *TSL* is given in Table 11. It can be seen from Table 11 that the setting of *TSL* has a significant impact on the effect of inventory decision-making. Properly improving the *TSL* can help to reduce the shortage, but also increase the collection amount. Due to the reduction of blood shortage, the emergency and severe case demand of each hospital are constantly met, so the fairness index is becoming smaller and smaller, and the demand satisfaction rate of each hospital is also becoming consistent. and the demand.

4.3.3. Simulation analysis of blood demand fluctuation

The actual demand will fluctuate to a certain range above or below the predicted demand. Within different fluctuation range, 20 demand events are generated, then, the sensitivity analysis of blood demand fluctuation is given in Table 12. It can be seen that the greater the fluctuation of demand, the greater the possible shortage.

The sensitivity analysis of *TSL* is also carried out under drastic fluctuation of demand (Table 13). The results show that the *TSL* still has an important impact on the decision-making. With the increase of the *TSL*, the blood shortage decreases and the collection amount increases.

The sensitivity analysis of *SS* is carried out under drastic demand fluctuation (Table 14). The results show that the setting of *SS* has an important impact on inventory decision.

From the above sensitivity analysis, the blood outdating is 0 under the EWA strategy, which indicates that the EWA strategy can solve the problem of blood waste in blood shortage period.

Table 9
Correlation coefficient of GRA.

Index	EWA(FIFO)	EWA(LIFO)	(s, S)(FIFO)	(s, S)(LIFO)	(s, Q)(FIFO)	(s, Q)(LIFO)	(t, S)(FIFO)	(t, S)(LIFO)
TSF	0.9753	0.9480	0.9838	0.9733	0.9785	0.9733	0.8171	0.7904
TSA	0.5179	0.4885	0.5121	0.4068	0.4779	0.8794	0.3602	0.3333
TO	1	1	1	0.9971	1	0.9732	1	1
TTF	0.8536	0.8255	0.9067	0.8794	0.9067	0.8794	0.8578	0.8413
TTA	0.5901	0.6172	0.8324	1	0.9430	1	1	1
TCF	0.6974	0.7338	0.8210	0.8313	0.7342	0.6816	0.7726	0.7119
TCA	0.9170	0.8161	0.7211	0.6855	0.7842	0.8201	0.9518	0.7802
AFI	1	1	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
GRD	0.9184	0.8856	0.8126	0.7286	0.7616	0.8607	0.7269	0.6577
Order	1	2	4	6	5	3	7	8

Note: gray relational degree (GRD).

Table 10
Sensitivity analysis of *SS*.

TSL	*SS*	TSF	TSA	TC	AFI	TO
2000	1.1	261.16	11 435.13	24 114	0.39	0
	1.3	227.28	9379.31	25 018	0.36	0
	1.6	227.28	8820.21	24 249	0.42	0
	1.8	227.28	8341.08	24 497	0.43	0

Table 11
Sensitivity analysis of *TSL*.

TSL	TSF	TSA	TC	AFI	TO
1000	297.58	10 508.26	21 999	0.29	0
1500	227.28	9058.34	24 934	0.36	0
2000	227.28	8341.08	24 497	0.43	0

Table 12
Sensitivity analysis of blood demand fluctuation.

Parameter	Fluctuation degree	TSF	TSA	TC	AFI	TO
$SS = 1.8$ $TSL = 2000$	20%	617.24	11 617.5	28 106	0.49	0
	10%	422.26	10 097.92	23 577	0.46	0
	5%	368.04	9854.33	24 558	0.45	0

Table 13
Sensitivity analysis of *TSL* under drastic fluctuation of demand.

Parameter	*TSL*	TSF	TSA	TC	AFI	TO
$SS = 1.8$ 20%	1000	765.54	15 169.45	23 840	0.35	0
	1500	617.24	11 901.49	27 798	0.49	0
	2000	617.24	11 617.5	28 106	0.49	0

Table 14
Sensitivity analysis of *SS* under drastic demand fluctuation.

