Personalized Multi-Stage Decision Support in Reverse Logistics Management

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Abstract. Reverse logistics has gained increasing importance as a profitable and sustainable business strategy. As a reverse logistics chain has strong internal and external linkages, the management of a reverse logistics chain becomes an area of organizational competitive advantage, in particular, with the growth of e-commerce applications. To effectively manage a reverse logistics chain always involves a decision optimization issue in which uncertain information, individual situation, multiple criteria and dynamic environment all need to be considered. This paper addresses the need of supporting reverse logistics managers in selecting an optimal alternative for goods return under their business objectives. Through analyzing the characteristics of reverse logistics chain, this paper proposes a personalized multi-stage decision-support model for reverse logistics management. It then presents a personalized fuzzy multi-criteria decision-making approach to assist managers to lead and control the reverse logistics within an uncertain and dynamic system.

1 Introduction

During the last decade many companies have realized that the opportunity to improve operations lies largely with procurement, distribution and logistics–the supply chain. As companies are increasing their levels of outsourcing, buying goods or services instead of producing or providing them by themselves, they are therefore spending increasing amounts on supply related activities. Logistics is one of the key elements of supply chain management [14, 17]. It refers to decide the best way of the movement of goods within a facility [12]. Logistics has become a hot competitive advantage as companies struggle to get the right stuff to the right place at the right time.

There are two logistics channels in a supply chain system of a company. Forward logistics channel concerns the movement of goods from source to the point of consumption. A backward movement can be happened to return goods to suppliers called reverse logistics [2, 10]. Forward logistics usually brings profit to all operational departments involved, while reverse logistics usually cannot. Some companies even perceive goods return as failure of their

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operations. However, the high rate of goods return from online purchases, the increasing environmental regulations and standards, and the growing consumer awareness of recycling have brought a need to rethink the significance of reserve logistics [15]. Some reports have shown that companies trying to hide from the significance of reverse logistics miss tremendous profit making opportunities [5, 6]. The reason is that companies can use reverse logistics as an opportunity for maintaining customer support, building good customer relationship and reach the ultimate business objective of profitability [14]. Moreover, many companies have discovered that effective management for a reverse logistics chain such as the reductions in inventory carrying costs, transportation costs and waste disposal costs can be also substantial with the supply chain program [13]. Companies like IBM, HP have tailored reverse logistics to their industry with it [7].

To effectively manage a reverse logistics chain involves finding the best way of movement of goods by evaluating a number of alternatives of goods return disposals under a set of business objectives. In the evaluation, a set of criteria are as constraints, such as buyer's demand, vendors' quota flexibility, repairer's capacity, purchase and repair values of the returned items, and time [3, 11]. In principle, this is a multi-criteria decision-making problem. However, there are several issues to result in a normal multi-criteria decision-making approach that cannot effectively support the decision-making in such reverse logistics management:

1. Multi-stage and dynamic: A reverse logistics chain involves a series of stages (operational functions). All the stages involved in the chain are interrelated in a way that a decision made at one stage affects the performance of next stages. That is, the decision objective(s) and alternatives at each stage (except the first one) are dynamically affected by the decision(s) made in previous stages/functions. A normal multi-criteria decision-making approach is not able to handle the multi-stage dynamic decision feature.
2. Personalization: Managers at different service stations of a reverse logistics chain making decisions are based on different evaluation criteria and different alternatives. For example, the alternatives to deal with a goods return in a collection station are totally different from one in a redistribute station. Managers at different stations need a personalized decision support, while the normal multi-criteria approach could hardly support such "personalized" decision-making of reverse logistics managers.
3. Uncertainty and imprecision: In practice, reverse logistics managers often imprecisely know the values of related constraints and evaluation criteria in selecting an optimal alternative. For example, they can only estimate inventory carrying costs and transportation costs of a particular set of goods to be returned. Also, the evaluation for any alternative of a goods return, logistics managers need assigning values for a number of selection criteria descriptors according to his/her specialized experience. These values assigned are often in linguistic terms, such as "high reusability", "low

reusability" for a set of goods to be returned. Obviously, the normal multi-criteria decision-making approach is not efficient to solve these problems in which uncertain information and imprecise linguistic expressions are involved.

This study aims to propose a decision-making approach which extends a normal multi-criteria approach to effectively handle the three issues: multi-stage, personalization, and uncertainty in reverse logistics management. This paper is organized as follows. Section 2 analyses the main operational functions in a reverse logistics chain and summarizes the characteristics of decision making in selecting the best way to handle goods return. A personalized multi-stage decision support model for reverse logistics management is established. Based on this established model, Sect. 3 proposes a personalized fuzzy multi-criteria decision-making approach which takes the form of optimizing procedures to provide an optimal way for logistics managers through evaluating related alternatives at any stage of a reverse logistic chain. A case-study example illustrates the power and details of the proposed approach in Sect. 4. Finally, a conclusion and future research plan are given in Sect. 5.

2 A Reverse Logistics Decision Support Model

This section firstly analyses the composition of a reverse logistics chain and the characteristics of goods return decision-making. It then presents a personalized multi-stage reverse logistics decision support model.

2.1 Reverse Logistics Chain

It is easy to think of logistics as managing the flow of products from the point of the view of the raw material acquisition to end customers. But the life of a product, from a logistics viewpoint, does not end with delivery to the end customer [1]. For many companies there is a reverse logistics chain that must be managed as well. Products may become obsolete, damaged or non-functioning and therefore need to be returned to their source points for repair or disposition. This procedure forms a reverse logistics chain. The reverse logistics chain may utilize all or some stages of the forward logistics chain or require a separate design, and terminates with the final disposition of a product. As a fairly new concept, a company's supply chain consists of both forward logistics and reverse logistics. The European working group on reverse logistics puts forward the following definition of reverse logistics including the goal and the process involved: "the process of planning, implementing and controlling flows of raw materials, in process inventory, and finished goods, from a manufacturing, distribution or use point to a point of recovery or point of proper disposal."

