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Location-allocation problem of reverse logistics for end-of-life vehicles based on the measurement of carbon emissions

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ABSTRACT

Faced with the contradiction between the rapid growth of car ownership and the low recovery rate of end-of-life vehicles, the reverse logistics services led by third-party recycling and dismantling companies for end-of-life vehicles (ELVs) in China are experiencing great challenges under the background of the low-carbon economy. This paper constructs a four-tier reverse logistics network model, which includes ELV sources, collection centers, remanufacturing centers and dismantlers. Meanwhile, this paper also develops a mixed integer linear programming mathematical model and solves the problem using the global optimization software Lingo. The optimization results of a real case in Xi'an prove the validity of the model in both present normal demands and increasing demand situations in the future. The total logistics network and the environmental costs are both reduced, and the utilization rate of the dismantling center is improved. The location and capacity rating strategies in dismantling centers have key effects on the total cost in the logistics network that are far beyond other decision variables. The supply capacity of the key facilities in Xi'an's ELV recycling network is far greater than the level of demand, causing a serious waste of resources. Hence, the layout model of an industrial park can help to reduce the total cost of the reverse logistics network if the dismantling center has a high utilization rate.

1. Introduction

Recycling, disassembling and remanufacturing of end-of-life vehicles (ELVs) are not only an important way to save resources and realize the sustainable use of resources, but also embody the social responsibility. In particular, ELVs are classified as hazardous waste and may cause serious environmental pollution and transportation safety problems with improper treatment; however, they are also potential sources of recyclable materials (Demirel, Demirel, & Gökçen, 2016). China could potentially reduce energy consumption by 7–9.4 billion kWh and 6.67–9.69 million tons of carbon dioxide per year before 2022 if all used automotive parts could be fully recycled and remanufactured (Özceylan, Demirel, Çetinkaya, & Demirel, 2017). Therefore, many new sustainable strategies, such as low carbon production, modular design, and lifecycle management, have been integrated to promote the efficiency of the Chinese automotive industry (Sutherland, Jenkins, & Haapala, 2010).

According to data from the China Association of Automobile Manufacturers (CAAM), the Chinese automotive industry has entered a rapid development period, and ownership of vehicles has exceeded 200 million by the end of 2017. Fig. 1 shows information about Chinese ELVs' recycling market from 2012 to 2017,[1] from which we can see that the recovery ratio is quite low (far below the average recovery ratio of 6 – 8% in developed countries). Only 30% of the scrapped vehicles are recovered through formal channels each year, therefore we have the following confusions: (1) Where are the remaining scrapped cars? (2) What are the hazards caused by the informal recycling channels? (3) Why do the majority of consumers choose informal recycling channels and what's wrong with the reverse supply chain of ELVs in China? Nearly 70% of the other scrapped cars go into the 'black market', with about half of them going through illegal dismantling channels and the other half going to rural areas in Western China for continued use (Hu & Wen, 2017). This not only impacts enthusiasm of the formal recovery and dismantling enterprises, but also brings serious hidden dangers to road traffic safety, environmental protection and resource utilization. According to the statistics of traffic department, nearly one fifth of the traffic accidents in Western China are caused by illegal assembled vehicles and vehicles that meet the scrap standards.

It is worth noting that the characteristics of the automotive remanufacturing industry in developing countries such as China are

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[1] The data come from the China Automotive Technology and Research Center (CATARC).

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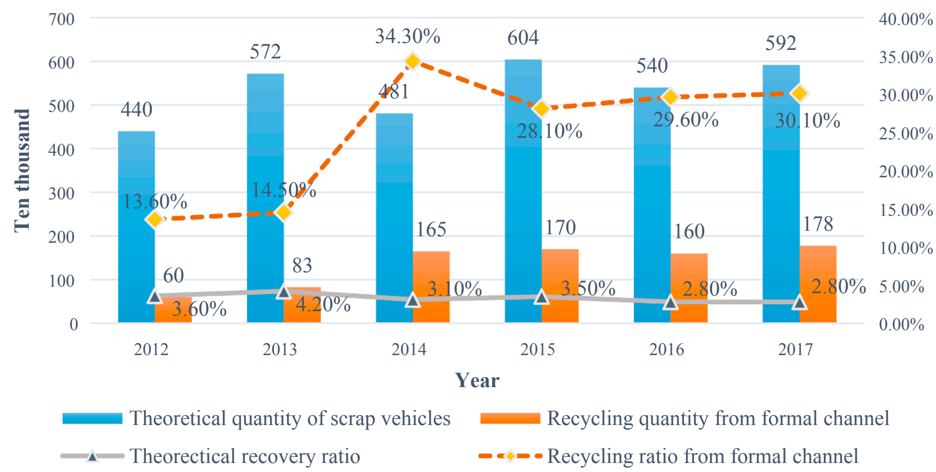

Fig. 1. Statistics of Chinese Vehicle Market from 2012 to 2017.

distinctly different from those in developed countries. In China, the third-party waste automobile recycling and dismantling enterprises are, at present, fully authorized by the governments. From the statistics of Chinese Renewal Association, the number of Authorized Treatment Facilities (ATFs) was 657 in 2017, and the total number of recycling outlets was 2763 with more than 35,000 employees. Although China is the largest vehicle market in the world, ELVs are poorly managed. Among these ATFs, only 43 have an annual disassembly capacity of more than 10,000 vehicles; 337 have an annual disassembly capacity of less than 1000 vehicles, which accounting for 51% of the total ATFs and only 7.8% of the total recovery quantities. It can be seen that the location of the recycling outlets and the third-party ATFs are still immature, and the problem of resource allocation in the reverse supply chain has not been solved properly. The complex recycling procedures and low economic benefits make the formal recycling channel lose its competitiveness. Thus it is imminent to optimize the recovery efficiency of ELVs' reverse supply chain to prevent more ELVs from flowing into the 'black market'.

In recent years, with the rapid increase in the quantity of ELVs, many policies and regulations have been implemented. Developing countries such as China, should improve the structure of the ELV supply chain and manage the ELV recycling process effectively to minimize costs, to face the challenges with 'black market' and opportunities arising from the low carbon economy. Based on above analysis, we design a network for fulfilling the government regulations as well as effective management of ELV recycling process through the optimization of the location-allocation problem. Then, the Mixed Integer Linear Programming (MILP) model strives to achieve an economic and environmental balance by considering both the economic value and reducing carbon emissions. In recent five years, the number of motor vehicles in Western China has increased by 20 million, with an annual increase of over 20% (faster than Eastern region of China). Hence, the proposed model is verified by a case study focusing on the location and allocation reverse logistics network design for third-party ELV recycling in Xi'an, the largest city of western China. Finally, we also present a model to conduct the validity test when the recycling demand of Western China is increasing in future.

The remainder of this paper is arranged as follows. Section 2 includes a literature review focusing on the location and allocation of ELV management. Our MILP model and basic analysis are discussed in Section 3. A case study about reverse logistics for ELVs in Xi'an is introduced in Section 4. In addition, Section 5 illustrates the projections and scenario analysis. Section 6 discusses the results from the above analysis. Finally, Section 7 provides our conclusions for the paper and develops managerial implications.

2. Literature review

Due to both economic and environmental benefits of end-of-life (EoL) product recycling, RL problems have been studied very often. The earliest general framework of the issues arising in the context of reverse logistics is suggested by Fleischmann et al. (1997), who subdivide the field into three main areas, namely distribution planning, inventory control, and production planning. In the last decades, economic, regulations and social engaging incentives have driven industrial sectors and governments to become active in reverse logistics. The economic incentives encourage the implementation of reverse logistics so that more profits from reduced consumption of raw materials, from adding value to recovered materials and from cost reduction (Demirel et al., 2016). Regulation incentives, i.e., the recent growth of government environmental regulations, related to EoL products have facilitated the development of reverse logistics processes in several industrial sectors (Paulo, Pedro, & José, 2010; Wang & Chen, 2013). The engagement of companies with society and environmental issues can also generate incentives to manage the return flows in a supply chain (Schultmann, Zumkeller, & Rentz, 2006; Sutherland et al., 2010). In our literature review, we focus on RL networks design and governmental carbon emission regulation on transportation. Then, we elaborate our main contributions to the existing literature.

2.1. RL network design

This section gives a brief overview of relevant studies in the design of reverse logistics networks for different EoL products and strategies. Although most RL network design papers deal with manufacturer or retailer recycling for returned items, there is a number of studies that consider other recycling modes. For instance, Sasikumar and Haq (2011) considered a multi-echelon and multi-product reverse logistics network and integrated with the selection process of best third-party reverse logistics provider (3PRLP) to achieve the target of cost minimization. Moreover, Suyabatmaz, Altekin, and Şahin (2014) discussed that manufacturer has decided to outsource the company reverse logistics (RL) activities to a 3PRLP. The authors present two hybrid simulation method for the RL network design of the 3PL to solve and compare when the recovery quantities are uncertain. Some of the papers such as Sasikumar, Kannan, and Haq (2010) and Fahimnia, Sarkis, Dehghanian, Banihashemi, and Rahman (2013) proposed mixed integer nonlinear programming (MINLP) or mixed integer linear programming (MILP) approach to minimize the total costs of the reverse logistics network. Özceylan and Paksoy (2013a) addressed a new multi-period and multipart MILP model for a closed-loop supply-chain to discuss the optimal values of the total network. They also presented the

Table 1
A summary of the recent literature on RL network design and carbon emission regulation.

