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Design and development of a fuzzy credibility-based reverse logistics network with buyback offers: A case study

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Abstract

The ever-growing stream of waste production has become a critical issue for many metropolitan areas. An effective strategy to address this problem has been the concept of reverse logistics (RL). This paper seeks to develop an appropriate product recovery approach for electronic waste generated in an urban area. Consequently, we have proposed an integrated fuzzy RL model with buyback (BB) offers based on the condition of used-products (UPs) at the time of return. However, this strategy contains a significant challenge, which derives from unpredictability surrounding the return rate of UPs due to its dependency on multiple external factors. Hence, a novel fuzzy probability function is developed to approximate UPs' chance of return. Besides that, the mathematical RL network's inherent uncertainty prompted us to employ the fuzzy credibility-based method in the model. Afterward, the model's objectives are locating and allocating collection centres to customer zones, determining flow between facilities and finding the optimal amount of gathered UPs and BB offers. Finally, we applied the model to a case study concerning product recovery in Mashhad city, Iran, and the results have proven its validity and utility.

Keywords

E-waste management, reverse logistics, buyback offer, uncertainty, fuzzy credibility-based programming, location–allocation planning

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Introduction

Nowadays, industrialization and globalization led to a skyrocketing production capacity in many countries, which has propelled waste production to an alarming level. Subsequently, catastrophic consequences such as environmental pollution, global warming and rapid depletion of natural resources have emerged. In the midst of these, the silver lining has been governments' introduction and enacting strict environmental legislation. For instance, we can mention the European Union waste electrical and electronic equipment (WEEE) and Japan electronic-waste (e-waste) regulation. The former enforces manufacturers to allocate proper resources to product recovery purposes, and the latter is a mandatory regulation tasking consumers to return their end-of-life (EOL) or used-product (UP) to specified collection centres (Anshassi et al., 2019). Furthermore, in recent years, there is a phenomenon of growing consciousness of environmental concerns among consumers. This environmental awareness is creating a favourability and inclination around purchasing eco-friendly products.

Consequently, a combination of restrictions and consumer desires has encouraged manufacturers to produce commodities with higher quality and durability, which even led to the reduction of unnecessary expenses and eventually improved revenues (Dowlatshahi, 2010). One primary stream of waste production is e-waste. In 2016 a report estimated that the global e-waste production has surpassed 44.7 million tons and is on a trajectory of 52 million tons until 2021 (Baldé et al., 2017). At this time, each European citizen discarded roughly around 15 kg of e-waste every year, which indicates the severity of this issue (Wang et al., 2016).

Moreover, the importance of e-waste management is contributed to two additional important characteristics. Firstly, it can be highly hazardous and detrimental to the environment (John et al., 2018). Secondly, it contains a considerable amount of precious metal such as gold, silver and palladium. According to National

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Institute for Material Science Japan [NIMS] (2015), a staggering amount of 6800 tons of gold and 60,000 tons of silver could be found in urban mines, which only a mere 20% of them adequately recycled. Hence, we argue that even if this issue is considered a distasteful burden by producers, it can herald an opportunity to restore a significant amount of resources with the proper perspective.

Krikke et al. (1999) defined reverse logistics (RL) as '*collecting, transportation, storage and process of EOL products*'. Fleischmann et al. (2000) pointed out that a proper RL network bears responsibility for collecting UPs and sorting and processing them based on their condition (e.g. recycling, repairing, remanufacturing, dissembling, reselling and scrapping). This specific representation of the RL model resonates closely with the requirements of an e-waste management problem. Moreover, ever since Jayaraman et al. (2003) paper introduced the basis of a RL network design, many researchers have published researches encompassing both the RL modelling and waste management scopes simultaneously. In general, these efforts have been mainly concerned with developing mathematical models to address upcoming and advanced problems such as considering limited capacity, uncertainty, a combination of different specialized procedures, multi-commodity and multi-objective ones (Baidya et al., 2020; Iacovidou et al., 2017; Kilic et al., 2015; Li et al., 2015). An exhaustive review paper on the related area was presented by Islam and Huda (2018) for further information.

A significant challenge in developing the RL network design is its inherent uncertainty. This issue has been an unavoidable feature of any mathematical logistics model, which originates from sources such as an inaccurate estimation of the potential number of UPs due to the lack of historical data, fluctuation in operating facilities expenses, transportation costs and some others (Aliahmadi et al., 2020; Kohneh et al., 2016; Luhandjula, 2006). One of the less-investigated sources of uncertainty in the RL model arises from approximating UPs return rate. Currently, competition among producers globally is quite fierce and potentially higher-value products (e.g. cell phones and laptops) are more present among consumers. This matter affects the RL process of these specific UPs because often, product holders expect to receive some sort of incentive offer to return (i.e. their reservation). Hence, without loss of generality, suppose the collection effort involves e-waste (i.e. potentially high salvage value UPs); any estimation of return rate without the presence of an incentive offer could lead to an ill-defined and imprecise description of the reality.

This phenomenon encouraged Klausner and Hendrickson (2000) to introduce the RL network design with a buyback (BB) policy. The motivation behind this strategy was that both RL company and product holders are usually sensitive toward the amount of BB offer and proper consideration of this relationship could provide a reliable estimation of the return rate. Needless to say that without any reservation from consumers, the inclusion of BB offer is unnecessary. The drawback of this paper was that it only focused on allocating fixed BB offers, creating a likely scenario that collected UPs would belong to the lowest-quality category, thus increasing the cost of the system. Therefore, Guide et al. (2003) studied a cellular phone company collection strategy and argued that allocating BB offers should be based on the quality of UPs at the time of return. This suggestion was quite reasonable because it was cost-efficient and aligned neatly with reality, given that even collection companies without any BB offer policy tend to sort collected UPs into different categories. Likewise, Ray et al. (2005) have proposed a trade-in rebates offer dependent on the age of UPs to encourage consumers to replace their UPs with new ones. In another approach, Wojanowski et al. (2007) attempted to utilize a probability function to approximate the return rate. They investigated a scenario where voluntary return flow was underwhelming; therefore, a deposit-refund strategy using uniform probability function (UPF) was implemented to estimate the return rate of UPs.

Furthermore, Aras and Aksen (2008) decided to integrate the RL network planning process with a BB offer mechanism. They developed a location–allocation mathematical model with BB offers dependent on the quality and distance of UPs. This successful integration encouraged scholars to use this strategy to address more advanced problems. Consequently, Aksen et al. (2009) investigated an integrated bi-level RL mathematical programming model. The two levels of objective function were concerned with minimizing the number of subsidy payments by the government while maximizing the total profit of the collection network, respectively.

Similarly, Dutta et al. (2016) have proposed a closed-loop supply chain network with a three-way recovery method and a BB offer policy. The model allocated BB offers based on the quality and age of UPs at the time of return and approximated return rate using a concave piece-wise probability function (PWPF). Some other notable efforts in this area are (Amirdadi and Dehghanian, 2021; Fattahi and Govindan, 2017; Masoudipour et al., 2017).

Consequently, an essential question that comes to mind is how many factors affect the product holder's decision to return? Or in other words, is it sufficient only to consider the condition of UPs in the process of estimating the return rate? Although the current body of work regarding RL network with BB offers is far more potent than those without it. However, the general proposition considering the UPs' condition as the sole factor for approximating the return rate is not entirely justifiable. We acknowledge that it might be the most crucial factor, but in reality, a product holder's willingness to return could be dependent on series of other factors as well (see Table 1).

Studies by Thierry et al. (1995), Tibben-Lembke (2002), Östlin et al. (2009) and Tekin Temur et al. (2014) highlighted several other influential factors. From Table 1, it can be inferred that these factors are diversified, emanate from different sources and overwhelming present among e-waste types of UPs. For instance, two consumers with an identical UP receiving an exact BB offer while having different education status (i.e. macro factors) or warranty period (i.e. micro factors) or distance from the closest collection centre (i.e. product-based factors) can exhibit different chances of return. Therefore, even in the presence of a

Table 1. List of factors influencing return rate of UPs.

Micro factors (Firm based)		Firm strategy
		Advertisements
		Giving information to customers
		The ability of the company to repair products
		Warranty period
Product-based	Condition (i.e. Quality and age)	Life cycle point of product
		The economic life of the product
		Rate of defects
		e-waste quantity
	Features	The complexity of product modularity
		Seasonality of product
		Product initial price
		Sales amount
		Easiness of product returns
Macro factors (Government and socioeconomic)		Legal enforcement
		Investment in the environment
		Customer segment
		Education status
		Population and population density
		Income

BB offer policy, any approximation of UPs return rate would still contain a certain degree of ambiguity and vagueness. Besides that, we stated that an inherent part of a mathematical RL network design is uncertainty. Therefore, a combination of possible inaccuracy in the estimation of RL model parameters and the fluctuating nature of consumers' decisions regarding returning or not could cause a difficult prospect for developing a reliable RL network with BB offers.