A reverse logistics chain involves a series of stages, each concerns a kind of activities associated with the management of goods (can be products, materials or components) return, with different facilities. These stages/facilities are interrelated in a way that a decision made at previous stage affects the decision making in the following stages. In general, the stages of a reverse logistics chain typically includes collection, combined testing/sorting/inspection/separation process, reprocessing/repairing or direct recovery and redistribution/resale/ reusing or disposal which can be also happened with other operational functions such as testing [2, 16]. As shown in Fig. 1, Supply, Manufacture, Distribution and Consumer form a flow of forward logistics. A reverse logistics flow has a backward movement from ‘Consumer” to “Supply.” Stage “Collection” refers to all activities rendering goods to be returned available and physically moving them to some point where a further treatment is taken care of. Testing (or inspection) determines whether collected goods are in fact reusable or how much work needs to be paid in order to make it usable. Sorting (or separation) decides what to do with each or a set of collected goods, including reprocessing and disposal. Thus, testing and sorting will result in splitting the flow of collected goods according to distinct treatment options. Reprocessing means the actual transformation of returned goods into usable products again. The transformation may take different forms including recycling, reconditioning, and remanufacturing. Disposal could be an option at this stage as well. Redistribution refers to directing reusable products to a potential reuse market and to physically moving them to future end customers. Therefore, the reverse logistics can simply be just reselling a product, or can be accompanies by a series of processes, as shown in Fig. 1, from collection to reuse or disposal [2, 16].

The important degrees of these operational functions are different in a goods return. Some functions may play more important roles than others for a particular goods return. The degree of importance of each operational

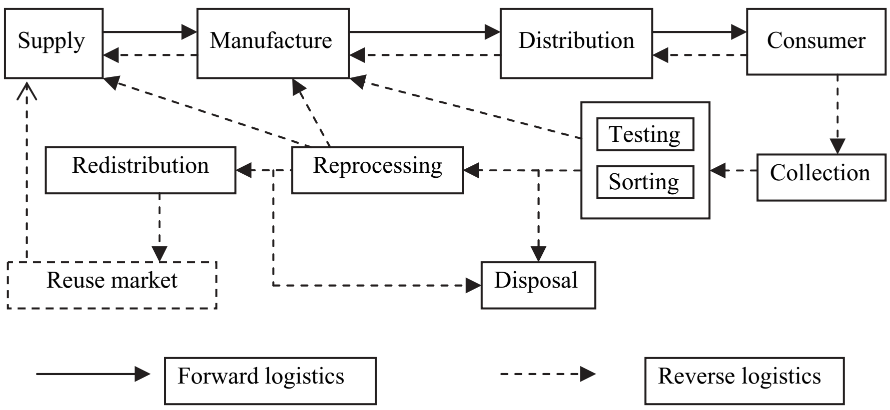

Fig. 1. Forward logistics chain and reverse logistics chain

function is also variable for different goods returns. This variance is mainly dependent on the business objective of the reverse logistics management. For example, if the business objective of a company's reverse logistics management is to provide customer services in warranties, then the function of "collection" may play a more important role in the reverse logistics chain than the reprocessing for the disassembly of products. If the business objectives is more environmentally related such as "reclaiming parts", the function of "sorting" may be more important. For a particular reverse logistics flow, some operation functions may not appear. For example, "reuse market" will not appear for many kinds of goods returned.

2.2 Characteristics of Goods Return Decision Making

There are several kinds of actors involved in reverse logistics activities in practice. They are independent intermediaries, specific recovery companies, reverse logistics service providers, municipalities taking care of waste collection, and public-private foundations created to take of goods recovery. The aims of different kinds of actors in a reverse logistics chain are different. For example, a manufacture may do recycling in order to prevent jobbers reselling its products at a lower price, while a collector may collect used products in order to establish a long-term customer relationship. These actors can also be logically differentiated into returners, receivers, collectors, processors and sales persons based on the features of their roles in a reverse logistics chain [2, 9]. The most important type of actors is "returner" as any stage can be a returner, including customers, in the whole reverse logistics chain, hence suppliers, manufactures, wholesalers and retailers.

Returners, at any operational stage of a reverse logistics chain, always need to decide how to best move current returned goods such as to return it to a factory for repairing or disposal it locally. Returners at different stages or at the same stage but with different goods returns may have different alternatives and different selection criteria to find the best way from these alternatives. For example, at the stage of "collection", the decision is mainly about planning and scheduling of recovery operations, and the transportation and the warehousing of returns have to be dealt with. At the stage of "sorting", returners need to determine whether or not to do recovery and which type of recovery if do. The recovery options are thus taken into account and judged. The decisions for a goods return at a previous stage will become constraints given for and impact directly on the decision activities of its following stages. For example, when one product is identified to be not usable any other decisions on storage, treatment, transportation for reusing process are not considerable except transportation for disposing processed wastes. Therefore, every decision has to bear the impact on the decisions at its previous stages.

Table 1. Example of relationships among returners' types, their business objectives and alternatives in a reverse logistics chain

Returner Types	Business Objectives (O)	Alternatives (A)
Collector	Maximizing customer relationship Minimizing customer service cost in warranties	Replacement Local storage Customer postal
Tester/Sorter	Minimizing total operational cost Maximizing customer relationship Maximizing satisfying environmental regulation	Recycling Remanufacturing Reuse Disposal
Processor	Minimizing total operational cost Maximizing customer services in warranties of repair	Local remanufacturing Recycling Disposal
Redistributor	Maximizing business profit Maximizing reclaiming parts Minimizing time	Resale Disposal Storage

The following characteristics have been seen through the above analysis:

1. reverse logistics management involves decision making at multiple stages;
2. decisions made at different stages are based on different alternatives and selection criteria;
3. at each stage, returners' business objectives, related alternatives and evaluation criteria are dynamic changed. The change is caused by both the features of returned goods and the actions of previous functions of the reverse logistics chain. The analysis reminds a personalized multi-stage decision support model to help the selection of the best way to handle a goods return in a reverse logistics chain.

In order to build the model, two sets of relationships have to be discussed. One is the dependence relationship between business objectives and alternatives, and the other is between business objectives and selection criteria.

Based on Fig. 1, returners can be classified into four basic types: collector, tester/sorter, processor, and redistributor, as shown in Table 1. The four types of returners are at four main functional stages of a reverse logistics chain respectively. For each type of returners, possible business objectives are shown in the column two of Table 1. Once a returner's business objectives for a particular goods return are determined, a set of alternatives can be identified. For example, two business objectives of a collector are to maximize customer relationship and to minimize customer services cost in warranties. Related alternatives are thus recycling, reconditioning and disposal as shown in the column three of Table 1. However, different companies may set up different

Table 2. Example of relationships among business objectives, selection criteria and related items in a reverse logistics chain

Objectives (O)	Selection Criteria (C)	Related Items
Minimizing total operational cost	Cost	Collection cost, storage cost, treatment cost, transportation cost for reusing processed wastes, transportation cost for disposing processed wastes, repair cost
Minimizing customer services in warranties	Time	Collecting time, treatment time, and transportation time
Maximizing customer relationship	Customer satisfaction	Product life stages (Introduction; Growth; Maturity; Decline) Time Usability
Maximizing business profit	Benefit Cost	Reusability Resale income Repair cost Transportation cost Redistribute cost

business objectives and related different alternatives for each type of returners. Related data can be obtained through data mining and other methods.