	Objective Function		Capacity Level		Solution Methodology				Application Field					Environmental Concerns	Carbon Emission Regulation		
Paper	S	M	Fixed	Variable	NLP	MILP	SP	HA	W	F	B	A	O		C&T	CET	CT
[1]	✓		✓					✓	✓								
[2]	✓		✓			✓			✓								
[3]		✓	✓			✓								✓	✓	✓	
[4]	✓		✓		✓								✓				
[5]		✓		✓			✓							✓			
[6]		✓	✓			✓								✓	✓		
[7]	✓		✓			✓			✓								
[8]	✓		✓			✓											
[9]		✓		✓				✓						✓	✓	✓	✓
[10]		✓	✓					✓						✓			
[11]		✓	✓			✓								✓	✓	✓	✓
[12]	✓		✓				✓						✓				
[13]		✓	✓					✓		✓				✓			
[14]	✓		✓			✓						✓					
[15]		✓	✓			✓		✓						✓			
[16]		✓	✓				✓	✓									
[17]		✓	✓			✓	✓							✓			
[18]	✓		✓		✓								✓				
[19]	✓		✓					✓					✓				
[20]	✓		✓			✓											
[21]	✓		✓				✓	✓			✓			✓			
[22]	✓		✓			✓						✓					
Our work		✓		✓		✓						✓		✓			✓

Source: [1] Kim, Yang, and Lee (2009), [2] Gomes, Barbosa-Povoa, and Novais (2011), [3] Diabat et al. (2013), [4] Fahimnia et al. (2013), [5] Ramezani et al. (2013), [6] Zhang and Xu (2013), [7] Achillas et al. (2012), [8] Toyasaki, Daniele, and Wakolbinger (2014), [9] Choudhary et al. (2015), [10] Diabat and Al-Salem (2015), [11] Fareeduddin et al. (2015), [12] John and Sridharan (2015), [13] Guo, Wang, Fan, and Gen (2017), [14] Özceylan et al. (2017), [15] Rahmani and Mahoodian (2017), [16] Soleimani, Govindan, Saghafi, and Jafari (2017), [17] Yu and Solvang (2017), [18] Gao, Feng, Wang, Zheng, and Tan (2018), [19] Jabbarzadeh, Haughton, and Khosrojerdi (2018), [20] Jerbia, Boujelben, Sehli, and Jemai (2018), [21] Ma and Li (2018), [22] Shankar, Bhattacharyya, and Choudhary (2018).

computational results under different scenarios to verify the applicability of the model (Özceylan & Paksoy, 2013b). The authors extended their previous model by considering uncertainty with the fuzziness method. They used the General Algebraic Modeling System (GAMS) software to solve the proposed problems in both studies. However, these two papers both do not take capacity level of facilities into consideration. Due to the NP-hard nature of location-allocation problem and massive data in real cases, different heuristic algorithm have been proposed in the purpose of solving the problem in a short computation time. Wang and Hsu (2010) and Roghanian and Pazhoheshfar (2014) solve the problem by using genetic algorithm, however testing the proposed model only with a theoretical example weaken their contributions. As for recent literatures: Chen, Wang, Wang, and Chen (2017) discussed a multi-objective closed-loop supply chain model through a particle swarm optimization (PSO) for a solar cell industry case, in order to provide highly favorable and effective solutions for reducing carbon dioxide emissions. Examined environmental effects without a carbon emission regulation consideration is the main limitation of this study. A tabulated summary of other relevant examples of RL network design for different EoL products are presented in Table 1. The table generalizes, for each of the papers, the objective function (whether the objective function is single or multi), capacity level of key facilities, solution methodology taken into account (NLP: nonlinear programming; MILP: mixed integer linear programming; SP: stochastic programming; HA: heuristic algorithm), application field (e.g. Waste Electrical & Electronic Equipment, food industry, battery industry, automotive industry or other industries), environmental concerns, detailed carbon emission regulation (C&T: cap-and-trade; CET: carbon emission trade; CT: carbon tax). As we can see from Table 1, there are few real case researches in the literature, and the majority of studies focus on models and algorithms. In addition to the given studies, although some RL network design models have been already applied to various industries, for example electronic, solar cell and furniture, only a few papers focus on ELV recycling industry (Mahmoudzadeh, Mansour, & Karimi, 2013; Merkisz-Guranowska, 2011). ELV recycling is a typical low-carbon industry and is an important factor in the sustainable development of the automotive industry (Wang & Chen, 2013). The classic ELV routing problem was studied by Schultmann et al. (2006). The proposed model was devoted to minimizing the total length of the tours between the dismantlers and relevant facilities in which the ELV shredding and cleaning processes were done in Germany. Zarei, Mansour, Husseinzadeh Kashan, and Karimi (2010) developed a conceptual framework of a reverse logistics network and proposed a mathematical model in which the new vehicle distributors are also responsible for collecting the ELVs. While solving the problem with a genetic algorithm to achieve good quality solutions strengthens the study, measurement the effectiveness of the proposed model without a real case application is one of the limitations. Ene and Öztürk (2015) considered the entire life cycle of the scrapped car recycling industry, including recycling, dismantling, crushing and remanufacturing. They constructed an MILP model based on profit maximization and minimization of pollution to determine the location and allocation variables of the key facilities. However, not considering future situation when recycling demand increases significantly is the lack of the study. Simic (2016) established an interval-parameter programming model for ELV management under strict environmental regulations, which addresses the complex relationship between different ELV management subsystems. To examine various constraint-violation probability levels, a case study is conducted, and the results are useful for the improvement of ELV management.

2.2. Carbon emission regulation on transportation

With the great concern of customers' environmental awareness, many researchers have drawn attention of government environmental regulations (Cui, Fan, Zhu, & Bi, 2014; Yang, Guo, & Ma, 2012). RL network design problems have been relatively well-studied, but carbon emission regulation have been considered only recently (Wang, Lai, &

Shi, 2011), and mostly in price and production decision studies. Chang, Xia, Zhu, Fan, and Zhao (2015) proposed two profit-maximization models for different demand market with carbon cap and trade mechanism. Qi, Wang, and Bai (2017) analyzed the pricing decision strategies in a decentralized supply chain from a game theoretical perspective and find the optimal pricing strategy for the participants under carbon cap regulation. Ji, Zhang, and Yang (2017) constructed an O2O retail supply chain decision model in the context of environmental regulation under three cases: no regulation, cap-and-trade regulation based on grandfathering mechanism, and cap-and-trade regulation based on benchmarking mechanism. Carbon dioxide emissions from transportation industry account for 1/4 of the total carbon dioxide emissions (Ma, Balthasar, Tait, Riera-Palou, & Harrison, 2012; Nanaki & Koroneos, 2016), and city vehicle amount both in the world and in China has increased rapidly in recent years (Tian & Chen, 2016; Zhang, Yang, & Chen, 2017), thereby various initiatives emphasize the importance of taking CO2 emissions account for automotive industry and ELVs recycling. Therefore, the government of China also issued relevant policies and regulations to improve the development of the ELV recycling industry (Hu & Wen, 2017).

A well-designed reverse logistics system will yield both economic and environmental benefits, so the consideration of government carbon emission regulation for reverse logistics system design is of significant importance. However, according to Table 1, only seven papers which relate to RL network design take into account carbon emission regulation. Rahmani and Mahoodian (2017) and Yu and Solvang (2017) model the uncertainty of demand considering carbon emission regulation, but both without real case studies to analyze the results of the model. Diabat and Al-Salem (2015) addressed a joint location-inventory problem and extend it to account for the reduction of carbon emissions. Another paper by Choudhary, Sarkar, Settur, and Tiwari (2015) proposed a quantitative optimization model for integrated forward/reverse logistics network design, which incorporates different carbon emission parameters into operational decision-making. In this paper, the authors also take capacity level of key facilities into consideration. However, these two papers both do not discuss detailed carbon emission regulation. Chaabane, Ramudhin, and Paquet (2012) constructed a life cycle assessment (LCA) model in RL network design. The principle is used to achieve the tradeoffs between economic and environmental objectives in the aluminum industry with Emission Trading Schemes (ETS). Evaluating of the model without social stainability is one of the limitations. A mathematical production planning problem with carbon cap and trade mechanism was developed by Zhang and Xu (2013) and Diabat, Abdallah, Al-Refaie, Svetinovic, and Govindan (2013). Compared with emission trading and cap-and-trade schemes, the impact of carbon tax on RL network design has just started in recent years. Fareeduddin, Hassan, Syed, and Selim (2015) presented optimization models based on carbon emission regulatory policies and compared three common regulatory policies: strict carbon caps, carbon tax, and carbon cap-and-trade. Carbon tax policy provides more flexibility but impose huge financial burden on the companies in order to reach certain emission target compared to other two policies.

2.3. Main contributions

Following the general retrospective look at the related literature, most of the literature on RL network design don't take carbon emission regulation into consideration. A few literatures that we concluded above (see Table 1) consider carbon emission trading and cap-and-trade scheme. Thus we proposed a RL location-allocation network design model of ELVs including both economic and environmental benefits under carbon tax regulation. The proposed general framework is justified by a real case study of Xi'an (China). Another gap is owing to its complexity, previous papers rarely discuss the constraints of the facility's capacity and only two papers Ramezani, Bashiri, and Tavakkoli-Moghaddam (2013) and Choudhary et al. (2015) from Table 1 consider this issue. On the other hand, no previous papers take into account the actual situation of the skip-level recycling in the customer zone. We propose in this paper to discuss both situations, and the sensitivity analysis of multiple decision variables is also presented to determine the key variables affecting the cost and efficiency of the recovery. And the long-term effectiveness of the model is verified in the context of increased demand, since the insights that can be derived from different period are different. Hence, the main contribution of this research is the optimization of location-allocation network for ELVs under carbon tax regulation.

3. Location-allocation network design for ELVs

To improve the management of ELVs, the six national ministries of China jointly issued 'the implementation of the pilot scheme notice about replacement of remanufactured products' in 2013 and decided to take the automobile engine, gearbox and other automotive parts as pilot products. When the remanufactured automotive parts meet certain conditions of replacement, the government will give the automotive parts remanufacturer a one-time subsidy (Ren, Bian, Xu, & He, 2015). At present, the third-party ELV recycling companies under the supervision of the government dominate China's ELV recycling market. The third-party recycling companies are Authorized Treatment Facilities (ATFs) that make sure that the ELVs are scrapped legally, i.e., ensuring that the 'five major components' are not sold and bought on the black market. ATFs are licensed and regulated by the Chinese Department of Commerce. To reflect the structure of the ELV recycling network, an investigation has been conducted in Xi'an. The main activities of the third-party recycling company are divided into three parts. First, the ELV registration is transferred from their last owners (customer zone) and allocated to the dismantling center. Second, the ELVs are dismantled into five categories: steel scrap (five major components, etc.); nonferrous metals (aluminum alloy, copper alloy and magnesium alloy, etc.); recyclable products (clear lines of tires, seats, mirrors, etc.); hazardous waste (waste oil, Freon, battery, etc.); and normal waste (broken glass, plastic, textiles, etc.). Third, the dismantled materials are sold to the corresponding recycling or remanufacturing facilities. For a third-party ELV recycling company, the optimization of the total cost and decision-making problem of the recycling network configuration is a reverse logistics network location-allocation problem (LAP).