This paper attempts to address this problem. To do so, we point out that in previous studies, researchers often correlated the parameters of return probability function (e.g. UF or PWPF) to the condition of UPs. Arguably, they suggested that both collection companies and consumers are attuned to the condition of UPs, while other remaining factors mainly affect consumers' decisions, thus opting that the former is far more critical. Here, we decided to maintain this assumption but complement it by considering the parameters of the return probability function as fuzzy variables. The fuzzy description of the return probability function enables us to cope with consumers' unpredictable and heterogeneous behaviour concerning BB offers. Therefore, we develop a RL mathematical model with BB offers under a fuzzy assumption regarding the approximation of the return rate and other parameters (e.g. potential number of UPs and transportation costs). Besides that, we adopted a fuzzy credibility-based (CB) method to deal with uncertainty in our approach. This method has been used effectively in similar studies concerning RL and waste management problems (Aliahmadi et al., 2021; Zhang and Huang, 2010). Additionally, the implementation of this technique contains solid compatibility with the fuzzy properties of the BB offer policy. Finally, to demonstrate our methodology in this paper, we summarize it as the following steps:

- In the next section, we initially present the PWPF introduced by Dutta et al. (2016), which under a deterministic assumption provides a reliable approximation of the return rate based on the quality and age (i.e. condition) of UPs. Then, to address uncertainty related to the effect of other factors, a fuzzy description for its parameters is defined. Then, we conducted a series of adjustments on the fuzzy PWPF to modify it into its corresponding discrete function. These two steps would enable us to completely linearize the fuzzy PWPF, which ultimately enhances our approach tractability by significantly reducing its solving complexity.
- Section 3 illustrates the proposed fuzzy RL model with BB offers. The model also addresses the uncertainty surrounding more customary parameters of the RL network. Therefore, plus the parameters of PWPF, the potential total number of existing UPs, transportation costs, the potential value of recovered UPs and the percentage of them that could be recycled or remanufactured, or disposed of have been considered as fuzzy numbers.
- Section 4 briefly introduces the CB chance constraint solution methodology and then implements it on the model to achieve its crisp counterpart. The overall goals are locating and allocating collection centres, finding optimal BB offers and the number of collected UPs while minimizing the system's total cost.
- In Section 5, the model has been applied to a case study related to an e-waste RL company in Mashhad, Iran, to evaluate its performance and draw insight.
- Finally, Section 6 encompasses the conclusion and some recommended directions for future directions on this topic.

Materials and methods

As we mentioned, the main concentration in this paper is to approximate the return rate of UPs while planning the RL network under an uncertain environment. Regarding this matter,

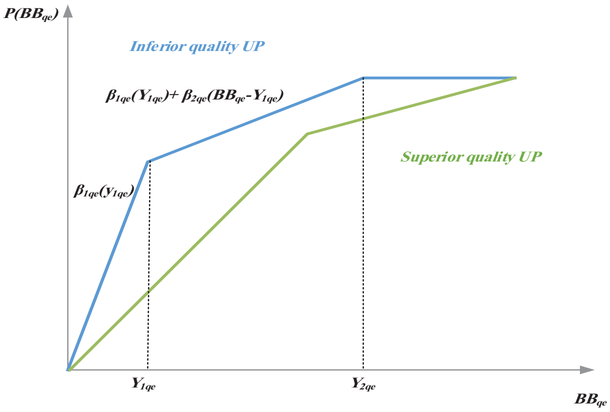

Figure 1. The concave pieces-wise probability function.

studies introduced several different methods, from offering a fixed offer to all of the UPs to dividing the potential number of them into several predefined categories of qualities and allocating BB offers to consumers, to even more flexible approaches such as using UPF to approximate the return rate and some others. Here, we decided to employ a concave PWPF first adopted by Dutta et al. (2016). This particular probability function approximates the return rate of UPs for a specific BB offer based on their quality and age at the time of return. In light of related papers, these two criteria can be stressed as the most important ones determining UPs' chance of return; therefore, we categorize UPs into Q, distinct levels of quality and E levels of age. We can write the PWPF as follows:

$$P(\mathrm{BB}_{qe}) = \begin{cases} \dfrac{\alpha_1 \mathrm{BB}_{qe}}{\alpha_1 y_{1qe} + \alpha_2 (y_{2qe} - y_{1qe})} & 0 < \mathrm{BB}_{qe} < y_{1qe} \\ \dfrac{\alpha_1 y_{1qe} + \alpha_2 (\mathrm{BB}_{qe} - y_{1qe})}{\alpha_1 y_{1qe} + \alpha_2 (y_{2qe} - y_{1qe})} & y_{1qe} < \mathrm{BB}_{qe} < y_{2qe} \\ 1 & \mathrm{BB}_{qe} \geq y_{2qe} \end{cases} \quad (1)$$

Where $y_{1qe}, y_{2qe} \geq 0$ and $P(\mathrm{BB}_{qe})$ demonstrates the probability of return for an offer BB_{qe} and depends on the quality and age of UP at the time of return. Also, for a specific type of UP α_1, α_2 are constant and $(\alpha_1 \leq \alpha_2)$. The parameters of y_{1qe}, y_{2qe} are the higher and lower bounds of BB offers and the decision-maker determines their values. Therefore, the superior quality or lower age levels of UPs would demand higher BB offers to reach a specific rate of return compared to inferior quality or higher age ones (see Figure 1). The y_{2qe} is the point that consumer willingness to return does not improve anymore. Thus, any increase above that limit would only add to the cost of the system. Additionally, the PWPF breakpoints indicate a change of attitude among consumers toward BB offers, and there is a capability to add more breakpoints to it as long as the slope of them would decrease. This specific characteristic of the PWPF provides an opportunity to estimate the complex behaviour of consumers with higher accuracy. Here, we can write the slopes of PWPF as:

$$\begin{aligned} \frac{\alpha_1}{\alpha_1 y_{1qe} + \alpha_2 (y_{2qe} - y_{1qe})} &= \beta_{1qe} \\ \frac{\alpha_2}{\alpha_1 y_{1qe} + \alpha_2 (y_{2qe} - y_{1qe})} &= \beta_{2qe} \end{aligned} \quad (2)$$

Where β_{1qe}, β_{2qe} denote the first and second interval slopes of the PWPF, respectively.

In the related studies, the most popular mechanism to approximate return rate has been the implementation of UPF. However, the PWPF is an extension of UPF and in terms of performance, dominates it without adding much complexity. Therefore, in this paper, we opted to utilize it instead. Now, to address the effect of other remaining factors on the product holder's willingness to return, we can write the fuzzy PWPF as:

$$P(\mathrm{BB}_{qe}) = \begin{cases} \tilde{\beta}_{1qe} \mathrm{BB}_{qe} & 0 \leq \mathrm{BB}_{qe} \leq \tilde{y}_{1qe} \\ \tilde{\beta}_{1qe} \tilde{y}_{1qe} + \tilde{\beta}_{2qe} (\mathrm{BB}_{qe} - \tilde{y}_{1qe}) & \tilde{y}_{1qe} < \mathrm{BB}_{qe} \leq \tilde{y}_{2qe} \\ 1 & \mathrm{BB}_{qe} > \tilde{y}_{2qe} \end{cases} \quad (3)$$

Equation (3) shows that the chance of a return for each UP with a certain quality and age receiving a specific BB offer would not be a definite measure. This leeway adds flexibility to the model and reduces its predisposition to strictly predict the actual UPs' return rate, which eventually mitigates its inaccuracy and unreliability.

The corresponding fuzzy discrete probability function

Before incorporating the fuzzy PWPF with the RL network, we point out a significant drawback in this process: the nonlinearity and complexity of the resultant model. Aras et al. (2008) proposed a right triangular probability function (RTPF) instead of UPF to approximate the return rate of UPs. Although theoretically, RTPF proved to be more precise in the process of estimating the UPs' return than UPF. Nonetheless, the intricacy of the outcome model forced the researchers to suffice to a restricted application and analysis of it. The reader should bear in mind that the whole idea of the RL network with BB offers is an integration of strategic and tactical decision-making processes, and the former is far more costly and critical. Therefore, we argue that if the process causes a high degree of complexity in the model, it could be very discouraging for practitioners to use it. Also, this paper seeks to develop a fuzzy RL model that could even further aggravate the severity of this issue.

That is why here, we have decided to tackle this problem by implementing several adjustments onto the fuzzy PWPF to improve its implementation practicability by reducing its intricacies. To achieve that, we take advantage of a linearization method introduced by Keyvanshokooh et al. (2013). This method converts the PWPF into its fuzzy discrete probability function (DPF) with a reasonable degree of accuracy. Here, we initially modified the deterministic PWPF into its discrete counterpart for convenience in explanation and then addressed its fuzzy properties.

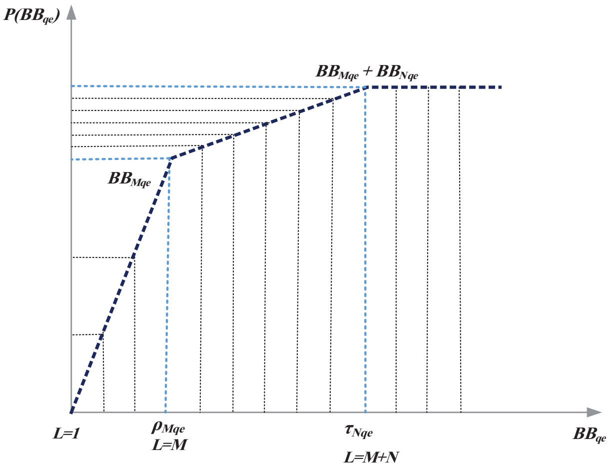

Figure 2. The corresponding discrete probability function.

Therefore, we divide the predefined set of BB offer $(0, y_{2qe}]$ (i.e. the denominator of the PWPF), which under a deterministic assumption for each UP with a certain quality and age is a fixed measure into L disjointed parts. Therefore, for each UP only several predetermined and a finite number of price levels can be allocated. Then, we allocate M numbers of these levels to the first interval, which is $(0, y_{1qe}]$ and N parts of it to the second interval, which is $(y_{1qe}, y_{2qe}]$. As mentioned, the slope of PWPF decreases after each breakpoint, so we have ($N \leq M$) and $\{M + N = L\}$. These relationships mean the first interval of the DPF always would contain a higher number of offers than the others (see Figure 2).

