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ORIGINAL ARTICLE

A general reverse logistics network design model for product reuse and recycling with environmental considerations

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Abstract Reverse logistics is believed to be one of the most promising solutions for capturing the remaining values from used products and has been extensively focused by both academics and practitioners during the past two decades. Conceptual framework, mathematical programming, and computational algorithms have been developed for decision-making at strategic, tactical, and operational levels of a reverse supply chain. In this paper, a novel idea for the design and planning of a general reverse logistics network is suggested and formulated through multi-objective mixed integer programming. The reverse logistics system is an independent network and comprises of three echelons for collection, remanufacturing, recycling, energy recovery, and disposal of used products. The mathematical model not only takes into account the minimization of system operating costs, but also considers minimization of carbon emissions related to the transportation and processing of used products, and the minimum rate of resource utilization is also required in order to minimize the waste of resources in landfill. Illustration, sensitivity analysis, and numerical experimentation are given to show the applicability and computational efficiency of the proposed model. This work provides an alternative approach to account both economic and environmental sustainability of a reverse logistics system. The result explicitly shows the trade-off between the costs and carbon emissions, cost effectiveness for improving environmental performance, and influences from resource utilization, all of which have great practical implication on decision-making of network configurations and transportation planning of a reverse logistics system. For future development of this work, suggestions are also given latter in this paper.

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Keywords Reverse logistics · Network design · Facility location · Transportation planning · Environmental impacts · Carbon emissions · Multi-objective programming · Mixed integer programming

1 Introduction

Reverse logistics refers to the process of designing, operating, controlling, and maintaining the effective and economic-efficient flow of raw materials, parts and components, finished products, in- and/or post-process inventories, as well as relevant capitals and information starting from the end customers towards the initial suppliers for capturing the remaining values of used products or waste disposal [1]. In recent years, the economic benefits from waste reuse and recycling [2], environmental concern from the public, and positive social impacts [3] have become the most important motivations for the implementation of reverse logistics in order to achieve sustainable development. Moreover, economic measures and legislative mechanisms are enforced in many countries for pushing the manufacturers to take responsibility of used product recovery. For instance, the directive [4] of the European Union (EU) on waste electrical and electronic equipment (WEEE) has introduced the extended producer responsibility to manufacturers of electrical and electronic products in the EU market, which specifies their responsibilities in collection and recycling of WEEE. In addition, managing the reverse logistics process and activities in an effective and economic-efficient manner not only helps companies to maximize the resource utilization, customer services [5], and competitiveness [6] but also helps them to build a more positive public image for taking into account of environmental responsibilities.

Planning and managing a reverse logistics system require comprehensive methodologies for decision-making at strategic, tactical, and operational levels among which network planning is one of the most researched topics. Network design for a logistical system is to determine the physical locations of different facilities and it is considered as one of the most important strategic decisions due to the long-term and significant influences on the profitability, responsiveness, robustness, and environmental impacts of a supply chain [7]. Conceptual framework, mathematical programming, and computational algorithms were developed in existing literature for a reverse logistics network design. However, most of the previous studies focus on economic benefits from the reuse, remanufacturing, and recycling of used products, and only a small portion accounts and formulates the environmental influences of reverse logistics activities. Due to this reason, this paper aims at providing an alternative approach through formulating a multi-objective mixed integer programming for a reverse logistics network design. The model considers two objectives: minimization of system operating costs and environmental influences, and carbon emissions are applied as the indicator for evaluating the environmental performance of reverse logistics in this study. Further, the minimum rate of resource utilization is also required in order to minimize the waste of resources in landfill. The objectives of the model are conflict in nature, because more investment, more advanced manufacturing and processing technologies are required for improving the environmental performance and utilization of used products. Therefore, the model justifies the trade-off between the two objectives in order to optimize both economic and environmental sustainability of reverse logistics.

The rest of the paper is organized as follows: Section 2 provides an extensive literature survey on reverse logistics models. Section 3 formulates a general reverse logistics network and a multi-objective mixed integer programming for designing an independent collection and recycling system. Section 4 introduces the normalization function for combining the two objective functions. Sections 5 and 6 present illustrative calculation, sensitivity analysis, and computational experimentation in order to show the applicability and computational efficiency of the proposed model. Section 7 summarizes the paper with suggestions for future improvement.

2 Literature review

During the past two decades, development of a conceptual framework and mathematical programming in the decision-making of reverse logistics activities has been extensively focused by both academics and practitioners. This section summarizes and reviews some of the previous literature associated with these reverse logistics models, and for an extensive review of reverse logistics and closed-loop supply chain management, refer to Govindan et al. [8]. An early attempt for the development of a theoretical decision-making model for assessing the feasibility to implement the reverse logistics by a third-party logistics provider was reported by Krumwiede and Sheu [9]. Lambert et al. [10] formulated a conceptual framework for decision support of reverse supply chain activities at strategic, tactical, and operational levels, and three real-world case studies with respect to each level of decision-making model are also provided to show the flexibility and applicability of the proposed conceptual framework.

Economic performance of a reverse logistics network is the paramount concern of previous models with consideration of either maximizing overall profits or minimizing costs. Demirel et al. [11] proposed a single objective mixed integer linear programming for minimizing the operating costs of a reverse logistics network of used vehicles. The costs for setting up a reverse logistics system include eight parts, and a GDP-dependent Gompertz function is also employed for predicting the generation of used vehicles in several continuous periods. Alumur et al. [12] investigated a multi-period mixed integer programming for a general reverse logistics system for the collection, inspection, remanufacturing, and recycling of used product. Dat et al. [13] developed a single objective cost-minimization model for a reverse logistics network design of WEEE. Zarei et al. [14] reported a mathematical model for the network design of an integrated forward and a reverse logistics system for recycling used vehicles. The model aims at minimizing the overall system operating costs and a genetic algorithm is also developed for calculating the optimal result. Mahapatra et al. [15] formulated a deterministic optimization model for minimizing the total costs of an integrated network in manufacturing. The model aims to simultaneously determine the level of both manufactured products in forward supply chain and remanufactured products in reverse logistics. Suyabatmaz et al. [16] investigated a hybrid simulation model for a reverse logistics network design from a third-party provider's perspective. Alshamsi and Diabat [17] proposed a mixed integer programming for determining the facility location, product allocation, and inventory level of a reverse logistics system. A single objective mathematical model with genetic algorithm for a reverse logistics network design of e-commerce was studied by Liu [18]. Similar researches are also provided by Dirmirel and Gokcen [5], Sasikumar et al. [19], Kannan et al. [20], Jonrinaldi and Zhang [21], Eskandarpour et al. [22], and Zaarour et al. [23].

Many researchers considered several conflicting objectives in reverse logistics network design and management. Chiang et al. [6] investigated a multi-objective particle swarm optimization algorithm for planning an integrated logistics system with multiple levels of facilities. The model includes four objectives: minimization of production costs, minimization of delivery costs, minimization of delivery time, and maximization of the production quality of the suppliers, through the entire supply chain. Lee et al. [24] proposed a bi-objective hybrid genetic algorithm for the network design of a general independent reverse logistics system. The model aims at managing the system costs and transportation tardiness in an optimum fashion. Lee et al. [25] formulated a bi-objective mixed nonlinear programming for minimizing both system operating costs and shipping time of an integrated logistics system. Pishvaee et al. [26] developed a bi-objective model for an integrated forward/reverse logistics network design which simultaneously minimizes the system costs and maximizes responsiveness. Yu et al. [27] developed a multi-objective linear programming for managing the reverse logistics of municipal solid waste. The model aims to find out the optimal trade-off among three objectives: minimization of costs, minimization of risks, and minimization of waste sent to landfill, through allocating waste to different treatments over several continuous periods. Pati et al. [28] investigated a multi-objective goal programming for a reverse logistics network design in wastepaper recycling industry. The model aims at minimizing logistics cost while simultaneously improving the product quality through segregation at source and improving environmental performance through increased recovery rate of wastepaper. The model is tested in a real-world case study and deep insight of the applicability is also given in this paper.

The formulation of uncertain input parameters related to the reverse logistics network design is also well developed. El-Sayed et al. [29] studied a multi-period mixed integer programming with stochastic input parameters for the integrated supply chain network design under risk. Salema et al. [30] applied a multi-scenario method to formulate the uncertainties of customer demands and return of used products in an integrated logistics network. Roghanian and Pazhoheshfar [31] investigated a stochastic mixed integer linear programming for a reverse logistics network design of used products. The model aims at minimization of overall system costs through determining the location of different types of facilities and the transportation strategy of used products, and a priority-based genetic algorithm is also developed for resolving the model. Ramezani et al. [32] took into account both uncertain parameters and multiple objectives, and they proposed a multi-objective stochastic programming for an integrated supply chain network design. The model aims at finding out the optimal balance of three objectives: maximization of total profits, maximization of responsiveness, as well as minimization of defect rate. Besides, the financial risks were also considered in this paper. Cardoso et al. [33] formulated a mathematical model for a logistics network design of an integrated forward/reverse supply chain under demand uncertainties. Hatefi and Jolai [34] investigated a robust and reliable model for integrated supply chain design considering both demand uncertainties and risk of disruptions. Uncertainties of parameters in a reverse logistics network design are also focused and formulated in Soleimani and Govindan [35], Niknejad and Petrovic [36], Keyvanshokooh et al. [37], and Wang and Yang [38].