To evaluate these alternatives, a number of selection criteria are set up. Each criterion is described by one or more related items which are strongly dependent on the corresponded business objectives. For example, when a company's business objective for a goods return is to minimize customer services in warranties, time including collect time, treatment time and transportation time, is the only assessment item for selection of a solution from related alternatives. Table 2 lists the possible business objectives, related selection criteria and involved assessment items. Same as Table 1, different companies may set up different criteria for the same business objective.

2.3 A Personalized Multi-stage Decision Support Model

Figure 2 shows the proposed personalized multi-stage decision support model. This model describes a whole decision-making process of a returner at any stage of a reverse logistics chain. In the model, when a returner's type is known, its business objectives can be identified based on the relationships shown in Table 1. After business objectives are determined, the returner is allowed to indicate a weight for each objective based on individual experience and knowledge. Related alternatives are then determined based on the relationships shown in Table 1 as well. As the alternatives of a goods return decision are totally related to its business objectives, when an objective's

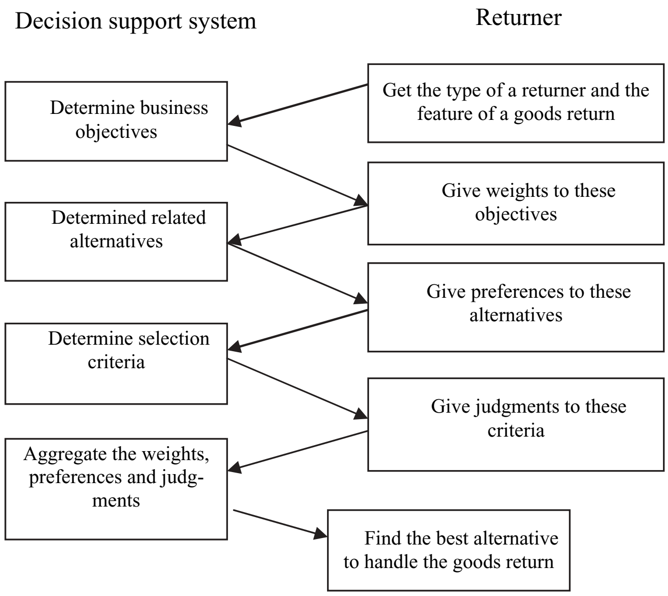

Fig. 2. A personalized multi-stage decision support model of reverse logistics management

weight is very low, its related alternatives and selection criteria will not be considered. To evaluate these alternatives, a set of selection criteria is determined based on information shown in Table 2. The types of returners and their preferences for business objectives may result in different sets of alternatives. Obviously, this decision process involves multiple layers of relationships: from the type of a returner to determining its business objectives, and then alternatives and finally selection criteria. This process has a personalized feature as each individual logistic manager may have a set of individual alternatives and individual preferences for assessing these alternatives with a particular set of goods return.

Uncertainty and imprecision are involved in the model. In practice, returners often describe and measure the degree of weights and their preferences in linguistic terms, such as "preferable" and "not really", "high" or "low" since a numerical evaluation is sometimes unacceptable. These linguistic terms are obviously with uncertainties [8]. Each criterion may involve a number of related selection items, estimation of these items' values is needed and these estimated values are often with imprecision. For example, when minimizing the total operational cost is the business objective of a goods return at an operational stage, five major time-varying cost items may need to be estimated and measured: collection cost, storage cost, treatment cost, transportation cost for reusing processed wastes, and transportation cost for disposing processed wastes [10]. All these estimations and measures often involve imprecise values.

The uncertainty and imprecision features will affect on the processing of a decision evaluation. When several layers of a goods return decision evaluation are synthesized into an aggregated result, that is, the weights of business objectives will be combined with the preferences of related criteria to selection alternatives, the uncertainty and imprecision features will be integrated into the final outcome, an optimal plan, for the particular goods to be returned. Therefore, the uncertainty issue has to be in the proposed decision-making approach.

3 A Personalized Fuzzy Multi-Criteria Decision-Making Approach for Reverse Logistics Management

As uncertainty is incorporated in the personalized multi-stage goods return decision process, the proposed decision-making approach must take into account the presentation and processing of imprecise information, and deal with its personalization and multi-stage issues at the same time. This section gives a personalized fuzzy multi-criteria decision-making approach to handle the three features for reverse logistics management problems.

3.1 Preliminaries of Fuzzy Sets

This section briefly reviews some basic definitions and properties of fuzzy sets from [18, 21, 22, 24]. These definitions and notations will be used throughout the paper until otherwise stated.

Let $F*(R)$ be the set of all finite fuzzy numbers on R. By the decomposition theorem of fuzzy set, we have

$$\tilde{a} = \bigcup_{\lambda \in (0,1]} \lambda[a_\lambda^L, a_\lambda^R] \,, \tag{1}$$

for every $\tilde{a} \in F(R)$.

Definition 1. *If $\tilde{a}$ is a fuzzy number and $a_\lambda^L > 0$ for any $\lambda \in (0,\ 1]$, then $\tilde{a}$ is called a positive fuzzy number. Let $F_+^*(R)$ be the set of all finite positive fuzzy numbers on R.*

Definition 2. *For any $\tilde{a},\ \tilde{b} \in F_+^*(R)$ and $0 < \lambda \in R$, the sum, scalar product and product of two fuzzy numbers $\tilde{a} + \tilde{b}, \lambda\tilde{a}$ and $\tilde{a} \times \tilde{b}$ are defined by the membership functions*

$$\mu_{\tilde{a}+\tilde{b}}(t) = \sup \min_{t=u+v} \{\mu_{\tilde{a}}(u), \mu_{\tilde{b}}(v)\} \,, \tag{2}$$

$$\mu_{\lambda\tilde{a}}(t) = \max\{0, \sup_{t=\lambda u} \mu_{\tilde{a}}(u)\} \,, \tag{3}$$

$$\mu_{\tilde{a}\times\tilde{b}}(t) = \sup \min_{t=u\times v} \{\mu_{\tilde{a}}(u),\ \mu_{\tilde{b}}(v)\} \,. \tag{4}$$

where we set $\sup\{\phi\} = -\infty$.

