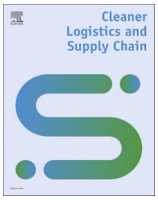
Cleaner Logistics and Supply Chain 11 (2024) 100155

Contents lists available at ScienceDirect

Cleaner Logistics and Supply Chain

journal homepage: www.journals.elsevier.com/cleaner-logistics-and-supply-chain



Uncertain programming model for designing multi-objective reverse logistics networks

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ARTICLE INFO

Keywords:
Reverse logistics network
Multi-objective programming
Uncertainty theory
End-of-life products
Non-dominated sorting genetic algorithm III

ABSTRACT

Given the contradiction between the rapid growth of products and the modest recovery rate of end-of-life products, there is a pressing need to understand the societal significance of establishing a reverse logistics network for end-of-life products. This research constructs an open-loop five-tier reverse logistic network model encompassing customers, centres for collection, disassembly and inspection, remanufacturing, and disposal. A multi-objective mixed-integer nonlinear programming model under uncertainty has been developed. Unlike previous research, this model accounts for surrounding residents' disutility of facilities while simultaneously minimizing economic costs and environmental impact. Besides, uncertainty theory is introduced in solving the proposed model. More specifically, the formulated model converts all uncertain variables into uncertain distributions by implementing the uncertain multi-objective programming method. Furthermore, a customised non-dominated sorting genetic algorithm III (NSGA-III) is proposed and is employed for the first time to address facility selection and recycling volume distribution within the network. The model is then validated using a real-life case study focusing on end-of-life vehicles in Changchun, China. This research could assist decision-makers in both governmental and private sectors in achieving a balanced approach to the interests of the economy, environment, and local communities comprehensively when designing reverse supply chains.

1. Introduction

With technological advancements rapidly unfolding and living standards rising worldwide, the demand for diverse and personalised products has consistently grown (Milisavljevic-Syed et al., 2023). This shift has resulted in shorter product life cycles, quicker turnover rates, and an accompanying surge in waste products. At the same time, global awareness about the environmental ramifications of industrial activities is rising, emphasising the urgent need for sustainability across all facets of our lives, especially in supply chain processes. Under these circumstances, reverse logistics, a crucial aspect of the sustainable supply chain plays a transformative role. By effectively managing the recycling of end-of-life products, reverse logistics not only aids in the conservation of natural resources but also offers economic benefits. It does this by adding value to waste while simultaneously reducing water, air, and soil pollution (Fleischmann et al., 1997).

Reverse logistics is a complex process that includes the collection, transportation, disassembly, inspection, and remanufacturing of end-of-life products. To ensure that waste recycling is successful, an efficient reverse logistics network must be in place. A well-structured reverse logistics network forms the foundation for a well-regulated reverse logistics system (Abdallah et al., 2012). This network is responsible for the retrieval and management of end-of-life products, such as those in the automotive industry. The end-of-life vehicles (ELVs) sector contributes significantly to waste production and pollution (Xia et al., 2023a). For example, in 2020, the global count of ELVs was estimated to be approximately 14.5 million, with China contributing about 3.24 million to this total (Xia et al., 2022). This figure underscores the importance of optimised reverse logistics networks handling the entire automotive reverse supply chain. This includes the recovery of used components, the compliance-based management and disposal of chemicals, and the effective recycling and remanufacturing of valuable materials.

Within the reverse logistics network, the arrangement of network nodes is foundational to its effective operation. This presents a facility location problem (FLP), which is critical for optimising the performance of the reverse logistics network. FLP involves an in-depth analysis of various logistics facility locations and quantities to validate its potential to reduce costs and environmental pollution while enhancing recovery

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https://doi.org/10.1016/j.clscn.2024.100155
Received 30 October 2023; Received in revised form 9 March 2024; Accepted 12 May 2024
Available online 17 May 2024
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rates. The number and location of facilities are intrinsically linked to the operational efficiency of the reverse logistics network (Kannan et al., 2023). More specifically, an optimal balance must be achieved between the number of recycling nodes and the volume of recycled items (Tavana et al., 2022). Although these facilities are necessary for society, residents prefer them far from their homes due to disruptions and pollution that might impact property values and quality of life. Ad hoc solutions such as blindly reducing facility quantity can slow network responsiveness, increasing operational costs and pollution emissions in transportation (Rahimi and Ghezavati, 2018). Thus, the model proposed in the present paper aims to minimize economic costs, environmental impact, and surrounding residents' disutility, creating a sustainable approach benefiting organisations economically, supporting environmental stewardship, and maintaining positive community relations.

In addition, specific gaps exist in current research, as discussed in Section 2.4. Existing uncertainty analysis methods, such as fuzzy and stochastic programming, have limitations, and there is a lack of research on uncertain multi-objective programming for reverse logistics network design. Moreover, while the non-dominated sorting genetic algorithm III (NSGA-III) demonstrates efficiency in handling multi-objective problems, it is underutilised in reverse logistics network optimisation, indicating the potential for improving multi-objective optimisation in this domain.

In response to the issues identified, this research puts forward a multi-objective model for optimizing the open-loop reverse logistics network for end-of-life products. A structured five-tier network is proposed, comprising customers, collection centres, disassembly and inspection centres, remanufacturing centres, and disposal centres. In real-world scenarios, numerous variable factors come into play, including fluctuating fuel prices, route options, vehicle types, processing procedures, and recycled quantity of end-of-life products, among others. To enhance the realism and applicability, uncertain parameters like transportation cost, waste ratio, and disposal cost are introduced, leading to the development of an uncertain multi-objective optimisation model. By leveraging the uncertainty theory (Liu, 2010), this model is transformed into an uncertain correspondence model. Then, a customised NSGA-III is proposed. This algorithm selects the alternative points for various facilities and directs the flow between them, abiding by the constraints of the construction process. The applicability and effectiveness of the model are validated through a case study on ELVs conducted in Changchun, China. The insights derived from this research could benefit policymakers, practitioners, and researchers interested in sustainable supply chain management and reverse logistics network design.

The rest of this paper is as follows. Section 2 presents a comprehensive literature review, focusing on reverse logistics networks for end-of-life products, theories addressing uncertain parameters, and artificial intelligence (AI)-based algorithms. Section 3 details the proposed multi-objective mixed integer nonlinear programming (MOMINLP) model. Section 4 illustrates the solution methodology, comprising uncertain multi-objective programming and a customised NSGA-III. Section 5 introduces a case study centred on ELVs in Changchun, China. Section 6 entails an in-depth discussion of the results of the analysis. Lastly, Section 7 draws a conclusion based on the research conducted and highlights future research.

2. Literature review

The literature review is organised into three main sections. The first section offers a brief overview of relevant studies in designing reverse logistics networks for end-of-life products. The second section evaluates solutions tailored for managing uncertain parameters. The third section focuses on heuristic methods for addressing the LAP in reverse logistics network design. In conclusion, the review highlights research gaps.

2.1. Reverse logistics network for end-of-life products

Various network configurations have been developed based on different facility arrangements. These configurations can be broadly categorised into two groups: open-loop and closed-loop network structures (Zhang et al., 2021). The closed-loop network structure refers to a supply chain where forward and reverse logistics are integrated. However, this research focuses explicitly on the open-loop network.

Meanwhile, a reverse logistics network model cannot be solved without an optimisation objective; thus, it is essential to determine the objective function in the design of a reverse logistics network. Objective functions are primarily categorised into three groups: single-objective, bi-objective, and multi-objective.

In single-objective models for reverse logistics network optimisation, the most common objectives are maximising total profits (Kim et al., 2018) or minimising costs (Kuşakcı et al., 2019). Bi-objective models provide a dual perspective, often seeking to balance profit and environmental benefits (Jin et al., 2019). Additionally, environmental considerations play a crucial role, with objectives centred on minimising carbon emissions (Xiao et al., 2019), reducing environmental impacts of facilities and processes (Feitó-Cespón et al., 2017), and maximising the environmental benefits of recycled products (Devika et al., 2014).

Moreover, researchers have explored social objectives, encompassing factors like layoffs (Govindan and Gholizadeh, 2021), income (Zohal and Soleimani, 2016), workforce balance (Bal and Satoglu, 2018), and worker safety (Devika et al., 2014). Beyond these social, economic, and environmental considerations, multi-objective models extend their focus to include less common objectives, such as service level (Feitó-Cespón et al., 2017), customer convenience (Wang et al., 2020), disruption risks of recycling factories (Simic, 2015), network coverage and flexibility (Subulan et al., 2015), job opportunities (Gao and Cao, 2020), population risk (Govindan et al., 2022), and maximum satisfying demand (Hashemi, 2021).

Even though these diverse objectives can significantly influence the design and performance of a reverse logistics network, few studies have examined the negative impact of these facilities on their surrounding residents (He et al., 2007). These facilities can adversely affect property values and the community quality for nearby residents, as they entail disruptions, noise and water pollution, traffic congestion, and other negative impacts caused by network operations. Prioritising the well-being of residents can help foster positive community relations, potentially reducing conflicts, legal issues, and complaints (ReVelle and Eiselt, 2005). However, if these facilities are located too far from urban areas, operating costs and transportation pollution tend to increase. Therefore, it becomes essential to strike a balance that aligns with the principles of corporate social responsibility and sustainable reverse supply chain management, thereby enhancing the overall value and impact of the reverse logistics network.

2.2. Solution to uncertain parameters

In the design of reverse logistics networks under uncertainty, a key challenge is addressing indeterminate phenomena, particularly in managing uncertain parameters. When managing end-of-life products, various options are available, including recycling, repairs at collection or disassembly centres, or remanufacturing by the original manufacturer. Therefore, the reverse flow is inherently more complex, involving numerous uncertain parameters within the reverse logistics network. These parameters encompass aspects such as the return quantity (Roudbari et al., 2021), return quality (Roghanian and Pazhoheshfar, 2014), return rates (Jerbia et al., 2018), quality recycling rates (Trochu et al., 2020), transportation cost (Ayvaz et al., 2015), and revenues (Jerbia et al., 2018).

To ensure the effectiveness of the location-allocation model, it is essential to consider these uncertain parameters when establishing the reverse logistics network. Uncertainty methods can be classified into

three categories, namely uncertainty programming based on probability theory, uncertainty programming based on fuzzy set theory, and uncertainty programming based on uncertainty theory (Chen et al., 2023).

Regarding the uncertainty programming based on probability theory, the key term is "random", which is dedicated to analysing random phenomena. Such phenomena yield that there can be one of many potential results influenced by chance. Parameters associated with these random phenomena are termed as stochastic parameters when designing reverse logistics networks (Govindan et al., 2017). Popular methods to address this uncertainty include stochastic programming (Jerbia et al., 2018) and chance-constrained programming (Mishra and Singh, 2020).

To differentiate with randomness, there are two mathematical systems for modelling subjective uncertainty. The first is uncertainty programming based on fuzzy set theory (Zadeh, 1965), which has been further developed into possibility measure theory (Zadeh, 1978). It evaluates objects and their associated fuzzy concepts as specific fuzzy sets, utilizing fuzzy mathematics to analyse non-exact phenomena. The method of fuzzy logic is extensively used to address such uncertainties (Phuc et al., 2017). The second is uncertainty programming based on uncertainty theory. To better deal with uncertainty, Liu (2010) introduced uncertainty theory to better comprehend its concept, subsequently establishing it as a mathematical discipline to model uncertainty using the belief degree framework. This theory employs uncertain variables to depict uncertain phenomena, grounded in a fresh axiomatic system encompassing uncertainty measures, variables, distributions, and their applications. A comprehensive literature review identified seven potential core sub-fields of uncertainty theory, and its findings indicate the escalating appeal of uncertainty theory and its burgeoning academic footprint (Zhou et al., 2023).