Table 1 presents the comparison of some of the previous mathematical models for reverse logistics system design and optimization from three perspectives: network structure, input parameter and consideration of influencing factors. Although a great number of previous models are contributed to deliver the optimal solution of reverse logistics network design and optimization, two shortcomings are observed. First, most previous models are single objective models with solo emphasize on economic performance, and data from the recent review by Govindan et al. [8] has revealed that only 12.4 % of the previous models are formulated considering multiple criteria. However, most decision-making processes in the real world involve multiple objectives with conflicting interests, so it is preferred to develop comprehensive multi-criteria decision-making tools for resolving this problem. Second, the environmental impacts of the reverse logistics activities themselves are not accounted in most previous models. Exceptions are provided by Kannan et al. [39], Diabat et al. [40], Bing et al. [41] and Pati et al. [28]. The first three articles account for environmental influences associated with reverse logistics activities through monetizing the carbon emissions (carbon market trading) and composite it with the overall system costs, while the other one optimizes the environmental impact through improving the recovery rate of wastepaper. This paper aims, however, at providing an alternative method for taking into account both economic and environmental sustainability of reverse logistics system through formulating a multi-objective mixed integer programming. The model includes two objective functions: (1) minimization of system costs and (2) minimization of carbon emissions associated with the transportation and processing of used products, and the optimal trade-off between the two objectives becomes therefore the focus. Further, the minimum utilization rate of used products is also required in this model.

3 Problem definition and modeling

This section formulates the general network and multi-objective mixed integer linear programming for reverse logistics system planning. In the reverse logistics system, used products from end customers are collected, inspected, disassembled and distributed accordingly for component reuse, material recycling, energy recovery and proper disposal. The problem focused in this paper is illustrated in Fig. 1. The general reverse logistics network is comprised of four echelons: customers, collection centers, treatment plants and markets. At the initial stage, used products are returned by

Table 1 Literature survey of reverse logistics network design and optimization

Article	Network structure		Input parameter		Influencing factor	
	IR[a]	IFR[b]	Exact	Inexact	EP[c]	MIF[d]
Demirel et al. [11]	√		√		√	
Alumur et al. [12]	√		√		√	
Dat et al. [13]	√		√		√	
Zarei et al. [14]		√	√		√	
Mahapatra et al. [15]		√	√		√	
Suyabatmaz et al. [16]	√			√	√	
Alshamsi and Diabat [17]	√		√		√	
Liu [18]	√		√		√	
Demirel and Gokcen [5]		√	√		√	
Sasikumar et al. [19]	√		√		√	
Kannan et al. [20]	√		√		√	
Jonrinaldi and Zhang [21]		√	√		√	
Eskandarpour et al. [22]	√		√		√	
Zaarour et al. [23]	√		√		√	
Chiang et al. [6]		√	√			√
Lee et al. [24]	√		√			√
Lee et al. [25]		√	√			√
Pishvaee et al. [26]		√	√			√
Yu et al. [27]	√		√			√
Pati et al. [28]	√		√			√
El-Sayed et al. [29]		√		√	√	
Salema et al. [30]		√		√	√	
Roghanian and Pazhoheshfar [31]	√			√	√	
Ramezani et al. [32]		√		√		√
Cardoso et al. [33]		√		√	√	
Hatefi and Jolai [34]		√		√		√
Soleimani and Govindan [35]	√			√	√	
Niknejad and Petrovic [36]		√		√	√	
Keyvanshokooh et al. [37]		√		√	√	
Wang and Yang [38]	√			√	√	
Kannan et al. [30]	√		√			√
Diabat et al. [31]		√	√			√
Bing et al. [32]	√		√			√

[a] Independent reverse logistics network

[b] Integrated forward/reverse logistics network

[c] Economic performance is the only focus

[d] Multiple influencing factors are accounted and formulated

customers or collected by third-party service providers at the collection centers where they are inspected, disassembled, processed and then sent to downstream plants for respective treatments. Four types of treatments of the parts and components from used products are depicted in the figure: repair and reuse, remanufacturing and recycling, energy recovery, and waste disposal. And the targeted markets of each type of treatment are also illustrated. The reused and repaired components are mainly sold in secondary markets, whereas the remanufactured and recycled materials and components are mainly targeted on primary market. For the parts and components which are not suitable for recycling and reuse, they are treated at incineration plant for energy recovery or disposed at landfill. The recovered energy can be used for power generation and space heating.

3.1 Model assumption

In order to simplify the model formulation, seven assumptions are first made as follows:

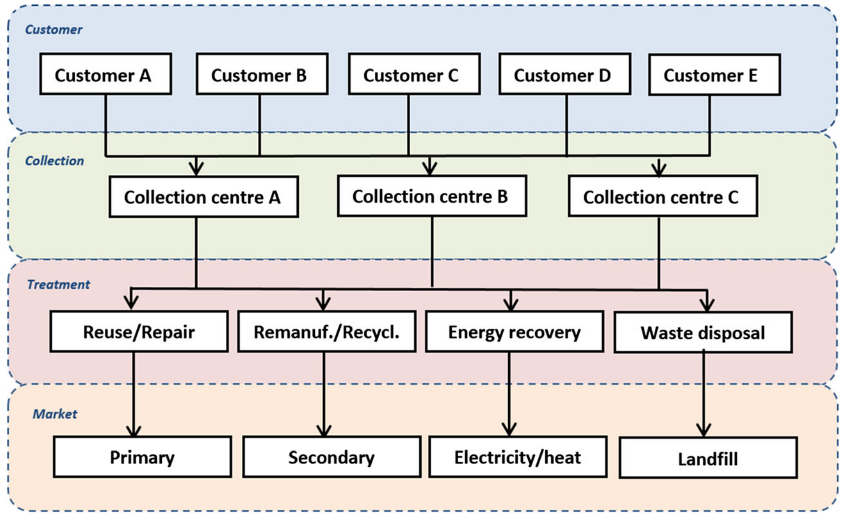


Fig. 1 General reverse logistics network

- The number and locations of customers and markets are known.
- Candidate locations for collection center, repair plant, remanufacturing plant, incineration plant, and landfill are known.
- Cost parameters, lower and upper facility requirements, conversion rates, carbon emission factors as well as other necessary parameters do not change within the studied period.
- Carbon emission from collection centers are not account due to its negligible impact comparing with other processing facilities.
- Direct shipment of used products from customers to treatments facilities is rule out.
- The used products can be repaired, remanufactured, recycled and recovered at a fixed rate.
- All the repaired and remanufactured products can be sold in both primary and secondary markets.
- For simplicity sake, the primary, secondary and energy markets are not distinguished in the model formulation due to the fact that they are usually overlapped with each other. For example, customer demands for reused products, recycled and remanufactured components, and recovered energy may be at the same location.

3.2 Definition of sets, parameters and variables

Sets and indices

c	Index of customers, $c \in C$
o	Index of collection centers, $o \in O$
p	Index of reuse and repair facilities, $p \in P$
r	Index of remanufacturing and recycling centers, $r \in R$
i	Index of incineration plants, $i \in I$
l	Index of landfills, $l \in L$
m	Index of markets, $m \in M$

Parameters

FO_o, FP_p, FR_r, FI_i, FL_l	Fixed facility operating costs of collection center o, reuse and repair facility p, remanufacturing and recycling center r, incineration plant i, and landfill l
VO_o, VP_p, VR_r, VI_i, VL_l	Unit processing costs at collection center o, reuse and repair facility p, remanufacturing and recycling center r, incineration plant i, and landfill l
T_{co}, T_{op}, T_{or}, T_{oi}, T_{ol}	Unit transportation costs of used products or disassembled parts in the route from customer c to collection center o, from collection center o to reuse and repair facility p, from collection center o to remanufacturing and recycling facility r, from collection center o to incineration plant i, and from collection center o to landfill l
T_{pm}, T_{rm}	Unit transportation costs of reused products from reuse and repair facility p to market m and from remanufacturing and recycling facility r to market m
ElC_{im}	Unit transmission costs of electricity/heat between incinerator i and market m
P_{pm}, P_{rm}	Profit of selling one unit of reused or recycled product at market m
P_{im}	Profit of selling one unit of electricity/heat at market m
θ_p, θ_r	Conversion rate of repaired or recycled products at reuse and repair facility p to market m and from remanufacturing and recycling facility r to market m
τ_i	Conversion rate of energy recovery at incinerator i
CaE_p, CaE_r, CaE_i, CaE_l	Carbon emission indicator of reuse and repair facility p, remanufacturing and recycling center r, incineration plant i, and landfill l
Ca_{co}, Ca_{op}, Ca_{or}, Ca_{oi}, Ca_{ol}	Carbon emission indicator of the transportation of used products and disassembled parts in the route from customer c to collection center o,