Theorem 1. *For any* $\tilde{a},\ \tilde{b} \in F_+^*(R)$ *and* $0\ <\ \alpha \in R$,

$$\tilde{a}+\tilde{b} = \bigcup_{\lambda\in(0,1]} \lambda\left[a_\lambda^L + b_\lambda^L,\ a_\lambda^R + b_\lambda^R\right],$$
$$\alpha\tilde{a} = \bigcup_{\lambda\in(0,1]} \lambda\left[\alpha a_\lambda^L,\ \alpha a_\lambda^R\right],$$
$$\tilde{a}\times\tilde{b} = \bigcup_{\lambda\in(0,1]} \lambda\left[a_\lambda^L \times b_\lambda^L,\ a_\lambda^R \times b_\lambda^R\right].$$

Definition 3. *For any* $\tilde{a} \in F_+^*(R)$ *and* $0 < \alpha \in Q_+$ *(Q_+ is a set of all positive rational numbers), the positive fuzzy number* $\tilde{a}$ *power of* λ *is defined by the membership function*

$$\mu_{\tilde{a}^\alpha}(t) = \sup \min_{t=u^\alpha}\{\mu_{\tilde{a}(u)}\} \tag{5}$$

where we set $\sup\{\phi\} = -\infty$.

Theorem 2. *For any* $\tilde{a} \in F_+^*(R)$ ***and*** $0\ <\ \alpha \in Q_+$,

$$\tilde{a}^\alpha = \bigcup_{\lambda\in(0,1]} \lambda\left[\left(a_\lambda^L\right)^\alpha,\ \left(a_\lambda^R\right)^\alpha\right].$$

Definition 4. *Let* $\tilde{a}$ *and* $\tilde{b}$ *be two fuzzy numbers. Then* $\tilde{a} = \tilde{b}$ *if* $a_\lambda^L = b_\lambda^L$ *and* $a_\lambda^R = b_\lambda^R$ *for any* $\lambda \in (0,1]$.

Definition 5. *If* $\tilde{a}$ *is a fuzzy number and* $0 < a_\lambda^L \le a_\lambda^R \le 1$, *for any* $\lambda \in (0,\ 1]$, *then* $\tilde{a}$ *is called a normalized positive fuzzy number.*

Definition 6. *A linguistic variable is a variable whose values are linguistic terms.*

Definition 7. *Let* $\tilde{a},\ \tilde{b} \in F^*(R)$, *then the quasi-distance function of* $\tilde{a}$ *and* $\tilde{b}$ *is defined as*

$$d(\tilde{a},\tilde{b}) = \left(\int_0^1 \frac{1}{2}\left[\left(a_\lambda^L - b_\lambda^L\right)^2 + \left(a_\lambda^R - b_\lambda^R\right)^2\right] d\lambda\right)^{\frac{1}{2}} \tag{6}$$

Definition 8. *Let* $\tilde{a},\ \tilde{b} \in F^*(R)$, *then fuzzy number* $\tilde{a}$ *is closer to fuzzy number* $\tilde{b}$ *as* $d(\tilde{a},\ \tilde{b})$ *approaches 0.*

Proposition 1. *If both* $\tilde{a}$ *and* $\tilde{b}$ *are real numbers, then the quasi-distance measurement* $d(\tilde{a},\ \tilde{b})$ *is identical to the Euclidean distance.*

Proposition 2. *Let* $\tilde{a},\ \tilde{b} \in F^*(R)$ *(1). If they are identical, then* $d(\tilde{a},\ \tilde{b}) = 0$.

2) If $\tilde{a}$ *is a real number or* $\tilde{b}$ *is a real number and* $d(\tilde{a},\ \tilde{b}) = 0$, *then* $\tilde{a} = \tilde{b}$.

Proposition 3. *Let* $\tilde{a},\ \tilde{b},\ \tilde{c} \in F^*(R)$, *then* $\tilde{b}$ *is closer to* $\tilde{a}$ *than* $\tilde{c}$ *if and only if* $d(\tilde{b},\tilde{a}) < d(\tilde{c},\tilde{a})$.

Proposition 4. *Let* $\tilde{a},\ \tilde{b} \in F^*(R)$. *If* $d(\tilde{a},0) < d(\tilde{b},0)$, *then* $\tilde{a}$ *is closer to 0 than* $\tilde{b}$.

3.2 Process of Personalized Fuzzy Multi-Criteria Decision-Making Approach for Reverse Logistics Management

Based on the model proposed in Sect. 2.3, we integrate the normal multi-criteria decision-making approach [19] and fuzzy number techniques [20] into our proposed personalized multi-stage decision model to accommodate the requirement of goods return decision-making in a reverse logistics chain, called the personalized fuzzy multi-criteria decision-making (PFMCDM) approach.

In this approach, we use any form of fuzzy numbers, called general fuzzy numbers, to handle linguistic terms and other uncertain values. The proposed approach is designed to include nine steps as follows:

Step 1. Setting up weights for business objectives and each objective's related evaluation criteria.

When a returner's type is identified, a set of business objectives $\boldsymbol{O} = \{\boldsymbol{O}_1,\ \boldsymbol{O}_2,\ \ldots,\ \boldsymbol{O}_n\}$are determined based on the information shown in Table 1. Let $WO = \{WO_1,\ WO_2,\ \ldots,\ WO_n\}$ be the weights of these objectives, $OW_i\ \in$\{*Absolutely not important, Strongly not important, Weakly not important, Medium important, Weakly more important, Strongly more important, Absolutely more important*\} and are described by general fuzzy numbers $a_1, a_2, \ldots a_n$. For an objective O_i, let $C_i = \{C_{i1},\ C_{i2}, \ldots,\ C_{it_i}\}, i = 1, 2, \ldots, n$, be a set of the selected criteria corresponding to the objective. Let $WC_i = \{WC_{i1},\ WC_{i2}, \ldots,\ WC_{it_i}\}, i = 1, 2, \ldots, n$, be the weights for the set of criteria, where $WC_{ij} \in$ \{*Absolutely not important, Strongly not important, Weakly not important, Medium important, Weakly more important, Strongly more important, Absolutely more important*\} and are described by general fuzzy numbers $c_1, c_2, \ldots c_t$. Both WO and WC_{ij} are given by reverse logistics decision makers.

Step 2. Finalizing the objectives and selection criteria by following rules

The objective (and its selection criteria) can be ignored when

(1) it has a very low weight;
(2) the degree of its weight is much less than others; or
(3) its related criteria is a subset of another selected objective's one.