While probability theory is a powerful tool for addressing uncertainty, it has certain limitations. Firstly, not all uncertain phenomena can be labelled as random. Additionally, the effectiveness of probability theory relies on the availability of sufficient historical data to describe stochastic parameters (Zhang et al., 2018). However, in many real-world cases, historical data may be lacking or invalid. This is particularly true for the field of reverse logistics networks for end-of-life products, which is still in its early stages, making it challenging to gather sufficient observational data (Xia et al., 2023b). Furthermore, although possibility measure theory satisfies normality, non-negativity, monotonicity, and semi-continuity, it lacks duality. This means that when fuzzy variables are used to describe parameter uncertainty, there may lead to counter-intuitive outcomes. For instance, selecting a scheme with a 100 % probability of success might also imply a 100 % possibility of investment failure. However, the foundation of uncertainty theory is based on uncertainty measures, including normality, duality, subadditivity, and product axiom. Even though uncertainty theory has been integrated into solving vehicle routing problem within reverse logistics network (Li et al., 2016), there is a shortage of research addressing location-allocation problems using uncertainty theory for the establishment and optimization of reverse logistics networks.

2.3. Heuristic approach

While the majority of research tends to use single-objective models, small-scale studies often resort to exact methods, such as ε-constraint method (Bal and Satoglu, 2018), leveraging commercial solvers like Lingo and CPLEX software. However, applying exact methods to large-scale problems can result in extended solution times and in some instances, might render the problems unsolvable.

While intelligent heuristic algorithms can deal with any form of objective function and constraint without understanding the inherent nature of the problem (Reddy et al., 2020), prevalent heuristics algorithms applied in reverse logistics network design include ant colony optimisation (ACO) (Zohal and Soleimani, 2016), simulated annealing (SA) algorithm (Fattahi and Govindan, 2017), tabu search (TS) algorithm (Zhen et al., 2019), particle swarm optimisation (PSO) algorithm (Soleimani and Kannan, 2015), artificial bee colony (ABC) algorithm (Lin et al., 2018), and benders decomposition (Reddy et al., 2019). However, these intelligent algorithms have their strengths but may require adaptations or are better suited for single-objective or specific problems.

While multi-objective models often employ a genetic algorithm (GA) for the weighted summation of the objectives, determining the precise weights of multi-objective functions proves challenging (Alshamsi and Diabat, 2017). Moreover, the model struggles to capture the inter-relational constraints among them accurately. However, there is a rising trend of researchers gravitating towards non-dominated sorting genetic algorithms (NSGA) for optimising large-scale complex location-allocation problems. As a typical genetic algorithm, NSGA is inspired by natural selection. It employs crossover, mutation, and selection operations to optimise the problems (Roghanian and Pazhoheshfar, 2014). For example, a customised non-dominated sorting genetic algorithm II (NSGAII) and a bespoke ABC algorithm have been employed to address the fuzzy mathematical programming challenges associated with municipal waste management (Hashemi, 2021). Meanwhile, some researchers have demonstrated that NSGA-III outperformed NSGA-II when tackling multi-objective problems (Ishibuchi et al., 2016), such as optimisation of an adiabatic styrene reactor (Chaudhari et al., 2022), where NSGA-III often exhibits superior performance in terms of diversity, hypervolume, and the number of objectives. However, NSGA-III is rarely used to solve multi-objective problems in optimising reverse logistics networks.

3. Research gaps

The literature review indicates the limited availability of the models related to reverse logistics network optimisation. Table 1 provides a summary of the related literature, reviewing the mathematical models developed and identifying the existing gaps in the literature. The gap analysis can be summarised as follows.

(1) While many studies primarily focus on optimising the reverse logistics network from an economic standpoint, fewer studies simultaneously address economic costs, sustainable environmental concerns, and the disutility issues surrounding residents face, as discussed in Section 2.1.
(2) Fuzzy and stochastic programming are commonly employed for uncertainty analysis, but they have certain limitations. Furthermore, there is a lack of research that explores the design optimisation of reverse logistics networks within the framework of uncertain multi-objective programming, as discussed in Section 2.2.
(3) Most intelligent heuristics algorithms for optimising reverse logistics network problems may require adaptations or are better suited for single-objective or specific types of problems. Despite NSGA-III demonstrating superior performance in efficiently handling multi-objective problems on certain test cases, it is rarely applied to solve the multi-objective optimisation problems in reverse logistics network design, as discussed in Section 2.3.

Optimising reverse logistics networks for end-of-life products is inherently complex characterised by numerous constraints. Consequently, the model proposed in the present paper belongs to a multi-objective mixed integer nonlinear programming problem under uncertainty.

4. Problem statement

Recycling and remanufacturing end-of-life products have emerged as crucial strategies for enterprises aiming to bolster their social reputation, enhance customer service, and reduce production costs.

Table 1
A summary of the recent literature on reverse logistics network design.

Ref.	Type	Problem Definition		Model	Objectives					Solution	Case
		Product	Param.	Type	Cost	Profit	Social	Env.	Others		Study
(Kannan et al., 2023)	OL	M	C	MIP	*			*		Exact	E-waste
(Tavana et al., 2022)	CL	M	U	MILP	*		*	*		Exact	Numerical experiment
(Gholizadeh et al., 2022)	OL	M	U	MINLP	*					Cross-entropy & GA & SA	Disposable appliances
(Reddy et al., 2022)	OL	S	U	MILP	*			*		Improved Benders Decomposition	Numerical experiment
(Harijani and Mansour, 2022)	OL	M	U	MILP	*					Exact	MSW
(Govindan and Gholizadeh, 2021)	OL	M	U	MILP	*					Cross-entropy algorithm	ELVs
(Hashemi, 2021)	OL	S	U	FMIP	*				*	NSGA-II & BCO	MSW
(Dutta et al., 2020)	CL	S	U	WGP	*		*	*		Exact	E-commerce
(Xiao et al., 2019)	OL	S	C	MILP	*			*		Exact	ELVs
(Zhen et al., 2019)	CL	M	U	MINLP	*					Tabu search algorithm	Numerical experiment
(Bal and Satoglu, 2018)	OL	M	C	GP	*		*	*	*	Augmented ε-constraint method II	WEEE
(Trochu et al., 2018)	OL	S	U	MILP	*					Exact	Recycled CRD wood
(Lin et al., 2018)	OL	S	C	MILP	*					BCO algorithm	ELVs
(Shankar et al., 2018)	CL	M	C	MILP		*				Exact	ELVs
(Alshamsi and Diabat, 2017)	OL	M	C	MILP		*				GA	Household appliances
(Zohal and Soleimani, 2016)	CL	S	C	MILP	*		*	*		Ant colony algorithm	Gold industry
(Simic, 2015)	OL	S	U	ISP		*			*	Exact	ELVs
(Subulan et al., 2015)	CL	S	U	FGP	*				*	Exact	Battery
(Roghanian and Pazhoheshfar, 2014)	OL	M	U	P-MILP	*					GA	Numerical experiment

*OL: open loop, CL: closed loop, S: single, M: multiple, C: certain, U: uncertain, Env.: environment, ISP: interval-stochastic programming, MIP: mixed-integer programming, MILP: mixed-integer linear programming, MINLP: mixed-integer nonlinear programming, GP: goal programming, FGP: fuzzy goal programming, FMIP: fuzzy mixed-integer programming, SP: stochastic programming, FMILP: fuzzy mixed-integer linear programming, P-MILP: probabilistic mixed-integer linear programming, WEEE: waste electric and electronic equipment, ELVs: end-of-life vehicles, NSGA: non-dominated sorting genetic algorithm, CRD: construction, renovation and demolition, MSW: municipal solid waste, WGP: weighted goal programming, BCO: bee colony optimization, GA: genetic algorithm, SA: simulated annealing.

Successfully executing these strategies necessitates appropriate reverse logistics network support, which entails the strategic location of facilities such as collection and remanufacturing centres and the effective management of product flows between these facilities. The efficacy and profitability of reverse logistics management hinge significantly on the soundness of the reverse logistics network design.

The proposed five-tier reverse logistics network is depicted in Fig. 1. Within the network, end-of-life products disposed of by consumers are sent to the closest collection centres. As storage facility providers, the collection centres accept and temporarily accumulate end-of-life products. Once a sufficient quantity has been accumulated, the products are transported to disassembly and inspection centres, which serve as the core element of the entire reverse logistics network. These centres are responsible for disassembling, testing, and sorting end-of-life products, as well as sending valuable waste materials to remanufacturing centres for processing and remanufacturing. Non-recyclable or non-reusable materials generated during disassembly, inspection, and remanufacturing are directed to the waste disposal centre, where they are processed using environmentally friendly technologies.

4.1. Assumptions

The development of the proposed mathematical model has considered the following assumptions. The implications associated with these assumptions are discussed in detail in section 6.

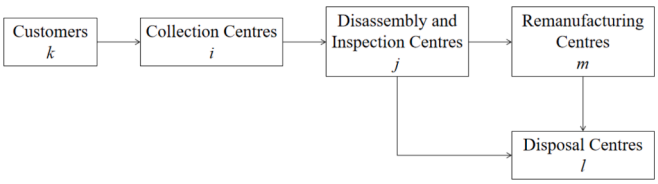

Fig. 1. Remanufacturing Reverse Logistics Network Structure Diagram.

(1) The focus of this research is on a single-period network designed for the recycling and remanufacturing of single end-of-life products. It does not include aspects such as service returns, product recalls, and warranty returns fall outside the scope of this research.
(2) Potential locations for all facilities have been pre-identified based on existing authorised facilities, with the distances between these facilities already determined.
(3) End-of-life products must be initially collected at a collection centre and are not sent directly to disassembly and inspection centres.
(4) Consumers from each predefined consumption region, who are both physically and financially responsible for the handover, will opt for the nearest collection centre. The quantity of recycled end-of-life products is uncertain, though its uncertainty distribution is known.
(5) The geographical location of each facility, as well as the distances between facilities, are defined by their respective latitude and longitude. The location of a customer zone is pinpointed by the centre of the corresponding distinct.
(6) There is no holding of inventory at any facility.
(7) Capacity of each centre needs to be considered, and the quantity of end-of-life products received by the collection centres, disassembly and inspection centres, and remanufacturing centres must not exceed their maximum processing capacity.
(8) The cost elements of the reverse logistics include the transportation cost between network nodes, and processing costs at disassembly and inspection, and remanufacturing centres.
(9) The quantity of end-of-life products, transportation and processing costs, waste ratios, estimated CO_2 emitted form transportation, and coefficient of side effects are uncertain variables.

4.2. Model notations

The notations comprising of indexes, parameters, and decision variables are illustrated in Table 2.