Now, we can write the deterministic corresponding DPF as follows:

$$P(\mathrm{BB}_{qe}) = \alpha_1 \sum_{m=1}^{M} \rho_{mqe} (\frac{m-1}{M-1}) + \alpha_2 \sum_{n=1}^{N} \tau_{nqe} (\frac{n}{N}) \tag{4}$$

Where ρ_{mqe}, τ_{nqe} are two auxiliary binary variables associating with BB offers for the first and second intervals, respectively. Hence, if a price level receives 1 as its value, it would be the optimal BB offer and 0, otherwise. For each UP with a certain quality and age, only one offer can be allocated. To ensure this, we add the following constraint:

$$\sum_{m} \rho_{mqe} = 1 \quad \forall q, e \tag{5}$$

Furthermore, according to the PWPF attitudes, the second expression of equation (4) only can be activated when the first expression receives its highest value, and in other circumstances, it must be 0. Therefore, we also require the following constraint:

$$\sum_{n} \tau_{nqe} \leq \rho_{Mqe} \quad \forall q, e \tag{6}$$

With a traceable transformation, we also can calculate the optimal BB offers as follows:

$$\mathrm{BB}_{qe} = \frac{\alpha_1}{\beta_{1qe}} \sum_{m}^{M} \rho_{mqe} (\frac{m-1}{M-1}) + \frac{\alpha_2}{\beta_{2qe}} \sum_{n}^{N} \tau_{nqe} (\frac{n}{N}) \tag{7}$$

Under the fuzzy assumption, we acknowledge that the denominator of probability function, unlike the previous scenario, does not have a definite value. However, we point out that the value of it continuously alternates between two minimum and maximum limits. This characteristic enables us to find two possible upper and lower bounds for the UPs' chance of return. Now, if we consider $\tilde{\alpha}_1$ as a fuzzy number with trapezoidal fuzzy properties, we can write its four prominent crisp values as:

$$\tilde{\alpha}_1 = (\alpha_1^1, \alpha_1^2, \alpha_1^3, \alpha_1^4) \tag{8}$$

Based on Liu and Liu (2002), the expected value (EV) of this fuzzy number can be written as follows:

$$\mathrm{EV}(\tilde{\alpha}_1) = \int_0^{\infty} \mathrm{Cr}(\tilde{\alpha}_1 \geq k) dk - \int_{-\infty}^{0} \mathrm{Cr}(\tilde{\alpha}_1 \leq k) dk \tag{9}$$

$$\mathrm{EV}(\tilde{\alpha}_1) = \frac{(\alpha_1^1 + \alpha_1^2 + \alpha_1^3 + \alpha_1^4)}{4} \tag{10}$$

Consequently, Equation (10) helps us to calculate two extreme limits of the fuzzy DPF denominator and write them as follows:

$$\begin{aligned} &\alpha_1^1 y_{1qe}^1 + \alpha_2^1 (y_{2qe}^1 - y_{1qe}^1) \leq \tilde{\alpha}_1 \tilde{y}_{1qe} \\ &+ \tilde{\alpha}_2 (\tilde{y}_{2qe} - \tilde{y}_{1qe}) \leq \alpha_1^4 y_{1qe}^4 + \alpha_2^4 (y_{2qe}^4 - y_{1qe}^4) \end{aligned} \tag{11}$$

As mentioned in this paper, we decided to use the fuzzy CB methodology to cope with uncertainty. Our primary motivation for this decision is that the CB technique is based on the EV of fuzzy parameters, which firmly guarantees computational reliability. Thus, the denominator EV is divided into $M + N$, which gives us a specific distance between each feasible BB offer, and we call it υ.

$$\frac{\mathrm{EV}(\alpha_1)\mathrm{EV}(y_{1qe}) + \mathrm{EV}(\alpha_2)(\mathrm{EV}(y_{2qe}) - \mathrm{EV}(y_{1qe}))}{M + N} = \upsilon \tag{12}$$

This measure enables us to calculate two consecutive BB offer levels for any crisp realization of the fuzzy denominator with the same increment as its EV denominator. Consequently, we demonstrate that by dividing two maximum and minimum measures of the denominator onto υ, we can calculate two possible lower and upper bounds for $M + N$, and write them as:

$$\frac{\alpha_1^1 y_{1qe}^1 + \alpha_2^1 (y_{2qe}^1 - y_{1qe}^1)}{\upsilon} = [M' + N'] \tag{13}$$

$$\frac{\alpha_1^4 y_{1qe}^4 + \alpha_2^4 (y_{2qe}^4 - y_{1qe}^4)}{\upsilon} = [M'' + N''] \tag{14}$$

$$[M' + N'] \leq M + N \leq [M'' + N''] \tag{15}$$

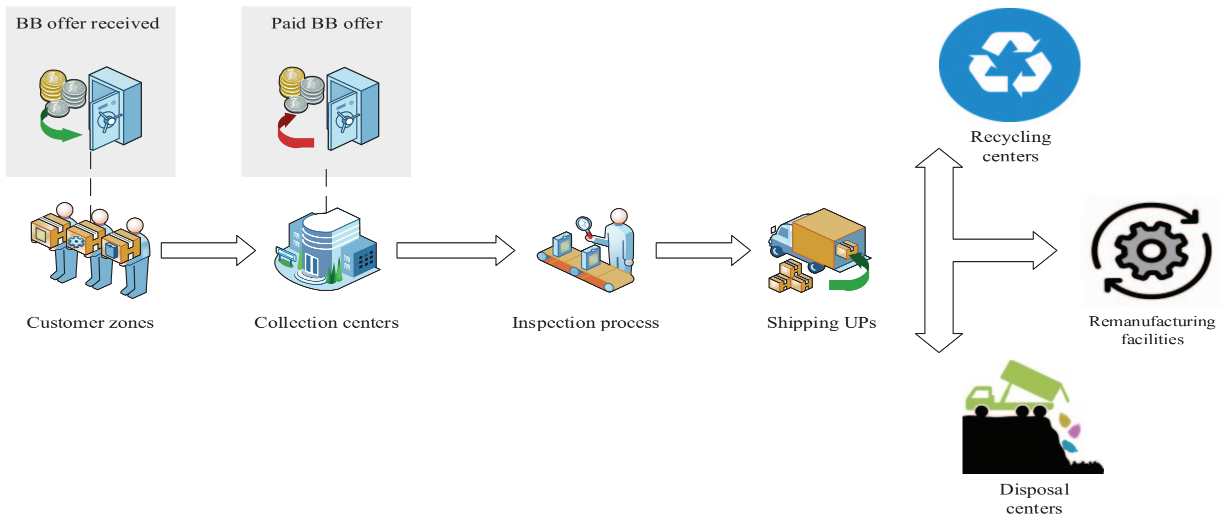

Figure 3. The framework of the reverse logistics network.

Then, because BB offer levels cannot be a decimal number, we have to calculate the absolute values. Finally, we can formulate the ultimate corresponding fuzzy DPF as follows:

$$P(\mathrm{BB}_{qe}) \leq \tilde{\alpha}_1 \sum_{m=1}^{M'} \rho_{mqe}\left(\frac{m-1}{M'-1}\right) + \tilde{\alpha}_2 \sum_{N=1}^{N'} \tau_{nqe}\left(\frac{n}{N'}\right) \tag{16}$$

$$P(\mathrm{BB}_{qe}) \geq \tilde{\alpha}_1 \sum_{m=1}^{M''} \rho_{mqe}\left(\frac{m-1}{M''-1}\right) + \tilde{\alpha}_2 \sum_{n=1}^{N''} \tau_{nqe}\left(\frac{n}{N''}\right) \tag{17}$$

It can be proven that equation (16) would have a higher or at least equal chance of the return for the same BB offer level in comparison to equation (17). Thus, the former demonstrates the possible upper chance of a return, and the latter illustrates the lower chance of it. Similarly, the fuzzy BB offers can be formulated as:

$$\mathrm{BB}_{qe} \leq \frac{\tilde{\alpha}_1}{\tilde{\beta}_{1qe}} \sum_{m}^{M'} \rho_{mqe}\left(\frac{m-1}{M'-1}\right) + \frac{\tilde{\alpha}_2}{\tilde{\beta}_{2qe}} \sum_{n}^{N'} \tau_{nqe}\left(\frac{n}{N'}\right) \tag{18}$$

$$\mathrm{BB}_{qe} \geq \frac{\tilde{\alpha}_1}{\tilde{\beta}_{1qe}} \sum_{m}^{M''} \rho_{mqe}\left(\frac{m-1}{M''-1}\right) + \frac{\tilde{\alpha}_2}{\tilde{\beta}_{2qe}} \sum_{n}^{N''} \tau_{nqe}\left(\frac{n}{N''}\right) \tag{19}$$

$$\mathrm{BB}_{qe} \leq y^4_{2qe} \tag{20}$$

Equation (20) indicates that the possible price cannot exceed its highest prominent crisp value for any specific BB offer. Therefore, equation (20) dominates equation (18) and rendering it redundant.

The proposed fuzzy RL network with BB offers

Here, we formulate an fuzzy mixed-integer non-linear programming (FMINLP) model for the RL network with BB offers. The general framework of the model is shown in Figure 3. The RL network is based on a drop-off strategy and encompasses three stages: customer zones, collection centres and specialized facilities (i.e. recycling centres, remanufacturing facilities and disposal centres). The first step is to collect UPs from consumers in each collection centre. Then, UPs are sorted into different groups based on their condition. Then, they are shipped to recycling centres or remanufacturing facilities, or disposal centres. Besides that, the model assumes that the government pays a predetermined subsidy to each collected UP and expects a minimum limit of the total existing UPs to be gathered. Finally, the proposed model goals are to determine the optimal number and location of collection centres, flow between specialized facilities while finding the optimal amount of UPs that should be collected and BB prices.

Before presenting the model, several other essential assumptions in the model are listed in the below paragraph:

- The potential locations of collection centres are known.
- The number and location of specialized facilities are known.
- Customer zones demand is dividable among different collection centres.
- Each collection centre has a predetermined capacity for UPs with a certain quality and age.
- Each quality level has a fuzzy predetermined portion of UPs that could be recycled or remanufactured or disposed of.