In this section, we introduced an MILP model for a reverse logistics network considering carbon emissions, which includes the last owners, third-party collection centers, dismantlers and shredders, and reuse and waste disposal centers (Fig. 2). The objective of the model is to minimize the total cost in a multistage ELV reverse logistics network, which includes the transportation costs, fixed site costs for dismantlers, operating costs for dismantling disassembly activities, cost of waste disposal, and environmental costs associated with carbon emissions. The environmental costs are measured by the greenhouse gas emissions, such as the CO2 generated by the transportation processes. The amount of carbon emissions is measured throughout the entire ELV recycling cycle from the customer zone to the reuse and waste disposal facilities.

The following assumptions regarding the regulation and current application in China have been considered in developing the mathematical model, particularly for the third-party ELV recycling company.

(1) Since the statistics show that the M1 type of vehicles (passenger vehicles with less than eight seats) accounted for 54% of the current ELV recycling market, the allocation strategy for the M1 type of car in a single cycle is considered.
(2) The unit transportation costs under different modes of transport are different, and ELVs must be registered in either a collection center or a dismantler. The ELV recycling network configuration is comprised of seven nodes, including the ELV sources, the collection center, the dismantler, the metal material recycling facility, the remanufacturing center, the landfill site, the hazardous waste

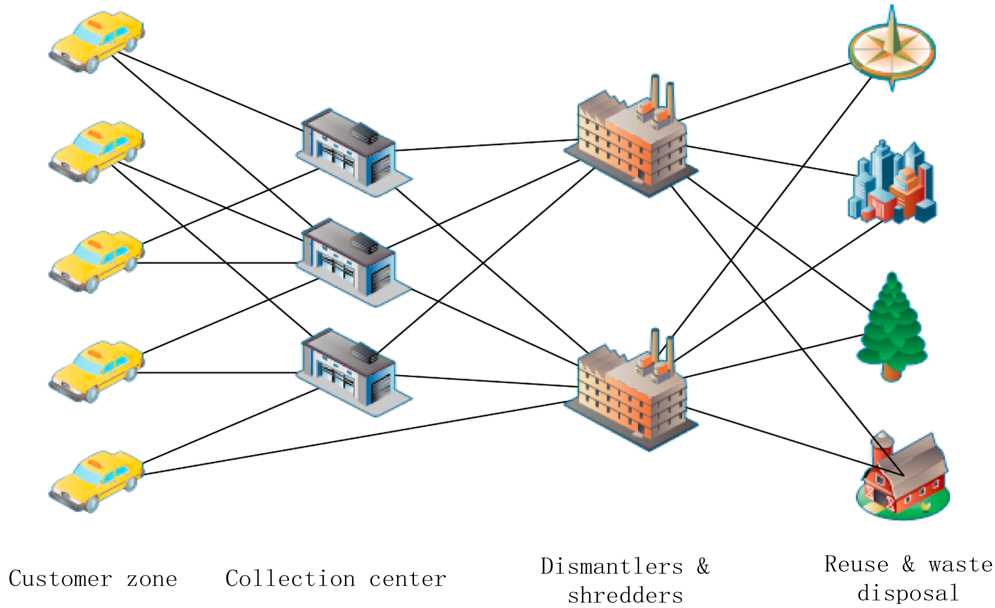

Fig. 2. ELV recycling network.

treatment facility, and the flow between the nodes. Dismantlers and hazardous waste disposal facilities must be authorized by the government (Tian & Chen, 2016).

(3) The inventory of scrap materials is not considered. The geographical location of each facility and the distance between each facility are determined by its latitude and longitude. The position of the customer zone is measured using the center of the relevant district.

(4) Greenhouse gas emissions are measured by measuring the emissions of three major greenhouse gases: carbon dioxide, methane and nitrous oxide. Internationally, the macrolevel calculation approach is represented by the IPCC (Intergovernmental Panel on Climate Change) Guidelines for National Greenhouse Gas Inventories. The basic idea of this method is to identify and calculate various carbon emissions sources. The advantage of this method is that the operation is simple, the data are easy to collect, and the standard is unified. The problem is that the carbon dioxide emission coefficient varies with different regions and different environments and must be measured practically.

$$\text{Total costs of } CO_2 = \text{The price of carbon tax} \times CO_2 \text{ emission factor} \times \text{Unit distance and weight of fuel consumption} \times \text{Distance} \times \text{Weight}$$

(5) The weight of ELVs will change after each processing node correspondingly, which will directly affect the cost of transport and the carbon emissions costs. In the complete ELV recycling network, assuming that the standard weight of the in flowed ELV is 1, the weight ratios of the outflowed material from the dismantlers to the remanufacturing center, metal material recycling facilities, hazardous waste treatment facilities and landfills are α, β, γ, and ε, respectively.

The proposed model can be formulated as follows:

3.1. Indexes

i ELV sources, $i = 1, 2, ..., I$
j collection centers, $j = 1, 2, ..., J$
k dismantlers, $k = 1, 2, ..., K$
q remanufacturing centers, $q = 1, 2, ..., Q$
p metal material recycling facilities, $p = 1, 2, ..., P$
u hazardous waste treatment facilities, $u = 1, 2, ..., U$
v Landfills, $v = 1, 2, ..., V$
o capacity level of dismantlers, $o = 1, 2, ..., O$

3.2. Parameters

J_j: the collection capacity of collection center j
K_{ko}: the ceiling dismantling ability o of dismantler k
U_u: the upper business capacity of hazardous waste treatment facility u
I_i: the total amount of ELV returned from ELV source i
d_{ij}^{sc}: distance between ELV source i and collection center j (km)
d_{ik}^{sd}: distance between ELV source i and dismantler k (km)
d_{jk}^{cd}: distance between collection center j and dismantler k (km)
d_{kq}^{dr}: distance between dismantler k and remanufacturing center q (km)
d_{kp}^{dm}: distance between dismantler k and metal material recycling facility p (km)
d_{ku}^{dh}: distance between dismantler k and hazardous waste treatment facility u (km)
d_{kv}^{dl}: distance between dismantler k and landfill v (km)
a_{ij}^{sc}: unit cost of transportation between ELV source i and collection center j (RMB/ton*km)
a_{jk}^{cd}: unit cost of transportation between collection center j and dismantler k (RMB/ton*km)
a_{ik}^{sd}: unit cost of transportation between ELV source i and dismantler k (RMB/ton*km)
a_{kq}^{dr}: unit cost of transportation between ELV dismantler k and remanufacturing center q (RMB/ton*km)
a_{kp}^{dm}: unit cost of transportation between ELV dismantler k and metal material recycling facility p (RMB/ton*km)
a_{ku}^{dh}: unit cost of transportation between ELV dismantler k and hazardous waste treatment facility u (RMB/ton*km)
a_{kv}^{dl}: unit cost of transportation between ELV dismantler k and Landfill v (RMB/ton*km)
s_{ko}: the fixed opening cost for dismantler k with capacity of o (RMB/ton)
c_k^d: unit cost of dismantling at dismantler k per vehicle (RMB)
c_u^h: unit cost of disposal at hazardous waste treatment facility u (RMB)

c_v^l: unit cost of disposal at landfill v (RMB)
f_{ij}^{sc}: energy consumption of unit distance per vehicle between ELV source i and collection center j (kg/ton*km)
f_{jk}^{cd}: energy consumption of unit distance per vehicle between collection center j and dismantler k (kg/ton*km)
f_{ik}^{sd}: energy consumption of unit distance per vehicle between ELV source i and dismantler k (kg/ton*km)
f_{kq}^{dr}: energy consumption of unit distance and weight between ELV dismantler k and remanufacturing center q (kg/ton*km)
f_{kp}^{dm}: energy consumption of unit distance and weight between ELV dismantler k and metal material recycling facility p (kg/ton*km)
f_{ku}^{dh}: energy consumption of unit distance and weight between ELV dismantler k and hazardous waste treatment facility u (kg/ton*km)
f_{kv}^{dl}: energy consumption of unit distance and weight between ELV dismantler k and Landfill v (kg/ton*km)
z_0: carbon dioxide emission factor
b_0: carbon tax of unit carbon dioxide emission
w: unit weight of ordinary end-life passenger cars of M1 type
α: weight percentage of scrap material outflowed from dismantlers to remanufacturing center
β: weight percentage of scrap material outflowed from dismantlers to metal material recycling facility
γ: weight percentage of scrap material outflowed from dismantlers to hazardous waste treatment facility
ε: weight percentage of scrap material outflowed from dismantlers to landfill.

3.2.1. Decision variables

e_{ko}: if establishing dismantler k with capacity$o$, 1; otherwise, 0
X_{ij}: recycling amount between ELV source i and collection center j
Y_{jk}: amount of ELVs flowed between collection center j and dismantler k
Z_{ik}: amount of ELVs flowed between ELV source i and dismantler k
F_{kp}: amount of materials flowed between ELV dismantler k and metal material recycling facility p
L_{kq}: amount of materials flowed between ELV dismantler k and remanufacturing center q
G_{ku}: amount of materials flowed between ELV dismantler k and hazardous waste treatment facility u
H_{kv}: amount of materials flowed between ELV dismantler k and Landfill v.