4.3. Mathematical model formulation

In this section, the proposed model is presented with objective and constraint definitions with respect to the defined sets, parameters, and decision variables.

$$\min Z_1 = \sum_{k=1}^{K}\sum_{i=1}^{I} QC_{ki} \times d_{ki} \times v_{ki} + \sum_{i=1}^{I}\sum_{j=1}^{J} QC_{ij} \times d_{ij} \times v_{ij} + \sum_{j=1}^{J} \times \sum_{m=1}^{M} QC_{jm} \times d_{jm} \times v_{jm} + \sum_{j=1}^{J}\sum_{l=1}^{L} \mu \times d_{jl} \times v_{jl} \times \sum_{i=1}^{I} QC_{ij} + \sum_{m=1}^{M}\sum_{l=1}^{L} \lambda \times d_{ml} \times v_{ml} \times \sum_{j=1}^{J} QC_{jm} + \sum_{j=1}^{J} \times \sum_{i=1}^{I} QC_{ij} \times e_j + \sum_{m=1}^{M}\sum_{j=1}^{J} QC_{jm} \times e_m \quad (1)$$

Eq. (1) indicates the objective function of minimizing the total cost of entire reverse supply chain, which contains transportation cost and processing cost.

$$\min Z_2 = \sum_{k=1}^{K}\sum_{i=1}^{I} tce_{ki} \times QC_{ki} + \sum_{i=1}^{I}\sum_{j=1}^{J} tce_{ij} \times QC_{ij} + \sum_{j=1}^{J}\sum_{m=1}^{M} tce_{jm} \times QC_{jm} + \sum_{j=1}^{J}\sum_{l=1}^{L} tce_{jl} \times \mu \times \sum_{i=1}^{I} QC_{ij} + \sum_{m=1}^{M}\sum_{l=1}^{L} tce_{ml} \times \lambda \times \sum_{j=1}^{J} QC_{jm} \quad (2)$$

Eq. (2) indicates the objective function of the problem that minimize environmental pollution which is measured by the carbon dioxide emissions. The amount of carbon dioxide emission is measured throughout the entire end-of-life products recycling from customers zone to the remanufacturing and waste disposal facilities, such as collection processes in transportation, inspection processes in disassembly and inspection centres, and remanufacturing processes in remanufacturing centres.

$$\min Z_3 = \sum_{k=1}^{K}\sum_{i=1}^{I} QC_{ki} \times d_{ki} \times \beta_i + \sum_{i=1}^{I}\sum_{j=1}^{J} QC_{ij} \times d_{ij} \times \beta_j + \sum_{j=1}^{J} \times \sum_{m=1}^{M} QC_{jm} \times d_{jm} \times \beta_m + \sum_{j=1}^{J}\sum_{i=1}^{I} QC_{ij}/G_j \times Y_j + \sum_{m=1}^{M} \times \sum_{j=1}^{J} QC_{jm}/G_m \times Y_m \quad (3)$$

Eq. (3) indicates the objective function of minimizing surrounding residents' disutility. Throughout the recycling process, encompassing inspection, disassembly, remanufacturing, and transportation, noise and wastewater are generated, posing potential concerns for noise and water pollution.

The definition of the constraints is shown as follows:

Subject to:

$$\sum_{i=1}^{I} QC_{ki} \times Y_i \le R_k\,, \forall k \quad (4)$$

Table 2
Model Notations.

Sets and Indexes	
K	Set of the user of end-of-life products with index k
I	Set of collection centres with index i
J	Set of disassembly and inspection centres with index j
M	Set of remanufacturing centres with index m
L	Set of disposal centres with index l
Parameters	
d_{ki}	Distance from the customer k to the collection centre i
d_{ij}	Distance from the collection centre i to the disassembly and inspection centre j
d_{jm}	Distance from the disassembly and inspection centre j to the remanufacturing centre m
d_{jl}	Distance from the disassembly and inspection centre j to the disposal centre l
d_{ml}	Distance from the remanufacturing centre m to the disposal centre l
G_j	Distance from the disassembly and inspection centre j to the residential area
G_m	Distance from the remanufacturing centre m to the residential area
Q_i	The maximum processing capacity of each collection centre i
Q_j	The maximum processing capacity of each disassembly and inspection centre j
Q_m	The maximum processing capacity of each remanufacturing centre m
v_{ki}	Per unit transporting cost from the customer k to the collection centre i, uncertain variable
v_{ij}	Per unit transporting cost from the collection centre i to the disassembly and inspection centre j, uncertain variable
v_{jm}	Per unit transporting cost from disassembly and inspection centre j to remanufacturing centre m, uncertain variable
v_{jl}	Per unit transporting cost from disassembly and inspection centre j to disposal centre l, uncertain variable
v_{ml}	Per unit transporting cost from remanufacturing centre m to disposal centre l, uncertain variable
μ	The waste ratio of end-of-life product at disassembly and inspection centre j, uncertain variable
λ	The waste ratio of end-of-life product at remanufacturing centre m, uncertain variable
e_j	Per unit processing cost of end-of-life product at the disassembly and inspection centre j, uncertain variable
e_m	Per unit processing cost of end-of-life product at the remanufacturing centre m, uncertain variable
tce_{ki}	Estimated CO_2 emitted for transportation from customer k to collection centre i, uncertain variable
tce_{ij}	Estimated CO_2 emitted for transportation from collection centre i to disassembly and inspection centre j, uncertain variable
tce_{jm}	Estimated CO_2 emitted for transportation from disassembly and inspection centre j to remanufacturing centre m, uncertain variable
tce_{jl}	Estimated CO_2 emitted for transportation from disassembly and inspection centre j to disposal centre l, uncertain variable
tce_{ml}	Estimated CO_2 emitted for transportation from remanufacturing centre m to disposal centre l, uncertain variable
β_i	Coefficient of side effects of collection centre i on surrounding residents, uncertain variable
β_j	Coefficient of side effects of disassembly and inspection centre j on surrounding residents, uncertain variable
β_m	Coefficient of side effects of remanufacturing centre m on surrounding residents, uncertain variable
R_k	The amount of end-of-life products that is collected from customer k, uncertain variable
α	Confidence level
Decision variables	
$Y_i = \begin{cases} 1 if collection center i is constructed, \\ 0 otherwise \end{cases}$	
$Y_j = \begin{cases} 1 if disassembly and inspection center j is constructed, \\ 0 otherwise \end{cases}$	
$Y_m = \begin{cases} 1 if remanufacturing center m is constructed, \\ 0 otherwise \end{cases}$	
QC_{ki}	The amount of end-of-life products dispatched from the customer k to the collection centre i
QC_{ij}	The amount of end-of-life products dispatched from collection centre i to disassembly and inspection centre j
QC_{jm}	The amount of end-of-life products dispatched from disassembly and inspection centre j to remanufacturing centre m

$$\sum_{j=1}^{J} QC_{ij} \times Y_j \le \sum_{i=1}^{I} QC_{ki} \times Y_i,\ \forall i,k \tag{5}$$

$$\sum_{m=1}^{M} QC_{jm} \times Y_m \le (1-\mu) \times \sum_{i=1}^{I} QC_{ij} \times Y_j,\ \forall j \tag{6}$$

$$\sum_{k=1}^{K} QC_{ki} \times Y_i \le Q_i, \forall i \tag{7}$$

$$\sum_{i=1}^{I} QC_{ij} \times Y_j \le Q_j, \forall j \tag{8}$$

$$\sum_{j=1}^{J} QC_{jm} \times Y_m \le Q_m, \forall m \tag{9}$$

$$1 \le \sum_{i=1}^{I} Y_i \le I, 1 \le \sum_{j=1}^{J} Y_j \le J, 1 \le \sum_{m=1}^{M} Y_m \le M \tag{10}$$

$$Y_i,\ Y_j, Y_m \in \{0,1\},\ i \in I,\ j \in J,\ m \in M \tag{11}$$

$$QC_{ki}, QC_{ij}, QC_{jm} \ge 0, k \in K,\ i \in I,\ j \in J,\ m \in M \tag{12}$$

Constraints (4) – (6) represent the balanced flow of end-of-life products between facilities. Constraints (7) – (9) represent the capacity constraints of the collection centres, disassembly and inspection centres, and remanufacturing centres. Constraints (10) – (12) impose the non-negativity and binary restrictions on decision variables.

5. Solution methodology

The research problem belongs to a complex end-of-life products management system with many of its components being uncertain. The methodology to solve such a research problem will include two steps. In the first step, with the help of uncertain multi-objective programming, the initial mathematical models are converted into an equivalent crisp model based on uncertain multi-objective programming. In the second step, the customised NSGA-III is used as the problem is a complex NP-hard with many constraints.

5.1. The equivalent crisp objective functions and constraints

The fundamental concepts in uncertainty theory encompass uncertainty measures, uncertain variables, and uncertainty distribution (Liu, 2010). Further elaboration on uncertain theory can be found in the Appendix. By leveraging these definitions and employing the uncertain multi-objective programming method, the initially proposed multi-objective model with uncertain variables is transformed into a definite model, as represented by Eqs. (13) – (17).

$$\begin{aligned}\min E(Z_1) = &\sum_{k=1}^{K}\sum_{i=1}^{I} QC_{ki} \times d_{ki} \times E(v_{ki}) + \sum_{i=1}^{I}\sum_{j=1}^{J} QC_{ij} \times d_{ij} \times E(v_{ij}) \\ &+ \sum_{j=1}^{J}\sum_{m=1}^{M} QC_{jm} \times d_{jm} \times E(v_{jm}) + \sum_{j=1}^{J}\sum_{l=1}^{L} E(\mu) \times d_{jl} \times E(v_{jl}) \\ &\times \sum_{i=1}^{I} QC_{ij} + \sum_{m=1}^{M}\sum_{l=1}^{L} E(\lambda) \times d_{ml} \times E(v_{ml}) \times \sum_{j=1}^{J} QC_{jm} + \sum_{j=1}^{J}\sum_{i=1}^{I} QC_{ij} \\ &\times E(e_j) + \sum_{m=1}^{M}\sum_{j=1}^{J} QC_{jm} \times E(e_m)\end{aligned} \tag{13}$$

$$\begin{aligned}\min E(Z_2) = &\sum_{k=1}^{K}\sum_{i=1}^{I} E(tce_{ki}) \times QC_{ki} + \sum_{i=1}^{I}\sum_{j=1}^{J} E(tce_{ij}) \times QC_{ij} + \sum_{j=1}^{J} \\ &\times \sum_{m=1}^{M} E(tce_{jm}) \times QC_{jm} + \sum_{j=1}^{J}\sum_{l=1}^{L} E(tce_{jl}) \times E(\mu) \\ &\times \sum_{i=1}^{I} QC_{ij} + \sum_{m=1}^{M}\sum_{l=1}^{L} E(tce_{ml}) \times E(\lambda) \times \sum_{j=1}^{J} QC_{jm}\end{aligned} \tag{14}$$

$$\begin{aligned}\min E(Z_3) = &\sum_{k=1}^{K}\sum_{i=1}^{I} QC_{ki} \times d_{ki} \times E(\beta_i) + \sum_{i=1}^{I}\sum_{j=1}^{J} QC_{ij} \times d_{ij} \times E(\beta_j) \\ &+ \sum_{j=1}^{J}\sum_{m=1}^{M} QC_{jm} \times d_{jm} \times E(\beta_m) + \sum_{j=1}^{J}\sum_{i=1}^{I} QC_{ij}/G_j \times Y_j + \sum_{m=1}^{M} \\ &\times \sum_{j=1}^{J} QC_{jm}/G_m \times Y_m\end{aligned} \tag{15}$$

Subject to:

$$\sum_{i=1}^{I} QC_{kit} \times Y_i \le \phi_{R_k}^{-1}(1-\alpha),\ \forall k \tag{16}$$

$$\sum_{m=1}^{M} QC_{jm} \times Y_m \le (1-\phi_{\mu}^{-1}(\alpha)) \times \sum_{i=1}^{I} QC_{ij},\ \forall j \tag{17}$$

5.2. Solution algorithm structure

The mathematical models are proposed to optimise three objectives in this research. A customised NSGA-III is utilised to address the multi-objective location-allocation problem. To evaluate the efficacy of NSGA-III, its results will be compared with those from the improved non-dominated sorting genetic algorithm II (NSGA-II).