Indices

Set of customer zones	I
Set of potential locations for establishing collection centres	J
Set of remanufacturing facilities	R
Set of recycling centres	O
Set of disposal centres	U

Parameters

Fuzzy opening and operation cost of each collection centre	$\tilde{F}_j$
Fuzzy unit transportation cost for each unit of UP from customer zones to collection centres	$\tilde{C}$
Fuzzy unit transportation cost for each unit of UP from collection centres to remanufacturing facilities	CR
Fuzzy unit transportation cost for each unit of UP from collection centres to recycling centres	CO
Fuzzy unit transportation cost for each unit of UP from collection centres to disposal centres	CU
Distance between customer zone *i* and collection centre *j*	d_{ij}
Distance between collection centre *j* and remanufacturing facility *r*	d_{jr}
Distance between collection centre *j* and recycling centre *o*	d_{jo}
Distance between collection centre *j* and disposal centre *u*	d_{ju}
Fuzzy potential number of product holders in customer zone *i* with quality *q* and age *e*	$\tilde{T}_{iqe}$
Capacity of collection centre *j* for UPs with quality *q* and age *e*	S_{jqe}
Fuzzy portion of UPs with quality *q* which could be remanufactured	PR_q
Fuzzy portion of UPs with quality *q* which could be recycled	PO_q
Fuzzy portion of UPs with quality *q* which should be disposed of	PU_q
Fuzzy value of remanufactured UP with quality *q* and age *e*	MV_{qe}
Fuzzy value of recycled UP with quality *q* and age *e*	RV_{qe}
Government subsidy allocated to each collected UP	SB
A minimum rate for collecting UPs set by the government	γ
A large number	M

Decision variables

1, if collection centre *j* is opened and 0, otherwise	X_j
The number of collected UPs in collection centre *j* with quality *q* and age *e* from customer zone *i*	R_{ijqe}
The number of UPs shipped from collection centre *j* to remanufacturing facility *r*	ZA_{jr}
The number of UPs shipped from collection centre *j* to recycling centre *o*	ZB_{jo}
The number of UPs shipped from collection centre *j* to disposal centre *u*	ZC_{ju}

With the help of the above notations, the proposed model can be formulated as follows:

$$\begin{aligned}&Min\\&\sum_i\sum_j\sum_q\sum_e R_{ijqe}P(\mathrm{BB}_{qe})\mathrm{BB}_{qe}+\sum_j\tilde{F}_jX_j\\&+\sum_i\sum_j\sum_q\sum_e\tilde{C}d_{ij}R_{ijqe}+\sum_j\sum_r\tilde{\mathrm{C}}\mathrm{R}d_{jr}ZA_{jr}+\\&\sum_j\sum_o\tilde{\mathrm{C}}\mathrm{O}d_{jo}ZB_{jo}+\sum_j\sum_u\tilde{\mathrm{C}}\mathrm{U}d_{ju}\mathrm{ZC}_{ju}\\&-\sum_i\sum_j\sum_q\sum_e R_{ijqe}(\tilde{\mathrm{P}}\mathrm{R}_q\tilde{\mathrm{M}}\mathrm{V}_{qe}+\tilde{\mathrm{P}}\mathrm{O}_q\tilde{\mathrm{R}}\mathrm{V}_{qe}+\mathrm{SB})\end{aligned} \tag{21}$$

Subject to:

$$\sum_i\sum_q\sum_e R_{ijqe}\le \mathrm{MX}_j \quad \forall j \tag{22}$$

$$\sum_j R_{ijqe}\le P(\mathrm{BB}_{qe})\tilde{T}_{iqe}\ \forall i,q,e \tag{23}$$

$$\sum_j\sum_r ZA_{jr}=\sum_i\sum_j\sum_q\sum_e\tilde{\mathrm{P}}\mathrm{R}_qR_{ijqe} \tag{24}$$

$$\sum_j\sum_o ZB_{jo}=\sum_i\sum_j\sum_q\sum_e\tilde{\mathrm{P}}\mathrm{O}_qR_{ijqe} \tag{25}$$

$$\sum_j\sum_u \mathrm{ZC}_{ju}=\sum_i\sum_j\sum_q\sum_e\tilde{\mathrm{P}}\mathrm{U}_qR_{ijqe} \tag{26}$$

$$\sum_i R_{ijqe}\le X_jS_{jqe}\ \ \forall j,q,e \tag{27}$$

$$\sum_i\sum_j\sum_q\sum_e R_{ijqe}\ge\gamma\sum_i\sum_q\sum_e\tilde{T}_{iqe} \tag{28}$$

$$P(\mathrm{BB}_{qe})\le 1\quad \forall q,e \tag{29}$$

$$X_j=\{1,0\}\ \forall j \tag{30}$$

$$R_{ijqe},\ ZA_{jr},\ ZB_{jo},\ \mathrm{ZC}_{ju},\ P(\mathrm{BB}_{qe}),\ \mathrm{BB}_{qe}\ge 0\quad \forall i,j,q,e,r,o,u \tag{31}$$

and constraints (5), (6), (16), (17), (19) and (20).

Equation (21) denotes the objective function that contains two main parts: the system costs and revenues. The initial six expressions calculate the total cost of BB offers, the setup and operation cost of collection centres and transportation costs from customer zones to collection centres and specialized facilities, respectively. The last expression is related to the system's revenues, which come from government subsidies and a salvage value of recycled and remanufactured UPs. Afterward, constraint (22) warrants that each customer zone only is allocated to an already established collection centre. Constraint (23) ensures that the total amount of collected UPs would not exceed the whole potential number of them. Constraints (24)–(26) control the flow in the system from collection centres to specialized facilities. Constraint (27) controls the capacity of collection centres. Constraint (28) is related to the government threshold for the minimum acceptable collection rate for the system. Constraint (29) verifies that the chance of a return for any BB offer would not exceed 100%. Constraints (30) and (31) indicate the model variables type and their non-negativity. The rest of the constraints are related to the BB offer policy that previously discussed.

Now, for simplification of the objective function; we can rewrite the first expression of it, which was associated with the total cost of BB offers as follows:

$$\begin{aligned}&\sum_i\sum_j\sum_q\sum_e R_{ijqe}P(\mathrm{BB}_{qe})\mathrm{BB}_{qe}\\&=\sum_i\sum_q\sum_e \tilde{T}_{iqe}\Big(\frac{(\tilde{\alpha}_1)^2}{\tilde{\beta}_{1qe}}\sum_{m=1}^{M}\rho_{mqe}\Big(\frac{m-1}{M-1}\Big)^2\\&+\frac{(\tilde{\alpha}_2)^2}{\tilde{\beta}_{2qe}}\sum_{n=1}^{N}\tau_{nqe}\Big(\frac{n}{N}\Big)^2\\&+\Big(\frac{\tilde{\alpha}_1\tilde{\alpha}_2}{\tilde{\beta}_{1qe}}+\frac{\tilde{\alpha}_1\tilde{\alpha}_2}{\tilde{\beta}_{2qe}}\Big)\Big(\sum_{m=1}^{M}\sum_{n=1}^{n}\Big(\frac{m-1}{M-1}\Big)\Big(\frac{n}{N}\Big)\rho_{mqe}\tau_{nqe}\Big)\end{aligned}\tag{32}$$

$$\begin{aligned}&\Big(\frac{\tilde{\alpha}_1\tilde{\alpha}_2}{\tilde{\beta}_{1qe}}+\frac{\tilde{\alpha}_1\tilde{\alpha}_2}{\tilde{\beta}_{2qe}}\Big)\Big(\sum_{m}^{M}\sum_{n}^{N}\Big(\frac{m-1}{M-1}\Big)\Big(\frac{n}{N}\Big)\rho_{mqe}\tau_{nqe}\Big)=0\\&\forall(m<L-N),q,e\end{aligned}\tag{33}$$

$$\begin{aligned}&\Big(\frac{\tilde{\alpha}_1\tilde{\alpha}_2}{\tilde{\beta}_{1qe}}+\frac{\tilde{\alpha}_1\tilde{\alpha}_2}{\tilde{\beta}_{2qe}}\Big)\Big(\sum_{m}^{M}\sum_{n}^{N}\Big(\frac{m-1}{M-1}\Big)\Big(\frac{n}{N}\Big)\rho_{mqe}\tau_{nqe}\Big)\\&=\tilde{\alpha}_1\tilde{\alpha}_2\Big(\frac{1}{\tilde{\beta}_{1qe}}+\frac{1}{\tilde{\beta}_{2qe}}\Big)\Big(\sum_{n}^{N}\Big(\frac{M-1}{M-1}\Big)\Big(\frac{n}{N}\Big)\tau_{nqe}\Big)\\&\forall(m\geq L-N),q,e\end{aligned}\tag{34}$$

$$\begin{aligned}&\sum_i\sum_j\sum_q\sum_e R_{ijqe}P(\mathrm{BB}_{qe})\mathrm{BB}_{qe}\\&=\sum_i\sum_q\sum_e \tilde{T}_{iqe}\Big(\frac{(\tilde{\alpha}_1)^2}{\tilde{\beta}_{1qe}}\sum_{m=1}^{M}\rho_{mqe}\Big(\frac{m-1}{M-1}\Big)^2\\&+\frac{(\tilde{\alpha}_2)^2}{\tilde{\beta}_{2qe}}\sum_{n=1}^{N}\tau_{nqe}\Big(\frac{n}{N}\Big)^2+\tilde{\alpha}_1\tilde{\alpha}_2\Big(\frac{1}{\tilde{\beta}_{1qe}}+\frac{1}{\tilde{\beta}_{2qe}}\Big)\Big(\sum_{n}^{N}\tau_{nqe}\Big(\frac{n}{N}\Big)\Big)\end{aligned}\tag{35}$$

Equation (35) shows the traceable equivalent of equation (32). From equations (33) and (34), we can discover that for all of $(m<L-N)$ the τ_{nqe} would be zero, which nullifies its whole expression. Therefore, this expression is operative when $(m\geq L-N)$. Also, in the first and second expressions of equation (35), two bounded integer variables are multiplied. This condition also can be linearized using the method mentioned earlier (Keyvanshokooh et al., 2013). Undeniably, this process would expand the computational size of the model but still creates fewer intricacies analogous to alternative nonlinear options. Finally, in section 5, we examine this aspect of the model by applying it to the case study.