Step 3. Setting up the relevance degree of each criterion on each alternative

Let $\boldsymbol{A} = \{\boldsymbol{A}_1, \boldsymbol{A}_2,\ \ldots,\ \boldsymbol{A}_m\}$ be a set of alternatives for a goods return decision, $AC_i^k = \{AC_{i1}^k,\ AC_{i2}^k, \ldots,\ AC_{it_i}^k\}$ be the relevance degree of $\boldsymbol{C}_i$ on alternatives $\boldsymbol{A}_k, i = 1, 2, \ldots, n, k = 1, 2, \ldots, m$, provided by returners, where $AC_{ij}^k\ \in$ \{*Very low, Low, Medium low, Medium, Medium high, High, Very high*\} and are described by general fuzzy numbers $b_1, b_2, \ldots, b_m$.

Step 4. Weight normalization

The weights for criteria are normalized based on $WC_i = \{WC_{i1}, WC_{i2}, \ldots, WC_{it_i}\}, i = 1, 2, \ldots, n, WC_{ij} \in \{a_j, j = 1, 2, \ldots 7\}$ and denoted as

$$WC_{ij}^* = \frac{WC_{ij}}{\sum_{j=1}^{t_i} WC_{ij0}^R}, \quad \text{for } i = 1, 2, \ldots,\ n,\ j = 1, 2,\ \ldots,\ t_i.$$

Step 5. Relevance degree calculation

To calculate the relevance degree OA_i^k of $\boldsymbol{O}_i$ on the alternatives $\boldsymbol{A}_k, i = 1, 2, \ldots, n, k = 1, 2, \ldots, m$, by using $OA_i^k = WC_i^* \times AC_i^k = \sum_{j=1}^{t_i} WC_{ij}^* \times AC_{ij}^k, i = 1, 2, \ldots, n, k = 1, 2, \ldots, m$.

Step 6. Relevance degree normalization

The relevance degree OA_i^k of $\boldsymbol{O}_i$ on the alternatives $\boldsymbol{A}_k, i = 1, 2, \ldots, n, k = 1, 2, \ldots, m$, are normalized based on $OA^k = \{OA_1^k,\ OA_2^k, \ldots,\ OA_n^k\}, k = 1, 2, \ldots, m$,

$$\overline{OA}_i^k = \frac{OA_i^k}{\sum_{i=1}^{n} OA_{i0}^{kR}}, \quad \text{for } i = 1, 2, \ldots, n, k = 1, 2, \ldots, m\ .$$

Step 7. Objective relevance degree calculation

Calculating the relevance degree S_k of $\boldsymbol{O}$ on alternatives $\boldsymbol{A}_k, k = 1, 2, \ldots, m$, by using $S_k = \overline{OA}^k \times WO = \sum_{j=1}^{t_i} \overline{OA}_i^k \times WO_i, k = 1, 2, \ldots, m$.

Step 8. The results $S_k, k = 1, 2, \ldots, m$ are normalized to be positive fuzzy numbers, and their ranges belong to the closed interval [0, 1]. We define fuzzy positive-ideal alternative (FPIS, S^*) and fuzzy negative-ideal alternative (FNIS, S^-) as:

$$S^* = 1 \quad \text{and} \quad S^- = 0.$$

The distance between each S_k and S^* is called a positive distance, and the distance between S_k and S^- is called a negative distance. The two kinds of distances are calculated respectively by

$d_k^* = d(S_k,\ S^*)$ and $d_k^- = d(S_k,\ S^-)$, $k = 1,\ 2,\ \ldots,\ m$, where

$$d(\tilde{a},\ \tilde{b}) = \left(\int_0^1 \frac{1}{2} \left[\left(a_\lambda^L - b_\lambda^L\right)^2 + \left(a_\lambda^R - b_\lambda^R\right)^2 \right] d\lambda \right)^{\frac{1}{2}}$$

is the distance measure between any two fuzzy numbers $\tilde{a},\ \tilde{b}$.

Step 9. A closeness coefficient is defined to determine the ranking order of alternatives once the d_k^* and d_k^- of each alternative A_k $(k = 1, 2, \ldots, m)$ are obtained. The closeness coefficient of each alternative is calculated as:

$$D_k = \frac{1}{2}(d_k^* + (1 - d_k^-)), \quad k = 1,\ 2, \ldots,\ m\ .$$

The alternative A_k that corresponds to the largest D_k, is the best suitable alternative for the particular goods return decision problem.

4 A Case-Study Example

This section gives an example to illustrate how to use the proposed approach to support goods return decision-making in reverse logistics management practice.

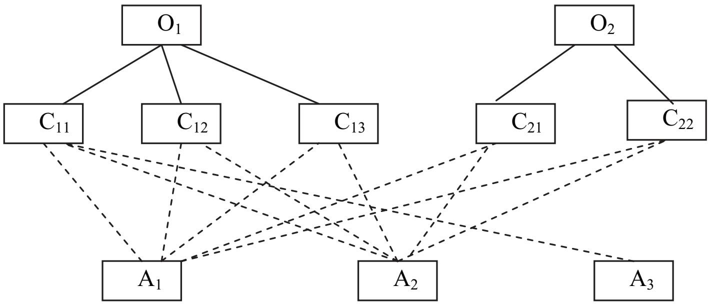

Fig. 3. An example of the interrelation among objectives, criteria and alternatives

A returner at the stage of collection for a reverse logistics chain needs to make a decision for a particular goods return. The returner has currently two objectives $\boldsymbol{O} = \{\boldsymbol{O}_1, \boldsymbol{O}_2\}$ and three alternatives $\boldsymbol{A} = \{\boldsymbol{A}_1, \boldsymbol{A}_2, \boldsymbol{A}_3\}$ for the goods return. The first objective can be evaluated by three criteria (C_{11}, C_{12}, C_{13}), and the second one can be evaluated by two criteria (C_{21}, C_{22}). The relationships among these business objectives, alternatives and evaluation criteria are shown in Fig. 3. By using the proposed approach, a solution from the alternatives which can maximally reach these business objectives will be selected.

As all linguistic terms provided by returners can be described by any kind of fuzzy numbers in the proposed approach, we assume that these linguistic terms are described by fuzzy numbers as shown in Table 3 and Table 4 respectively.