5.2.1. Non-dominated sorting genetic algorithm III (NSGA-III)

NSGA-III is a sophisticated multi-objective optimisation algorithm designed for problems with three or more objectives. It introduces the innovative concept of reference points, allowing NSGA-III to deliver uniform coverage and diverse solution sets in high-dimensional objective spaces (Deb and Jain, 2013).

The standard NSGA-III is usually designed for a specific variable type, like binary, integer, or continuous variables. However, many real-world optimisation challenges involve mixed decision variables. Thus, NSGA-III has been enhanced to handle optimisation problems with mixed variables adeptly. The improved NSGA-III processes multiple variable types simultaneously with greater efficiency, permitting distinct sampling, selection, crossover, and mutation strategies for each variable category. Not only is the enhanced NSGA-III more adaptable and customisable, but it also offers superior comprehension and search efficiency. The flowchart for improved NSGA-III is depicted in Fig. 2, and its pseudo-code is shown in Algorithm 1.

Algorithm 1. NSGA-III Based on Mixed Variables

Input: Population size *N*, Number of generations *G*, Reference directions *R*
Input: Crossover probability P_c, Mutation probability P_m
1: Generate reference directions *R* using **get_reference_directions()**
2: Initialize population P_O using **MixedVariableSampling()** with *N* individuals
3: Evaluate the fitness of each individual in P_O
4: **for** $g = 1$ to G **do**
5: Select parents from P_{g-1} using random selection
6: Create offspring population Q_g by:
7: Applying **MixedVariableMating()** on parents with:
8: Different **crossover** (with prob. P_c) for Integer and Binary variables
9: Different **mutation** (with prob. P_m) for Integer and Binary variables

(*continued on next page*)

(*continued*)

Algorithm 1. NSGA-III Based on Mixed Variables

10: Evaluate the fitness of each individual in Q_g
11: Combine parent and offspring populations: $R_g = P_{g-1} \cup Q_g$
12: Eliminate duplicates in R_g using **MixedVariableDuplicateElimination()**
13: Perform non-dominated sorting on R_g to classify individuals into different fronts: $F_1, F_2, \ldots$
14: Let P_g be an empty population
15: $i = 1$
16: **while** $|P_g| + |F_i| \leq N$ **do**
17: Compute the perpendicular distance of each individual in F_i to the reference points
18: Add individuals of F_i to P_g
19: $i = i + 1$
20: **end while**
21: **if** $|P_g| < N$ **then**
22: Use the reference point-based niching method to choose the remaining individuals
23: **end if**
24: **end for**

5.2.2. Non-dominated sorting genetic algorithm II (NSGAII)

While NSGA-II and NSGA-III share a similar framework, their primary distinction lies in the selection mechanism. More specifically, NSGA-II employs the crowding distance method for selecting the Pareto solution set, rather than using reference points (Deb et al., 2002). This crowding distance approach falls short in effectively managing multi-objective challenges. Besides, the standard NSGA-III has been enhanced with mixed variables, and its pseudo-code is presented in Algorithm 2.

Algorithm 2. NSGA-II Based on Mixed Variables

Input: Population size N, Number of generations G
Input: Crossover probability P_c, Mutation probability P_m
1: Initialize population P_O using **MixedVariableSampling()** with N individuals
2: Evaluate the fitness of each individual in P_O
3: **for** $g = 1$ to G **do**
4: Select parents from P_{g-1} using random selection
5: Create offspring population Q_g by:
6: Applying **MixedVariableMating()** on parents with:
7: Different **crossover** (with prob. P_c) for Integer and Binary variables
8: Different **mutation** (with prob. P_m) for Integer and Binary variables
9: Evaluate the fitness of each individual in Q_g
10: Combine parent and offspring populations: $R_g = P_{g-1} \cup Q_g$
11: Eliminate duplicates in R_g using **MixedVariableDuplicateElimination()**
12: Perform non-dominated sorting on R_g to classify individuals into different fronts: $F_1, F_2, \ldots$
13: Let P_g be an empty population
14: $i = 1$
15: **while** $|P_g| + |F_i| \leq N$ **do**
16: Compute crowding distance for all individuals in F_i
17: Add individuals of F_i to P_g
18: $i = i + 1$
19: **end while**
20: Sort individual in F_i based on crowding distance
21: Fill P_g with individuals from F_i in descending order of crowding distance until $P_g = N$
22: **end for**

6. Case study

The proposed model was implemented in a real-world case study focused on end-of-life vehicles (ELVs) recycling. Designing a reverse logistics network for ELVs is challenging due to its spatio-temporal dispersion, terminal uncertainty, and its complexity of resource utilization. The process of recycling and utilizing ELVs includes activities like recycling, disassembly, remanufacturing, and waste disposal. These activities are integral and rely heavily on a well-structured reverse logistics network. Based on the existing network in Changchun, China, this research establishes a multi-objective ELVs reverse logistics network model.

6.1. Description of the problem

Changchun, the capital of Jilin Province, has a vivid automotive industry. Despite its standing as one of the China's premier automobile hubs, its ELVs recycling industry remains in its initial stage. Currently, Changchun have four primary collections centres (I_1, I_2, I_3, I_4), five disassembly and inspection centres (J_1, J_2, J_3, J_4, J_5), two remanufacturing centres (M_1, M_2), and two waste disposal centres (L_1, L_2), spread across its various districts. The 13 customer zones ($K_1, K_2, \cdots, K_{13}$) of Changchun are considered as potential ELVs sources in this research.

The deterministic parameters representing maximum processing capacities are determined using data collection from China Automotive Green Dismantling System (FAW Group) and the Changchun Bureau of Statistics (Changchun Bureau of Statistics, 2023) for the year 2018. These maximum processing capacities are outlined as follows: (i) collection centres have maximum processing capacities (Q_i) of 250, 420, 375, and 500 units per month, respectively; (ii) disassembly and inspection centres have maximum processing capacities (Q_j) of 250, 420, 170, 500, and 290 units per month, respectively; (iii) remanufacturing centres possess maximum processing capacities (Q_m) of 750 and 400 units per month, respectively.

The deterministic parameters for the distances between facilities and their nearby residential areas are acquired using Google Maps. The facility and customer locations can be visualized in Fig. 3. The distances are detailed as follows: (i) the distances from the disassembly and inspection centres to the residential areas (G_j) are 2, 1.9, 1.3, 1.5, and 1.9 km, respectively; (ii) the distances from the remanufacturing centres to the residential areas (G_m) are 2.4 and 3.7 km, respectively; (iii) the distance between facilities are provided in Table 3.

Additionally, to derive proper estimates of non-deterministic parameters, a combination of data is utilised from industry surveys, government reports, extensive literature reviews, and realistic assumptions as references. The non-deterministic parameters are characterised by uncertain variables, and their uncertainty distributions are obtained based on uncertainty theory, as presented in Table 4.

The designed experimental problems are solved using the customised NSGA-III, and its result is compared with that of the improved NSGA-II. These are developed in Python programming (version 3.8) (Blank and Deb, 2020) and executed on a Core (TM) i7-10510U 1.80 GHz processor.

For the parameters of NSGA-III, population size (*pop_size*) should be a multiple of the number of reference points (*RP*). The *RP* is determined by the number of reference direction (*n_partitions*) and the number of objectives (*M*), as described by Eq. (18).

$$\mathrm{RP} = \left(\mathrm{M} + \mathrm{n}_{\mathrm{partitions}} - 1\right)!/(\mathrm{M}-1)! \times \mathrm{n}_{\mathrm{partitions}}! \tag{18}$$

For this research, the number of reference direction (*n_partitions*) is set to 12, and the number of objectives (*M*) is 3. Consequently, the population size (*pop_size*) is set to 364. Further, other parameters for the customised NSGA-III are set as follows: number of generation (*n_gen*) is 400, crossover probability (P_c) is 0.7, and mutation probability (P_m) is 0.1. To ensure the validity of comparisons, the population size, number of generations, crossover probability, and mutation probability are maintained consistently between NSGA-III and NSGA-II. Additionally, the confidence level α used in Eqs. (16) to (17) to satisfy the flow constraint is set at 0.9.

6.2. Results

This section analyses the computational results obtained through customised NSGA-III to validate the effectiveness and efficiency of the proposed mathematical model. The optimal values for each objective with a confidence level $\alpha = 0.9$ are represented in Table 5.

The computational time for customised NSGA-II is 28.77 mins, while the computational time for customised NSGA-III is 29.06 mins.

The Hypervolume (HV) quantifies the volume of the region dominated by Pareto frontiers in the objective space, offering a means to evaluate the convergence and diversity of Pareto frontiers (Zitzler and Thiele, 1999). The convergence curve for the customised NSGA-III and NSGA-II are shown in Fig. 5. The experimental results demonstrate the

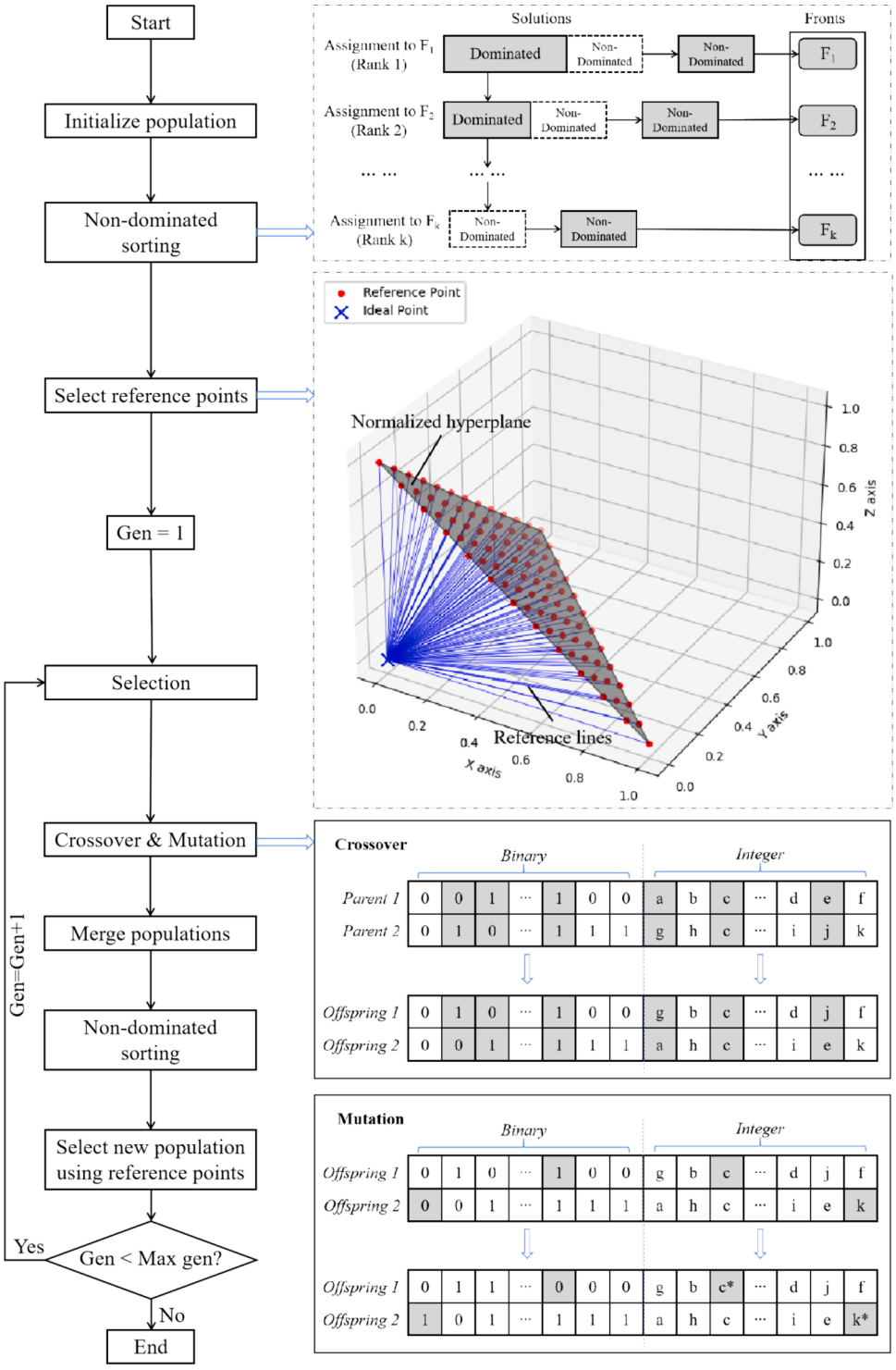

Fig. 2. The flowchart for improved NSGA-III.

convergence of the proposed algorithm.

