A Novel Stochastic Optimization Model for Reverse Logistics Network Design of End-of-Life Vehicles: A Case Study of Istanbul

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Abstract
Waste management is gaining crucial importance as recycling aims at transforming produced waste into value for the economy. As the automotive industry is growing fast worldwide, recycling end-of-life vehicles (ELVs) attracts great research attention. Due to the promulgated regulations, multiple players like the last owners, manufacturers, treatment centres, and municipalities require a more cooperative engagement. The participation of multiple actors in the recycling process of ELVs brings various uncertainties. Additionally, parameters of the recycling process, like the number of vehicles withdrawn per year, cost items, and material composition tend to change due to technological, social, and economic developments. The automotive industry has crucial importance in the Turkish economy, which is highly affected by socio-political and economic issues. Furthermore, the Istanbul metropolitan area has the highest rate of vehicle ownership in Turkey. For that purpose, this paper proposes a scenario-based real-life stochastic optimization model to improve ELV supply chain network management in Istanbul. Sensitivity analyses to changes in scenario occurrence probabilities and changes in the amount of collected ELVs are performed to question the consistency of the study. The results of the mathematical model highlight that the operational cost items have the greatest ratio comparing the other cost items in the model. Furthermore, the results of the sensitivity analysis underline that the operational costs and selling prices of the materials from the ELVs have a significant impact on the profitability of ELVs’ recycling process. In addition, uncertainty in the number of ELVs has a significant effect on both operational and strategical decision-making processes. This research can be extended in the direction of examining the effectiveness of ELV management in Turkey since Istanbul could represent the whole of Turkey with its economic and cultural characteristics. Further works can also try to implement the novel concept of a “socially resilient supply chain” in the ELVs’ management.

Keywords End-of-life vehicle · Decision-making · Stochastic programming · Scenario-based optimization · Uncertainty

1 Introduction

As a result of rapidly growing industrialization, environmental pollution is becoming a more crucial issue to cope with. Approximately 91.8 million vehicles (passenger cars, light commercial vehicles, heavy trucks, buses, and coaches) were produced in 2019 [1]. The produced output is roughly equivalent to a global turnover of €2.6 trillion. It would be the eighth-largest economy in the world if motor vehicle production is a country.

The waste management of special products like end-of-life vehicles (ELVs) is a critical ecological problem that the world faces regarding its swiftly increasing amount and composition of hazardous materials [2]. The recycling of ELVs is not only important for economic output but also environmental benefits. It is an important part
of the circular economy. Besides, the vehicles which are not withdrawn from exploitation at their retirement age will yield both environmental pollution and traffic accidents [3]. This obligated authorities to take serious steps and provide action plans [4]. The European Union (EU) introduced the Directive 2000/53/EC in an attempt to reduce the amount of waste by prescribing stringent eco-efficiency targets for the reuse, recycling, and recovery of vehicles.

The recycling of ELVs was put into focus in Turkey. The country is in the process of EU membership and full implementation of the ELV Directive is of critical importance. Besides, Turkey is among the world’s biggest producers of motor vehicles (Fig. 1). The average age of passenger cars registered to traffic was 12.9 in 2019 [5]. Furthermore, vehicles at the retirement age are becoming a bigger threat as the number of vehicles on the road is rising. Istanbul has by far the highest number of motor vehicles in Turkey [6]. As it is a metropolitan city, Istanbul has a very high rate of domestic migration rate due to social and economic factors. Its rapid population increase correlates with the increasing number of motor vehicles. Apart from these, the huge number of vehicles, geographical location, availability of a high-skilled labour force, and financial opportunities are making Istanbul an advantaged city for the recycling business. As a result, there is a strong motivation to develop an advanced mathematical optimization model and improve ELV supply chain network management in this mega-city.