	from collection center o to reuse and repair facility p, from collection center o to remanufacturing and recycling facility r, from collection center o to incineration plant i, and from collection center o to landfill l
Ca_{pm}, Ca_{rm}	Carbon indicator of the transportation of reused and recycled products from reuse and repair facility p to market m and from remanufacturing and recycling facility r to market m
S_{co}, S_{op}, S_{or}, S_{oi}, S_{ol}	Distance from customer c to collection center o and from collection center o to reuse and repair facility p, remanufacturing and recycling facility r, incineration plant i and landfill l
S_{pm}, S_{rm}	Distance from reuse and repair facility p to market m and from remanufacturing and recycling facility r to market m
fr_{co}, fr_{op}, fr_{or}, fr_{oi}, fr_{ol}	Frequency of transportation of used products and disassembled parts in the route from customer c to collection center o, from collection center o to reuse and repair facility p, from collection center o to remanufacturing and recycling facility r, from collection center o to incineration plant i, and from collection center o to landfill l
fr_{pm}, fr_{rm}	Frequency of transportation from reuse and repair facility p to market m and from remanufacturing and recycling facility r to market m
LO_o,LO_p, LO_r, LO_i, LO_l	Lower bound requirement of collection center o, reuse and repair facility p, remanufacturing and recycling center r, incineration plant i, and landfill l
UP_o,UP_p, UP_r, UP_i, UP_l	Upper bound requirement of collection center o, reuse and repair facility p, remanufacturing and recycling center r, incineration plant i, and landfill l
NU_o,NU_p, NU_r, NU_i	Maximum number to open of collection center o, reuse and repair facility p, remanufacturing and recycling center r, incineration plant i, and landfill l
β_c	Generation of used product at customer c
$Rate_{\text{utilization}}$	Required utilization rate of used products
γ_p, γ_r,	Percentage of used product with respect to reuse at plant p and recycling at plant r
ϑ_{co}, ϑ_{op}, ϑ_{or}, ϑ_{oi}, ϑ_{ol}	Route capacity from customer c to collection center o, from collection center o to reuse and repair facility p, from collection center o to remanufacturing and recycling facility r, from collection center o to incineration plant i, and from collection center o to landfill l
ϑ_{pm}, ϑ_{rm}	Route capacity from reuse and repair facility p to market m and from remanufacturing and recycling facility r to market m
Decision variables	
q_o, q_p, q_r, q_i, q_l	Binary decision variables determine if a facility is open or not at the candidate locations of collection center o, reuse and repair facility p, remanufacturing and recycling center r, incineration plant i, and landfill l
a_{co}, a_{op}, a_{or}, a_{oi}, a_{ol}	Quantity of used products and disassembled parts transported in the route from customer c to collection center o, from collection center o to reuse and repair facility p, from collection center o to remanufacturing and recycling facility r, from collection center o to incineration plant i, and from collection center o to landfill l
a_{pm}, a_{rm}	Quantity of reused and recycled products transported from reuse and repair facility p to market m and from remanufacturing and recycling facility r to market m
v_{im}	Electricity/heat from waste incinerator i sold in market m

3.3 Objective functions

The model determines the number and locations of collection centers, repair/reuse plants, recycling/remanufacturing plants and incinerators, as well as the transportation strategy of used products, disassembled components and renewed products. The model is formulated based upon multi-objective mixed integer programing and the optimal trade-off between two objective functions is focused

Minimize:

$$Cost = FX + VX + TX + TTX - PX \tag{1}$$

The first objective function of the multi-objective mixed integer programming for design and planning of a general multi-echelon reverse logistics network is formulated in Eq. (1). The overall system costs are comprised of five components: fixed facility operating costs (FX), variable processing costs (VX), transportation costs (TX), transmission costs of electricity/heat (TTX), and profits from selling the renewed products and energy (PX).

$$\begin{aligned} FX = &\sum_{o \in O} FO_o q_c + \sum_{p \in P} FP_p q_p + \sum_{r \in R} FR_r q_r \\ &+ \sum_{i \in I} FI_i q_i + \sum_{l \in L} FL_l q_l \end{aligned} \tag{1a}$$

$$\begin{aligned} VX = &\sum_{o \in O} VO_o \sum_{c \in C} a_{co} + \sum_{p \in P} VP_p \sum_{o \in O} a_{op} \\ &+ \sum_{r \in R} VR_r \sum_{o \in O} a_{or} + \sum_{i \in I} VI_i \sum_{o \in O} a_{oi} \\ &+ \sum_{l \in L} VL_l \sum_{o \in O} a_{ol} \end{aligned} \tag{1b}$$

$$TX = \sum_{c\in C}\sum_{o\in O} T_{co}a_{co} + \sum_{o\in O}\sum_{p\in P} T_{op}a_{op} + \sum_{o\in O}\sum_{r\in R} T_{or}a_{or} + \sum_{o\in O}\sum_{i\in I} T_{oi}a_{oi} + \sum_{o\in O}\sum_{l\in L} T_{ol}a_{ol} + \sum_{p\in P}\sum_{m\in M} T_{pm}a_{pm} + \sum_{r\in R}\sum_{m\in M} T_{rm}a_{rm} \quad (1c)$$

$$TTX = \sum_{i\in I}\sum_{m\in M} ElC_{im}v_{im} \quad (1d)$$

$$PX = \sum_{m\in M}\sum_{p\in P} P_{pm}\theta_p \sum_{o\in O} a_{op} + \sum_{m\in M}\sum_{r\in R} P_{rm}\theta_r \sum_{o\in O} a_{or} + \sum_{m\in M}\sum_{i\in I} P_{im}\tau_i \sum_{o\in O} a_{oi} \quad (1e)$$

The cost components can be calculated through Eqs. (1a)–(1e). The variable processing costs and transportation costs are directly proportional to the amount of used products or disassembled components. Based upon the assumption of the model, the used products can be converted to repaired products, recycled materials and products, and recovered energy at a fixed conversion rate.

Minimize:

$$Carbon\ Emission = CEF + CET \quad (2)$$

The second objective function is formulated in Eq. (2), and it minimizes the environmental influences of reverse logistics system. In this research, environmental influences are evaluated by the carbon emissions related to the transportation and processing of used products. Excessive carbon emissions are considered as one of the most significant environmental challenges leading to global warming and climate change. Due to this reason, tremendous efforts have been spent in order to reduce carbon emissions. As shown in Eq. (2), the carbon emissions of reverse logistics include two parts: carbon emissions from processing of used products (*CEF*) and carbon emissions from the transportation (*CET*).

$$CEF = \sum_{p\in P} CaE_p \sum_{o\in O} a_{op} + \sum_{r\in R} CaE_r \sum_{o\in O} a_{or} + \sum_{i\in I} CaE_i \sum_{o\in O} a_{oi} + \sum_{l\in L} CaE_l \sum_{o\in O} a_{ol} \quad (2a)$$

$$CET = \sum_{c\in C}\sum_{o\in O} Ca_{co}S_{co}fr_{co} + \sum_{o\in O}\sum_{p\in P} Ca_{op}S_{op}fr_{op} + \sum_{o\in O}\sum_{p\in P} Ca_{or}S_{or}fr_{or} + \sum_{o\in O}\sum_{p\in P} Ca_{oi}S_{oi}fr_{oi} + \sum_{o\in O}\sum_{p\in P} Ca_{ol}S_{ol}fr_{ol} + \sum_{p\in P}\sum_{m\in M} Ca_{pm}S_{pm}fr_{pm} + \sum_{r\in R}\sum_{m\in M} Ca_{rm}S_{rm}fr_{rm} \quad (2b)$$

The carbon emission components are calculated by Eqs. (2a) and (2b). The first formula calculates the carbon emissions from reuse and repair facility p, remanufacturing and recycling center r, incineration plant i, and landfill l. Herein, the carbon emission indicators CaE_p, CaE_r, CaE_i, CaE_l are introduced to represent the amount of carbon emissions for processing one unit weight of used products at respective facilities. It is noted that the facility carbon emission indicator is inversely related to the unit processing costs, and that means higher investments and more advanced manufacturing technologies are required in reverse logistics system in order to reduce carbon emissions and improve the environmental performance [42]. Besides, energy recovery at incineration plant has a much higher carbon indicator comparing with other processing technologies. The second equation determines the carbon emissions of transportation in reverse logistics system. Carbon emissions of transportation is directly proportional to the number or frequency of transportation within a fixed period and distance between two connecting facilities. The carbon indicators Ca_{co}, Ca_{op}, Ca_{or}, Ca_{oi}, Ca_{ol}, Ca_{pm}, Ca_{rm} represent the average level of carbon emission for shipping one unit weight of used products in each trip. The average level of carbon emissions of transport vehicles are generally determined by the engine type, technical level, fuel consumption, load of transport vehicles, terrain driven and driver tendencies [43].

$$fr = \frac{\sum a}{D} \quad (2c)$$

In Eq. (2b), the frequency of transportation within a fixed period is usually an operational decision determined by respective companies in reverse logistics system, and it is related to the storage capacity, transport fleet capacity, operational strategy, amount of used products, and the amount of disassembled components. However, this research only focuses on the design of a general reverse logistics network at the strategic level, and operational decisions, i.e., inventory level, scheduling, routing, etc., are not taken into account, and Eq. (2c) is then formulated for simplifying the problem. Equation (2c) regulates a general rule for the linearization of Eq. (2b), which specifies the frequency of transportation within a fixed period is directly proportional to the amount of used products ($\sum a$) and inversely proportional to the load capacity of transport vehicles (D). This means more numbers of transportation (higher frequency) are required when the amount of used products transported within a fix period of time increases, and the frequency of transportation decreases when larger transport vehicles are used for the same account of used products.