The analysis compared the results of each objective function at a confidence level ranging from 0.7 to 0.9 to assess the impact of changes in the average value of each objective function, as shown in Fig. 6.

At different confidence levels, the location schemes for the collection centres, disassembly and inspection centres, and remanufacturing centres remain unchanged. However, the quantity of recycled ELVs at the collection centres increases with the rise in confidence level. At confidence levels of 0.7, 0.8, and 0.9, the average recycled quantities obtained by NSGA-III are 46, 103, and 204, respectively.

7. Discussion

This research aims to optimise an open-loop reverse logistics network for end-of-life products by designing a model under uncertainty. A case study on ELVs conducted in Changchun, China serves to validate the effectiveness and efficiency of the proposed MOMINLP model, resolved using the specified solution methodology. Thus, the main research results are analysed as follows.

Initially, varying objective preferences yield different criteria for facility selection, and a decrease in CO_2 emission and disutility to nearby

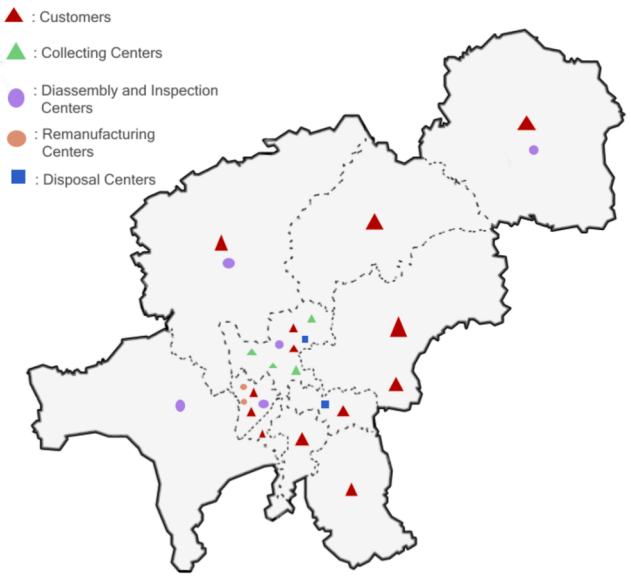

Fig. 3. The locations of facilities and customers (Changchun City).

residents likely results in a surge in total cost (see Table 5). When prioritising cost minimisation, the first scheme emerges as the most favourable. Viewing from a standpoint of reducing CO_2 emissions, the second scheme stands out as the optimal one. Additionally, when considering minimising disutility to surrounding residents, the third scheme proves to be the most beneficial. Observing the optimal solutions of each objective function, it is evident that the three objective functions exert mutual constraints. For instance, when the priority assigned to the disutility of nearby residents supersedes that of the total cost, there is an increase in the total cost by 0.402 %, coupled with a 3.61 % reduction in residents' disutility. This could be attributed to the disutility of nearby residents being inversely proportional to the distance from residential areas; hence, selections under the third priority scheme tend to select facilities or transport routes located farther from residential zones. Moreover, an inverse relationship exists between CO_2 emissions and costs, potentially due to the augmented economic costs incurred from opting for greener transport modes and routes during transport.

Secondly, comparing the two algorithms, regarding the quality and diversity of solutions, illustrates superior performance by customised NSGA-III (see Table 6 and Fig. 4). When observing the average value of each objective, the results produced by customised NSGA-III were consistently lower than those by customised NSGA-II. Specifically, the gap observed between customised NSGA-III and customised NSGA-II in calculating average costs, CO_2 emissions, and disutility to nearby residents is 43.86 %, 48.14 %, and 49.25 %, respectively. Furthermore, this research employs the spacing metric to assess the diversity of the Pareto solution set by quantifying the distance between the solutions within the set, a metric indicator also used in previous research (Hashemi, 2021) for comparing the performance of AI-based algorithms. A smaller spacing metric indicates a more diverse solution set as the solutions are more uniformly distributed. Given that customised NSGA-III possesses a lower spacing metric, it is inferred that customised NSGA-III is potentially more adept at encapsulating the diversity of Pareto frontiers, offering decision-makers a broader array of distinct and feasible solutions to select from.

Table 3
Distances between facilities (km).

	Collection centre *i*			
	1	2	3	4
Customers *k*				
1	193	19.1	44.2	24.8
2	183	13.8	33.6	23.1
3	185	12	35.4	22.3
4	199	14.8	43.1	20.2
5	190	3.3	31	11.3
6	170	15.5	29.6	25.2
7	231	24.1	50	27.8
8	189	24.7	48.9	29.6
9	105	68	49.7	69.3
10	89.9	78.9	52.6	83.5
11	141	65	52.5	53.5
12	250	62.6	82.4	71.9
13	4.1	165.8	136.6	169.1
Disassembly and inspection centre *j*				
1	66.7	71.4	108.2	75.2
2	82.4	80.5	57.6	84.5
3	169.6	167.7	150.8	171
4	6.9	11.9	32	5.2
5	21.1	25.8	48	29.3

Table 3. Continued Table

	Disassembly and inspection centre *j*					Disposal centre *l*	
	1	2	3	4	5	1	2
Remanufacturing centre *m*							
1	49.4	46.1	190.7	23.8	1	36.8	18.7
2	42.3	104.7	193.9	30.7	6.9	34.3	20.2
Disposal centre *l*							
1	75.6	90.7	182.2	29.4	38.2	–	–
2	66.4	87	173.9	10.4	19.7	–	–

Table 4
Uncertainty distributions for uncertain variables.

Parameter	Distribution	Parameter	Distribution
v_{ki}	~L (0.5,3.5) ¥	tce_{ki}	~L (0.2,0.25) kg CO^2/km
v_{ij}	~L (0.1,0.25) ¥	tce_{ij}	~L (0.13,0.24) kg CO^2/km
v_{jl}	~L (0.1,0.25) ¥	tce_{jm}	~L (0.13,0.24) kg CO^2/km
v_{jm}	~L (0.1,0.25) ¥	tce_{ml}	~L (0.13,0.24) kg CO^2/km
v_{ml}	~L (0.1,0.25) ¥	tce_{jl}	~L (0.13,0.24) kg CO^2/km
e_m	~L (600,1200) ¥	β_i	~L (0.02,0.04)
e_j	~L (450,800) ¥	β_j	~L (0.01,0.03)
μ	~N (0.1,0.63)	β_m	~L (0.01,0.03)
λ	~N (0.08,0.44)	R_1	~Z(28,47,70) unit
R_2	~Z(35,42,67) unit	R_3	~Z(38,126,171) unit
R_4	~Z(40,90,145) unit	R_5	~Z(21,38,76) unit
R_6	~Z(1,3,5) unit	R_7	~Z(1,3,5) unit
R_8	~Z(1,2,3) unit	R_9	~Z(10,17,38) unit
R_{10}	~Z(438,1593,2039) unit	R_{11}	~Z(18,100,162) unit
R_{12}	~Z(22,42,77) unit	R_{13}	~Z(14,33,44) unit

Table 5
Optimal values for each objective using the customized NSGA-III.

No.	Objectives	Pareto Z_1	Z_2	Z_3	Flow from *K* to *I*	The optimal solutions
1	Z_{1min}	543,730	80	3,213	204	Y_i= {I_1,I_2,I_3,I_4}; Y_j= {J_1,J_2,J_3,J_4,J_5}; Y_m= {M_1,M_2}
2	Z_{2min}	549,862	80	3,175	206	Y_i= {I_1,I_2,I_3,I_4}; Y_j= {J_1,J_2,J_3,J_4,J_5}; Y_m= {M_1,M_2}
3	Z_{3min}	545,921	81	3,097	202	Y_i= {I_1,I_2,I_3,I_4}; Y_j= {J_1,J_2,J_3,J_4,J_5}; Y_m= {M_1,M_2}

A comparative analysis with NSGA-II is presented to demonstrate the performance of the proposed NSGA-III. The solutions obtained by the customised NSGA-III and NSGA-II are compared based on quality and spacing metrics, as shown in Table 6 and Fig. 4. f_{best}, f_{worst}, and f_{avg} *represent* the best, worst and average values, respectively.

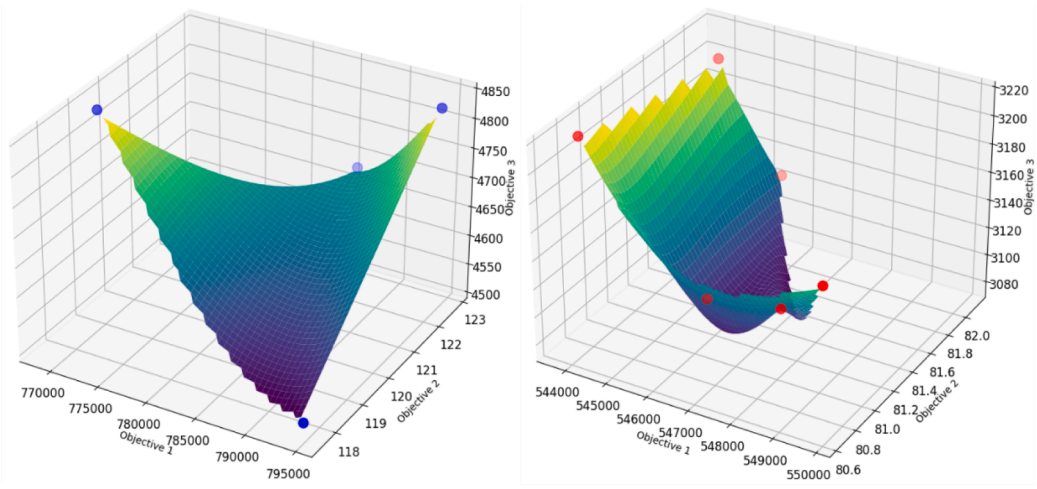

Fig. 4. Pareto fronts using customised NSGA-II (a) and NSAG-III (b).