The fuzzy CB chance constraint solution

The fuzzy linear mathematical modelling method was initially introduced by Zimmermann (1978). In the problem at hand, the state of uncertainty originates from two epistemic sources of customary parameters (e.g. the potential number of UPs in customer zones) and the mechanism of estimating UPs' return rate. Hence, we opted to employed fuzzy CB chance constraints programming in this paper. The renowned pioneers in this field were Liu and Liu (2002). They highlighted four main reasons to demonstrate this approach superiority compared to the other possibility and necessity techniques. Firstly, as touched upon, CB is founded on the EV concept, making it firmly reliable. Secondly, this approach, unlike the other two necessity and possibility methods, is self-dual. This feature means that if an event under the CB approach receives 1 as its confidence level, it assures that the event would happen, which is not the case in other methods. Thirdly, it can cope with both triangular and trapezoidal fuzzy numbers. Lastly, this method ensures that a certain level of fuzzy constraints confidence levels would be met in any scenario for a mathematical model. Over the years, the fuzzy credibility chance constraint method has been applied and improved by many scholars in similar areas (Li et al., 2013; Xu et al., 2017). However, in this paper, we adopted a specific fuzzy CB approach developed by Zhu and Zhang (2009), which its implementation process does not add additional auxiliary constraints to the model. Together, we suggest this methodology would be hugely beneficial, given the nature of the proposed model that involves a combination of strategic and tactical decision-making.

Now, if we assume $\tilde{\psi}$ as a fuzzy variable. Then, we can write it trapezoidal fuzzy crisp equivalent as $(\psi^1,\psi^2,\psi^3,\psi^4)$. According to Liu and Liu (2002), its membership function can be written as:

$$\varpi(\psi)=\begin{cases}\dfrac{k-\psi^1}{\psi^2-\psi^1} & \psi^1\leq k\leq\psi^2\\[2mm]\dfrac{k-\psi^2}{\psi^3-\psi^2} & \psi^2\leq k\leq\psi^3\\[2mm]\dfrac{k-\psi^3}{\psi^4-\psi^3} & \psi^3\leq k\leq\psi^4\\[2mm]0 & otherwise\end{cases}\tag{36}$$

In equation (36) $k \geq 0$ and represents an event confidence level. To calculate the credibility value of this event, Liu and Liu (2002) proven the following formula:

$$\mathrm{Cr}\{\tilde{\psi} \geq k\} = \frac{1}{2}(Possibilty\{\tilde{\psi} \geq k\} + Necessity\{\tilde{\psi} \geq k\}) \quad (37)$$

In the next step, we can write the credibility measure of $\tilde{\psi} \geq k$, $\tilde{\psi} \leq k$ as follows:

$$\mathrm{Cr}\{\tilde{\psi} \leq k\} = \begin{cases} 0 & -\infty < k \leq \psi^1 \\ \dfrac{k-\psi^1}{2(\psi^2-\psi^1)} & \psi^1 < k \leq \psi^2 \\ \dfrac{1}{2} & \psi^2 < k \leq \psi^3 \\ \dfrac{k-2\psi^3+\psi^4}{2(\psi^4-\psi^3)} & \psi^3 < k \leq \psi^4 \\ 1 & \psi^4 < k < +\infty \end{cases} \quad (38)$$

$$\mathrm{Cr}\{\tilde{\psi} \geq k\} = \begin{cases} 1 & -\infty < k \leq \psi^1 \\ \dfrac{2\psi^2-\psi^1-k}{2(\psi^2-\psi^1)} & \psi^1 < k \leq \psi^2 \\ \dfrac{1}{2} & \psi^2 < k \leq \psi^3 \\ \dfrac{\psi^4-k}{2(\psi^4-\psi^3)} & \psi^3 < k \leq \psi^4 \\ 0 & \psi^4 < k < +\infty \end{cases} \quad (39)$$

Consequently, Zhu and Zhang (2009) demonstrated that if $\tilde{\psi}$ is a fuzzy trapezoidal variable and $(\lambda \geq 0.5)$ then, we can write its credibility measure as follows:

$$\mathrm{Cr}\{\tilde{\psi} \leq k\} \geq \lambda \Leftrightarrow k \geq (2-2\lambda)\psi^3 + (2\lambda-1)\psi^4 \quad (40)$$

$$\mathrm{Cr}\{\tilde{\psi} \geq k\} \geq \lambda \Leftrightarrow k \leq (2\lambda-1)\psi^1 + (2-2\lambda)\psi^2 \quad (41)$$

Finally, with the help of equations (10), (40) and (41), and the α-critical cuts method explored by Liu (2004), the linear crisp traceable counterpart of the FMINLP model could be formulated as:

$$\begin{aligned} &Min \\ &\sum_i\sum_q\sum_e((\frac{T^1_{iqe}+T^2_{iqe}+T^3_{iqe}+T^4_{iqe}}{4}) \\ &(\frac{(\alpha^1_1+\alpha^2_1+\alpha^3_1+\alpha^4_1)^2}{4(\beta^1_{1qe}+\beta^2_{1qe}+\beta^3_{1qe}+\beta^4_{1qe})})\sum_m^M\rho_{mqe}(\frac{m-1}{M-1})^2 \\ &+(\frac{(\alpha^1_2+\alpha^2_2+\alpha^3_2+\alpha^4_2)^2}{4(\beta^1_{2qe}+\beta^2_{2qe}+\beta^3_{2qe}+\beta^4_{2qe})})\sum_n^N\tau_{nqe}(\frac{n}{N})^2 \\ &+(\frac{\alpha^1_1+\alpha^2_1+\alpha^3_1+\alpha^4_1}{4})(\frac{\alpha^1_2+\alpha^2_2+\alpha^3_2+\alpha^4_2}{4}) \\ &(\frac{4}{\beta^1_{2qe}+\beta^2_{2qe}+\beta^3_{2qe}+\beta^4_{2qe}}+\frac{4}{\beta^1_{1qe}+\beta^2_{1qe}+\beta^3_{1qe}+\beta^4_{1qe}})\sum_n^N(\frac{n}{N})\tau_{nqe}) \\ &+\sum_j(\frac{F^1_j+F^2_j+F^3_j+F^4_j}{4})X_j \\ &+\sum_i\sum_j\sum_q\sum_e(\frac{C^1+C^2+C^3+C^4}{4})d_{ij}R_{ijqe} \\ &+\sum_j\sum_r(\frac{\mathrm{CR}^1+\mathrm{CR}^2+\mathrm{CR}^3+\mathrm{CR}^4}{4})d_{jr}ZA_{jr} \\ &+\sum_j\sum_o(\frac{\mathrm{CO}^1+\mathrm{CO}^2+\mathrm{CO}^3+\mathrm{CO}^4}{4})d_{jo}ZB_{jo} \\ &+\sum_j\sum_u(\frac{\mathrm{CU}^1+\mathrm{CU}^2+\mathrm{CU}^3+\mathrm{CU}^4}{4})d_{ju}\mathrm{ZC}_{ju} \\ &-\sum_i\sum_j\sum_q\sum_e R_{ijqe}((\frac{\mathrm{PR}^1_q+\mathrm{PR}^2_q+\mathrm{PR}^3_q+\mathrm{PR}^4_q}{4}) \\ &(\frac{(\mathrm{MV}^1_{qe}+\mathrm{MV}^2_{qe}+\mathrm{MV}^3_{qe}+\mathrm{MV}^4_{qe}}{4}) \\ &+(\frac{(\mathrm{PO}^1_q+\mathrm{PO}^2_q+\mathrm{PO}^3_q+\mathrm{PO}^4_q}{4})(\frac{(\mathrm{RV}^1_{qe}+\mathrm{RV}^2_{qe}+\mathrm{RV}^3_{qe}+\mathrm{RV}^4_{qe}}{4})+\mathrm{SB}) \end{aligned} \quad (42)$$

Subject to:

$$\sum_j R_{ijqe} \leq P(\mathrm{BB}_{qe})((2\lambda_i-1)T^1_{iqe}+(2-2\lambda_i)T^2_{iqe}) \ \forall i,q,e \quad (43)$$

$$\begin{aligned} P(\mathrm{BB}_{qe}) &\leq ((2\sigma_{qe}-1)\alpha^1_1+(2-2\sigma_{qe})\alpha^2_1)\sum_m^{M'}\rho_{mqe}(\frac{m-1}{M'-1}) \\ &+((2\sigma_{qe}-1)\alpha^1_2+(2-2\sigma_{qe})\alpha^2_2)\sum_n^{N'}\tau_{nqe}(\frac{n}{N'}) \ \forall q,e \end{aligned} \quad (44)$$

$$\begin{aligned} P(\mathrm{BB}_{qe}) &\geq ((2-2\sigma_{qe})\alpha^3_1+(2\sigma_{qe}-1)\alpha^4_1)\sum_m^{M''}\rho_{mqe}(\frac{m-1}{M''-1}) \\ &+((2-2\sigma_{qe})\alpha^3_2+(2\sigma_{qe}-1)\alpha^4_2)\sum_n^{N''}\tau_{nqe}(\frac{n}{N''}) \ \forall q,e \end{aligned} \quad (45)$$

$$\begin{aligned} \mathrm{BB}_{qe} &\geq \frac{(2-2\sigma_{qe})\alpha^3_1+(2\sigma_{qe}-1)\alpha^4_1}{(2-2\sigma_{qe})\beta^3_{1qe}+(2\sigma_{qe}-1)\beta^4_{1qe}}\sum_m^{M''}\rho_{mqe}(\frac{m-1}{M''-1}) \\ &+\frac{(2-2\sigma_{qe})\alpha^3_2+(2\sigma_{qe}-1)\alpha^4_2}{(2-2\sigma_{qe})\beta^3_{2qe}+(2\sigma_{qe}-1)\beta^4_{2qe}}\sum_n^{N''}\tau_{nqe}(\frac{n}{N''}) \quad \forall q,e \end{aligned} \quad (46)$$