3.3. Formulation

3.3.1. Minimize

$$\begin{aligned}\min \quad C = {}& \textstyle\sum_{k=1}^{K}\sum_{o=1}^{O} s_{ko}e_{ko} + (\sum_{i=1}^{I}\sum_{j=1}^{J} wa_{ij}^{sc}d_{ij}^{sc}X_{ij} \\ & + \textstyle\sum_{j=1}^{J}\sum_{k=1}^{K} wa_{jk}^{cd}d_{jk}^{cd}Y_{jk} \\ & + \textstyle\sum_{i=1}^{I}\sum_{k=1}^{K} wa_{ik}^{sd}d_{ik}^{sd}Z_{ik} + \sum_{k=1}^{K}\sum_{q=1}^{Q} a_{kq}^{dr}d_{kq}^{dr}L_{kq} \\ & + \textstyle\sum_{k=1}^{K}\sum_{p=1}^{P} a_{kp}^{dm}d_{kp}^{dm}F_{kp} \\ & + \textstyle\sum_{k=1}^{K}\sum_{u=1}^{U} a_{ku}^{dh}d_{ku}^{dh}G_{ku} + \sum_{k=1}^{K}\sum_{v=1}^{V} a_{kv}^{dl}d_{kv}^{dl}H_{kv}) \\ & + (\textstyle\sum_{i=1}^{I}\sum_{j=1}^{J} wz_0b_0f_{ij}^{sc}d_{ij}^{sc}X_{ij} \\ & + \textstyle\sum_{j=1}^{J}\sum_{k=1}^{K} wz_0b_0f_{jk}^{cd}d_{jk}^{cd}Y_{jk} + \sum_{i=1}^{I}\sum_{k=1}^{K} wz_0b_0f_{ik}^{sd}d_{ik}^{sd}Z_{ik} \\ & + \textstyle\sum_{k=1}^{K}\sum_{q=1}^{Q} z_0b_0f_{kq}^{dr}d_{kq}^{dr}L_{kp} \\ & + \textstyle\sum_{k=1}^{K}\sum_{p=1}^{P} z_0b_0f_{kp}^{dm}d_{kp}^{dm}F_{kp} + \sum_{k=1}^{K}\sum_{u=1}^{U} z_0b_0f_{ku}^{dh}d_{ku}^{dh}G_{ku} \\ & + \textstyle\sum_{k=1}^{K}\sum_{v=1}^{V} z_0b_0f_{kv}^{dl}d_{kv}^{dl}H_{kv}) \\ & + (\textstyle\sum_{j=1}^{J}\sum_{k=1}^{K} c_k^{d}Y_{jk} + \sum_{i=1}^{I}\sum_{k=1}^{K} c_k^{d}Z_{ik}) \\ & + (\textstyle\sum_{k=1}^{K}\sum_{u=1}^{U} c_u^{h}G_{ku} + \sum_{k=1}^{K}\sum_{v=1}^{V} c_v^{l}H_{kv}) \end{aligned} \tag{1}$$

3.3.2. Constraints

$$\sum_{i=1}^{I} X_{ij} \leqslant J_i \qquad \forall\, j = 1 - J \tag{2}$$

$$\sum_{i=1}^{I} Z_{ik} + \sum_{j=1}^{J} Y_{jk} \leqslant \sum_{o=1}^{O} K_{ko}e_{ko} \qquad \forall\, k = 1 - K \tag{3}$$

$$\sum_{k=1}^{K} G_{ku} = U_u \qquad \forall\, u = 1 - U \tag{4}$$

$$\sum_{o=1}^{O} e_{ko} \leqslant 1 \qquad \forall\, k = 1 - K \tag{5}$$

$$\sum_{i=1}^{I} z_{ik} + \sum_{j=1}^{J} Y_{jk} \leqslant W\sum_{o=1}^{O} e_{ko} \qquad \forall\, k = 1 - K \tag{6}$$

$$\sum_{p=1}^{P} F_{kp} + \sum_{u=1}^{U} G_{ku} + \sum_{v=1}^{V} H_{kv} + \sum_{q=1}^{Q} L_{kq} \leqslant W\sum_{o=1}^{O} e_{ko} \qquad \forall\, k = 1 - K \tag{7}$$

$$\sum_{j=1}^{J} X_{ij} + \sum_{k=1}^{K} Z_{ik} = I_i \qquad \forall\, i = 1 - I \tag{8}$$

$$\sum_{i=1}^{I} X_{ij} = \sum_{k=1}^{K} Y_{jk} \qquad \forall\, j = 1 - J \tag{9}$$

$$w\Big(\sum_{i=1}^{I} Z_{ik} + \sum_{j=1}^{J} Y_{jk}\Big) = \sum_{q=1}^{Q} L_{kq} + \sum_{p=1}^{P} F_{kp} + \sum_{u=1}^{U} G_{ku} + \sum_{v=1}^{V} H_{kv} \quad \forall\, k = 1 - K \tag{10}$$

$$\alpha w\sum_{i=1}^{I} I_i = \sum_{k=1}^{K}\sum_{q=1}^{Q} L_{kq} \tag{11}$$

$$\beta w\sum_{i=1}^{I} I_i = \sum_{k=1}^{K}\sum_{p=1}^{P} F_{kp} \tag{12}$$

$$\gamma w\sum_{i=1}^{I} I_i = \sum_{k=1}^{K}\sum_{v=1}^{V} H_{kv} \tag{13}$$

$$\varepsilon w\sum_{i=1}^{I} I_i = \sum_{k=1}^{K}\sum_{u=1}^{U} G_{ku} \tag{14}$$

$$e_{ko} \in \{0, 1\} \qquad \forall\, k = 1 - K \quad \forall\, o = 1 - O \tag{15}$$

$$X_{ij} \geqslant 0, \quad Y_{jk} \geqslant 0, \quad Z_{ik} \geqslant 0, \quad Z_{ik} \in Z, \quad \forall\, i = 1 - I \quad \forall\, j = 1 - J \quad \forall\, k = 1 - K \tag{16}$$

$$F_{kp} \geqslant 0, \quad G_{ku} \geqslant 0, \quad H_{kv} \geqslant 0, \quad L_{kq} \geqslant 0 \quad \forall\, k = 1 - K \quad \forall\, p = 1 - P \quad \forall\, q = 1 - Q \quad \forall\, v = 1 - V \quad \forall\, u = 1 - U \tag{17}$$

The objective function has three main components. The first component represents the fixed location cost of dismantlers. According to assumption 2′s structure of the reverse network and the measurement of distance on assumption 3, the second component represents the cost of transportation for each line of the network. The third component represents the total costs of the carbon dioxide emissions incurred in the recycling process based on assumption 4.

Constraint (2) indicates the recycling capacity of the collection centers. Constraint (3) determines the processing capacity limits of the dismantler$k$ with capacity$o$. Constraint (4) stipulates the limit of operational capacity of the hazardous waste treatment facility. Constraint (5) ensures that the capacity level of each dismantler is uniquely determined. Constraints (6–7) indicate that only the established dismantlers can provide transit and disassembly services for the entire network, where$W$ is a sufficiently large positive number. Constraint (8) represents that the demand of each ELV source is equal to the total amount from the ELV sources to the collection centers and dismantlers. Constraints (9–10) represent the equilibrium of flows to the collection centers and dismantlers, respectively. Constraints (11–14) indicate that the total demand for recycling is consistent with the recovered volume of sales or waste disposal after dismantling. Finally, constraints (15–17) stipulate the characteristics of the decision variables. Overall, constraints (2–5) indicate the capacity restriction constraints of each facility and the basic condition for the establishment of dismantling centers, which is the key innovation point based on the ELV recycling network (assumption 2) compared with previous studies. Constraints (6–7) ensure that every node in the ELV recycling network must be established to provide services. Constraints (8–14) represent the flow equilibrium condition of each facility node, especially consistent with assumption 5 about the weight of the ELVs after each processing node. Lastly, constraints (15–17) determine the requirements of the decision variables based on the network structure.

4. A case study

We applied the previous model to a practical case study of a real-life problem in Xi'an for ELV recycling. Analyzing real data with the proposed model, we attempted to answer the following questions: What is the current recycling scheme for location and allocation? What are the quantities of ELVs, components, materials and waste that should flow between facilities? How should the existing situation be optimized?

4.1. Description of the problem

Xi'an is the capital of Shaanxi Province, which is located at 34°16′North, 108°54′East, approximately 1080 km to the southwest of Beijing. In 2017, the scale of GDP was 747 billion, ranking first place in the western region of China. Xi'an is the core node of the 'Chinese Belt and Road Initiative' strategy and is comprised of 13 districts. Moreover, Xi'an is an important historical and educational city, but the industry of ELV recycling is still in the preliminary stage. The districts of Xi'an, population, area and number of ELVs are given in Table 2. Prior to 2013, there was only one authorized ELV dismantling company in Xi'an; there were two facilities in 2014–2015 and three by 2016. Moreover, 2 main collection centers, 2 remanufacturing centers, 3 metal material recycling facilities and 2 hazardous waste treatment facilities were operating in different districts of Xi'an. All of the points where the dismantlers and shredders are located are taken as potential sites for recycling processes. The 13 districts of Xi'an are taken as ELV sources in the problem.

Cooperation does not exist between the three ELV dismantling companies, who try as much as possible to occupy the market share for their own business objectives. The Shaanxi Province ELV Dismantling Company (SP for short) receives ELVs directly from the urban district and recycles vehicles indirectly from other regions through its collection center in the Chang'an district. The Shaanxi Xinhui dismantling company (XH for short) and the Shaanxi Dinghe Dismantling Company (DH for short) collect ELVs indirectly from all districts through a collection center in the Weiyang district. XH and DH Company have better brand image and a superior reputation than that of SP Company. For all types of remanufactured materials and hazardous waste disposal, the three companies have specialized long-term partners. Overall, the dismantling companies have their own independent recycling systems and stable cooperation from upstream to downstream; therefore, no horizontal cooperative relationship exists either. The ELV recycling network data of Xi'an are shown in Fig. 3.

Table 2
Districts of Xi'an City.