Table 3. An example of linguistic terms and related fuzzy numbers

Linguistic Terms	Fuzzy Numbers
Absolutely not important (ANI)	$\bigcup_{\lambda\in[0,\,1]} \lambda[0,\ \frac{\sqrt{1-\lambda}}{10}]$
Strongly not important (SNI)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{\lambda}}{10},\ \frac{\sqrt{9-8\lambda}}{10}]$
Weakly not important (WNI)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{8\lambda+1}}{10},\ \frac{\sqrt{25-16\lambda}}{10}]$
Medium important (MI)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{16\lambda+9}}{10},\ \frac{\sqrt{49-24\lambda}}{10}]$
Weakly more important (WI)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{24\lambda+25}}{10},\ \frac{\sqrt{81-32\lambda}}{10}]$
Strongly more important (SI)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{32\lambda+49}}{10},\ \frac{\sqrt{100-19\lambda}}{10}]$
Absolutely more important (AI)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{19\lambda+81}}{10},\ 1]$

Table 4. An example of linguistic terms and related fuzzy numbers

Linguistic Terms	Fuzzy Numbers
Very low (VL)	$\bigcup_{\lambda\in[0,\,1]} \lambda[0,\ \frac{\sqrt{1-\lambda}}{10}]$
Low (L)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{\lambda}}{10},\ \frac{\sqrt{9-8\lambda}}{10}]$
Medium low (ML)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{8\lambda+1}}{10},\ \frac{\sqrt{25-16\lambda}}{10}]$
Medium (M)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{16\lambda+9}}{10},\ \frac{\sqrt{49-24\lambda}}{10}]$
Medium high (MH)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{24\lambda+25}}{10},\ \frac{\sqrt{81-32\lambda}}{10}]$
High (H)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{32\lambda+49}}{10},\ \frac{\sqrt{100-19\lambda}}{10}]$
Very high (VH)	$\bigcup_{\lambda\in[0,\,1]} \lambda[\frac{\sqrt{19\lambda+81}}{10},\ 1]$

The power and details of the proposed approach for the goods return case study example are described as follows.
Step 1. A returner gives weights to O_1 and O_2, weights of C_{11}, C_{12} and C_{13} for O_1 and weights of $C_{21,}C_{22}$ for O_2 respectively:

$\boldsymbol{WO}$ = {*Strongly not important, Strongly more important*}
$\boldsymbol{WC}_1$ = {*Strongly not important, Strongly not important, Strongly more important*}
$\boldsymbol{WC}_2$ = {*Strongly not important, Strongly more important*}

Step 2. The two objectives and their criteria are finalized:

$\boldsymbol{WO}$ = {*Strongly not important, Strongly more important*}
$\boldsymbol{WC}_1$ = {*Strongly not important, Strongly not important, Strongly more important*}
$\boldsymbol{WC}_2$ = {*Strongly more important, Strongly not important*}

Step 3. The returner provides relevant degrees of C_{ij} on $A_{k.}$ $(k = 1, 2, 3)$:

$AC_1^1 = \{AC_{11}^1,\ AC_{12}^1,\ AC_{13}^1\} = \{$*Medium high, Low, High*$\}$
$AC_2^1 = \{AC_{21}^1,\ AC_{22}^1\} = \{$*Low, High*$\}$
$AC_1^2 = \{AC_{11}^2,\ AC_{12}^2,\ AC_{13}^2\} = \{$*High, Low, Medium high*$\}$
$AC_2^2 = \{AC_{21}^2,\ AC_{22}^2\} = \{$*Low, High*$\}$
$AC_1^3 = \{AC_{11}^3,\ AC_{12}^3,\ AC_{13}^3\} = \{$*High, High, Medium high*$\}$
$AC_2^3 = \{AC_{21}^3,\ AC_{22}^3\} = \{$*Low, High*$\}$

Step 4. The weights proposed in Step 1 are normalized.
Because $\sum_{j=1}^{3} WC_{1j0}^R = 1.6,\ \sum_{j=1}^{2} WC_{2j0}^R = 1.3$, we got

$$WC_{11}^* = WC_{12}^* = \bigcup_{\lambda\in[0,\,1]} \lambda \left[\frac{\sqrt{\lambda}}{16}, \frac{\sqrt{9-8\lambda}}{16}\right],$$

$$WC_{13}^* = \bigcup_{\lambda\in[0,\,1]} \lambda \left[\frac{\sqrt{32\lambda+49}}{16}, \frac{\sqrt{100-19\lambda}}{16}\right],$$

$$WC_{21}^* = \bigcup_{\lambda\in[0,\,1]} \lambda \left[\frac{\sqrt{\lambda}}{13}, \frac{\sqrt{9-8\lambda}}{13}\right],$$

$$WC_{22}^* = \bigcup_{\lambda\in[0,\,1]} \lambda \left[\frac{\sqrt{32\lambda+49}13}{,} \frac{\sqrt{100-19\lambda}}{13}\right].$$

Step 5. Calculating the relevance degree OA_i^k of $\boldsymbol{O}_i$ on alternatives $\boldsymbol{A}_k, i = 1, 2$ and $k = 1, 2, 3,$ we have

$$\begin{aligned} OA_1^1 &= WC_1^* \times AC_1^1 = \sum_{j=1}^{3} WC_{1j}^* \times AC_{1j}^1 \\ &= \bigcup_{\lambda\in[0,\,1]} \lambda\Bigg[\frac{\sqrt{\lambda(24\lambda+25)}}{160} + \frac{33\lambda+49}{160}, \\ &\quad \frac{\sqrt{(9-8\lambda)(81-32\lambda)}}{160} + \frac{109-27\lambda}{160}\Bigg] \end{aligned}$$

$$\begin{aligned} OA_2^1 &= WC_2^* \times AC_2^1 = \sum_{j=1}^{2} WC_{2j}^* \times AC_{2j}^1 \\ &= \bigcup_{\lambda\in[0,\,1]} \lambda\left[\frac{2\sqrt{\lambda\,(32\lambda+49)}}{130}, \frac{2\sqrt{(9-8\lambda)\,(100-19\lambda)}}{130}\right] \end{aligned}$$

$$\begin{aligned} OA_1^2 &= WC_1^* \times AC_1^2 = \sum_{j=1}^{3} WC_{1j}^* \times AC_{1j}^2 \\ &= \bigcup_{\lambda\in[0,\,1]} \lambda\Bigg[\frac{\sqrt{\lambda\,(32\lambda+49)}}{160} + \frac{32\lambda+49}{160} + \frac{\sqrt{(32\lambda+49)\,(24\lambda+25)}}{160}, \\ &\quad \frac{\sqrt{(9-8\lambda)\,(100-19\lambda)}}{160} + \frac{9-8\lambda}{160} + \frac{\sqrt{(100-19\lambda)\,(81-32\lambda)}}{160}\Bigg] \end{aligned}$$