On the other hand, a reverse logistics network design is complicated by the uncertainty of return products in terms of quantity, quality, and supply timing, integrating and coordinating different forward and reverse flows. A high level of uncertainty is one of the characteristics of reverse logistics networks [8]. Uncertainties with the data in decision-making play a crucial role in designing ELV supply chain networks [9]. Figure 2 shows the number of vehicles withdrawn from traffic in Istanbul and Turkey in the period 2005–2018 [10]. Besides, Fig. 2 reveals the proportion of the number of withdrawn vehicles from traffic in Istanbul to the total withdrawn amount in Turkey. Based on Fig. 2, it is identified that the number of withdrawn vehicles is not consistent within the analyzed period. The following can be additionally outlined: (1) The number of withdrawn vehicles in Istanbul and Turkey has highly uncertain characteristics, and (2) According to the rates of withdrawn vehicles, Istanbul has a crucial role in Turkey for the recycling of ELVs.

As the main motivation factors are mentioned above, this study aims to develop an optimization model for an open-loop reverse logistic network for ELVs in Istanbul and fully implement the ELV Directive. The presented stochastic mixed-integer linear programming mathematical model determines the optimum number and locations of network entities and allocates the optimum material flows between them under an uncertain environment.

The remainder of this study is organized as follows: Sect. 2 presents a review of related research is presented. Section 3 provides the problem statement and methodology. This section also gives a formulation, assumptions, and description of a real-life case study of Istanbul. Section 4 gives the case study results and discussions. Lastly, Sect. 5 presents the conclusions of the work and indicates possible extensions for future research.
The recycling of ELVs attracted significant interest from researchers in recent years. Numerous papers dealing with the ELV management problem are presented in the literature [11]. The papers which are dealing with location-allocation problems are relevant for this work. First, an extensive content analysis overview of the relevant papers is provided in the following sub-section. Afterward, the papers are further summarized in Table 1 to additionally highlight the contribution of this study.

A facility location problems of ELVs in the German automobile industry were focused on in 2005 [12]. A closed-loop supply chain (CLSC) model for ELVs was analyzed in 2006 [13]. In 2008, a facility location model with a multi-period reverse logistics optimization approach was presented [14]. Similarly, an uncapacitated collection network model for ELVs in Mexico was developed in 2009 [15].

In 2011, the ELV collection centres’ location problem via mixed-integer linear programming (MILP) approach was dealt with [16]. In the same year, a sustainable network for ELVs with a mixed-integer lexicographic goal approach was designed [17]. In 2013, a MILP modeling approach was used for determining the optimal topology and material flows in the future ELV recycling network [18]. Another study in 2013 proposed a simulation approach to determine optimum locations for ELV dismantlers [19]. Furthermore, bi-objective MILP models were employed to reorganize and construct the ELV recycling network in Poland in [20]. Another location-allocation problem was solved in 2013, which focuses on scrap yards of ELVs in Iran via the MILP approach [21].

In 2015, as an uncertainty approach, a two-stage interval-stochastic programming model for sustainable management of ELV allocation under uncertainty was developed [22]. A fuzzy risk explicit MINP model was formulated for ELV recycling planning in the EU by the same author in [23]. A multi-period, multi-stage network design model for ELVs was presented in [24]. A multi-stage interval-stochastic model for ELV allocation was presented in [2]. In 2016, an interval-parameter two-stage stochastic full-infinite programming model for ELV allocation management under uncertainties was proposed in [25]. Furthermore, an interval-parameter chance-constraint programming model for uncertainty-based decision-making in the vehicle recycling industry was presented in [26]. A MILP model was presented for reverse logistics network design of ELV recycling management with including different actors taking part in [27]. In 2017, a multi-echelon, multi-product reverse logistics network was designed by formulating a fuzzy MILP model in [28]. A case study was presented that deals with CLSC management for ELV treatment in [29].

In 2018, a MILP based facility location-allocation model was proposed for ELVs [30]. In the same year, a
| Year | Optimization model | Single-multi objectivity | Type of objective function(s) | Type of parameter(s) | Type of supply chain | Solution approach |
|------|-------------------|-------------------------|-------------------------------|----------------------|----------------------|-------------------|
|      | LP | NLP | MILP | MINP | Single | Multi | Max | Min | Det | Prob | Fuzzy | OL | CL | E | H | MH |
| 2005 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2006 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2008 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2009 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2011 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2013 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2015 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2016 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2017 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2018 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2020 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2022 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2023 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2024 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2025 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2026 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2027 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2028 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2029 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
Table 1 (continued)

| Year | Optimization model | Single-multi objectivity | Type of objective function(s) | Type of parameter(s) | Type of supply chain | Solution approach |
|------|--------------------|--------------------------|-------------------------------|-----------------------|----------------------|-------------------|
|      | LP | NLP | MILP | MINP | Single | Multi | Max | Min | Det | Prob | Fuzzy | OL | CL | E | H | MH |
| 2018 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2018 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2018 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2020 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Our study | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