District	Population in 2016 (million)	Area in 2016 (km^2)	No. of ELVs in 2016
Urban area	6.27	827	11,574
Gaoling	0.28	294	1349
Lintong	0.67	915	1241
Changan	1.03	1583	1225
Yanliang	0.25	244	420
Zhouzhi	0.57	2974	1006
Lantian	0.63	1969	684
Huyi	0.56	1255	1045

To optimize the amount of transported quantities between the facilities, the available data on the number of vehicles deregistered in Xi'an in 2016 are obtained from the Bureau of Statistics of Shaanxi Province. The flows from customers to collection centers and dismantlers, and from collection centers to dismantlers are shown in Tables 3 and 4, respectively.

We utilized governmental ELV reports and an in-depth literature review in addition to an industry survey to develop a cost estimation. The costs listed in Table 5 shows that in the existing recycling situation in Xi'an, the location cost accounts for 45.26% of the cumulative cost, transportation costs account for 3.78%, environmental costs account for 13.91% including carbon emissions costs and waste disposal costs, and dismantling costs hold a share of 37.05%. The relative proportion of the cost terms will vary with the parameters due to the current demands being too small and a lower-level carbon tax compared to that of developed countries.

4.2. An optimization solution based on Lingo

The global optimal solution provided by Linear Interactive and General Optimizer (Lingo10.0) is used to solve and optimize the real case problem of location and allocation for ELV recycling. Since the core of Lingo's solution is the branch and bound method (B-and-B), this method provides accurate optimization results. This real-life case is a typical mixed integer programming problem (MILP) model for location and allocation. The global optimal result obtained by Lingo is shown in Table 6, and the number of iterations is 1617. The settings described above resulted in a problem with 83 variables, including 52 integer variables, and 38 constraints. The specific statistical results are shown in Table 7. The detailed results of global optimization by Lingo are shown in Tables 8–10.

The horizontal comparison of the cost savings (%) after optimization is shown in Fig. 4.

Based on the data of the ELV recycling industry in Xi'an in 2016, total cost reduction reaches 36.83%, and each cost item is reduced to different degrees. It is confirmed that the optimization model proposed in this paper is a better and valid solution to the location and allocation problem of the ELVs based on the carbon emission measurement. The global optimization solution to the optimal recycling network of Xi'an's ELV recycling industry can be seen in Fig. 5.

5. Scenario analysis and managerial insights

5.1. Sensitivity analysis

The Reduced Cost in the Optimal Simplex Method of Linear Programming Problem represents the degree of change in the objective function value caused by a small change in the decision variable. It can also be considered as the change in the objective function when the variable value increases by one unit. In addition, the corresponding reduced cost of the basic variable in the optimal simplex tableau must be zero, and the reduced cost of the non-basic variable indicates the amount that the objective function will increase when the decision variable increases by one unit, which is the coefficient of the non-basic variable in the simplex table. The analysis results of the reduced costs

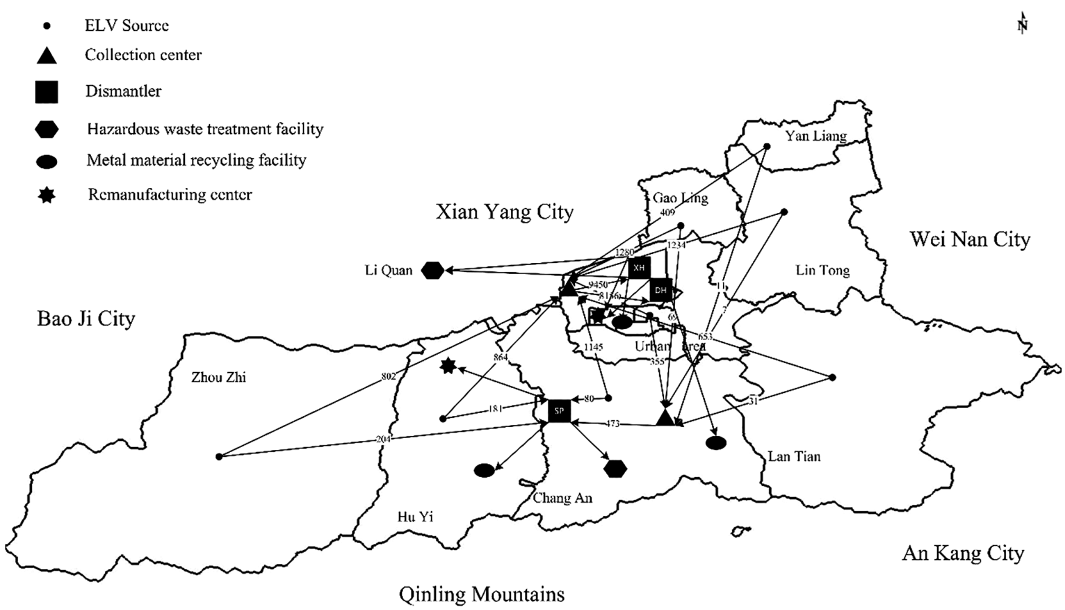

Fig. 3. Current location and allocation situation of ELVs in Xi'an.

Table 3
ELV current recycling scheme from customers to collection centers and dismantlers.

District	No. of ELVs in 2016	To Chang'an Collection Center	To Weiyang Collection Center	To SP Dismantling Company
Urban area	11,574	355	11,219	0
Gaoling	1349	69	1280	0
Lintong	1241	7	1234	0
Changan	1225	0	1145	80
Yanliang	420	11	409	0
Zhouzhi	1006	0	802	204
Lantian	684	31	653	0
Huyi	1045	0	864	181

Table 4
ELV current recycling scheme from collection centers to dismantlers.

Collection center	Dismantlers		
	Xinhui	Dinghe	Shaanxi Prov
The agency point in Chang'an District	0	0	473
Fengshou road in Weiyang District	9450	8156	0

corresponding to typical decision variables in different decision stages in the optimization of the reverse logistics network are given in Tables 11–17.

According to the above sensitivity analysis report, we can draw the following conclusions:

- The location of the dismantler and capacity level decision (capacity design) are key factors affecting the total cost and have a much greater impact than do the other decision variables.
- Among all the decision stages, the decision-making regarding the recycling amount transferred from the ELV sources to the dismantlers and the collection centers to the dismantlers are more important than are the other stages.

Table 6
Results based on Lingo software.

Solver Status	Model	State	Objective	Feasibility	Iterations
	MILP	Global Opt	5,194,513	0.63798e−012	1617

Table 7
Lingo solution statistics.

Solver Status	Variables	Integers	Constraints	Solver	Extended steps
	83	52	38	B-and-B	5

The relaxation variable (Slack or Surplus) in Lingo presents an ample degree of constraints. When the slack variable is negative, the solution is not feasible. Dual Prices represent the amount of change in the objective function value for each additional unit of constant value in the right of the inequality constraint. In particular, the "tightly constrained" duality price is not zero when the constraint corresponding to the optimal solution has already taken the equal sign. The key constraint dual price is shown in Table 18.

From the above table, the dual prices corresponding to collection centers, the dismantlers and hazardous waste treatment facilities are zero, and we can see that the supply of key facilities in Xi'an's ELV recycling network is much larger than the real demand and that a serious waste of resources exists to a certain extent. From the perspective of the shadow price, the processing capacity of the facilities is not in shortage, and it is not necessary to increase the supply capacity of the nodes until the demand for ELV recycling in this city is significantly improved.

Table 5
The current cost table of ELV recycling in Xi'an in 2016 (¥10,000).

Cost term	Location cost	Transport cost	Carbon emission cost	Dismantling cost	Waste treatment cost	Total
Money	372.2	31.082	0.298	304.634	114.078	822.292

Table 8
Cost Table 1 of Lingo solution (¥10,000).

Objective function	Dismantlers	Chosen or not	Capacity	Location cost	Delivery cost
To minimize the total cost	Xinhui	No	–	–	23.31
	Dinghe	Yes	High level	106.49	
	Shaanxi Prov	No	–	–	

Table 9
Cost Table 2 of Lingo solution (¥10,000).

Cost term	Carbon emission cost	Waste treatment cost	Dismantling cost	Total
Money	0.225	111.264	278.160	519.451

5.2. Economic and environmental equilibrium analysis

In this paper, the calculation of the total cost of the reverse logistics network includes four parts: location cost, transportation cost, carbon emission cost, dismantling cost and waste disposal cost. The location cost, transportation cost, dismantling cost and waste disposal cost of a reverse logistics network represent the economic cost. The environmental cost is a reflection of the environmental responsibility, such as the carbon emission cost. To discuss whether conflicts between the economic cost and environmental cost when optimizing the reverse logistics network of ELVs exist, we can compare the results of this paper to the relevant literature and perform an environmental equilibrium analysis.

The essence of an environment and economic equilibrium analysis in the reverse logistics network optimization problem is whether the economic cost savings must come at the expense of environmental costs, that is, whether there is a conflict between the two costs when solving the location-allocation optimization process and whether it can obtain balanced optimization results. Hui, Chao, and Jun (2013) constructed a dual objective function optimization model of a logistics network that minimized both the environmental cost and the economic cost. Their research indicated that there must be a conflict between the environmental cost and the carbon emission cost, that is, to reduce economic costs, carbon emissions will inevitably increase. Moreover, the Pareto optimal curve indicates that carbon emissions can be reduced to a greater extent by increasing the cost of logistics and that a significant reduction in economic costs will inevitably lead to a sharp increase in carbon emissions. The relationship between the two curves is shown in Fig. 6.

According to the results of the case study above, the reverse logistics network optimization can achieve a reduction in economic costs of 36.84%, while reducing the cost of carbon emissions by 24.50%, which is inconsistent with the previous conclusions. The specific results are shown in Table 19.

The numerical analysis of the results shows that the cost of carbon emissions is less than 0.04% of the total cost, which is much less than the economic cost, so the total cost depends largely on the economic cost. In this case, the decision variables corresponding to economic costs, such as the location cost, often have a larger Reduced Cost, and the carbon cost estimating method in this paper is consistent with transportation costs, which is not associated with location costs.