$$\begin{aligned} OA_2^2 &= WC_2^* \times AC_2^2 = \sum_{j=1}^{2} WC_{2j}^* \times AC_{2j}^1 \\ &= \bigcup_{\lambda\in[0,\,1]} \lambda\left[\frac{2\sqrt{\lambda\,(32\lambda+49)}}{130}, \frac{2\sqrt{(9-8\lambda)\,(100-19\lambda)}}{130}\right] \end{aligned}$$

$$OA_1^3 = WC_1^* \times AC_1^3 = \sum_{j=1}^{3} WC_{1j}^* \times AC_{1j}^3$$

$$= \bigcup_{\lambda \in [0,\,1]} \lambda \left[\frac{2\sqrt{\lambda\,(32\lambda+49)}}{160} + \frac{\sqrt{(32\lambda+49)\,(24\lambda+25)}}{160}\,, \right.$$

$$\left. \frac{2\sqrt{(9-8\lambda)\,(100-19\lambda)}}{160} + \frac{\sqrt{(100-19\lambda)\,(81-32\lambda)}}{160} \right]$$

$$OA_2^3 = WC_2^* \times AC_2^3 = \sum_{j=1}^{2} WC_{2j}^* \times AC_{2j}^1$$

$$= \bigcup_{\lambda \in [0,\,1]} \lambda \left[\frac{2\sqrt{\lambda\,(32\lambda+49)}}{130},\ \frac{2\sqrt{(9-8\lambda)\,(100-19\lambda)}}{130} \right]$$

Step 6. Normalizing the relevance degree OA_i^k of $\boldsymbol{O}_i$ on the alternatives $\boldsymbol{A}_k$ based on $OA^k = \{OA_1^k,\ OA_2^k, \ldots,\ OA_n^k\}, i = 1, 2$ and $k = 1, 2, 3$.

$$\overline{OA}_1^1 = \bigcup_{\lambda \in [0,\,1]} \lambda \left[\frac{\sqrt{\lambda\,(24\lambda+25)}}{160 \times 1.3115} + \frac{33\lambda+49}{160 \times 1.3115}, \right.$$

$$\left. \frac{\sqrt{(9-8\lambda)\,(81-32\lambda)}}{160 \times 1.3115} + \frac{109-27\lambda}{160 \times 1.3115} \right]$$

$$\overline{OA}_2^1 = \bigcup_{\lambda \in [0,\,1]} \lambda \left[\frac{2\sqrt{\lambda\,(32\lambda+49)}}{130 \times 1.3115},\ \frac{2\sqrt{(9-8\lambda)\,(100-19\lambda)}}{130 \times 1.3115} \right]$$

$$\overline{OA}_1^2 = \bigcup_{\lambda \in [0,\,1]} \lambda \left[\frac{\sqrt{\lambda\,(32\lambda+49)}}{160 \times 1.2678} + \frac{32\lambda+49}{160 \times 1.2678} + \frac{\sqrt{(32\lambda+49)\,(24\lambda+25)}}{160 \times 1.2678}\,, \right.$$

$$\left. \frac{\sqrt{(9-8\lambda)\,(100-19\lambda)}}{160 \times 1.2678} + \frac{9-8\lambda}{160 \times 1.2678} + \frac{\sqrt{(100-19\lambda)\,(81-32\lambda)}}{160 \times 1.2678} \right]$$

$$\overline{OA}_2^2 = \bigcup_{\lambda \in [0,\,1]} \lambda \left[\frac{2\sqrt{\lambda\,(32\lambda+49)}}{130 \times 1.2678},\ \frac{2\sqrt{(9-8\lambda)\,(100-19\lambda)}}{130 \times 1.2678} \right]$$

$$\overline{OA}_1^3 = \bigcup_{\lambda \in [0,\,1]} \lambda \left[\frac{2\sqrt{\lambda\,(32\lambda+49)}}{160 \times 1.3990} + \frac{\sqrt{(32\lambda+49)\,(24\lambda+25)}}{160 \times 1.3990}\,, \right.$$

$$\left. \frac{2\sqrt{(9-8\lambda)\,(100-19\lambda)}}{160 \times 1.3990} + \frac{\sqrt{(100-19\lambda)\,(81-32\lambda)}}{160 \times 1.3990} \right]$$

$$\overline{OA}_2^3 = \bigcup_{\lambda \in [0,\,1]} \lambda \left[\frac{2\sqrt{\lambda\,(32\lambda+49)}}{130 \times 1.3990},\ \frac{2\sqrt{(9-8\lambda)\,(100-19\lambda)}}{130 \times 1.3990} \right].$$

Step 7. Calculating the relevance degree S_k of $\boldsymbol{O}$ on the alternatives $\boldsymbol{A}_k$ by using $S_k = \overline{OA}^k \times WO = \sum_{j=1}^{t_i} \overline{OA}_i^k \times WO_i, k = 1, 2, 3$.

$$
\begin{aligned}
S_1 = \overline{OA}^1 \times WO = & \bigcup_{\lambda \in [0,\ 1]} \lambda \Bigg[\frac{\sqrt{\lambda}}{10} \left(\frac{\sqrt{\lambda(24\lambda+25)}}{160 \times 1.3115} + \frac{33\lambda+49}{160 \times 1.3115} \right) \\
& + \frac{\sqrt{32\lambda+49}}{10} \times \frac{2\sqrt{\lambda(32\lambda+49)}}{130 \times 1.3115}, \frac{\sqrt{9-8\lambda}}{10} \\
& \times \left(\frac{\sqrt{(9-8\lambda)(81-32\lambda)}}{160 \times 1.3115} + \frac{109-27\lambda}{160 \times 1.3115} \right) + \frac{\sqrt{100-19\lambda}}{10} \\
& \times \frac{2\sqrt{(9-8\lambda)(100-19\lambda)}}{130 \times 1.3115} \Bigg] \\
S_2 = \overline{OA}^2 \times WO = & \bigcup_{\lambda \in [0,\ 1]} \lambda \Bigg[\frac{\sqrt{\lambda}}{10} \left(\frac{\sqrt{\lambda(32\lambda+49)}}{160 \times 1.2678} + \frac{32\lambda+49}{160 \times 1.2678} \right. \\
& \left. + \frac{\sqrt{(32\lambda+49)(24\lambda+25)}}{160 \times 1.2678} \right) + \frac{\sqrt{32\lambda+49}}{10} \times \frac{2\sqrt{\lambda(32\lambda+49)}}{130 \times 1.2678}, \\
& \frac{\sqrt{100-19\lambda}}{10} \times \frac{2\sqrt{(9-8\lambda)(100-19\lambda)}}{130 \times 1.2678} + \frac{\sqrt{9-8\lambda}}{10} \\
& \times \left(\frac{\sqrt{(9-8\lambda)(100-19\lambda)}}{160 \times 1.2678} + \frac{9-8\lambda}{160 \times 1.2678} \right. \\
& \left. + \frac{\sqrt{(100-19\lambda)(81-32\lambda)}}{160 \times 1.2678} \right) \Bigg] \\
S_3 = \overline{OA}^3 \times WO = & \bigcup_{\lambda \in [0,\ 1]} \lambda \Bigg[\frac{\sqrt{\lambda}}{10} \left(\frac{2\sqrt{\lambda(32\lambda+49)}}{160 \times 1.3990} \right. \\
& \left. + \frac{\sqrt{(32\lambda+49)(24\lambda+25)}}{160 \times 1.3990} \right) + \frac{\sqrt{32\lambda+49}}{10} \times \frac{2\sqrt{\lambda(32\lambda+49)}}{130 \times 1.3990}, \\
& \frac{\sqrt{100-19\lambda}}{10} \times \frac{2\sqrt{(9-8\lambda)(100-19\lambda)}}{130 \times 1.3990} + \frac{\sqrt{9-8\lambda}}{10} \\
& \times \left(\frac{2\sqrt{(9-8\lambda)(100-19\lambda)}}{160 \times 1.3990} + \frac{\sqrt{(100-19\lambda)(81-32\lambda)}}{160 \times 1.3990} \right) \Bigg]
\end{aligned}
$$