$$\mathrm{BB}_{qe} \leq y^4_{2qe} \ \forall q,e \quad (47)$$

$$\sum_j\sum_r ZA_{jr} \leq \sum_i\sum_j\sum_q\sum_e((2\delta_q-1)\mathrm{PR}^1_q+(2-2\delta_q)\mathrm{PR}^2_q)R_{ijqe} \quad (48)$$

$$\sum_{j}\sum_{o} ZB_{jo} \leq \sum_{i}\sum_{j}\sum_{q}\sum_{e}((2\delta_q - 1)\mathrm{PO}_q^1 + (2 - 2\delta_q)\mathrm{PO}_q^2)R_{ijqe} \tag{49}$$

$$\sum_{j}\sum_{u} \mathrm{ZC}_{ju} \leq \sum_{i}\sum_{j}\sum_{q}\sum_{e}((2\delta_q - 1)\mathrm{PU}_q^1 + (2 - 2\delta_q)\mathrm{PU}_q^2)R_{ijqe} \tag{50}$$

$$\sum_{i}\sum_{j}\sum_{q}\sum_{e} R_{ijqe} \geq \gamma \sum_{i}\sum_{q}\sum_{e}((2 - 2\lambda_j)T_{iqe}^3 + (2\lambda_j - 1)T_{iqe}^4 \tag{51}$$

$$\rho_{mqe}, \tau_{nqe} = \{1, 0\} \ \ \forall m, n, q, e \tag{52}$$

$$\lambda_i, \delta_q, \sigma_{qe} \geq 0.5 \quad \forall i, q, e \tag{53}$$

And constraints (5), (6), (22), (27) and (29)–(31).

The three variables $\lambda_i.\delta_q.\sigma_{qe}$ denote the credibility level of constraints. The decision-maker determines their values. In some of the papers for simplicity of work, their values are assumed to be identical (Hatefi et al., 2015; Pishvaee et al., 2012).

Case study results

In order to test our model validity and utility, we decided to apply it to a comprehensive case study and analyse responses from it. We took advantage of the software GAMS 24.0.1 and its CLPEX solver application and a computer with a configuration of Core i7 processor, Ram 16 GB and Windows 10 operator for computational purposes. The case that we investigate here is related to a waste management company in the Iran city of Mashhad. The city municipal governing body has recently adopted a long-term plan to increase its capacity to recover and recycle or adequately scarp e-waste generated by its citizens. To achieve this goal, they have decided to employ RL companies to embark on this task on their behalf. Furthermore, to encourage competition apart from subsidies paid for each collected UPs, annually substantial bonuses would be granted to the most successful RL companies.

Here, we have decided to investigate a RL company eager to grasp this opportunity. The current framework of this RL company is a drop-off system; therefore, it requires multiple collection centres spread across the city for consumers to deliver UPs. The company currently collects all types of waste but plans to focus on e-waste, and if necessary, accommodate its system (e.g. expand its network and bring new equipment). Additionally, it intends to categorize collected UPs into three groups of cell phones, computers (e.g. monitors and laptops) and household appliances (e.g. refrigerators and television). Besides that, it considers several predetermined weight groups to classify the UPs; for example, most of the top freezer refrigerators are assumed to have a similar weight range.

Moreover, the company entertains the idea of allocating BB offers based on their UPs type, condition and weight. Its network has been established in the city of Mashhad and assumes each district as a customer zone. The detail of the city's geography is depicted in Figure 4. Currently, 13 customer zones and five collection centres are in service. The company can afford to establish four additional collection centres. In the city of Mashhad, two remanufacturing facilities, one recycling centre and four disposal centres providing services for e-waste purposes. Now, with the help of masked data available to us, we aim to evaluate the performance of the RL company under the application of the proposed model.

Notably, to employ the BB policy due to three different types of UPs, we need to approximate the return rate using three distinct DPF (in terms of a coefficient related to the type of UPs). Also, we associate the UPs' condition and weight category to the two factors of quality and age, respectively. This process means that for determining the marginal probability of acceptance instead of UPs' age, their weight range has been considered. Additionally, the effect of other less influential factors is addressed through the fuzzy return rate assumption. For instance, often, the process of returning cell phones in comparison to television sets seems more convenient. Here, for each type of UPs, three quality and weight levels are considered. Without loss of generality, we assumed that for both quality and weight, the higher-levels have superior salvage value than lower-level ones.

Afterward, the model has been solved (all the costs are based on Iran's official currency Toman). For the sake of convenience, the same confidence level has been considered for all of the fuzzy constraints. Results of the total cost of the system and the total number of collection centres are shown in Figure 5. We can see that each time the minimum satisfaction level of fuzzy constraints has gone up, the system's total cost has risen, but the number of collection centres fluctuated. Furthermore, we mentioned three distinct return functions in the model for three types of UP. Notably, Type 3 UPs (i.e. household appliances) are expected to comprise more than 72% of return flow in this investigated RL company. Here, we focus on the results of Type 3 and precisely its total collected number and the optimal rate of the collection (see Figures 6 and 7).

In all of the scenarios for the confidence levels, the total amount of collected UPs has been half of the existing ones due to an obligation related to the government's minimum acceptable collection rate. From the charts, it can be inferred that the whole collection process is costly for the company (mainly due to inefficient performance of recycling and remanufacturing centres leading to low salvage value for even higher-quality UPs and also a limited available number of them). In these circumstances, the

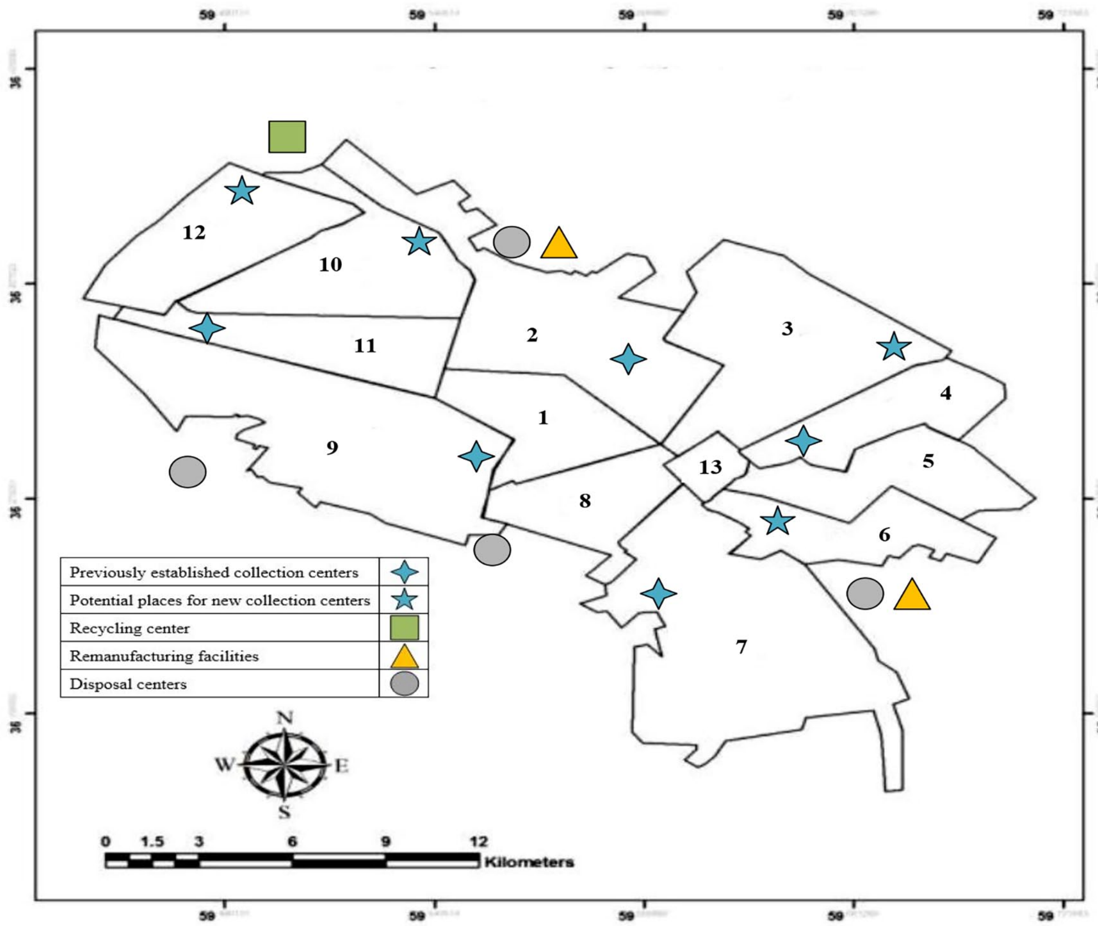

Figure 4. The map of the city of Mashhad districts.