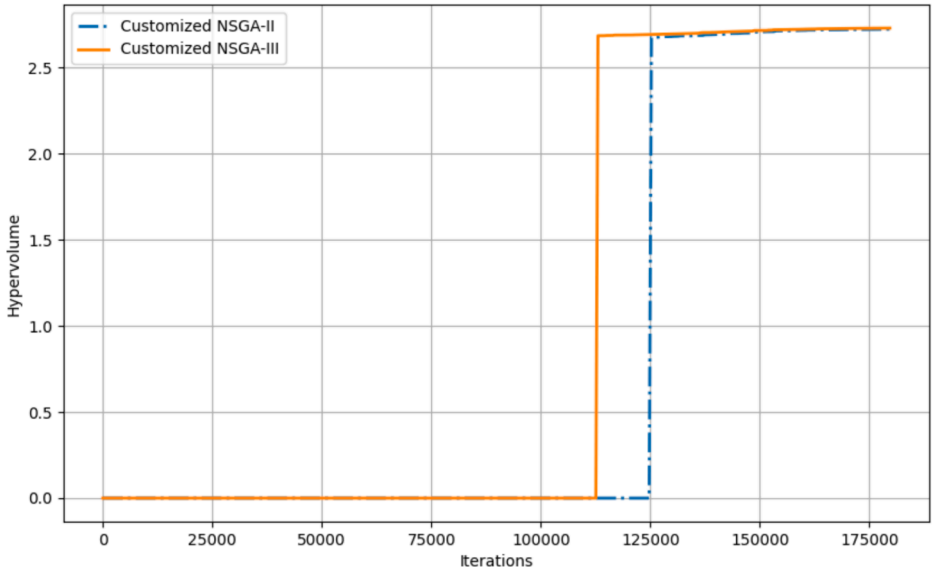

Fig. 5. Convergence curve.

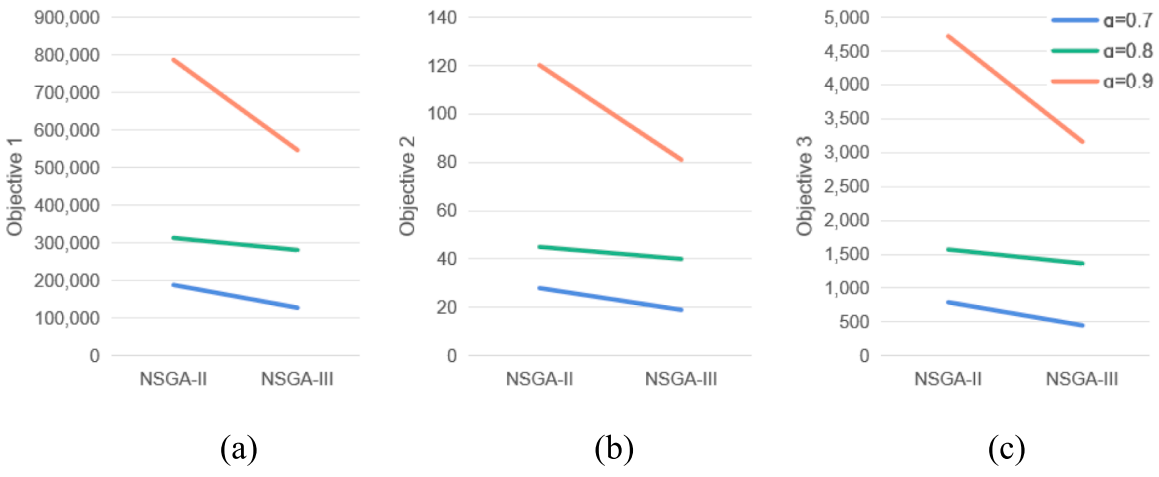

Fig. 6. Average Pareto values for Objective 1 (a), Objective 2 (b), and Objective 3 (c) at different confidence levels.

Table 6
Results comparison between customized NSGA-II and NSAG-III.

	Z_1			Z_2			Z_3			Spacing metric
	f_{best}	f_{worst}	f_{avg}	f_{best}	f_{worst}	f_{avg}	f_{best}	f_{worst}	f_{avg}	
NSGA-II	768,645	794,695	785,909	117	122	120	4,518	4,835	4,715	8031.44
NSGA-III	543,730	549,862	546,294	80	82	81	3,097	3,213	3,159	460.57

Thirdly, customised NSGA-III outperforms customised NSGA-II across the convergence curve, although it exhibits marginally lower operating efficiency than customised NSGA-II. Customised NSGA-II has a shorter runtime than customised NSGA-III, indicating that while customised NSGA-III is not optimal in terms of time efficiency, the difference between them is minimal. Nonetheless, customised NSGA-III converges more rapidly and ultimately attains superior hypervolume values (refer to Fig. 5). A higher hypervolume value implies that the discovered solution possesses both high quality and diversity. More specifically, both curves initiate at zero, suggesting the possibility of no solutions having been identified initially. Subsequently, the curve for customised NSGA-III elevates first, followed by customised NSGA-II, denoting that customised NSGA-III identifies optimal solutions more swiftly than customised NSGA-II during the initial iterations. The curve for customised NSGA-III concludes at a higher point than that of customised NSGA-II, indicating that customised NSGA-III finds a superior solution set that encompasses a broader objective space. This finding corroborates the outcomes of previous researcher (Chaudhari et al., 2022; Khettabi et al., 2021), which demonstrated that NSGA-III offers a more diverse range of optimal operating conditions than NSGA-II. Ultimately, both curves plateau, indicating that the algorithm has converged and that further iterations are unlikely to lead to significant improvements.

Fourth, despite the consistency of location selection schemes as confidence levels increase, both the recycled quantities and the optimisation results of the objectives show an upward trend. Initially, at varying confidence levels, the location selection schemes remain unchanged, indicating that the model deems this to be the most efficient strategy across different confidence levels. Additionally, as confidence levels rise, recycled quantities increase. This is due to the higher confidence levels demanding greater recycling rates or more proactive resource allocation. The utilisation of the uncertainty theory based on belief degree can lead to more proactive decision-making, ensuring improved outcomes under uncertainty. Subsequently, the optimisation results for the three objectives exhibit an upward trend with increasing confidence levels. The elevation in confidence levels necessitates enhanced system robustness and increased risk resilience across the logistics network. However, this heightened demand for system stability comes at the cost of increased economic costs, CO_2 emissions, and disutility to nearby resident.

In accordance with model validation, this research offers a comprehensive theoretical and practical guide for manufacturers seeking to optimise multi-objective reverse logistics networks for end-of-life products with uncertainty. While the assumptions of the proposed model provide a structured starting point for defining the problem and solution framework, the flexibility inherent in the model enables adaptations to various real-world scenarios within reverse logistics networks. For instance, the model can be extended to accommodate scenarios involving product recalls and product returns. Although our specific case study focuses on the recycling of ELVs within the automotive industry, the applicability of this model extends to recycling in other industries, such as WEEE, household appliances, MSW, and electric vehicle batteries.

From a theoretical perspective, our work contributes to the field by advancing the design of optimisation algorithms for reverse logistics networks and enriching the body of knowledge pertaining to optimisation under uncertain conditions. Firstly, uncertain multi-objective programming is firstly employed to address the optimisation of location-allocation problems within the reverse logistics network, providing an innovative approach to handle the uncertain parameters. Additionally, the customised NSGA-III generates a set of efficient Pareto solutions, allowing for the selection of facility strategy based on the available budget, organisation policies, and objective preferences.

On a practical level, this research significantly enhances operational efficiency and minimises the impact of uncertainties on reverse logistics networks. The proposed model has the potential for application in formulating comprehensive, integrated management plans for end-of-life products for any region worldwide. Operations managers within organisations focused on end-of-life product management can leverage the optimal solutions derived from this model to determine suitable facility locations and develop their operational plans on a monthly or yearly basis. By promoting resource treatments such as remanufacturing and recycling, these solutions contribute to the reduction of raw material consumption, enhancement of resource utilisation rates, and lend support to the development of a circular economy.

In addition, the limitation of this research is that this model primarily focuses on a single period. Additionally, when developing the environmental pollution model, the focuses is predominantly on waste emissions resulting from transportation, with limited consideration given to emissions during the processing and remanufacturing phases.

8. Conclusion

Reverse supply chain management emerges as a potent strategy for conserving resources and mitigating pollution. It not only empowers enterprises to curtail costs but also elevates customer satisfaction and bolsters their public image. The operational efficacy of a reverse logistics system hinges directly on the designs of its network structure. Hence, the reasonable design of a reverse logistics network becomes imperative.

This research introduces a MOMINLP model under uncertainty aimed at minimising economic costs, environmental impact, and the disutility experienced by nearby residents in handling end-of-life products. The incorporation of uncertainty theory provides an effective method for managing uncertain variables within the context of conflicting multiple objectives. The uncertainties, expressed as uncertain distributions, are handled through uncertain multi-objective programming. Subsequently, the customised NSGA-III is employed to tackle the multi-objective problems under uncertainty. The performance of the customised NSGA-III is compared with that of the customised NSGA-II, with the case study serving as a testament to the efficacy of the proposed solution methods.

Therefore, the main contributions have been outlined from the focus of this research:

(1) The optimisation of a location-allocation network for end-of-life products while accounting for surrounding residents' disutility of facilities simultaneously with economic aspects and environmental factors has not been studied before.
(2) The proposed mathematical model with uncertain parameters first employs uncertain multi-objective programming.
(3) This research develops a customised NSGA-III based on mixed variables to solve the modelled problem setting efficiently.
(4) The proposed model with comprehensive considerations of uncertainty in parameters is tested on a case study of end-of-life vehicles.

While the effectiveness of the proposed method is validated, several further research has emerged. In future studies, firstly, the integration of traditional forward logistics networks with reverse logistics networks for disassembled and remanufacturable products should be explored. This hybrid facility network could enable collaborative decision-making on facility location, as well as the distribution of production and recycling volumes, by allowing equipment sharing between forward and reverse logistics facilities. Secondly, the development of a multi-period optimisation model incorporating dynamic inventory should be considered. The model can be divided into various periods, such as growth, maturity, and decline. It can also effectively capture the dynamic attributes by accounting for fluctuating remanufacturing and storage capacities, which can be expanded as needed. Lastly, the environmental impact can be measured using waste emission models that account for the waste generated during the processing and remanufacturing stages of end-of-life products, or through specific life cycle assessment methodologies, such as the Eco-Indicator 99 methodology.

This research addresses the complexities of the MOMINLP model and offers an innovative integration of uncertain multi-objective programming with customised NSGA-III for its resolution. The methodologies devised herein provide a robust framework for establishing end-of-life product recycling networks. Within the decision-making process of network establishment, it furnishes a solid theoretical foundation. Furthermore, the modelling approach demonstrated in this research exhibits adaptability to diverse industries. In essence, this research serves as a blueprint for constructing a profitable and environmentally sustainable reverse supply chain.

CRediT authorship contribution statement

Hanbing Xia: Conceptualization, Methodology, Software, Validation, Writing – original draft. **Zhiyuan Chen:** Methodology, Software. **Jelena Milisavljevic-Syed:** Supervision, Writing – review & editing. **Konstantinos Salonitis:** Supervision, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix

Some foundational concepts and properties of uncertainty theory are introduced.

Let Γ be a nonempty set with L as a σ-algebra over Γ. Each element Λ within L is termed an event. A set function M that maps from L to [0,1] is defined as an uncertain measure, provided it adheres to the following axioms as Eqs. (19)–(22) (Liu, 2010).

Axiom 1 (Normality Axiom). For the universal set .Γ

$$\mathrm{M}\{\Gamma\} = 1 \tag{19}$$

Axiom 2 (Duality Axiom). For any event .Λ

$$\mathrm{M}\{\Lambda\} + \mathrm{M}\{\Lambda^{c}\} = 1 \tag{20}$$

Axiom 3 (Subadditivity Axiom). For every countable sequence of .Λ_i

$$\mathrm{M}\left\{\bigcup_{i=1}^{\infty}\Lambda_i\right\} \le \sum_{i=1}^{\infty}\mathrm{M}\{\Lambda_i\} \tag{21}$$

Axiom 4 (Product Axiom). Consider the uncertainty spaces (Γ_k, L_k, M_k) for $k = 1, 2, \cdots$. The product uncertain measure M is defined such that it satisfies.

$$\mathrm{M}\left\{\prod_{k=1}^{\infty}\Lambda_k\right\} = \bigwedge\nolimits^{\infty}{}_{k=1}\,\mathrm{M}_k\{\Lambda_k\} \tag{22}$$

where Λ_k represents events arbitrarily selected from L_k.