3.4 Constraints

The constraints formulated in the model are presented as the following nine groups:

$$\left(\sum_{c\in C}\beta_c-\sum_{l\in L}\sum_{o\in O}a_{ol}\right)\Big/\sum_{c\in C}\beta_c\geq Rate_{utilization} \quad (3)$$

Equation (3) guarantees the requirement for the resource utilization rate of the reverse logistics system is met. The primary objective of reverse logistics is to capture the remaining value of used products through recycling of materials and recovery of energy. Landfill is the final destination of waste management system, and the remaining value vanishes when the used products are sent to landfill. Besides, it also has significant environmental pollutions to the air, surface water, and underground water, so it is the least sustainable option for the treatment of used products [27]. Due to this reason, Eq. (3) is defined to ensure a high resource utilization rate of reverse logistics. The numerical value of the left hand side part of this formula increases when the amount of used products sent to landfill decreases, which means more remaining value of used products can be recovered through the production of reused products, recycled materials and products, and recovered electricity.

$$\sum_{c\in C}a_{co}\geq LO_oq_o,\ \forall o\in O \quad (4)$$

$$\sum_{o\in O}a_{op}\geq LO_pq_p,\ \forall p\in P \quad (5)$$

$$\sum_{o\in O}a_{or}\geq LO_rq_r,\ \forall r\in R \quad (6)$$

$$\sum_{o\in O}a_{oi}\geq LO_iq_i,\ \forall i\in I \quad (7)$$

$$\sum_{o\in O}a_{ol}\geq LO_lq_l,\ \forall l\in L \quad (8)$$

The second group of constraints is formulated in Eqs. (4)–(8) and restricts the used products or disassembled parts processed at each facility are more than its lower bound. This requirement guarantees the utilization of the opened facilities in reverse logistics network is maintained at a high level in order to avoid waste of resources and take advantage of economy of scale.

$$\sum_{c\in C}a_{co}\leq UP_oq_o,\ \forall o\in O \quad (9)$$

$$\sum_{o\in O}a_{op}\leq UP_pq_p,\ \forall p\in P \quad (10)$$

$$\sum_{o\in O}a_{or}\leq UP_rq_r,\ \forall r\in R \quad (11)$$

$$\sum_{o\in O}a_{oi}\leq UP_iq_i,\ \forall i\in I \quad (12)$$

$$\sum_{o\in O}a_{ol}\leq UP_lq_l,\ \forall l\in L \quad (13)$$

The third group of constraints is formulated in Eqs. (9)–(13) and assures the used products or disassembled parts processed at each facility are less than its upper bound so that the facility's capacity is not exceeded.

$$\sum_{o\in O}q_o\leq NU_o \quad (14)$$

$$\sum_{p\in P}q_p\leq NU_p \quad (15)$$

$$\sum_{r\in R}q_r\leq NU_r \quad (16)$$

$$\sum_{i\in I}q_i\leq NU_i \quad (17)$$

$$\sum_{l\in L}q_l\leq NU_l \quad (18)$$

Equations (14)–(18) restrict the maximum number of candidate locations can be selected for opening collection centers, repair/reuse plants, recycling/remanufacturing plants, incineration plants and landfill, respectively.

$$\sum_{o\in O}a_{co}=\beta_c,\ \forall c\in C \quad (19)$$

Equation (19) assures that the used products generated at each customer location is entirely collected and sent for respective treatment.

$$\sum_{c\in C}a_{co}=\sum_{p\in P}a_{op}+\sum_{r\in R}a_{or}+\sum_{i\in I}a_{oi}+\sum_{l\in L}a_{ol},\ \forall o\in O \quad (20)$$

$$\sum_{p\in P}a_{op}\leq\gamma_p\sum_{c\in C}a_{co},\ \forall o\in O \quad (21)$$

$$\sum_{r\in R}a_{or}\leq\gamma_r\sum_{c\in C}a_{co},\ \forall o\in O \quad (22)$$

$$\sum_{i\in I} a_{oi} \le \gamma_i \sum_{c\in C} a_{co},\ \forall o\in O \tag{23}$$

$$\gamma_p + \gamma_r + \gamma_i \le 1 \tag{24}$$

Equations (20)–(24) formulate the flow balance constraint at collection centers. Equation (20) guarantees the incoming flow of used products equal to the outgoing flow of disassembled components at each collection center. Equations (21)–(23) assure the amount of disassembled components sent for repair, recycling and energy recovery cannot exceed their maximum number. Equation (24) restricts the summation of the conversion rate cannot exceed 1, which means the rate for reuse, repair, remanufacturing, recycling and energy recovery cannot more than 100 %.

$$\sum_{m\in M} a_{pm} = \theta_p \sum_{o\in O} a_{op},\ \forall p\in P \tag{25}$$

$$\sum_{m\in M} a_{rm} = \theta_r \sum_{o\in O} a_{or},\ \forall r\in R \tag{26}$$

$$\sum_{m\in M} v_{im} = \tau_i \sum_{o\in O} a_{oi},\ \forall i\in I \tag{27}$$

Equations (25)–(27) are the flow balance constraints for repair/reuse plant, remanufacturing/recycling plant and incinerator in reverse logistics network. Equations (25)–(26) assure the incoming flow of disassembled components equal to the outgoing flow of repaired or recycled products. Equation (27) specifies the rate of electricity generation from the combustion of waste materials.

$$a_{co} \le \vartheta_{co} q_o,\ \forall c\in C,\ o\in O \tag{28}$$

$$a_{op} \le \vartheta_{op} q_o q_p,\ \forall o\in O,\ p\in P \tag{29}$$

$$a_{or} \le \vartheta_{or} q_o q_r,\ \forall o\in O,\ r\in R \tag{30}$$

$$a_{oi} \le \vartheta_{oi} q_o q_i,\ \forall o\in O,\ i\in I \tag{31}$$

$$a_{ol} \le \vartheta_{ol} q_o q_l,\ \forall o\in O,\ l\in L \tag{32}$$

$$a_{pm} \le \vartheta_{pm} q_p,\ \forall p\in P,\ m\in M \tag{33}$$

$$a_{rm} \le \vartheta_{rm} q_r,\ \forall r\in R,\ m\in M \tag{34}$$

Equations (28)–(34) are route capacity constraints for the reverse logistics network restricting the maximum amount transported in each trip cannot exceed its capacity. Route capacity is determined by the mode of transportation, frequency of transportation and capacity of the upstream facilities [28]. When the route capacity is large enough or unlimited, parameter ϑ is replaced by an infinite large number in order to restrict the transportation of used products or disassembled components cannot exist if the candidate location is not selected to open the respective facility.

$$q_o,\ q_p,\ q_r, q_i, q_l \in \{0,\ 1\},\ \forall o\in O,\ \forall p\in P,\ \forall r\in R,\ \forall i\in I,\ \forall l\in L \tag{35}$$

$$a_{co},\ a_{op},\ a_{or},\ a_{oi},\ a_{ol},\ a_{pm},\ a_{rm},\ v_{im} \ge 0,\ \forall c\in C,\ \forall o\in O, \forall p\in P,\ \forall r\in R, \forall i\in I,\ \forall l\in L, \forall m\in M \tag{36}$$

The last group of constraints is the requirement for variables. Equation (35) formulates the binary requirement of the variables for determining if the candidate location is selected to open a new facility. Equation (36) regulates all the variables related to the transportation of used products, disassembled parts, and recycled products/energy cannot be a negative value.

4 Normalization function

In this paper, the objective function Eq. (2) is not monetized, which means the carbon emissions are not measured by the same units of system operating costs, so the two objective functions are not able to be combined directly through the weighted sum method. In order to aggregate those two objective functions with different measurements in this model, the normalization equation is employed and formulated in Eqs. (37), (37a)–(37c). This normalization function has been well developed and extensively applied in previous studies for aggregating multiple objectives with different measurements, and more introduction and application of the normalization function is given in Sheu [44], Nema and Gupta [45], Sheu and Lin [46], Yu et al. [47], and Hu and Sheu [48]. Decision-making, at the strategic level in particular, is a process involving both subjective evaluation from the decision-makers and objective data of the system [49], normalization function enables the interaction between the decision-makers' preference and system planning of a reverse logistics network so as to optimally balance the objectives of system operating costs and environmental impacts.

$$\min Objective = (Oj_c,\ Oj_{co2}) \cdot (Wt_c,\ Wt_{co2}) \tag{37}$$

Subject to:

$$Oj_c = (Cost - Cost_{min}) / (Cost_{max} - Cost_{min}) \tag{37a}$$

$$Oj_{co2} = (Carbon - Carbon_{min}) / (Carbon_{max} - Carbon_{min}) \tag{37b}$$

$$Wt_c + Wt_{co2} = 1 \tag{37c}$$

Equations (3)–(36).