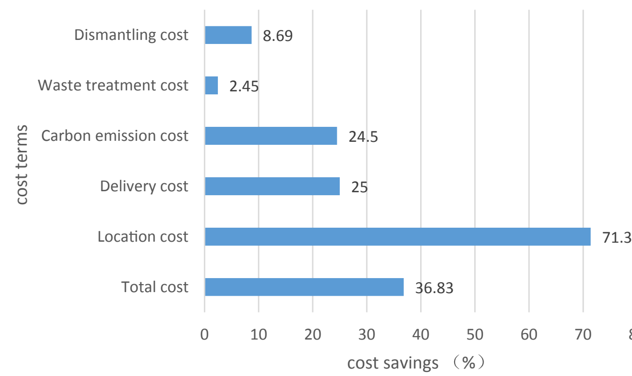

Fig. 4. The cost savings of the optimization results.

Therefore, the correlation between the cost of carbon emissions and the economic cost in the process of optimization is not certain. In other words, when the Reduced Cost of the decision variables corresponding to the economic costs, such as location costs and dismantling costs, is relatively larger than the Reduced Cost of the variables corresponding to the transport costs and carbon emissions costs, it is likely to lead to the economic costs and the environment cost having a negative correlation. In contrast, it will lead to a positive correlation between the two and then balanced optimization results can be obtained.

5.3. The validity test when demand is increasing

According to the actual situation of ELV recycling in Xi'an from 2013 to 2016, the annual compound growth rate of recycling reached 144.69%, and the ELV industry developed very rapidly. However, at the end of 2016, Xi'an's ELV recycling rate was only 0.716%, although there were 258.85 million motor vehicles in holding. In this condition, the recycling level is far lower than the level is supposed to be, so the current ELV recycling demand in Xi'an is very incomplete; the specific statistics data are shown in Fig. 7. Based on the historical data, we predict that the recycling rates of waste vehicles in Xi'an will experience rapid growth. Hence, it is necessary to test the validity of the model under different demand scenarios. According to the current recycling amount of 18,544 vehicles in Xi'an in 2016 with the maximum dismantling capacity of 54,000 vehicles, the demand will gradually increase with a gradient of 0.3 times to a maximum demand level that is limited by the maximum dismantling capacity, which is 2.9 times the current demand. Therefore, the validity and flexibility test of the model proposed in this paper when facing various demand scenarios in the long-term planning of the reverse logistics network of ELV recycling is shown as follows.

Fig. 8 shows the total cost comparison of the original and the optimized model. From the results, we can see that the model maintains a

Table 10
Cost comparison table (¥10,000).

	Total cost	Location cost	Delivery cost	Carbon emission cost	Dismantling cost	Waste treatment cost
Original scheme	822.292	372.2	31.082	0.298	304.634	114.078
Prioritization scheme	519.451	106.49	23.310	0.225	278.160	111.264
Savings (%)	36.83	71.39	25.00	24.50	8.69	2.45

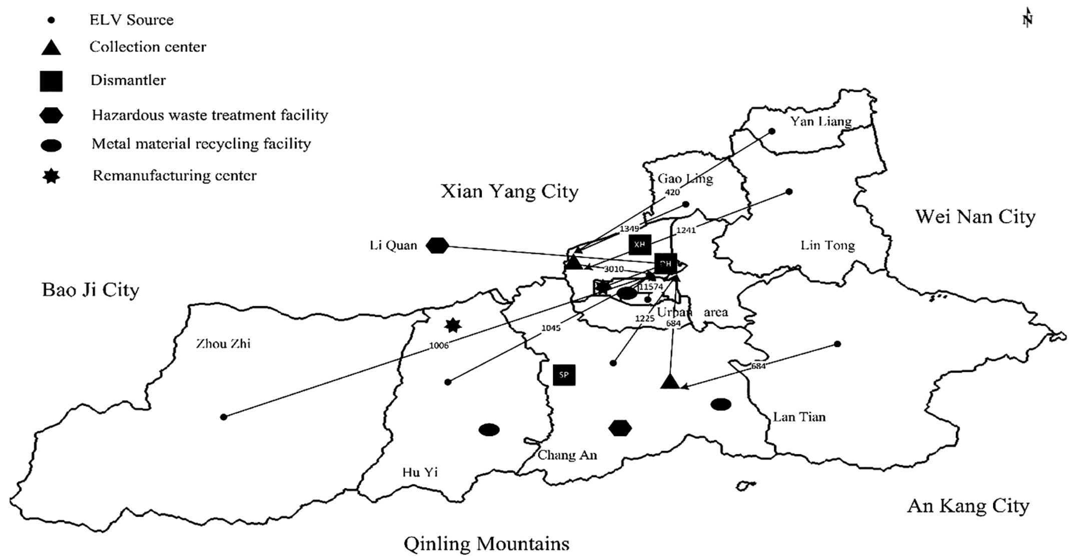

Fig. 5. Optimal solution to the location and allocation problem of ELV recycling in Xi'an.

Table 11
Decision variables sensitivity analysis report of ELV sources to collection centers.

Decision variables	$T_1(1,1)$	$T_1(1,2)$	$T_1(2,1)$	$T_1(2,2)$	$T_1(3,1)$	$T_1(3,2)$
Reduced Cost	7.183	5.352	21.597	22.113	17.230	19.249

Table 12
Decision variables sensitivity analysis report of ELV sources to dismantlers.

Decision variables	$T_2(2,3)$	$T_2(3,1)$	$T_2(3,2)$	$T_2(3,3)$	$T_2(4,1)$	$T_2(4,2)$
Reduced Cost	165.110	199.167	171.925	162.106	188.604	158.545

Table 13
Decision variables sensitivity analysis report of collection centers to dismantlers.

Decision variables	$T_3(1,1)$	$T_3(1,2)$	$T_3(1,3)$	$T_3(2,1)$	$T_3(2,2)$	$T_3(2,3)$
Reduced Cost	184.844	155.399	135.481	179.927	150.200	132.450

Table 14
Decision variables sensitivity analysis report of dismantlers to metal material recycling facilities.

Decision variables	$T_4(1,1)$	$T_4(1,2)$	$T_4(1,3)$	$T_4(2,1)$	$T_4(2,2)$	$T_4(2,3)$
Reduced Cost	1.690	4.689	0.000	1.272	4.780	0.000

Table 15
Decision variables sensitivity analysis report of dismantlers to hazardous waste treatment facilities.

Decision variables	$T_5(1,1)$	$T_5(1,2)$	$T_5(2,1)$	$T_5(2,2)$	$T_5(3,1)$	$T_5(3,2)$
Reduced Cost	0.019	1990.441	0.000	1990.846	4.872	1998.192

cost saving rate between 7.19% and 36.83% during the process of the total demand gradually approaching the maximum dismantling ability. It confirms that the model is effective under the various demand levels.

As we can see in Fig. 8, the optimized total cost interval gradually 'shut down' the cost savings rate reduction. According to the optimization results above, the cost of location accounts for more than 20% of the total cost, and the cost savings ratio increases to 71.39% when facing double the demand. However, as the demand gradually approaches the maximum dismantling capacity, the value of location decision variables shifts from 0 to 1, which means that more dismantlers are selected and that the capacity level is gradually increased. As a consequence, the cost savings rate decreases from 71.39% to 0%, which leads directly to the decline in the total cost savings rate and a "closed" optimized cost interval form. However, the cost savings rate remains positive when the demand is enlarged to the maximum dismantling capacity (approximately 2.9 times the original demand), indicating that the model can effectively optimize the total cost when the major demand levels are lower than the maximum dismantling capacity. To further prove the conclusion, under the assumption of increasing the dismantling capacity of the three dismantlers up to 1.5 times, the trend of the optimized cost interval will change from 'closed' to 'open', and the cost savings will be improved again. The last point with a star in the horizontal axis means when the demand is increased to 2.8 times the original demand and the capacity of dismantling is increased up to 1.5 times the original dismantling capacity, and the cost saving rate is increased as well as the optimized cost interval.

In addition, the optimization solution by Lingo reveals that the industrial park mode with the dismantler as the core facility can lower the total cost when the demand reaches the limited maximum dismantling capacity. Taking the demand increasing to 2.8 times the original demand as an example, the optimal location is to choose the Shaanxi Province Recycling Company as the core dismantler, which formed an industrial park mode. The details are shown in Fig. 9.

When the utilization ratio of the dismantler is at a high level, the dismantler in the Huyi District collects all of the ELV sources from its nearest districts, such as the Zhouzhi and Chang'an Districts. Then, the materials flow to metal material recycling facilities, remanufacturing centers and hazardous waste treatment facilities near or in Huyi District, which forms an ELV recycling and remanufacturing industry chain with the Shaanxi Province ELVs Recycling Co as the core point. The industrial park mode leads to a better cost savings result.

6. Discussion of results

When comparing the current recycling situation with the optimized results, we find that the existing rates of ELV recycling and dismantling are relatively low, partly due to the heavy recycling costs. The total cost is reduced by 36.83%, through the sharing of the dismantlers and

Table 16
Decision variables sensitivity analysis report of dismantlers to remanufacturing centers.

Decision variables	$T_6(1,1)$	$T_6(1,2)$	$T_6(2,1)$	$T_6(2,2)$	$T_6(3,1)$	$T_6(3,2)$
Reduced Cost	3.253	0.000	3.017	0.000	0.000	7.197

Table 17
Decision variables sensitivity analysis report of dismantlers' location decision.