The triplet (Γ, L, M) is referred to as a uncertainty space, in which an uncertain variable is defined as Eqs. (23)–(29) (Liu, 2010).

Definition 2.1 An uncertain variable is defined as a measurable function ξ mapping from an uncertainty space (Γ, L, M) to the real numbers. Specifically, for any Borel set B of real numbers, the set.

$$\{\xi \in \mathrm{B}\} = \{\gamma \in \Gamma \,|\, \xi(\gamma) \in \mathrm{B}\} \tag{23}$$

constitutes an event.

Definition 2.2 The uncertain variables $\xi_1, \xi_2, \cdots, \xi_n$ are deemed independent if for any Borel sets $B_1, B_1, \cdots, B_1$ of real numbers, the following holds.

$$\mathrm{M}\left\{\bigcap_{i=1}^{n}(\xi_i \in \mathrm{B}_i)\right\} = \bigwedge\nolimits^{n}{}_{i=1}\,\mathrm{M}\{\xi_i \in \mathrm{B}_i\} \tag{24}$$

Definition 2.3 For an uncertain variable ξ, its uncertainty distribution ϕ is given by

$$\phi(x) = \mathrm{M}\{\xi \le x\} \tag{25}$$

where x is any real number.

Definition 2.4 Consider ξ as an uncertain variable with a regular uncertainty distribution ϕ. The inverse function ϕ^{-1} is termed the inverse uncertainty distribution of ξ.

Definition 2.5. Given ξ as an uncertain variable, its expected value is defined as

$$E[\xi] = \int_0^{\infty} M\{\xi \geq x\}dx - \int_{-\infty}^{0} M\{\xi \leq x\}dx \tag{26}$$

provided that at least one of the integrals converges to a finite value.

Definition 2.6 An uncertain variable ξ is termed linear if it possesses a linear uncertainty distribution given by

$$\Phi(x) = \begin{cases} 0, if x < a \\ (x-a)/(b-a), if a \leq x \leq b \\ 1, if x > b \end{cases} \tag{27}$$

denoted by L(a, b) where a and b are real numbers with a < b.

Definition 2.7 An uncertain variable ξ is labeled zigzag if it exhibits a zigzag uncertainty distribution given by

$$\Phi(x) = \begin{cases} 0, if x < a \\ (x-a)/2(b-a), if a \leq x < b \\ (x+c-2b)/2(c-b), if b \leq x < c \\ 1, if x > c \end{cases} \tag{28}$$

denoted by Z(a, b, c) where a, b, and c are real number satisfying a < b < c.

Definition 2.8 An uncertain variable ξ is termed normal if it possesses a normal uncertainty distribution given by

$$\phi(x) = \left(1 + \exp\left(\pi(e-x)/\sqrt{3}\sigma\right)\right)^{-1}, x \in R \tag{29}$$

denoted by N(e, σ) where e and σ are real numbers with σ > 0.

Theorem 2.1 Given uncertain variables $\xi_1, \xi_2, \cdots, \xi_n$ and a real-valued measurable function f, the expression $f(\xi_1, \xi_2, \cdots, \xi_n)$ is also an uncertain variable (Liu, 2010).

Theorem 2.2. Consider ξ as an uncertain variable with a regular uncertainty distribution ϕ. If its expected value exists, it can be expressed as Eq. (30) (Liu, 2010).

$$E[\xi] = \int_0^1 \phi^{-1}(\alpha)d\alpha \tag{30}$$

Theorem 2.3 Let $\xi_1, \xi_2, \cdots, \xi_n$ be independent uncertain variables with regular uncertainty distributions $\phi_1, \phi_2, \cdots, \phi_n$ respectively. If the function $f(x_1, x_2, \cdots, x_n)$ is strictly increasing with respect to $x_1, x_2, \cdots, x_m$ and strictly decreasing with respect to $x_{m+1}, x_{m+2}, \cdots, x_n$, then $\xi = f(\xi_1, \xi_2, \cdots, \xi_n)$ is an uncertain variable with an inverse uncertainty distribution given by Eq. (31) (Liu, 2010).

$$\Psi^{-1}(\alpha) = f\left(\phi_1^{-1}(\alpha), \cdots, \phi_m^{-1}(\alpha), \phi_{m+1}^{-1}(1-\alpha), \cdots, \phi_n^{-1}(1-\alpha)\right) \tag{31}$$

Uncertain Multi-objective Programming

Uncertain multi-objective programming is a type of mathematical model where both the objectives and the constraints encompass uncertain variables (Liu and Chen, 2015). In fact, the uncertain multi-objective programming model aligns with a deterministic multi-objective programming model.

Diven x as a decision vector and ξ as an uncertain vector, with return functions $f_1(x, \xi), f_2(x, \xi), \cdots, f_m(x, \xi)$, and uncertain constraints denoted as $g_j(x, \xi)$, and specified confidence levels α_p, the uncertain multi-objective programming model can be represented by Eqs. (32)–(34).

$$\begin{cases} min[E[f_1(x,\xi)], E[f_2(x,\xi)], \cdots, E[f_m(x,\xi)]] \\ subject to: \\ M\left\{g_j(x,\xi) \leq 0\right\} \geq \alpha_j, j = 1, 2, \cdots, p \end{cases} \tag{32}$$

Assume $f(x, \xi) = h_1(x)\xi_1 + h_2(x)\xi_2 + \cdots + h_n(x)\xi_n + h_0(x)$ where $h_1(x)$, $h_2(x)$, ⋯, $h_n(x)$, $h_0(x)$ are real-valued functions and $\xi_1, \xi_2, \cdots, \xi_n$ are independent uncertain variables.

$$E[f(x, \xi)] = h_1(x)E[\xi_1] + h_2(x)E[\xi_2] + \cdots + h_n(x)E[\xi_n] + h_0(x) \tag{33}$$

Assume that g_j are strictly increasing with respect to $\xi_1, \xi_2, \cdots, \xi_{s_j}$ and strictly decreasing with respect to $\xi_{s_{j+1}}, \xi_{s_{j+2}}, \cdots, \xi_n$ for $j = 1, 2, \cdots, m$. Then, for $j = 1, 2, \cdots, p$, $M\{g_j(x, \xi) \leq 0\} \geq \alpha_j$ corresponds to Eq. ().

$$g_j\left(x, \phi_1^{-1}(\alpha_j), \cdots, \phi_{s_j}^{-1}(\alpha_j), \phi_{s_j+1}^{-1}(1-\alpha_j), \cdots, \phi_n^{-1}(1-\alpha_j)\right) \leq 0 \tag{34}$$

References

Abdallah, T., Diabat, A., Simchi-Levi, D., 2012. Sustainable supply chain design: a closed-loop formulation and sensitivity analysis. Prod. Plan. Control 23 (2–3), 120–133. https://doi.org/10.1080/09537287.2011.591622.

Alshamsi, A., Diabat, A., 2017. A Genetic Algorithm for Reverse Logistics network design: A case study from the GCC. J. Clean. Prod. 151, 652–669. https://doi.org/10.1016/j.jclepro.2017.02.096.

Ayvaz, B., Bolat, B., Aydın, N., 2015. Stochastic reverse logistics network design for waste of electrical and electronic equipment. Resour. Conserv. Recycl. 104, 391–404. https://doi.org/10.1016/j.resconrec.2015.07.006.

Bal, A., Satoglu, S.I., 2018. A goal programming model for sustainable reverse logistics operations planning and an application. J. Clean. Prod. 201, 1081–1091. https://doi.org/10.1016/j.jclepro.2018.08.104.

Blank, J., Deb, K., 2020. Pymoo: Multi-objective optimization in python. IEEE Access 8, 89497–89509. https://doi.org/10.1109/ACCESS.2020.2990567.