Herein, Oj_x and Wt_x represent the individual deviation with the benchmark and the respective weight of objective function

Table 2 Parameters of candidate locations of collection center and repair facility

Candidate	Collection center				Repair and reuse facility				
	FO_o	VO_o	LO_o	UO_o	FP_p	VP_p	CaE_p	LO_p	UP_p
1	495,828	26	12,133	271,161	602,641	33		5081	166,887
2	526,274	31	10,073	262,174	634,120	27		7080	174,678
3	539,499	25	11,902	264,663	732,459	27		6800	156,025
4	417,032	21	16,677	298,238	864,177	34		9785	149,237
5	478,979	30	19,706	258,642	794,549	28		5693	130,490
6	450,372	35	23,620	255,537	681,543	25		7274	168,888
7	518,243	29	17,077	286,267	643,154	26		5905	108,812
8	645,642	24	24,715	346,115	648,177	29		6864	144,213
9	467,972	28	28,348	193,255	726,774	30		9758	209,034
10	527,410	34	22,299	328,346	647,628	28		7958	116,496

x. The individual deviation with the benchmark of each objective can be computed through Eqs. (37a) and (37b), and the benchmark is determined by the deviation between maximum and minimum values of respective objective functions. The weight determines the importance of a corresponding objective function in the evaluation of overall performance of a reverse logistics network, and Eq. (37c) must be satisfied. The multi-objective model for reverse logistics network planning can then be rewritten as normalization function Eqs. (37)–(37c) combined with constraints Eqs. (4)–(36). The numerical value of the normalization function becomes smaller when the reverse logistics network configuration is optimized with respect to the given weights, and the maximum value of Eq. (37) cannot be more than 1.

5 Numerical experiments

The applicability of the model is presented through an illustrative example in this section. The illustrative example formulates a small-scale problem reflecting a real-world decision-making of reverse logistics network planning. The reverse logistics network includes ten customers, ten candidate locations for collection centers, ten candidate locations for repair plants, ten candidate locations for recycling and remanufacturing plants, five candidate locations for incineration plants, three candidate locations for landfill, and five markets for reused/recycled products and recovered energy. The units of parameters and variables are not specified in this illustrative example. Moreover, all the relevant data are generated randomly through giving a certain interval to each set of parameters in order to have a better representation of the generality of the problem it aims to describe. For example, the amount of used products at each customer is a random number generated between 30,000 and 100,000, and in this example, they are 90,300, 33,218, 55,442, 55,203, 57,189, 53,435, 72, 800, 48,429, 70,222, 79,326, respectively. Tables 2, 3, and 4 present the relevant parameters of the candidate locations of collection center, repair plant, recycling and remanufacturing plant, incineration plant, and landfill. The other parameters including unit profit at each market and conversion rate are also generated in the same way. It is noted that the unit

Table 3 Parameters of candidate locations of recycling and energy recovery facility

Candidate	Recycling and remanufacturing facility					Energy recovery facility				
	FR_r	VR_r	CaE_r	LO_r	UR_r	FI_i	VI_i	CaE_i	LO_i	UP_i
1	993,095	37	3	11,273	183,795	519,407	22	17	7762	125,449
2	920,959	35	4	11,229	129,324	501,271	20	18	7731	191,833
3	962,726	37	3	11,418	236,038	585,023	24	15	7135	155,390
4	859,489	32	3	13,038	113,595	671,875	21	18	9707	199,690
5	768,164	38	4	14,932	153,254	668,867	21	18	8314	154,560
6	781,594	31	4	14,145	182,676					
7	849,049	37	3	12,828	143,391					
8	726,527	37	3	13,595	167,647					
9	839,241	30	3	11,953	231,760					
10	930,057	38	4	14,178	121,393					

Table 4 Parameters of candidate locations of landfill

Candidate	Landfill				
	FL_l	VL_l	CaE_l	LO_l	UR_l
1	278,798	17	7	9146	215,471
2	279,093	18	7	9146	182,063
3	348,594	19	8	7496	274,474

processing cost is inversely related to the carbon emissions at each facility, because more investment and advanced processing technologies and equipment are used for improving the environmental performance. Equation (38) is adapted from Wang et al. [42] for depicting this relationship in a mathematical way. Herein, α and β are adjustment parameters. In this example, both of them are generated randomly within the given interval. In addition, energy recovery through incineration of used products has a much higher carbon emission factor than other types of treatment.

$$CaE_x = \alpha \frac{1}{VX_x} + \beta \tag{38}$$

The maximum number of collection centers, repair plants, recycling and remanufacturing plants, and incineration plants to be selected are set to two for each type of facilities, and the maximum number for landfill is one. The distance between two facilities is randomly generated between 2 and 15, and the distance matrix between customers and candidate locations of collection center is presented in Table 5. Both unit transportation costs and carbon emission factor are directly related to the transport distance and truckload, however, they are inversely related with each other. This assumption is reasonable due to the fact that decreasing carbon emissions require higher technical standards of transport vehicles and this usually leads to a higher cost. The unit transportation cost matrix and carbon emission factor matrix can then be assumed, and the other relevant parameter matrix are also generated with the similar method but not presented in detail. In addition, the resource utilization rate of the reverse logistics system should be more than 70 %, and the weight of individual cost objective and individual carbon emission objective are given as 0.5 and 0.5, respectively, in order to calculate the optimal overall performance.

The mathematical programming is coded and solved by using Lingo 11.0 optimization solver on a personal laptop with Intel@ Core i3 2.4GHz CPU and 4GB RAM under Window 7 operating system, and each of the optimal value of individual costs, individual carbon emissions and overall optimal performance can be obtained within 90 s. The optimal value of maximum costs, minimum costs, maximum carbon emissions, minimum carbon emissions and overall performance are 82,996,720, 39,264,610, 55,183,390, 39,393,050, and 0.1743, respectively. Table 6 shows the network configuration, total costs, total carbon emissions, and costs and carbon emissions related to facility operation and transportation in different scenarios, and the transportation strategy in each scenario is presented in Table 7. It is noted that the maximum value of each individual objective is calculated only for determining the denominator in the normalization function, so the material flows of those objectives are not detailed and presented.

As shown in the tables, when the individual costs are minimized, candidate locations *o4*, *o8*, *p2*, *p3*, *i6* are selected for opening the new facilities. The used products generated in *c1*, *c4*, *c6*, *c8* and *c10* are sent to collection center *o4*, and used products generated in *c2*, *c3*, *c4*, *c5*, *c7* and *c9* are treated at collection center *o8*. The repaired products from *p2* and *p3* are sold in markets *m3* and *m1*. The remanufactured and recycled products from *r6* are sold in market *m5*, and the electricity generated at *i1* and *i2* are sold in market *m2* and *m3*. The result maximizes the profits generated from selling the repaired products and recovered electricity in the market while minimizes the transportation costs through selecting the

Table 5 Distance matrix between customers and candidate locations of collection center

Customer	Collection center									
	$o=1$	$o=2$	$o=3$	$o=4$	$o=5$	$o=6$	$o=7$	$o=8$	$o=9$	$o=10$
$c=1$	12	8	9	7	9	5	10	13	10	14
$c=2$	8	11	5	13	10	9	5	7	8	7
$c=3$	14	15	9	13	13	14	11	11	8	11
$c=4$	8	14	15	13	8	12	5	15	12	9
$c=5$	12	5	9	13	9	15	11	5	10	8
$c=6$	11	9	13	6	12	14	11	12	5	15
$c=7$	7	10	8	9	12	11	10	7	5	7
$c=8$	7	13	13	8	7	6	7	15	5	13
$c=9$	15	10	11	13	9	12	12	9	5	5
$c=10$	8	10	9	8	13	9	9	12	12	15

Table 6 Optimal values and network configuration of each individual objective and overall performance

Objective	Network configuration					Cost	FC/t[a] (%)	TC/t[b] (%)	Emission	FE/t[c] (%)	TE/t[d] (%)	RuR[e] (%)
	o	*p*	*r*	*i*	*l*							
Max cost	4, 10	4, 5	1, 8	4, 5	3	82,996,720	45.2	54.8	48,968,340	33.3	66.7	70
Min cost	4, 8	2, 3	6	1, 2		39,264,610	84.6	15.4	46,818,480	29.5	70.5	100
Max carbon	7, 8	7		2, 4	1	52,885,160	59.7	40.3	55,183,390	33.5	66.5	70
Min carbon	7, 8	1, 5	6, 10	3	1	67,636,050	57.1	42.9	39,393,050	19.2	80.8	85
Min overall	4, 8	2, 6	6	1, 5		43,089,080	79	21	43,517,890	25.9	74.1	100

[a] Portion of facility cost in total cost (FC/t = facility cost/total cost)

[b] Portion of transportation cost in total cost (TC/t = transportation cost/total cost)

[c] Portion of carbon emissions of facilities in total carbon emissions (FE/t = carbon emissions of facilities/total emission)

[d] Portion of carbon emissions of transportation in total emissions (TE/t = carbon emissions of transportation/total emissions)

[e] Resource utilization rate (RuR = utilized amount/total generation of used products) and the same abbreviation is applied in the subsequent tables

combination of facilities with smaller transport distances. When the individual carbon emissions are minimized, candidate locations *o7*, *o8*, *p1*, *p5*, *r6*, *r10*, and *i3* are selected, and the allocation of used products and disassembled components to respective facilities is integrated and optimized in order to reduce the overall carbon emissions related to the transportation of used products and disassembled components.