Decision variables	E(1,1)	E(1,2)	E(2,1)	E(2,2)	E(3,1)	E(3,2)
Reduced Cost	536,700	1,073,400	532,500	1,064,900	791,900	1,583,700

removing of the two dismantlers. Moreover, the capacity utilization rate of the chosen dismantler named Dinghe is raised from 37.07% to 84.29%. Therefore, the economic and environmental costs are reduced, and the resource-recycling rate is guaranteed. Among all of the factors that affect total costs, the location and capacity level decision of the dismantler is the key factor, and its influence is much larger than that of the other decision variables. At the same time, the freight volume of the customer zone flowing to the dismantler and the collection center flowing to the dismantler have a greater impact on the objective function. From the perspective of the shadow price, the dual prices of the capacity constraints of the dismantler and the waste disposal point are both zero, which reflects the serious waste of the key facilities resources in the ELV recycling logistics network of Xi'an. The results of the economic and environmental equilibrium analysis challenge the existing research conclusions that there is a negative correlation between the environmental cost and the economic cost when optimizing the total cost of the logistics network (Elhedhli & Merrick, 2012; Shaw, Shankar, & Yadav, 2013). This paper shows that if the parameters meet certain conditions, the economic cost and environmental cost could achieve Pareto optimal.

Moreover, when the demand gradually approaches the maximum dismantling capacity, the model maintains the cost savings rate of 7.19 − 36.83%, which confirms the validity of the model for the ELV recycling network at varying demand levels. At the same time, by expanding the maximum dismantling capacity, it is proven that the cost savings rate is always greater than zero if the optimized solution is the feasible solution, and the cost gradient between the existing plan and the optimized plan can change from a tight shape to a loose shape.

We hope that the optimal solution of the proposed MILP model could assist logistics managers and the government in China and other developing countries in which the supervision of the recycling industry is not mature to cope with the following issues: How should ELVs be collected from customer? How should the reverse logistics network be planned? How are the total costs minimized? How should the environmental costs be measured? How can the relevant regulations be fulfilled and the 'black market' competition be reduce? In the future, our proposed model can also maintain validity when demand is increasing.

7. Conclusion

Although the rapid pace of development and sharply increasing production of vehicles cannot be ignored, the lack of capital and investments, severe 'black market' competition, and chaos in industrial regulations are also reasons for the low recycling rate of ELVs in China. Hence, a MILP model is developed in order to minimize the total costs (location, transportation and environment) arising from the improper management of ELVs. At the same time, the model is successful in taking both the location, quantity and capacity level of the key facilities into consideration at the same time, which increases the complexity of the reverse logistics network model and makes up the existing research

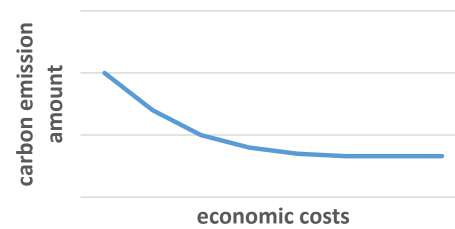

Fig. 6. Pareto optimal curve of economic cost and carbon emissions.

Table 19
Comparison between economic cost and environmental cost (¥10,000).

Term	Total	Economic cost	Carbon emission cost
Original scheme	822.292	821.994	0.298
Optimized scheme	519.451	519.226	0.225
Savings (%)	36.83	36.84	24.50

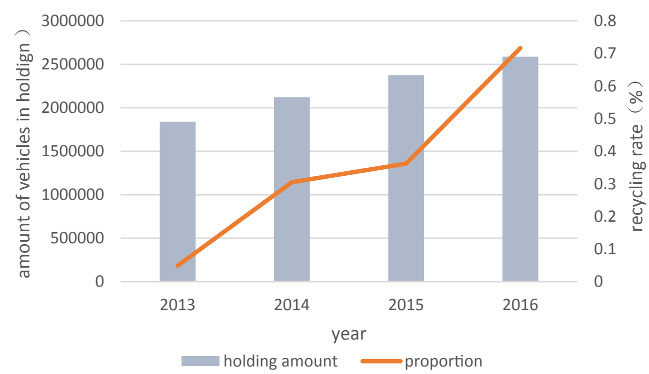

Fig. 7. Trends of motor vehicles in holding and the ELV recycling rate in Xi'an.

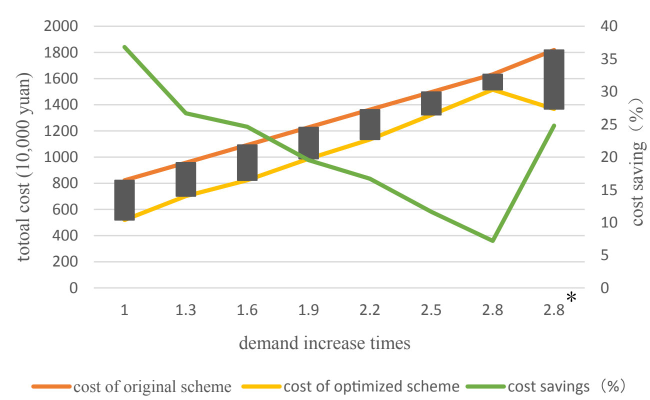

Fig. 8. Total cost of the recycling network in the context of increased demand.

Table 18
Sensitivity analysis report of dual price with constraints.

Constraints	Constraints of collection center processing capacity	Dismantling capacity limitation of dismantler	Waste disposal capacity limitation
Dual Prices	0	0	0

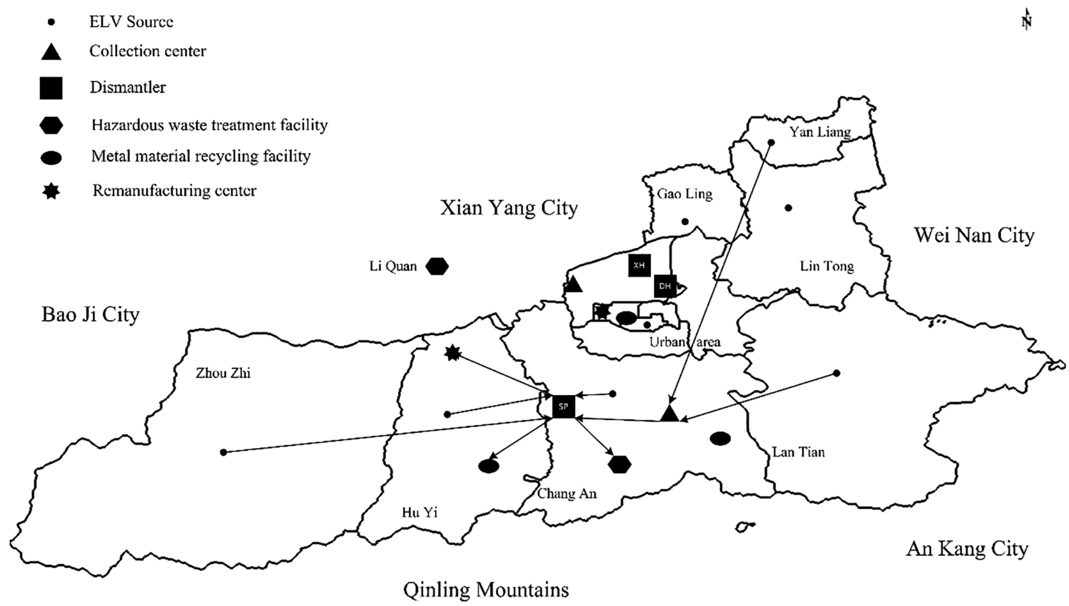

Fig. 9. Total cost optimization of the recycling network when demand increases.

gap. Moreover, the proposed MILP model is based on the real-life case of Xi'an, where some customer zones are directly transported to the dismantlers without the collection centers. Finally, we analyze the sensitivity of the optimization results and find that economic costs and environmental costs can be reduced simultaneously when the proportion of environmental costs is quite low. At the same time, we test the validity of the proposed model when demand is increasing.

The above findings provide vital managerial implications for the ELV reverse logistics system from two levels: macro environment and micro industry. For the macro environment, the government could reduce the economic burden of enterprises through tax incentive policies, which can enhance the vitality and efficiency of the industry. On the other hand, the government should improve the industrial barriers and force more ELVs into formal recycling channels through the improvement of ELV recycling standards and the strengthening of supervision. For the micro industry, the logistics managers should rationally arrange the quantity and capacity level of key facilities in the network, including the collection center and dismantler, based on actual demand, and reduce the waste of resources and environmental pollution caused by excess supply. When the capacity of the dismantler achieves a higher utilization rate, constructing an ELV recycling industrial park with the dismantler as the regional core could reduce the cost of the entire industry chain.

Further studies could develop stochastic or fuzzy MILP models that consider uncertain quantities of ELVs. In addition, a closed-loop supply chain network can be designed that consists of both forward and reverse logistics for ELV recycling simultaneously to analyze the impact of environment costs on different participants in the network.

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References

Achillas, C., Aidonis, D., Vlachokostas, C., Moussiopoulos, N., Banias, G., & Triantafillou, D. (2012). A multi-objective decision-making model to select waste electrical and electronic equipment transportation media. *Resources, Conservation and Recycling, 66*, 76–84.

Chaabane, A., Ramudhin, A., & Paquet, M. (2012). Design of sustainable supply chains under the emission trading scheme. *International Journal of Production Economics, 135*(1), 37–49.

Chang, X., Xia, H., Zhu, H., Fan, T., & Zhao, H. (2015). Production decisions in a hybrid manufacturing–remanufacturing system with carbon cap and trade mechanism. *International Journal of Production Economics, 162*, 160–173.

Chen, Y. W., Wang, L. C., Wang, A., & Chen, T. L. (2017). A particle swarm approach for optimizing a multi-stage closed loop supply chain for the solar cell industry. *Robotics and Computer-Integrated Manufacturing, 43*, 111–123.

Choudhary, A., Sarkar, S., Settur, S., & Tiwari, M. K. (2015). A carbon market sensitive optimization model for integrated forward–reverse logistics. *International Journal of Production Economics, 164*, 433–444.

Cui, L. B., Fan, Y., Zhu, L., & Bi, Q. H. (2014). How will the emissions trading scheme save cost for achieving china's 2020 carbon intensity reduction target? *Applied Energy, 136*(12), 1043–1052.

Demirel, E., Demirel, N., & Gökçen, H. (2016). A mixed integer linear programming model to optimize reverse logistics activities of end-of-life vehicles in Turkey. *Journal of Cleaner Production, 112*, 2101–2113.