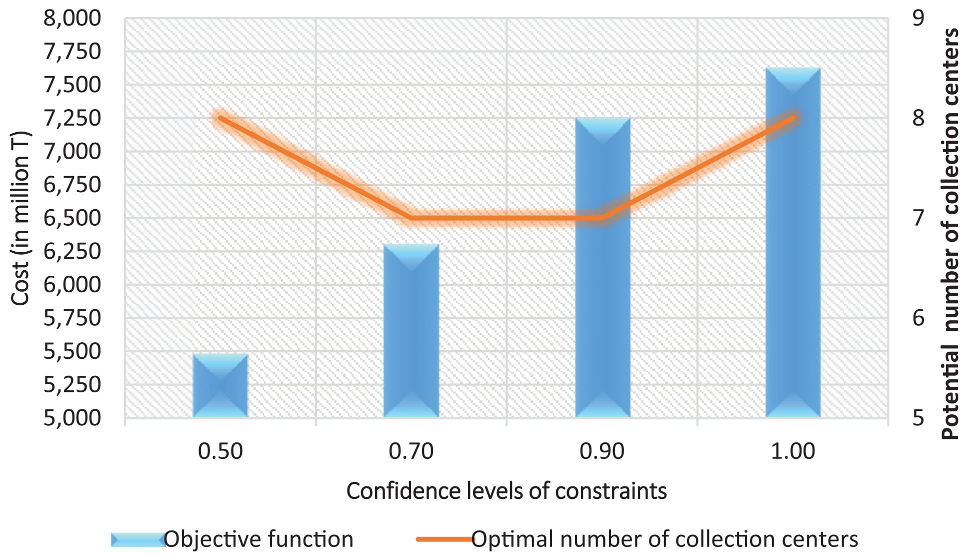

Figure 5. The total cost of the system for different scenarios of confidence levels.

importance of the appropriate BB offer policy to reduce unnecessary costs becomes more crucial because the municipal officials must recognize the RL company to receive extra bonuses to cover its expenses.

Moreover, we point out that increasing the system confidence levels causes a gradual prioritization in collecting cheaper UPs that demand lower BB offers. This matter is less noticeable in the graph of return rate given that, in reality, the potential numbers of different quality and weight levels of UPs do not exactly match each other. However, this trend is more discernible in the graph of the total number of collected UPs where we find out that the number of UPs with quality 3 and age 3 (i.e. the highest value

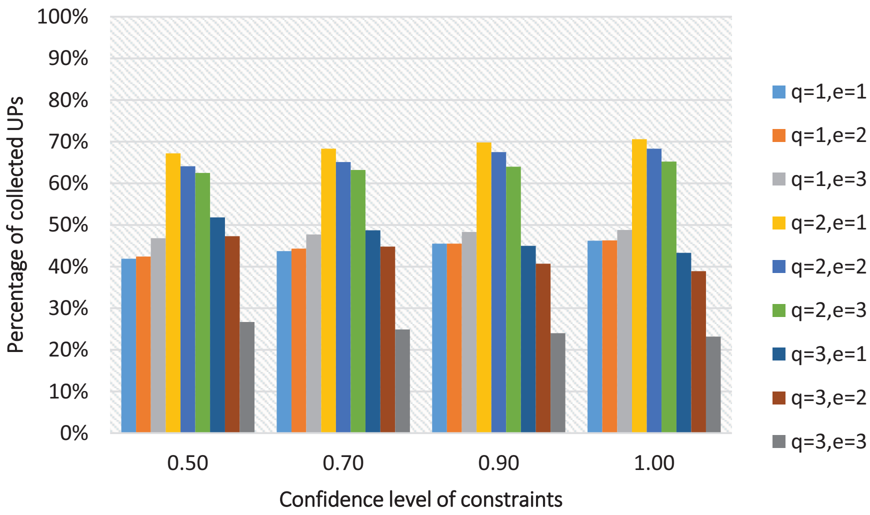

Figure 6. The return rate of Type 3 UPs.

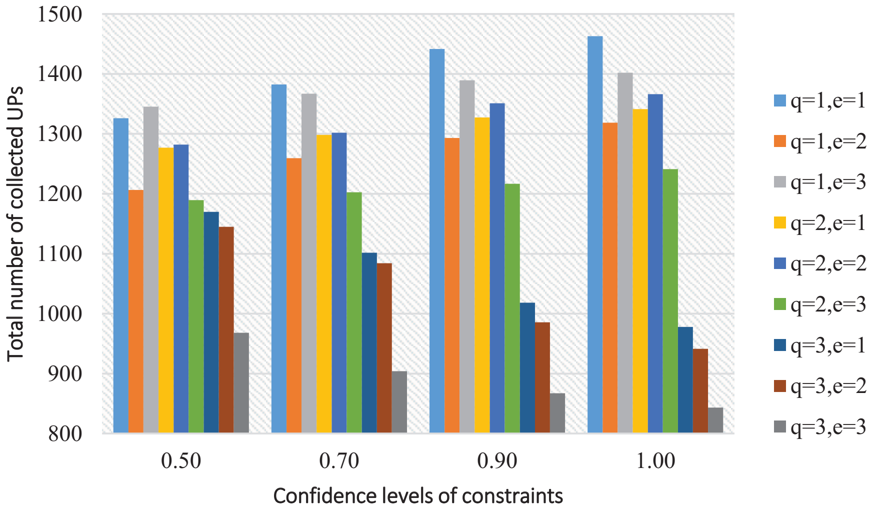

Figure 7. The total number of collected Type 3 UPs.

category) gathered when all confidence levels were 0.5 is 968. On the other hand, in the worst-case scenario where confidence levels are 1, the measure of the same variable is 843. Furthermore, the model solving process time took 137 minutes and 48 seconds and considered a year-long planning period; it does sound viable and practicable. Finally, it is safe to say that the proposed model greatly empowers the RL company by enhancing its capability to collect more efficiently.

Computational experiment

To better understand the model behaviour, we decided to apply it to an experiment with the same parameters from the previous case study, except eliminating the obligation to collect a minimum 50% rate of existing UPs. However, we still assume that the subsidy for each collected would be given to the company. Notably, if we do not include the subsidy, no collection would be made by the system. The results are shown in Figures 8 and 9. As can be seen, in such circumstances, it requires transforming the model into a maximizing profits problem, which enables the company to freely collect as many UPs that would be profitable for it. From Figure 9, we can deduce that even with the presence of subsidy, the potential profit levels are low compared to the scale of actual case study total costs.

Besides that, the inefficiency in the collection process causes the model to significantly lower the overall optimal collection rate and focus more on inferior quality UPs (e.g. for the confidence level of 1, the optimal collection rate has downgraded from 50% in the actual case to less than 14% in the experiment). The reason behind this outcome derives from the lack of infrastructure and advanced recycling facilities, which renders the difference between superior quality and inferior quality salvage values (recycling or remanufacturing) so low that it does not eclipse the difference between their optimal BB offer demands, creating a situation where the collection of lowest quality UPs as the best strategy. This experiment also demonstrates the proposed model's

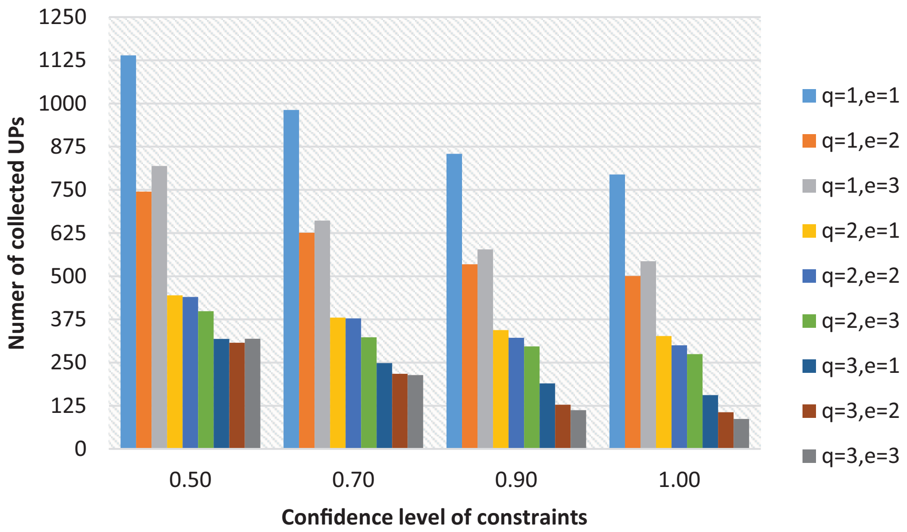

Figure 8. The total number of collected Type 3 UPs in the experiment.

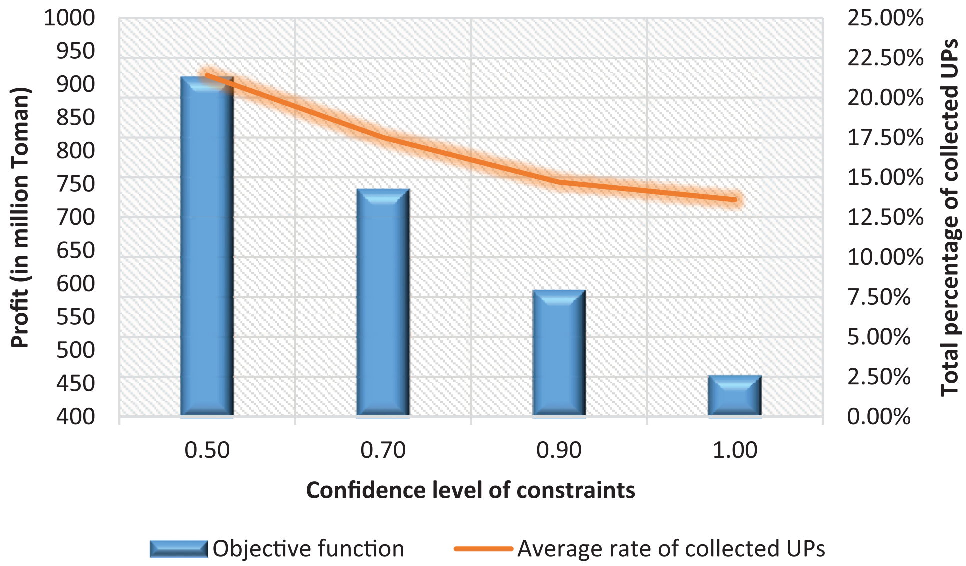

Figure 9. The total profit and rate of collection of the system in the experiment.

capability to deal with problems in which the RL network might be a profitable endeavour. Apart from that, both the actual case study and the subsequent experiment highlight that the product recovery in Mashhad is very costly in current circumstances and can only be viable for any company if they receive substantial financial support. Therefore, this matter draws attention to more investment in new and advanced infrastructure for product recovery purposes in the city.