Parameter	*SS*	TSF	TSA	TC	AFI	TO
TSL = 1500 20%	1.3	617.25	11 979.22	27 650	0.45	0
	1.6	617.25	11 901.5	27 798	0.49	0
	1.8	617.24	11 901.49	27 798	0.49	0
TSL = 2000 20%	1.3	617.25	13 310.4	26 572	0.41	0
	1.6	628.06	11 935.88	27 553	0.45	0
	1.8	67	10 601.87	55 863.77	0.49	0

5. Conclusion

This paper investigates the decision-making problem of blood supply chain considering the lifetime distribution of blood products under uncertain supply and demand environment. A simulation method of blood supply chain decision-making based on DESS is established. In the simulation process, blood collection decision, blood allocation decision and blood transshipment decision are integrated. This paper proposes an EWA inventory strategy and designs a sensitivity analysis tool for some key inventory parameters. The main contributions of this paper are as follows: (1) in order to minimize the transshipping time and maximize the freshness of the delivered blood, an optimization model of transshipment is established to study the decision-making rules of transshipment amount. (2) With the goal of the best fairness and the minimum shortage, an allocation planning model with multi-priority is established. (3) Based on the indexes of blood shortage, outdating and the fairness index, we compare and analyze different inventory strategies, and find that EWA inventory strategy is the best strategy. (4) Sensitivity analysis experiment shows that *SS*, *TSL* and fluctuation range of demand have important influence on the effect of blood inventory control. Various kinds of random events that may occur should be repeatedly simulated and tested, and then reasonable inventory control parameters should be determined according to the actual needs.

The substitution problem of blood groups under extreme shortage situation should be considered, and the boundary conditions and optimization schemes of different blood group substitution strategies in the dynamic decision-making process of blood supply chain should be studied in further research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. The process of equivalency proof of chance constraint

Blood center demand D_o is the aggregate demand of the hospital, that is

$$D_o^k = \sum_{h\in H} d_h^A + \sum_{h\in H} d_h^F = \sum_{h\in H} fd_h + \sum_{h\in H} rd_h, h = 1, 2, \ldots, n \tag{A.1}$$

Among them,

$$\sum_{h\in H} fd_h = \sum_{h\in H} d_{he}^A + \sum_{h\in H} d_{hs}^A + \sum_{h\in H} d_{he}^F + \sum_{h\in H} d_{hs}^F, h = 1, 2, \ldots, n \tag{A.2}$$

$$\sum_{h\in H} rd_h = \sum_{h\in H} d_{hg}^A + \sum_{h\in H} d_{hg}^F, h = 1, 2, \ldots, n \tag{A.3}$$

$$d_{hg}^F \sim N(\overline{d}_{hg}^F, (\sigma_{hg}^F)^2), \ \forall h = 1, 2, \ldots, n \tag{A.4}$$

$$d_{hg}^A \sim N(\overline{d}_{hg}^A, (\sigma_{hg}^A)^2), \ \forall h = 1, 2, \ldots, n \tag{A.5}$$

Then D_o also follows the normal distribution.

$$D_o \sim N(\sum_{h\in H} d_{he}^A + \sum_{h\in H} d_{hs}^A + \sum_{h\in H} d_{he}^F + \sum_{h\in H} d_{hs}^F + \sum_{h\in H} \overline{d}_{hg}^F + \sum_{h\in H} \overline{d}_{hg}^A, \sum_{h\in H} (\sigma_{hg}^F)^2 + \sum_{h\in H} (\sigma_{hg}^A)^2) \tag{A.6}$$