*LP* linear programming, *NLP* non-linear programming, *MILP* mixed-integer linear programming, *MINP* mixed-integer non-linear programming, *OL* open-loop, *CL* closed-loop, *E* exact, *H* heuristics, *MH* meta-heuristics.
A MILP model was developed with a multi-echelon inventory, multi-period planning, and multi-product scenario [31]. A mixed-integer bi-level linear programming model to locate distribution centres for collecting ELV parts was developed in [32]. In 2019, a problem of designing the ELV reverse logistics network was presented and solved via a fuzzy mixed-integer linear programming approach in [4]. A MILP model for building up a four-tier reverse logistics network model was presented in [33]. An interval-parameter Conditional value-at-risk two-stage stochastic program for management of ELVs and reducing system risk was formulated in [34]. In 2020, the impact of take-back prices and subsidies was investigated by establishing a mixed-integer nonlinear optimization model for centralized ELV recycling [35]. More recently, in 2021, a sustainable-resilient multi-product and multi-period reverse logistics network (RLN) for ELVs in Iran was provided [36]. A system dynamic analysis of formal and informal dismantling markets in the Indian context is provided in [37]. A multi-objective fuzzy mathematical model to solve the RLN design problem was formulated in [38]. A risk-based robust MILP model for decentralized CLSC networks was introduced in [39]. A single-period deterministic MILP model for the reverse logistics routing of collected ELVs was provided in [40]. Finally, a three-objective CLSC network model was developed in [41] to account for multi-facilities, multi-periods, and an automotive industry single-product scenario.

3 Material and Methods

3.1 Problem Statement

The EU introduced Directive 2000/53/EC in 2000 to create a sustainable ELV management system. This directive limited the usage of hazardous substances in vehicles and set specific eco-efficiency targets for the reuse, recycling, and recovery of ELVs. Turkey is in the harmonization process with the EU as it aims to become its member. Therefore, the Ministry of Environment and Urbanization has adopted the ELV Directive in 2009 [42].

The reverse logistic network for ELVs in Turkey is presented in Fig. 3. It has two main activities: transportation and processing of ELVs. The recycling of ELVs starts with its transportation to collection centres or dismantler facilities. According to the ELV Directive, vehicle owners are responsible for transporting their ELVs, while collection centres are responsible for transferring them to dismantler facilities within sixty days [42]. In dismantler facilities removal of fuel, oil, toxic and noxious fluids, and other fluids (e.g., coolant fluid) are completed before starting dismantling operations. Afterwards, valuable parts from vehicles are disassembled and sold to second-hand markets. Furthermore, some components are sent to recycling facilities in this stage; e.g., removed non-reusable batteries, fluids, and tires are forwarded to battery recycling facilities, fluid recycling facilities, and tire recycling facilities, respectively. Shredder
facilities are responsible for hulks shredding, separation of the various metallic fractions, and partial recycling of generated automobile shredder residue (ASR). Ferrous and non-ferrous metals are transferred to recycling facilities. ASR is a combination of different materials; i.e., glass, plastic, foam rubber, textile, etc. It is mainly landfilled due to its heterogeneous and complex matrix. In the recycling facilities, incoming components are separated into recyclable and hazardous materials categories. The recycled materials are sold to other suppliers and hazardous materials are sent to landfills.

3.2 Modeling Formulation

The following assumptions have been made to consider full implementation of the ELV Directive of Turkey:

1. Last owners are responsible for returning their vehicles to collection centres;
2. Producers are responsible for taking back ELVs from the last owners without any charge;
3. Centers of 39 districts of Istanbul are accepted as ELV sources;
4. Distances between the facilities are determined via Google Maps as the longest driving distance from each other due to restrictions with the heavyweight highway transportation in Istanbul;
5. The candidate locations of shredder and dismantler facilities are determined from the existing facilities.