Diabat, A., Abdallah, T., Al-Refaie, A., Svetinovic, D., & Govindan, K. (2013). Strategic closed-loop facility location problem with carbon market trading. *IEEE Transactions on engineering Management, 60*(2), 398–408.

Diabat, A., & Al-Salem, M. (2015). An integrated supply chain problem with environmental considerations. *International Journal of Production Economics, 164*, 330–338.

Elhedhli, S., & Merrick, R. (2012). Green supply chain network design to reduce carbon emissions. *Transportation Research Part D: Transport and Environment, 17*, 370–379.

Ene, S., & Öztürk, N. (2015). Network modeling for reverse flows of end-of-life vehicles. *Waste management, 38*, 284–296.

Fahimnia, B., Sarkis, J., Dehghanian, F., Banihashemi, N., & Rahman, S. (2013). The impact of carbon pricing on a closed-loop supply chain: An Australian case study. *Journal of Cleaner Production, 59*, 210–225.

Fareeduddin, M., Hassan, A., Syed, M. N., & Selim, S. Z. (2015). The impact of carbon policies on closed-loop supply chain network design. *Procedia CIRP, 26*, 335–340.

Fleischmann, M., Bloemhof-Ruwaard, J., Dekker, R., Van der Laan, E., van Nunen, J., & Van Wassenhove, L. (1997). Quantitative models for reverse logistics. *European Journal of Operational Research, 103*, 1–17.

Gao, Y., Feng, Y., Wang, Q., Zheng, H., & Tan, J. (2018). A multi-objective decision making approach for dealing with uncertainty in EOL product recovery. *Journal of Cleaner Production, 204*, 712–725.

Gomes, M. I., Barbosa-Povoa, A. P., & Novais, A. Q. (2011). Modelling a recovery network for WEEE: A case study in Portugal. *Waste management, 31*(7), 1645–1660.

Guo, J., Wang, X., Fan, S., & Gen, M. (2017). Forward and reverse logistics network and route planning under the environment of low-carbon emissions: A case study of Shanghai fresh food E-commerce enterprises. *Computers & Industrial Engineering, 106*, 351–360.

Hu, S., & Wen, Z. (2017). Monetary evaluation of end-of-life vehicle treatment from a social perspective for different scenarios in China. *Journal of Cleaner Production, 159*, 257–270.

Jabbarzadeh, A., Haughton, M., & Khosrojerdi, A. (2018). Closed-loop supply chain network design under disruption risks: A robust approach with real world application. *Computers & Industrial Engineering, 116*, 178–191.

Jerbia, R., Boujelben, M. K., Sehli, M. A., & Jemai, Z. (2018). A stochastic closed-loop supply chain network design problem with multiple recovery options. *Computers &*

Industrial Engineering, 118, 23–32.
Ji, J., Zhang, Z., & Yang, L. (2017). Comparisons of initial carbon allowance allocation rules in an O2O retail supply chain with the cap-and-trade regulation. *International Journal of Production Economics, 187*, 68–84.
John, S. T., & Sridharan, R. (2015). Modelling and analysis of network design for a reverse supply chain. *Journal of Manufacturing Technology Management, 26*(6), 853–867.
Kim, H., Yang, J., & Lee, K. D. (2009). Vehicle routing in reverse logistics for recycling end-of-life consumer electronic goods in South Korea. *Transportation Research Part D: Transport and Environment, 14*(5), 291–299.
Hui, L., Chao, Y., & Jun, Y. (2013). Trade-offs between cost and carbon emissions in logistics network design. *Industrial Engineering and Management, 18*, 61–73.
Mahmoudzadeh, M., Mansour, S., & Karimi, B. (2013). To develop a third-party reverse logistics network for end-of-life vehicles in Iran. *Resources, Conservation and Recycling, 78*, 1–14.
Ma, H., & Li, X. (2018). Closed-loop supply chain network design for hazardous products with uncertain demands and returns. *Applied Soft Computing, 68*, 889–899.
Merkisz-Guranowska, A. (2011). End-of-life vehicles recycling network design. *Journal of KONES, 18*, 261–268.
Nanaki, E. A., & Koroneos, C. J. (2016). Climate change mitigation and deployment of electric vehicles in urban areas. *Renewable Energy, 99*, 1153–1160.
Ma, H., Balthasar, F., Tait, N., Riera-Palou, X., & Harrison, A. (2012). A new comparison between the life cycle greenhouse gas emissions of battery electric vehicles and internal combustion vehicles. *Energy Policy, 44*(5), 160–173.
Özceylan, E., & Paksoy, T. (2013a). A mixed integer programming model for a closed-loop supply-chain network. *International Journal of Production Research, 51*(3), 718–734.
Özceylan, E., & Paksoy, T. (2013b). Fuzzy multi-objective linear programming approach for optimising a closed-loop supply chain network. *International Journal of Production Research, 51*(8), 2443–2461.
Özceylan, E., Demirel, N., Çetinkaya, C., & Demirel, E. (2017). A closed-loop supply chain network design for automotive industry in Turkey. *Computers & Industrial Engineering, 113*, 727–745.
Paulo, F., Pedro, N., & José, A. (2010). Strategies for meeting EU end-of-life vehicle reuse/recovery targets. *Journal of Industrial Ecology, 10*, 77–93.
Qi, Q., Wang, J., & Bai, Q. (2017). Pricing decision of a two-echelon supply chain with one supplier and two retailers under a carbon cap regulation. *Journal of Cleaner Production, 151*, 286–302.
Rahmani, D., & Mahoodian, V. (2017). Strategic and operational supply chain network design to reduce carbon emission considering reliability and robustness. *Journal of Cleaner Production, 149*, 607–620.
Ramezani, M., Bashiri, M., & Tavakkoli-Moghaddam, R. (2013). A new multi-objective stochastic model for a forward/reverse logistic network design with responsiveness and quality level. *Applied Mathematical Modelling, 37*(1–2), 328–344.
Ren, J., Bian, Y., Xu, X., & He, P. (2015). Allocation of product-related carbon emission abatement target in a make-to-order supply chain. *Computers & Industrial Engineering, 80*, 181–194.
Roghanian, E., & Pazhoheshfar, P. (2014). An optimization model for reverse logistics network under stochastic environment by using genetic algorithm. *Journal of Manufacturing Systems, 33*(3), 348–356.
Sasikumar, P., & Haq, A. N. (2011). Integration of closed loop distribution supply chain network and 3PRLP selection for the case of battery recycling. *International Journal of Production Research, 49*(11), 3363–3385.
Sasikumar, P., Kannan, G., & Haq, A. N. (2010). A multi-echelon reverse logistics network design for product recovery—A case of truck tire remanufacturing. *The International Journal of Advanced Manufacturing Technology, 49*(9–12), 1223–1234.
Schultmann, F., Zumkeller, M., & Rentz, O. (2006). Modeling reverse logistic tasks within closed-loop supply chains: An example from the automotive industry. *European Journal of Operational Research, 171*(3), 1033–1050.
Shankar, R., Bhattacharyya, S., & Choudhary, A. (2018). A decision model for a strategic closed-loop supply chain to reclaim End-of-Life Vehicles. *International Journal of Production Economics, 195*, 273–286.
Shaw, K., Shankar, R., & Yadav, S. S. (2013). Modeling a low-carbon garment supply chain. *Production Planning & Control, 24*, 851–865.
Simic, V. (2016). Interval-parameter chance-constraint programming model for end-of-life vehicles management under rigorous environmental regulations. *Waste Management, 52*, 180–192.
Soleimani, H., Govindan, K., Saghafi, H., & Jafari, H. (2017). Fuzzy multi-objective sustainable and green closed-loop supply chain network design. *Computers & Industrial Engineering, 109*, 191–203.
Sutherland, J. W., Jenkins, T. L., & Haapala, K. R. (2010). Development of a cost model and its application in determining optimal size of a diesel engine remanufacturing facility. *CIRP Annals, 59*(1), 49–52.
Suyabatmaz, A.Ç., Altekin, F. T., & Şahin, G. (2014). Hybrid simulation-analytical modeling approaches for the reverse logistics network design of a third-party logistics provider. *Computers & Industrial Engineering, 70*, 74–89.
Tian, J., & Chen, M. (2016). Assessing the economics of processing end-of-life vehicles through manual dismantling. *Waste Management, 56*, 384–395.
Toyasaki, F., Daniele, P., & Wakolbinger, T. (2014). A variational inequality formulation of equilibrium models for end-of-life products with nonlinear constraints. *European Journal of Operational Research, 236*(1), 340–350.
Wang, L., & Chen, M. (2013). Policies and perspective on end-of-life vehicles in China. *Journal of Cleaner Production, 44*, 168–176.
Wang, H. F., & Hsu, H. W. (2010). A closed-loop logistic model with a spanning-tree based genetic algorithm. *Computers & Operations Research, 37*(2), 376–389.
Wang, F., Lai, X., & Shi, N. (2011). A multi-objective optimization for green supply chain network design. *Decision Support Systems, 51*(2), 262–269.
Yang, J., Guo, J., & Ma, S. (2012). Low-carbon city logistics distribution network design with resource deployment. *Journal of Cleaner Production, 119*, 223–228.
Yu, H., & Solvang, W. D. (2017). A carbon-constrained stochastic optimization model with augmented multi-criteria scenario-based risk-averse solution for reverse logistics network design under uncertainty. *Journal of Cleaner Production, 164*, 1248–1267.
Zarei, M., Mansour, S., Husseinzadeh Kashan, A., & Karimi, B. (2010). Designing a reverse logistics network for end-of-life vehicles recovery. *Mathematical Problems in Engineering*.
Zhang, J. H., Yang, B., & Chen, M. (2017). Challenges of the development for automotive parts remanufacturing in china. *Journal of Cleaner Production, 140*, 1087–1094.
Zhang, B., & Xu, L. (2013). Multi-item production planning with carbon cap and trade mechanism. *International Journal of Production Economics, 144*(1), 118–127.