Theorem 1. *Suppose that function $g(x, \xi)$ has the form $g(x, \xi) = a_1x_1 + a_2x_2 + \cdots + a_nx_n - b$, where $\xi = (a_1, a_2, \ldots, a_n, b)$, a_i and b are independent normal distribution random variables, $i = 1, 2, \ldots, n$, then the equivalent form of chance constraint $\Pr\left\{\sum_{i=1}^n a_ix_i \le b\right\} \ge \alpha$ is $\sum_{i=1}^n E(a_i)x_i + \Phi^{-1}(\alpha)\sqrt{\sum_{i=1}^n V(a_i){x_i}^2 + V(b)} \le E(b)$, where Φ^{-1} is the inverse function of probability distribution function of standard normal distribution.*

Corollary. *If the constraint condition of the above model is at least true with the confidence level α, i.e. $P\left\{\sum_b \sum_m B_{bm} \le \lambda(D_o - IP_o)\right\} \ge \alpha$, then applying the above theorem, it can be transformed into the form of $\sum_b \sum_m B_{bm} \le \lambda(\sum_{h\in H} d_{he}^A + \sum_{h\in H} d_{hs}^A + \sum_{h\in H} d_{he}^F + \sum_{h\in H} d_{hs}^F + \sum_{h\in H} \overline{d}_{hg}^F + \sum_{h\in H} \overline{d}_{hg}^A - IP_o) - \lambda\Phi^{-1}(\alpha)\sqrt{\sum_{h\in H}(\sigma_{hg}^F)^2 + \sum_{h\in H}(\sigma_{hg}^A)^2}$.*

It can be proved as following.

$$\text{hypothesis}\, \lambda(D_o - IP_o) \sim N\left(\begin{array}{l}\lambda(\sum_{h\in H} d_{he}^A + \sum_{h\in H} d_{hs}^A + \sum_{h\in H} d_{he}^F + \sum_{h\in H} d_{hs}^F + \sum_{h\in H} \overline{d}_{hg}^F + \sum_{h\in H} \overline{d}_{hg}^A - IP_o) \\ , \lambda^2\left(\sum_{h\in H}(\sigma_{hg}^F)^2 + \sum_{h\in H}(\sigma_{hg}^A)^2\right)\end{array}\right),$$

Then $y(x) = \sum_b \sum_m B_{bm} - \lambda(D_o - IP_o)$ obeys the normal distribution, and its expectation is:

$$\begin{aligned} E(y(x)) &= \sum_b \sum_m B_{bm} - E(\lambda(D_o - IP_o)) \\ &= \sum_b \sum_m B_{bm} - \lambda(\sum_{h\in H} d_{he}^A + \sum_{h\in H} d_{hs}^A + \sum_{h\in H} d_{he}^F + \sum_{h\in H} d_{hs}^F + \sum_{h\in H} \overline{d}_{hg}^F + \sum_{h\in H} \overline{d}_{hg}^A - IP_o) \end{aligned} \tag{A.7}$$

The variance was as follows:

$$V(y(x)) = \lambda^2\left(\sum_{h\in H}(\sigma_{hg}^F)^2 + \sum_{h\in H}(\sigma_{hg}^A)^2\right) \tag{A.8}$$

So,

$$\begin{aligned} \eta = &\frac{\left[\sum_b \sum_m B_{bm} - \lambda(D_o - IP_o)\right]}{\lambda\sqrt{\sum_{h\in H}(\sigma_{hg}^F)^2 + \sum_{h\in H}(\sigma_{hg}^A)^2}} \\ &- \frac{\left[\sum_b \sum_m B_{bm} - \lambda(\sum_{h\in H} d_{he}^A + \sum_{h\in H} d_{hs}^A + \sum_{h\in H} d_{he}^F + \sum_{h\in H} d_{hs}^F + \sum_{h\in H} \overline{d}_{hg}^F + \sum_{h\in H} \overline{d}_{hg}^A - IP_o)\right]}{\lambda\sqrt{\sum_{h\in H}(\sigma_{hg}^F)^2 + \sum_{h\in H}(\sigma_{hg}^A)^2}} \sim N(0, 1) \end{aligned} \tag{A.9}$$