Changchun Bureau of Statistics. http://tjj.changchun.gov.cn/. [Accessed 05 May 2023].
Chaudhari, P., Thakur, A.K., Kumar, R., Banerjee, N., Kumar, A., 2022. Comparison of NSGA-III with NSGA-II for multi objective optimization of adiabatic styrene reactor. Mater. Today:. Proc. 57, 1509–1514. https://doi.org/10.1016/j.matpr.2021.12.047.
Chen, L., Dong, T., Peng, J., Ralescu, D., 2023. Uncertainty Analysis and Optimization Modeling with Application to Supply Chain Management: A Systematic Review. Mathematics 11 (11), 2530. https://doi.org/10.3390/math11112530.
Deb, K., Jain, H., 2013. An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints. IEEE Trans. Evol. Comput. 18 (4), 577–601. https://doi.org/10.1109/TEVC.2013.2281535.
Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans. Evol. Comput. 6 (2), 182–197. https://doi.org/10.1109/4235.996017.
Devika, K., Jafarian, A., Nourbakhsh, V., 2014. Designing a sustainable closed-loop supply chain network based on triple bottom line approach: A comparison of metaheuristics hybridization techniques. Eur. J. Oper. Res. 235 (3), 594–615. https://doi.org/10.1016/j.ejor.2013.12.032.
Dutta, P., Mishra, A., Khandelwal, S., Katthawala, I., 2020. A multiobjective optimization model for sustainable reverse logistics in Indian E-commerce market. J. Clean. Prod. 249, 119348 https://doi.org/10.1016/j.jclepro.2019.119348.
Fattahi, M., Govindan, K., 2017. Integrated forward/reverse logistics network design under uncertainty with pricing for collection of used products. Annals of Operations Research 253, 193–225. https://doi.org/10.1007/s10479-016-2347-5.
FAW Group. https://www.faw.com.cn/#page1. [Accessed 05 December 2023].
Feitó-Cespón, M., Sarache, W., Piedra-Jimenez, F., Cespón-Castro, R., 2017. Redesign of a sustainable reverse supply chain under uncertainty: A case study. J. Clean. Prod. 151, 206–217. https://doi.org/10.1016/j.jclepro.2017.03.057.
Fleischmann, M., Bloemhof-Ruwaard, J.M., Dekker, R., Van der Laan, E., Van Nunen, J. A., Van Wassenhove, L.N., 1997. Quantitative models for reverse logistics: A review. Eur. J. Oper. Res. 103 (1), 1–17. https://doi.org/10.1016/S0377-2217(97)00230-0.
Gao, X. & Cao, C. (2020) A novel multi-objective scenario-based optimization model for sustainable reverse logistics supply chain network redesign considering facility reconstruction. *ournal of Cleaner Production,* 270, 122405. https://doi.org/10.1016/j.jclepro.2020.122405.
Gholizadeh, H., Goh, M., Fazlollahtabar, H., Mamashli, Z., 2022. Modelling uncertainty in sustainable-green integrated reverse logistics network using metaheuristics optimization. Comput. Ind. Eng. 163, 107828 https://doi.org/10.1016/j.cie.2021.107828.
Govindan, K., Gholizadeh, H., 2021. Robust network design for sustainable-resilient reverse logistics network using big data: A case study of end-of-life vehicles. Transportation Research Part e: Logistics Transportation Review 149, 102279. https://doi.org/10.1016/j.tre.2021.102279.
Govindan, K., Fattahi, M., Keyvanshokooh, E., 2017. Supply chain network design under uncertainty: A comprehensive review and future research directions. European Journal of Operational Research 263 (1), 108–141. https://doi.org/10.1016/j.ejor.2017.04.009.
Govindan, K., Nosrati-Abarghooee, S., Nasiri, M.M., Jolai, F., 2022. Green reverse logistics network design for medical waste management: A circular economy transition through case approach. J. Environ. Manage. 322, 115888 https://doi.org/10.1016/j.jenvman.2022.115888.
Harijani, A.M., Mansour, S., 2022. Municipal solid waste recycling network with sustainability and supply uncertainty considerations. Sustainable Cities Society 81, 103857. https://doi.org/10.1016/j.scs.2022.103857.
Hashemi, S.E., 2021. A fuzzy multi-objective optimization model for a sustainable reverse logistics network design of municipal waste-collecting considering the reduction of emissions. J. Clean. Prod. 318, 128577 https://doi.org/10.1016/j.jclepro.2021.128577.
He, B., Yang, C. & Ren, M.-M. (2007) A fuzzy multi-objective programming for optimization of reverse Logistics for Solid Waste through genetic algorithms. *Fourth international conference on fuzzy systems and knowledge discovery*. Haikou, China. IEEE, 416-420.
Ishibuchi, H., Imada, R., Setoguchi, Y. & Nojima, Y. (2016) Performance comparison of NSGA-II and NSGA-III on various many-objective test problems. *2016 IEEE Congress on Evolutionary Computation (CEC)*. Vancouver, BC, Canada. IEEE, 3045-3052.
Jerbia, R., Boujelben, M.K., Sehli, M.A., Jemai, Z., 2018. A stochastic closed-loop supply chain network design problem with multiple recovery options. Comput. Ind. Eng. 118, 23–32. https://doi.org/10.1016/j.cie.2018.02.011.
Jin, H., Song, B.D., Yih, Y., Sutherland, J.W., 2019. A bi-objective network design for value recovery of neodymium-iron-boron magnets: A case study of the United States. J. Clean. Prod. 211, 257–269. https://doi.org/10.1016/j.jclepro.2018.11.101.
Kannan, D., Solanki, R., Darbari, J.D., Govindan, K., Jha, P., 2023. A novel bi-objective optimization model for an eco-efficient reverse logistics network design configuration. J. Clean. Prod. 394, 136357 https://doi.org/10.1016/j.jclepro.2023.136357.
Khettabi, I., Boutiche, M., Benyoucef, L., 2021. NSGA-II vs NSGA-III for the sustainable multi-objective process plan generation in a reconfigurable manufacturing environment. IFAC-PapersOnLine 54 (1), 683–688. https://doi.org/10.1016/j.ifacol.2021.08.180.
Kim, J., Do Chung, B., Kang, Y., Jeong, B., 2018. Robust optimization model for closed-loop supply chain planning under reverse logistics flow and demand uncertainty. J. Clean. Prod. 196, 1314–1328. https://doi.org/10.1016/j.jclepro.2018.06.157.
Kuşakcı, A.O., Ayvaz, B., Cin, E., Aydın, N., 2019. Optimization of reverse logistics network of End of Life Vehicles under fuzzy supply: A case study for Istanbul Metropolitan Area. J. Clean. Prod. 215, 1036–1051. https://doi.org/10.1016/j.jclepro.2019.01.090.
Li, X., Zhou, J., Zhao, X., 2016. Travel itinerary problem. Transp. Res. B Methodol. 91, 332–343. https://doi.org/10.1016/j.trb.2016.05.013.
Lin, Y., Jia, H., Yang, Y., Tian, G., Tao, F., Ling, L., 2018. An improved artificial bee colony for facility location allocation problem of end-of-life vehicles recovery network. J. Clean. Prod. 205, 134–144. https://doi.org/10.1016/j.jclepro.2018.09.086.
Liu, B., 2010. Uncertainty theory. Springer.
Liu, B., Chen, X., 2015. Uncertain multiobjective programming and uncertain goal programming. Journal of Uncertainty Analysis Applications 3, 1–8. https://doi.org/10.1186/s40467-015-0036-6 0.
Milisavljevic-Syed, J., Li, J., Xia, H., 2023. Realisation of responsive and sustainable reconfigurable manufacturing systems. Int. J. Prod. Res. 1–22 https://doi.org/10.1080/00207543.2023.2233625.
Mishra, S., Singh, S.P., 2020. A stochastic disaster-resilient and sustainable reverse logistics model in big data environment. Annals of Operations Research 1–32. https://doi.org/10.1007/s10479-020-03573-0.
Phuc, P.N.K., Yu, V.F., Tsao, Y.-C., 2017. Optimizing fuzzy reverse supply chain for end-of-life vehicles. Comput. Ind. Eng. 113, 757–765. https://doi.org/10.1016/j.cie.2016.11.007.
Rahimi, M., Ghezavati, V., 2018. Sustainable multi-period reverse logistics network design and planning under uncertainty utilizing conditional value at risk (CVaR) for recycling construction and demolition waste. J. Clean. Prod. 172, 1567–1581. https://doi.org/10.1016/j.jclepro.2017.10.240.
Reddy, K.N., Kumar, A., Ballantyne, E.E., 2019. A three-phase heuristic approach for reverse logistics network design incorporating carbon footprint. Int. J. Prod. Res. 57 (19), 6090–6114. https://doi.org/10.1080/00207543.2018.1526422.
Reddy, K.N., Kumar, A., Sarkis, J., Tiwari, M.K., 2020. Effect of carbon tax on reverse logistics network design. Computers Industrial Engineering 139, 106184. https://doi.org/10.1016/j.cie.2019.106184.
Reddy, K.N., Kumar, A., Choudhary, A., Cheng, T.E., 2022. Multi-period green reverse logistics network design: An improved Benders-decomposition-based heuristic approach. Eur. J. Oper. Res. 303 (2), 735–752. https://doi.org/10.1016/j.ejor.2022.03.014.
ReVelle, C.S., Eiselt, H.A., 2005. Location analysis: A synthesis and survey. Eur. J. Oper. Res. 165 (1), 1–19. https://doi.org/10.1016/j.ejor.2003.11.032.
Roghanian, E., Pazhoheshfar, P., 2014. An optimization model for reverse logistics network under stochastic environment by using genetic algorithm. J. Manuf. Syst. 33 (3), 348–356. https://doi.org/10.1016/j.jmsy.2014.02.007.
Roudbari, E.S., Ghomi, S.F., Sajadieh, M.S., 2021. Reverse logistics network design for product reuse, remanufacturing, recycling and refurbishing under uncertainty. J. Manuf. Syst. 60, 473–486. https://doi.org/10.1016/j.jmsy.2021.06.012.
Shankar, R., Bhattacharyya, S., Choudhary, A., 2018. A decision model for a strategic closed-loop supply chain to reclaim End-of-Life Vehicles. Int. J. Prod. Econ. 195, 273–286. https://doi.org/10.1016/j.ijpe.2017.10.005.
Simic, V., 2015. A two-stage interval-stochastic programming model for planning end-of-life vehicles allocation under uncertainty. Resour. Conserv. Recycl. 98, 19–29. https://doi.org/10.1016/j.resconrec.2015.03.005.
Soleimani, H., Kannan, G., 2015. A hybrid particle swarm optimization and genetic algorithm for closed-loop supply chain network design in large-scale networks. App. Math. Model. 39 (14), 3990–4012. https://doi.org/10.1016/j.apm.2014.12.016.
Subulan, K., Taşan, A.S., Baykasoğlu, A., 2015. A fuzzy goal programming model to strategic planning problem of a lead/acid battery closed-loop supply chain. J. Manuf. Syst. 37, 243–264. https://doi.org/10.1016/j.jmsy.2014.09.001.
Tavana, M., Kian, H., Nasr, A.K., Govindan, K., Mina, H., 2022. A comprehensive framework for sustainable closed-loop supply chain network design. J. Clean. Prod. 332, 129777 https://doi.org/10.1016/j.jclepro.2021.129777.
Trochu, J., Chaabane, A., Ouhimmou, M., 2018. Reverse logistics network redesign under uncertainty for wood waste in the CRD industry. Resour. Conserv. Recycl. 128, 32–47. https://doi.org/10.1016/j.resconrec.2017.09.011.
Trochu, J., Chaabane, A., Ouhimmou, M., 2020. A carbon-constrained stochastic model for eco-efficient reverse logistics network design under environmental regulations in the CRD industry. J. Clean. Prod. 245, 118818 https://doi.org/10.1016/j.jclepro.2019.118818.
Wang, B., Hao, H. & Li, H. (2020) Reverse logistics network design considering customer convenience and low carbon emissions. *Journal of Physics: Conference Series*. Kunming, China. IOP Publishing, 012153.
Xia, H., Han, J. & Milisavljevic-Syed, J. (2022) Forecasting the Number of End-of-Life Vehicles: State of the Art Report. *16th International Design Conference (Online)*. Croatia. Cambridge University Press.
Xia, H., Han, J. & Milisavljevic-Syed, J. (2023) Predicting the Quantity of Recycled End-of-Life Products Using a Hybrid SVR-Based Model. *ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. Boston, Massachusetts, USA.
Xia, H., Han, J., Milisavljevic-Syed, J., 2023b. Predictive modeling for the quantity of recycled end-of-life products using optimized ensemble learners. Resour. Conserv. Recycl. 197, 107073 https://doi.org/10.1016/j.resconrec.2023.107073.
Xiao, Z., Sun, J., Shu, W., Wang, T., 2019. Location-allocation problem of reverse logistics for end-of-life vehicles based on the measurement of carbon emissions. Computers Industrial Engineering 127, 169–181. https://doi.org/10.1016/j.cie.2018.12.012.
Zadeh, L.A., 1965. Fuzzy Sets. *Information Control* 8 (3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X.
Zadeh, L.A., 1978. Fuzzy sets as a basis for a theory of possibility. Fuzzy Sets Systems 1 (1), 3–28. https://doi.org/10.1016/0165-0114(78)90029-5.

Zhang, B., Li, H., Li, S., Peng, J., 2018. Sustainable multi-depot emergency facilities location-routing problem with uncertain information. Applied Mathematics Computation 333, 506–520. https://doi.org/10.1016/j.amc.2018.03.071.

Zhang, X., Zou, B., Feng, Z., Wang, Y., Yan, W., 2021. A review on remanufacturing reverse logistics network design and model optimization. Processes 10 (1), 84. https://doi.org/10.3390/pr10010084.

Zhen, L., Sun, Q., Wang, K., Zhang, X., 2019. Facility location and scale optimisation in closed-loop supply chain. Int. J. Prod. Res. 57 (24), 7567–7585. https://doi.org/10.1080/00207543.2019.1587189.

Zhou, J., Jiang, Y., Pantelous, A.A., Dai, W., 2023. A systematic review of uncertainty theory with the use of scientometrical method. Fuzzy Optimization Decision Making 22 (3), 463–518. https://doi.org/10.1007/s10700-022-09400-4.

Zitzler, E., Thiele, L., 1999. Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach. IEEE Trans. Evol. Comput. 3 (4), 257–271. https://doi.org/10.1109/4235.797969.

Zohal, M., Soleimani, H., 2016. Developing an ant colony approach for green closed-loop supply chain network design: a case study in gold industry. J. Clean. Prod. 133, 314–337. https://doi.org/10.1016/j.jclepro.2016.05.091.

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Uncertain programming model for designing multi-objective reverse logistics networks

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2024-06-01
Elsevier
https://doi.org/10.1016/j.clscn.2024.100155
Xia H, Chen Z, Milisavljevic-Syed J, Salonitis K. (2024) Uncertain programming model for designing multi-objective reverse logistics networks. Cleaner Logistics and Supply Chain. Volume 11, June 2024, Article number 100155

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