As it is highlighted in Fig. 2, the number of withdrawn vehicles in Istanbul and Turkey has highly uncertain characteristics. Moreover, Istanbul has a crucial role in Turkey for the recycling of ELVs. On the other hand, fluctuations in the local currency in Turkey has a significant impact on prices in the automotive industry which has a significant potential impact on the number of withdrawn vehicles in Istanbul. For the reasons mentioned above, a scenario-based stochastic optimization model is presented in this study to deal with the potential uncertainties.

Indices, Parameters and Decision Variables are presented in the Appendices section.

The proposed model is formulated as follows:

\[
\text{Min } FC + TC + OC - RV
\]  

The objective function (1) has four sub-components, which are fixed cost (FC), transportation cost (TC), operating cost (OC), and total revenue (RV).

\[
FC = \sum_{k=1}^{K} f_k e_k + \sum_{l=1}^{L} f_l e_l
\]  

Fig. 4 Locations of the available ELV recycling network entities in Istanbul
Table 2 Cost parameters

| Fixed cost | Transportation cost (₺/km-ton) | Operation cost (₺/ton) |
|------------|-------------------------------|------------------------|
| \( f_d(t) \) | 2,500,000                      | \( t_{ij} \) 1.0       | \( d_{c_{kl}} \) 980  |
| \( f_s(t) \) | 887,500                       | \( t_{klt} \) 1.0      | \( s_{kl} \) 135     |
| \( t_{kt} \) | 0.4                           | \( l_{c_{st}} \) 250   |                      |
| \( t_{klt} \) | 0.2                           | \( r_{c_{st}} \) 450   |                      |
| \( t_{kst} \) | 0.5                           |                        |                      |
| \( t_{lat} \) | 0.5                           |                        |                      |

\( FC \) represents fixed costs to set up new dismantler and shredder facilities (2).

\[
TC = \sum_{a=1}^{\Omega} p_a \left( \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} t_{ij} \cdot A_{ij} \cdot d_{ij} + \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{t=1}^{T} t_{kt} \cdot B_{kt} \cdot d_{kt} + \sum_{k=1}^{K} \sum_{l=1}^{L} \sum_{t=1}^{T} t_{klt} \cdot Y_{klt} \cdot d_{klt} + \sum_{k=1}^{K} \sum_{l=1}^{L} \sum_{t=1}^{T} t_{kst} \cdot Z_{kst} \cdot d_{kst} \right) \quad (3)
\]

\( TC \) represents the cost of transportation in the whole network (3).

\[
OC = \sum_{a=1}^{\Omega} p_a \left( \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} B_{klt} \cdot d_{c_{kl}} + \sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{t=1}^{T} X_{jk} \cdot d_{c_{jk}} + \sum_{k=1}^{K} \sum_{l=1}^{L} \sum_{t=1}^{T} Y_{klt} \cdot d_{c_{klt}} + \sum_{l=1}^{L} \sum_{k=1}^{K} \sum_{t=1}^{T} Z_{kst} \cdot d_{c_{kst}} \right) \quad (4)
\]

\( OC \) represents the cost of dismantling, shredding, recycling, and disposal operations in the network (4).

\[
RV = \sum_{a=1}^{\Omega} p_a \left( \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{t=1}^{T} (s_{1t} \cdot Q_{1km}^{a} + s_{2t} \cdot Q_{2km}^{a} + s_{3t} \cdot Q_{3km}^{a} + s_{4t} \cdot Q_{4km}^{a} + s_{5t} \cdot Q_{5km}^{a} + \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{t=1}^{T} (z_{1t} \cdot P_{1mni}^{a} + z_{2t} \cdot P_{2mni}^{a}) \right) \quad (5)
\]

Apart from the cost components, \( RV \) represents total revenue that comes from selling reusable/remanufacturable items and ferrous and non-ferrous metals to second-hand markets and recycling facilities (5).

subject to:

\[
\sum_{j=1}^{J} A_{ij}^{a} + \sum_{k=1}^{K} B_{kjt}^{a} = R_{ij}^{a} \forall a, i, t \quad (6)
\]