Table 7 Transportation strategy of the optimal solution of individual costs, individual carbon emissions and overall performance

Variable	Min cost		Min carbon		Min overall	
	Itinerary	Amount	Itinerary	Amount	Itinerary	Amount
a_{co}	(1, 4)	90,300	(1, 8)	90,300	(1, 4)	90,300
	(2, 8)	33,218	(2, 8)	33,218	(2, 8)	33,218
	(3, 8)	55,442	(3, 7)	15,960	(3, 8)	55,442
	(4, 4)	26,748	(3, 8)	39,482	(4, 4)	55,203
	(4, 8)	28,455	(4, 7)	41,032	(5, 8)	57,189
	(5, 8)	57,189	(4, 8)	14,171	(6, 8)	53,435
	(6, 4)	53,435	(5, 7)	57,189	(7, 8)	72,800
	(7, 8)	72,800	(6, 7)	53,435	(8, 4)	48,429
	(8, 4)	48,429	(7, 8)	72,800	(9, 8)	70,222
	(9, 8)	70,222	(8, 7)	48,429	(10, 4)	34,084
	(10, 4)	79,326	(9, 7)	70,222	(10, 8)	45,242
			(10, 8)	79,326		
a_{op}	(4, 2)	89,471	(7, 5)	85,880	(4, 2)	89,471
	(8, 3)	95,198	(8, 1)	98,789	(8, 6)	98,198
a_{or}	(4, 6)	89,471	(7, 10)	85,880	(4, 6)	89,471
	(8, 6)	24,141	(8, 6)	98,789	(8, 6)	93,205
a_{oi}	(4, 1)	119,295	(7, 3)	114,507	(4, 1)	119,295
	(8, 1)	6154	(8, 3)	40,883	(8, 1)	6154
	(8, 2)	191,833			(8, 5)	122,770
a_{ol}			(8, 1)	90,836		
a_{pm}	(2, 3)	53,683	(1, 5)	59,274	(2, 3)	53,683
	(3, 1)	57,119	(5, 2)	51,528	(6, 2)	57,119
a_{rm}	(6, 5)	56,806	(6, 2)	49,395	(6, 5)	91,338
			(10, 3)	42,940		
v_{im}	(1, 2)	1,254,490	(3, 3)	1,403,771	(1, 2)	1,254,490
	(2, 3)	1,918,330	(3, 4)	150,130	(5, 5)	1,227,698

In the optimal solution of overall system performance, candidate locations *o4* and *o8* are selected for opening collection centers, candidate *p2* and *p6* are selected for opening repair plant, candidate *r6* is selected for opening recycling plant, and candidates *i1* and *i5* are chosen for opening incineration plants. The used products generated in *c1*, *c4*, *c8* and *c10* are sent to collection center *o4*, and used products generated in *c2*, *c3*, *c5*, *c6*, *c7*, *c9* and *c10* are sent to collection center *o8*. The repaired products from *p2* and *p6* are sold in market *m3* and *m2*, the recycled products from *r6* are sold in market *m5*, and the electricity generated at *i1* and *i5* are sold in market *m2* and *m5*. The optimal value of the overall system performance equals to 0.1743 with respect to the given weigh of each objective function, and the resource utilization rate of the reverse logistics system is 100 %.

Based upon the analysis of the optimal result of each scenario, several managerial implications are discussed and summarized as follows:

(1) Comparing with the maximum individual costs scenario, the facility operating costs decrease by 11.4 % while the transportation costs decrease by 86.7 % in the optimal solution of minimum individual costs objective. This implies for dealing with fixed amount of used products, the facility operating costs may only have slightly change in different scenarios due to the relatively small variations in fixed facility costs and variable unit processing costs, however, the transportation costs can be significantly reduced through the optimal combination of facilities and allocation of materials.

(2) Comparing with the maximum individual carbon emissions scenario, the carbon emissions of facility operation decrease by 59 % while the carbon emissions of transportation decrease by 13.3 % in the optimal solution of minimum individual carbon emissions objective. This implies the carbon emissions of both facility operation and transportation can be reduced through optimal planning of a reverse logistics network. And it is also observed more reduction in facility related carbon emissions can be achieved through the implementation of lower carbon emission processing technologies, but this leads to an increase in system operating costs by 27.9 %.

(3) In the minimum individual costs scenario, the utilization rate of resources reaches 100 %. This implies more economic benefits can be obtained through the reuse and repair, recycling and remanufacturing, and energy recovery of used products. The result of this scenario has revealed the primary objective of reverse logistics and proved its effectiveness in achieving circular economy. Landfill is not opened in this scenario mainly due to the value loss of used products. Furthermore, the distance to the candidate locations of landfills is longer than other facilities in order to reduce environmental impacts on residential areas, and this leads to an increase in transportation costs.

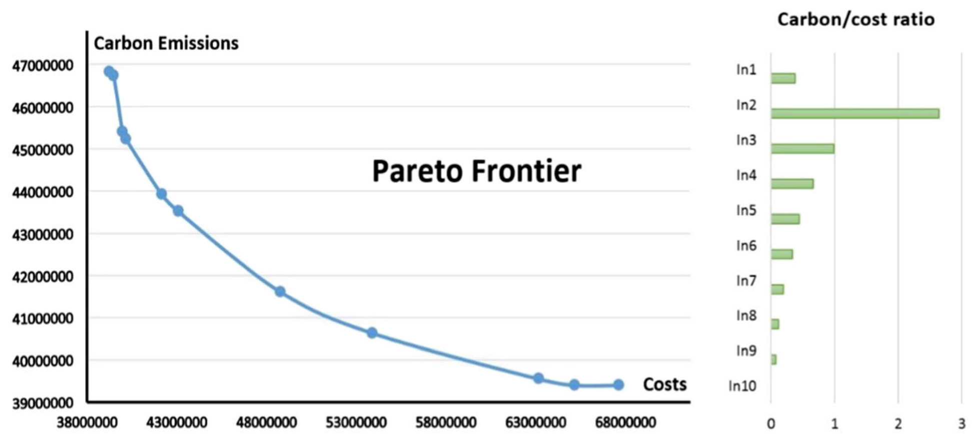
(4) In the minimum individual carbon emissions scenario, only one incineration plant is opened for generating electricity from used products while two incinerators are opened in other scenarios. Besides, the resource utilization rate is at 85.2 % and one landfill is selected for treating the used products. This result reveals the fact that, although energy recovery through incineration of used products has very good economic benefits and significantly reduces the volume of waste, it results in more carbon emissions to the environment. Due to this reason, the used products sent for incineration are greatly reduced in this scenario.

(5) In the optimal overall system performance scenario, the trade-off between system operating costs and carbon emissions is balanced with respect to the given weights. The resource utilization rate achieves 100 % in order to take advantage of circular economy while only one incineration plant is opened for reducing the carbon emissions to the environment. This result provides supply chain managers with suggestions on how to improve the overall system performance through two methods: improving the benefits from circular economy and implementing advanced processing technologies for reducing carbon emissions.

(6) In the optimal overall system performance scenario, it is noted that the system operating costs approach 91.2 % of the individual minimum costs and the carbon emissions obtain 90.5 % of the individual minimum carbon emissions. This result reveals the levels to what extend the best performance of each individual objective can be achieved in the optimal overall system performance scenario.

In the following part, sensitivity analyses are conducted targeting two groups of critical parameters: the corresponding weights of costs and carbon emissions (Wt_c and Wt_{co2}), and the required resource utilization rate of used products ($Rate_{\text{utilization}}$). The purpose of the sensitivity analyses is to investigate the influences of those key parameters on system operating costs, carbon emissions as well as the overall performance of reverse logistics network. In the first sensitivity analysis, Wt_c gradually increases from 0 to 1 at the same interval of 0.1 while Wt_{co2} decreases accordingly, and the other parameters remain the same.