The inequality $\sum_b \sum_m B_{bm} \le \lambda(D_o - IP_o)$ is equivalent to:

$$\begin{aligned}
\eta &= \frac{\left[\sum_b \sum_m B_{bm} - \lambda(D_o - IP_o)\right]}{\lambda\sqrt{\sum_{h\in H}(\sigma^F_{hg})^2 + \sum_{h\in H}(\sigma^A_{hg})^2}} \\
&- \frac{\left[\sum_b \sum_m B_{bm} - \lambda(\sum_{h\in H} d^A_{he} + \sum_{h\in H} d^A_{hs} + \sum_{h\in H} d^F_{he} + \sum_{h\in H} d^F_{hs} + \sum_{h\in H} \overline{d}^F_{hg} + \sum_{h\in H} \overline{d}^A_{hg} - IP_o)\right]}{\lambda\sqrt{\sum_{h\in H}(\sigma^F_{hg})^2 + \sum_{h\in H}(\sigma^A_{hg})^2}} \\
&\le - \frac{\left[\sum_b \sum_m B_{bm} - \lambda(\sum_{h\in H} d^A_{he} + \sum_{h\in H} d^A_{hs} + \sum_{h\in H} d^F_{he} + \sum_{h\in H} d^F_{hs} + \sum_{h\in H} \overline{d}^F_{hg} + \sum_{h\in H} \overline{d}^A_{hg} - IP_o)\right]}{\lambda\sqrt{\sum_{h\in H}(\sigma^F_{hg})^2 + \sum_{h\in H}(\sigma^A_{hg})^2}}
\end{aligned} \tag{A.10}$$

So the chance constraint $P\left\{\sum_b \sum_m B_{bm} \le \lambda(D_{om} - IP_{om})\right\} \ge \alpha$ is equivalent to:

$$P\left\{\eta \le - \frac{\left[\sum_b \sum_m B_{bm} - \lambda(\sum_{h\in H} d^A_{he} + \sum_{h\in H} d^A_{hs} + \sum_{h\in H} d^F_{he} + \sum_{h\in H} d^F_{hs} + \sum_{h\in H} \overline{d}^F_{hg} + \sum_{h\in H} \overline{d}^A_{hg} - IP_o)\right]}{\lambda\sqrt{\sum_{h\in H}(\sigma^F_{hg})^2 + \sum_{h\in H}(\sigma^A_{hg})^2}}\right\} \ge \alpha \tag{A.11}$$

where η obeys the standard normal distribution, so the above chance constraint holds if and only if

$$\Phi^{-1}(\alpha) \le - \frac{\sum_b \sum_m B_{bm} - \lambda(\sum_{h\in H} d^A_{he} + \sum_{h\in H} d^A_{hs} + \sum_{h\in H} d^F_{he} + \sum_{h\in H} d^F_{hs} + \sum_{h\in H} \overline{d}^F_{hg} + \sum_{h\in H} \overline{d}^A_{hg} - IP_o)}{\lambda\sqrt{\sum_{h\in H}(\sigma^F_{hg})^2 + \sum_{h\in H}(\sigma^A_{hg})^2}} \tag{A.12}$$

The results are as follows:

$$\begin{aligned}
\sum_b \sum_m B_{bm} \le{}& \lambda(\sum_{h\in H} d^A_{he} + \sum_{h\in H} d^A_{hs} + \sum_{h\in H} d^F_{he} + \sum_{h\in H} d^F_{hs} + \sum_{h\in H} \overline{d}^F_{hg} + \sum_{h\in H} \overline{d}^A_{hg} - IP_o) \\
&- \lambda\Phi^{-1}(\alpha)\sqrt{\sum_{h\in H}(\sigma^F_{hg})^2 + \sum_{h\in H}(\sigma^A_{hg})^2}
\end{aligned} \tag{A.13}$$

The proof is over.

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