Sensitivity analysis

This section analyses the model's two critical parameters and examines its attitude further. Hence, we evaluate the two effects of the number of BB offer levels (i.e. L) and the first slope of fuzzy DPF (i.e. $\tilde{\beta}_{1qe}$) on the model responses, respectively. The graph in Figure 10 indicates that if we increase BB offer levels (i.e. softening the BB offer restriction in the model), the system's total cost decreases. However, we should notice that increasing BB levels from 12 to 30 results in less than 2% improvement, demonstrating the linearization method relative precision. Afterward, Figure 11 displays an increase from 0.57 to 0.73 in the EV of the first slope of fuzzy DPF, leading to a roughly 10% boost in the system's total cost. This connection proves the model validity because if we elevate the slope of fuzzy DPF, the overall chance of acceptance will go up, and ultimately the collection process would be less costly and demonstrates the significant impact of the inclusion of BB policy in the model.

Comparative analysis: The proposed model versus a deterministic approach

Finally, to evaluate the efficiency of the fuzzy CB approach in the model, we use a technique introduced by Pishvaee et al. (2012).

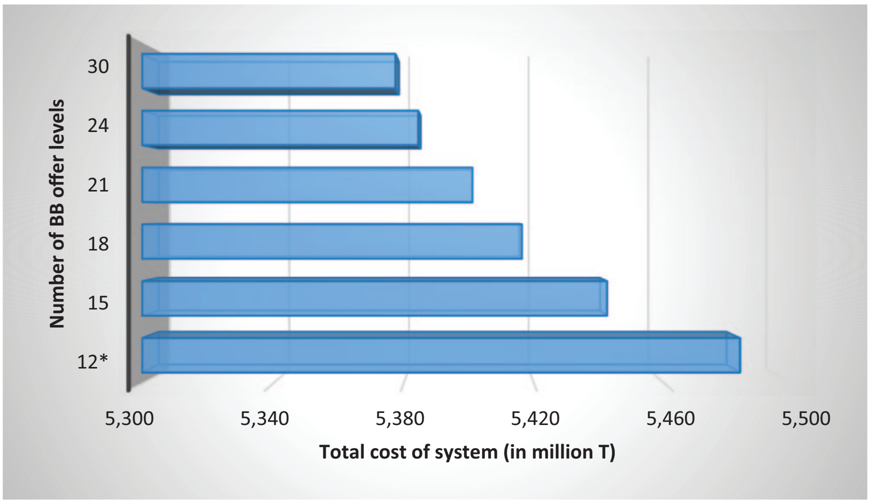

Figure 10. The effect of the number of BB offer levels.

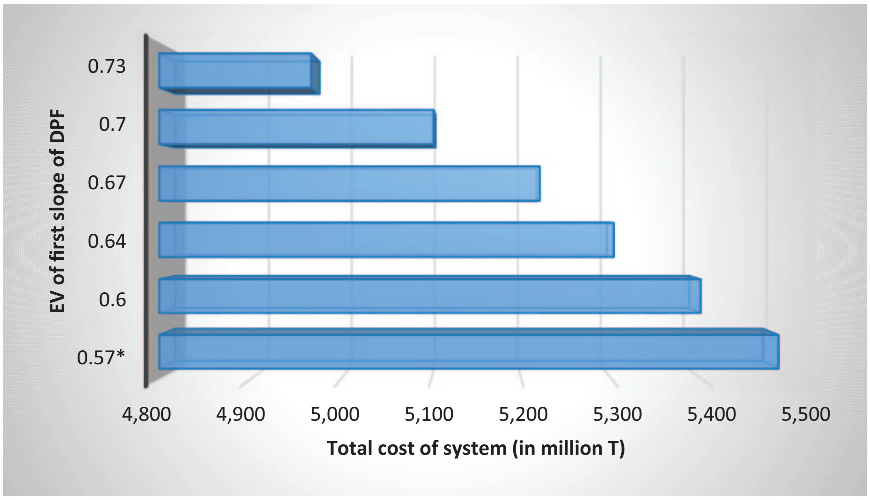

Figure 11. The effect of the first slope of fuzzy DPF.

This way, we attempt to run an analogy between the proposed model and its corresponding deterministic scenario. Hence, several random-realizations (RR) for the fuzzy parameters of the model are generated. If we consider $\check{\chi}$ as a fuzzy trapezoidal number with four prominent values of $(\chi^1{\cdot}\chi^2{\cdot}\chi^3{\cdot}\chi^4)$. Any RR of $\tilde{\chi}$ must be between its two upper and lower bounds $\chi_{RR} = [\chi^1, \chi^4]$. Furthermore, an essential element in this technique is that in each tests all the variables would receive new values except those associated with the strategic decisions in each iteration. Therefore, we assume the locations of collection centres to be fixed in all of the RR iterations.

The procedure above is carried out on the model by generating 10 RRs. The results are shown in Table 2. The average and standard deviation of the system's total cost in the deterministic approach are considerably higher than the proposed fuzzy CB model. Additionally, from Figure 12, it can be discovered that the cost of the fuzzy CB model dominates its deterministic approach affirming its superiority in process.

Conclusions

This paper investigated an effective way to handle e-waste generated in urban areas by introducing the RL network with BB offers under uncertain conditions. We argued that e-waste generally might not have an acceptable return rate without the presence of an incentive offer. That is why including a fair offer in the RL network seemed necessary to convince product holders to return. On top of that, we discussed that a possible approach for allocating BB offers is to associate those offers with UPs' conditions at the time of return. However, we found out that this matter could lead to a false prediction of consumers' behaviour patterns and imprecise estimation of the return rate in reality. That is why we attempted to address other factors on product holder decisions regarding returning UP. Thus, we proposed an FMINLP model to deal with epistemic uncertainty in both parameters of the RL model and UPs' chance of return. Afterward, we described how by using fuzzy PWPF for a specific BB offer, an estimation of the

Table 2. Results of comparative analysis.

RR number	The objective function (in million tons)		
	Deterministic model	Proposed model with 0.5 confidence levels	Proposed model with 0.7 confidence levels
1	6284.55	5398.41	6083.41
2	6351.52	5408.72	6041.93
3	6199.64	5434.96	6095.61
4	6403.72	5460.33	6104.66
5	6512.85	5498.76	6127.58
6	6217.73	5471.79	6039.14
7	6513.90	5470.26	6074.19
8	6570.52	5447.35	6051.37
9	6603.27	5482.83	6100.72
10	6393.25	5470.19	6062.85
Average	6405.01	5460.77	6078.15
Standard deviation	143.35	29.42	32.09

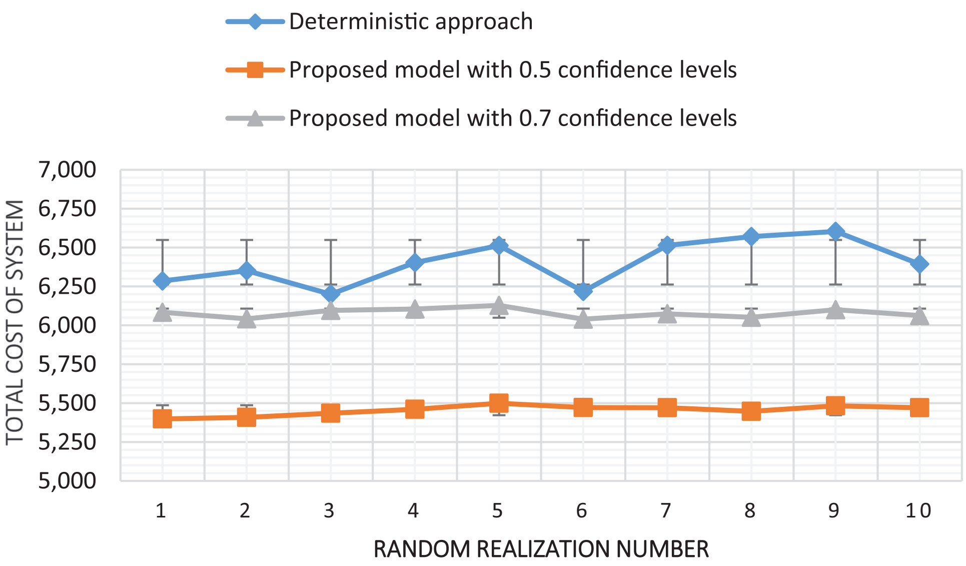

Figure 12. Results of comparative analysis.

return rate of UP assuming the quality, age and other influential criteria could be obtained.

Moreover, a linearization method is conducted on the PWPF, transforming it into a DPF. Then, with the help of the fuzzy CB method and the EV concept, the fuzzy DPF has been converted to its crisp correspondence. Finally, an extensive case study related to the RL company in Mashhad, Iran, was applied to the model in which the results and analysis underscored its utility and advantages.

For future efforts, we acknowledge that the concept of the RL network integration with BB offers has been explored relatively well in recent years; however, we also point out that due to the growing stream of waste production, there are still many cases that might have been less scrutinized or wholly ignored. Similar to this study, one could investigate the RL network with incentive offers, which established its collection centres. Nevertheless, a significant difference could be that the producer wants to collect UPs by merging several of its sale stores with collection sites (e.g. mobile companies). Here, there is an opportunity to be less occupied with network planning and explore incentive offer policy in greater detail. Furthermore, we suggest that adding more dimensions to the development of an e-waste RL model could be promising and even necessary in the collection process of specific UPs. We remark that the RL company could control its collection rate more purposefully through a dynamic time period planning strategy. For instance, consumers often substantially increase their spending on replacing their UPs with new commodities around holidays (e.g. New Year); thus, a lower BB offer might be enough to satisfy their reservation in this particular period. Lastly, we note that the application of this approach is extensive in current circumstances, and simply many parts of it yet to be thoroughly comprehended.

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