The Pareto optimal curve of the example is first generated based upon the optimal values of the test scenarios, and it is shown in Fig. 2. The Pareto frontier explicitly illustrates the trade-off between system operating costs and carbon emissions, and it also provides a set of optimal scenarios for decision makers. In general, it is clearly observed that more investment is required for reducing the carbon emissions of a



Scenarios	*S0*	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*
Wt_c	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1	0
Wt_{co2}	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1

Fig. 2 Pareto frontier of the example carbon emissions vs. system operating costs

reverse logistics system. Also, it is noted that, with the system operating costs increase, the Pareto optimal curve becomes more flat with decreased slope particularly after scenario *S5*. This fact reveals that, when the weight of system operating costs is more than 0.5, the carbon emissions can be significantly reduced with a small increase in system operating costs, and that means the investment at this stage is extremely effective to improve the environmental performance of a reverse logistics system. However, as shown in the figure, much more money has to be spent for decreasing carbon emissions when the weight of carbon emissions is more than 0.5. Further, it is also observed from scenarios *S9* and *S10* that, when Wt_{co2} approaches 1, the increased investment does not result in a better environmental performance.

$$Ratio^{\frac{Carbon}{cost}}_{Interval(x)} = \frac{\left(Carbon\ Emission_{scenario(x-1)} - Carbon\ Emission_{scenario(x+1)}\right)}{\left(Cost_{scenario(x+1)} - Cost_{scenario(x-1)}\right)} \tag{39}$$

The analysis of the Pareto frontier of the example has clearly illustrated the cost effectiveness for decreasing carbon emissions with respect to the change of corresponding weights of Wt_c and Wt_{co2}, and it therefore provides deep managerial insights for decision makers on the portfolio between system operating costs and environmental performance in different circumstances. In addition, quantitative analysis for assessing cost effectiveness is also given in Fig. 2. The carbon/cost ratio is calculated using the absolute value of the decrease in carbon emissions divides the increase of the operating costs in each interval between two neighboring scenarios, and it indicates how much carbon emissions can be reduced by increasing one unit cost. The formula of the carbon/cost ratio is given in Eq. (39). The result helps decision makers to determine the optimal or most effective allocation of weight to the objectives in order to achieve the optimal balance between system operating costs and carbon emissions.

The change of costs and carbon emissions associated with facilities and transportation in reverse logistics network is illustrated in Fig. 3. As shown in the figure, the increase of system operating costs is mainly caused by the increased transportation costs, and that means the optimal transportation planning is the key success factor to maintain system operating costs at a lower level. For carbon emissions, the decrease is primarily contributed by the decrease in carbon emissions of facilities when Wt_c is more than Wt_{co2}, and that means the

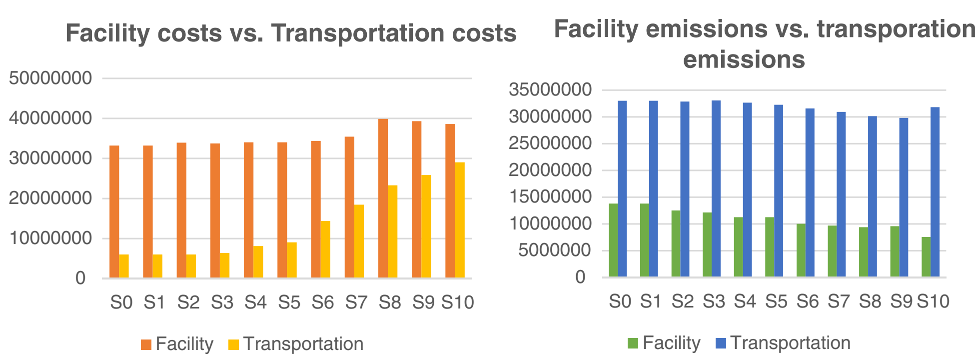


Fig. 3 Facility costs vs. transportation costs and carbon emissions of facilities vs. carbon emissions of transportation costs from *S0* to *S10*

Table 8 Optimal value and resource utilization rate of each individual objective and the gap between the maximum and minimum value

$Rate_{\text{utilization}}$ (%)	Maximum costs		Minimum costs		Gap (value) (%)	Maximum carbon emissions		Minimum carbon emissions		Gap (value) (%)
	Value	RuR[a](%)	Value	RuR[a](%)		Value	RuR[a](%)	Value	RuR[a](%)	
0	83,124,990	58	39,264,610	100	112	55,688,540	65	39,393,050	85	41
40	83,124,990	58	39,264,610	100	112	55,688,540	65	39,393,050	85	41
70	82,996,720	70	39,264,610	100	112	55,183,390	70	39,393,050	85	40
80	82,665,400	80	39,264,610	100	111	54,173,860	80	39,393,050	85	38
90	81,678,490	90	39,264,610	100	108	52,900,080	90	39,393,050	100	34
100	80,960,230	100	39,264,610	100	106	51,611,840	100	39,393,050	100	31

[a] Resource utilization rate (RuR = utilized amount/total generation of used products)

environmental performance of a reverse logistics system can be improved dramatically through more investment on the implementation of advanced and environmentally friendly processing technologies of used products at this stage. However, when Wt_{co2} plays more important role in decision-making, the reduction of carbon emissions is mainly determined by the transportation. The result has revealed the likelihood of a win-win situation in a reverse logistics network design, and it has also provided the general strategy for improving both economic and environmental performances of a reverse logistics system. In a simple words, it is to implement advanced processing technologies while simultaneously optimize the transportation planning, and the focus may vary with respect to the changing combination of weights.

In the second sensitivity analysis, we are interested on how the required resource utilization rate of used products ($Rate_{\text{utilization}}$) influences decision-making in a reverse logistics network design and six scenarios with incremental $Rate_{\text{utilization}}$ (0, 40, 70, 80, 90, and 100 %) are investigated. Table 8 presents the optimal value and actual resource utilization rate of the individual costs and carbon emissions objectives with respect to the change of required resource utilization rate, and the gap between the maximum and minimum value is also given in this table. As shown in the table, with the increase of $Rate_{\text{utilization}}$, the minimum costs and minimum carbon emissions are not changed, but the maximum values decrease and the gap decreases accordingly. The result illustrates a smaller deviation in system performance can be achieved through the implementation of more stringent regulations in resource utilization from used products. However, on the other hand, it also indicates more improvements may be obtained through the optimization of a reverse logistics network when the requirement for resource utilization is not in place.

Besides, the break-even points from which the system performance starts to change with the increase or decrease of required utilization rate can be obtained. It is observed that the break-even point of $Rate_{\text{utilization}}$ is 58 % for maximum costs and is 65 % for maximum carbon emissions, and the maximum values of those two objectives will not change until the break-even points are reached. Furthermore, it is noted that the break-even point of $Rate_{\text{utilization}}$ for minimum carbon emissions is 85 %, and the numerical value remains the same when the required utilization rate is more than 85 %. This result means the optimal value of minimum carbon emissions can be reached as long as the actual resource utilization rate is not less than 85 %.

Figure 4 presents the curves of costs and carbon emissions with respect to the change of required resource utilization rate. As shown in the figure, the costs and carbon emissions are

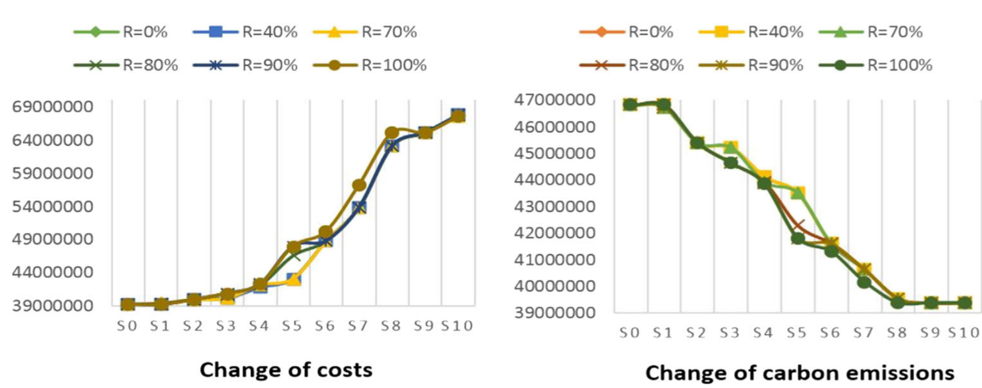


Fig. 4 Sensitivity analysis of change of costs and change of carbon emissions with respect to different required resource utilization rate

almost the same in different scenarios when only one objective function dominates the decision-making, however, more costs and less carbon emissions can be obtained with the increase of $Rate_{\text{utilization}}$ when the costs objective and carbon emissions objective are given to the similar weight. Figure 5 illustrates the costs and carbon emissions related to facilities and transportation in each scenario with the increase of $Rate_{\text{utilization}}$. From the figure, we can observe the similar results as discussed in Fig. 3. However, it is noted, in scenario *S10*, the carbon emissions of facilities greatly decreases when $Rate_{\text{utilization}}$ is more than the break-even point, but the significant increase in carbon emissions of transportations makes the total emissions remaining at the same value. The result provides decision makers with interactions between the resource utilization rate and other critical parameters in the design of a reverse logistics network, and it also helps policy makers to determine the required resource utilization rate of used products.

6 Computational performance

Decision-making in the real-world case study may include more parameters and decision variables, we are interested in the computational performance of the proposed multi-objective mixed integer programming for a reverse logistics network design under medium-scale and large-scale problems. In the computational experimentation, the relevant parameters are randomly generated with the same interval used in the illustrative example. In order to have more practical meaning, one assumption adopted in the computational experimentation is that the number of candidate locations for incineration plants and landfills are much fewer than other types of facilities, because those facilities are strictly regulated due to their significant impacts on the environment and the available locations are relatively limited comparing with other facilities. In addition, the model is relaxed to an uncapacitated problem through eliminating the capacity constraints that will lead to infeasible solutions, because the reverse logistics system will become insufficient to deal with the increased amount of used products if both the number of facilities and facility capacities are restricted. This relaxation may also have practical meaning in decision-making, which determines the required capacity at different facilities.