Step 8. The results $S_k, \ \ k = 1, 2, 3$ are normalized to be positive fuzzy numbers, and their ranges belong to closed interval [0, 1]. Positive distance and negative distance are then calculated respectively by

$$
\begin{aligned}
d_1^* = d(S_1,\ S^*) = \Bigg(\int_0^1 \frac{1}{2} \Bigg[\Bigg(& \frac{\sqrt{\lambda}}{10} \left(\frac{\sqrt{\lambda(24\lambda+25)}}{160 \times 1.3115} + \frac{33\lambda+49}{160 \times 1.3115} \right) \\
& + \frac{\sqrt{32\lambda+49}}{10} \times \frac{2\sqrt{\lambda(32\lambda+49)}}{130 \times 1.3115} - 1 \Bigg)^2 \\
& + \Bigg(\frac{\sqrt{9-8\lambda}}{10} \left(\frac{\sqrt{(9-8\lambda)(81-32\lambda)}}{160 \times 1.3115} + \frac{109-27\lambda}{160 \times 1.3115} \right) \\
& + \frac{\sqrt{100-19\lambda}}{10} \times \frac{2\sqrt{(9-8\lambda)(100-19\lambda)}}{130 \times 1.3115} - 1 \Bigg)^2 \Bigg] d\lambda \Bigg)^{\frac{1}{2}} = 0.80143
\end{aligned}
$$

$$
\begin{aligned}
d_2^* &= d(S_2,\ S^*) = 0.78983 \\
d_3^* &= d(S_3,\ S^*) = 0.81200
\end{aligned}
$$

$$
\begin{aligned}
d_1^- = d(S_1, S-) = \Bigg(\int_0^1 \frac{1}{2} \Bigg[\Bigg(& \frac{\sqrt{\lambda}}{10} \left(\frac{\sqrt{\lambda(24\lambda+25)}}{160 \times 1.3115} + \frac{33\lambda+49}{160 \times 1.3115} \right) \\
& + \frac{\sqrt{32\lambda+49}}{10} \times \frac{2\sqrt{\lambda(32\lambda+49)}}{130 \times 1.3115} - 0 \Bigg)^2 \\
& + \Bigg(\frac{\sqrt{9-8\lambda}}{10} \left(\frac{\sqrt{(9-8\lambda)(81-32\lambda)}}{160 \times 1.3115} + \frac{109-27\lambda}{160 \times 1.3115} \right) \\
& + \frac{\sqrt{100-19\lambda}}{10} \times \frac{2\sqrt{(9-8\lambda)(100-19\lambda)}}{130 \times 1.3115} - 0 \Bigg)^2 \Bigg] d\lambda \Bigg)^{\frac{1}{2}} \\
= 0.26982 &
\end{aligned}
$$

$$
\begin{aligned}
d_2^- &= d(S_2,\ S-) = 0.27534 \\
d_3^- &= d(S_3,\ S-) = 0.25811
\end{aligned}
$$

Step 9. After d_k^* and d_k^- of each alternative A_k $(k = 1, 2, 3)$ are obtained, the closeness coefficient of each alternative is calculated as:

$$
\begin{aligned}
D_1 &= \frac{1}{2}\left(d_1^* + (1 - d_1^-)\right) = \frac{1}{2}(0.80143 + (1 - 0.26982)) = 0.76581 \\
D_2 &= \frac{1}{2}\left(d_2^* + (1 - d_2^-)\right) = \frac{1}{2}(0.78983 + (1 - 0.27534)) = 0.75725 \\
D_3 &= \frac{1}{2}\left(d_3^* + (1 - d_3^-)\right) = \frac{1}{2}(0.81200 + (1 - 0.25811)) = 0.77695\,.
\end{aligned}
$$

As $D_3 = \max\{D_1, D_2, D_3\}$, the alternative A_3 is the best alternative for the returner, that is, the option maximally satisfies the business objectives for the particular goods return in the particular stage of reverse logistics chain.

5 Conclusions

There is a growing interest in exploiting reverse logistics models and developing decision support systems to enhance reverse logistics management [4]. Moreover, the interrelated relationship and dynamic feature in reverse logistics chain management require the capabilities of personalized multi-stage decision support. Uncertainty is inherent in the environment in which a reverse logistics chain propagates through a series of stages, and makes the chain management and control problems more complex. This study first analyses the characteristics of a reverse logistics chain and builds a set of corresponding relationships among goods returners, business objectives, alternatives and selection criteria. The paper then proposes a personalized multi-stage decision model and two sets of dynamic relationships among above decision compounds. Based on these results, a personalized fuzzy multi-criteria decision-making approach is developed. By using the approach, an alternative solution that meets maximally the business objectives under the preference of the logistics manager is selected to handle a goods return in reverse logistics.

The further study includes the development of a decision support system to implement the proposed approach. It will be expected to be applied in practice to enhance the efficiency and effectiveness of decision work for reverse logistics management problems. In order to validate the approach, a set of laboratory experiments will be further organized and more applications will be carried out. Also, the decision support system will be developed as online software and then embedded into e-logistics systems to support decision makers online choosing a suitable way to handle goods return problems in reverse logistics.

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