Ten scenarios with increased number of parameters, variables, and integer variables are tested in the computational experimentation and the result is presented in Table 9. As shown in the table, the size of the problems increases gradually in terms of both total variables and integer variables. The number of total variables from scenario 1 to 10 are 191, 250, 405, 565, 665, 790, 1045, 1455, 2060, and 4890, respectively, and the number of integer variables from scenario 1 to 10 are 21, 25, 30, 40, 40, 40, 45, 55, 60, and 90, respectively. The CPU times increase dramatically with the increase of the size of problem; however, some exceptions, e.g., maximum costs in scenarios 7, 8, and 9, are observed especially when the size

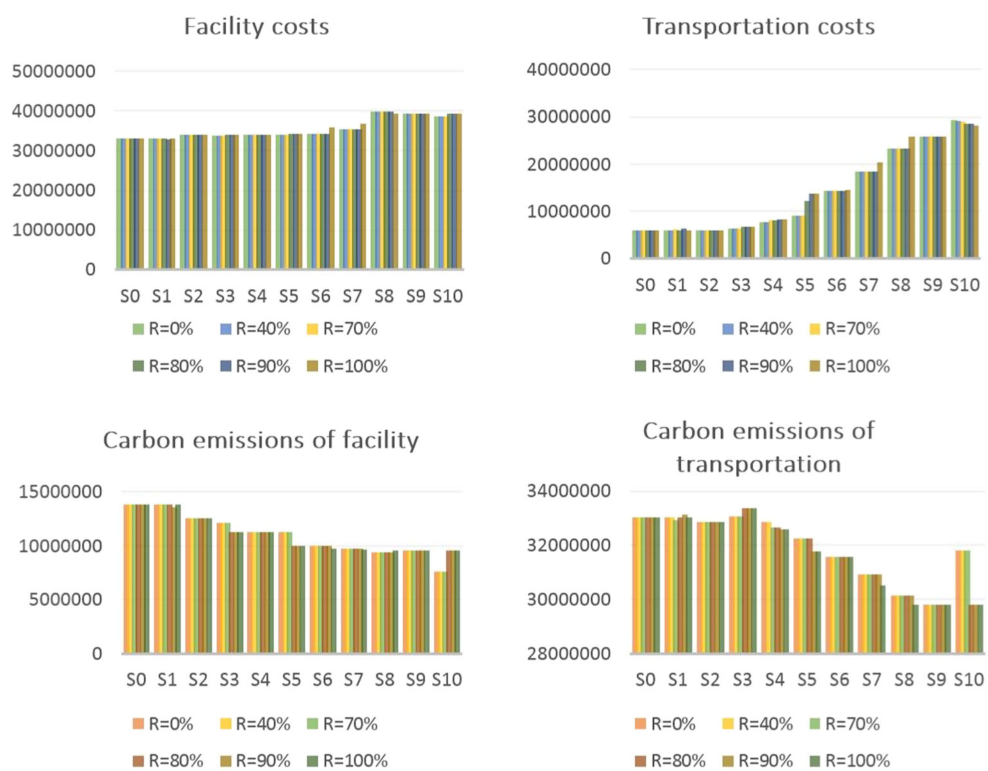


Fig. 5 Costs and carbon emissions related to facilities and transportations in each scenario

Table 9 Size of problem and computational performance of each test scenarios

Scenario	Parameters							Decision variables		CPU times (s)				
	C	*O*	*P*	*R*	*I*	*L*	*M*	Total	Integer	Max*C*[a]	Min*C*[b]	Max*E*[c]	Min*E*[d]	Ov*P*[e]
1	5	5	5	5	3	3	5	191	21	2	6	3	2	11
2	10	5	5	5	5	5	5	250	25	3	7	3	4	79
3	10	10	5	5	5	5	5	405	30	6	29	56	4	122
4	10	10	10	10	5	5	5	565	40	6	37	49	14	305
5	20	10	10	10	5	5	5	665	40	53	64	14	20	779
6	20	10	10	10	5	5	10	790	40	15	60	96	36	985
7	20	15	10	10	5	5	10	1045	45	741	172	73	39	1158
8	20	20	10	10	10	5	10	1455	55	727	1117	62	166	1004
9	30	20	10	10	10	10	20	2060	60	272	1258	55	114	1223
10	50	30	20	20	10	10	30	4890	90	1071	1064	437	1036	1356

[a] Max*C*: maximum costs

[b] Min*C*: minimum costs

[c] Max*E*: maximum carbon emissions

[d] Min*E*: minimum carbon emissions

[e] Ov*P*: optimal overall system performance

of the problems are at the same level. In general, the first three scenarios are considered as small-scale problems and can be resolved within 2 min. The next five scenarios are considered as medium-scale problems and require 6–1200 s to find the optimal solution. The last two scenarios are considered as large-scale problems with more than 2000 decision variables among which more than 60 are integers, up to 1400 s CPU times may be required for resolving large-scale problems. The result of the computational experimentation provides rough estimation of the time required for obtaining the optimal value of the model with respect to the size of problems.

7 Conclusion

In recent years, reverse logistics has been increasingly focused in order to capture the remaining values from used products through reuse, repair, recycling, remanufacturing, and energy recovery. A significant number of previous studies have focused on both theoretical development and mathematical modeling of reverse logistics problems. This paper has presented an alternative method through multi-objective mixed integer programming for network design of a general four-echelon reverse logistics system including customers, collection centers, repair and reuse plants, recycling and remanufacturing plants, incinerators, and landfills. The mathematical model includes two objective functions: (1) minimization of overall reverse logistics costs, and (2) minimization of carbon emissions of the transportation and processing of used products. Comparing with previous models for reverse logistics system planning, the most significant contribution of this study is to take into account of more comprehensive influencing factors in order to improve both economic and environmental sustainability of reverse logistics.

Conventionally, reverse logistics aims primarily at taking advantage of circular economy. However, reuse and recycling of used product in an improper way may lead to secondary pollution, so the environmental consideration of a reverse logistics system is of great importance. In this paper, the environmental influence is evaluated by carbon emissions from the processing and transportation of used products. Furthermore, the required resource utilization rate is also considered in order to minimize the amount of used products sent to landfill. The result has clearly presented the trade-off between system operating costs and environmental impacts of reverse logistics activities, and it has also provided decision makers with deep managerial insights of the interactions among different parameters in the reverse logistics network design. In general, more investment are involved and more advanced processing technology are implemented in order to decrease the carbon emissions of a reverse logistics system, and the optimal transportation planning is of significant importance to minimize both system operating costs and environmental impacts. Besides, with the increase of the required resource utilization rate, the system operating costs increase while the carbon emissions decrease, and this has revealed the requirement of resource utilization push the optimal solution towards more environmentally friendly system planning of reverse logistics.

The main output of the proposed model for decision-making in reverse logistics are summarized as follows:

1. Optimal location selection and transportation strategy of a reverse logistics network design with respect to the given parameters and weights.
2. The cost effectiveness curve for reducing carbon emissions can be generated through the sensitivity analysis of changing weights, and this helps decision makers to determine the optimal or most effective allocation of weight to the objective functions.
3. The impact of the required resource utilization rate on system operating costs and carbon emissions can be obtained through the sensitivity analysis, and this helps the policy makers to determine the value of required resource utilization rate.
4. Through the relaxation of constraints, the model can also suggest either the required capacity of facilities (eliminating capacity constraint) or the minimum number of facilities required (eliminating number of facilities constraints) in the reverse logistics system.
5. The expected time consumption can be roughly estimated through comparing the size of problem with the result of computational efficiency presented in section 6.

This paper has made a new attempt for designing and formulating a sustainable reverse logistics network, and illustration, sensitivity analysis, and computational experimentation provide deep insight of its practical application in decision-making of a reverse logistics network design. Besides, the main limitations, challenges, and suggestions for future improvements are also discussed as follows:

1. Sustainability of a system can be evaluated by not only carbon emissions and resource utilization, but also can be measured by water pollution, energy consumption as well as some other economic, social, and environmental indicators [50]. Hence, the future development of the reverse logistics network design is suggested to focus on more comprehensive evaluation of sustainability of a reverse logistics system. Further, the evaluation and formulation of social sustainability is considered as another very important influencing factor and should be accounted in future study.
2. This paper employs a very important assumption: all the repaired products, recycled products, and recovered energy will be sold in the markets. However, the uncertainty related to customer demands for those products and energy is usually inevitable as it is for other products, and this will significantly increase the level of difficulty in the design and planning of a reverse logistics system. Therefore, future development is suggested to formulate a reverse logistics system considering the uncertainties of market demands, and the system planning of reverse logistics may also be conducted under the environment with competitors.
3. Reverse logistics systems are sometimes developed for treating multiple types of used products, and the difference with respect to the costs and environmental influences of different types of products becomes extremely important in such condition. Therefore, the design of a reverse logistics network with considerations of the characteristics of multiple types of used products is suggested in future studies.
4. Computational efficiency is another concern particularly when the size of problem becomes extremely large; a lot of CPU times may be required to determine the optimal configuration of a reverse logistics system. Due to this reason, development of a more advanced, effective, and reliable computational algorithm for the reverse logistics network design [31, 51–53] is also suggested in future study.

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