Constraints (6)–(19) represent the balance equations in the network. Constraints (6) represent the amount of ELVs transferred from sources to collection centres and dismantler facilities.

\[
\sum_{i=1}^{I} A_{ij}^{a} = \sum_{k=1}^{K} X_{kjt}^{a} \forall a, j, t \quad (7)
\]

Constraints (7)–(16) secure the amount of transported ELVs from dismantler facilities to shredder facilities, second-hand markets, and recycling facilities.

\[
\sum_{i=1}^{I} Y_{klt}^{a} = \alpha \left( \sum_{j=1}^{J} X_{jk}^{a} + \sum_{i=1}^{I} B_{kjt}^{a} \right) \forall a, k, t \quad (8)
\]

Table 3 Prices of reusable/ recycled components/materials (₺/year)

|          | \( s_{1t} \) | \( s_{2t} \) | \( s_{3t} \) | \( s_{4t} \) | \( s_{5t} \) | \( z_{1t} \) | \( z_{2t} \) |
|----------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
|          | 1,200        | 6,000        | 6,250        | 3,100        | 6,000        | 250          | 750          |

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Composition rates of ELVs

\[
\sum_{m=1}^{M} Q_{km}^{\omega} = \mu_5 \left( \sum_{j=1}^{J} \delta_{jkt}^{\omega} + \sum_{l=1}^{L} B_{lkt}^{\omega} \right) \forall \omega, k, t
\]

(13) \[
\sum_{k=1}^{K} \gamma_{ikt}^{\omega} \leq cap_{ikt} \forall \omega, l, t
\]

(22)

\[
P \sum_{p=1}^{P} V_{kpt}^{\omega} = \lambda_1 \left( \sum_{j=1}^{J} \delta_{jkt}^{\omega} + \sum_{l=1}^{L} B_{lkt}^{\omega} \right) \forall \omega, k, t
\]

(14) \[
\sum_{k=1}^{K} \gamma_{ikt}^{\omega} \leq cap_{ikt} \forall \omega, p, t
\]

(23)

\[
R \sum_{r=1}^{R} W_{krt}^{\omega} = \lambda_2 \left( \sum_{j=1}^{J} \delta_{jkt}^{\omega} + \sum_{l=1}^{L} B_{lkt}^{\omega} \right) \forall \omega, k, t
\]

(15) \[
\sum_{k=1}^{K} W_{krt}^{\omega} \leq cap_{r} \forall \omega, r, t
\]

(24)

\[
S \sum_{s=1}^{S} U_{kst}^{\omega} = \lambda_3 \left( \sum_{j=1}^{J} \delta_{jkt}^{\omega} + \sum_{l=1}^{L} B_{lkt}^{\omega} \right) \forall \omega, k, t
\]

(16) \[
\sum_{k=1}^{K} U_{kst}^{\omega} \leq cap_{s} \forall \omega, s, t
\]

(25)

\[
U \sum_{u=1}^{U} Z_{lut}^{\omega} = \beta \sum_{k=1}^{K} \delta_{klt}^{\omega} \forall \omega, l, t
\]

(17) \[
\sum_{k=1}^{K} Z_{lut}^{\omega} \leq cap_{lt} \forall \omega, u, t
\]

(26)

Constraints (17)–(19) provide the balance of material amounts transported from shredder facilities to landfilling and recycling facilities.

\[
N \sum_{n=1}^{N} P_{1nt}^{\omega} = \gamma_1 \sum_{k=1}^{K} Y_{ikt}^{\omega} \forall \omega, l, t
\]

(18)

\[
N \sum_{n=1}^{N} P_{2nt}^{\omega} = \gamma_2 \sum_{k=1}^{K} Y_{ikt}^{\omega} \forall \omega, l, t
\]

(19) \[
\sum_{r=1}^{R} e_{lt} \leq M_1 e_{r} \forall k
\]

(29)

\[
\sum_{l=1}^{L} A_{ijt}^{\omega} \leq cap_{jt} \forall \omega, j, t
\]

(20) \[
\sum_{l=1}^{L} e_{lt} \leq M_1 e_{r} \forall k
\]

(30)

Constraints (20)–(26) secure that amount of ELV transported must be less than or equal to the capacity of collection centres, dismantler facilities, shredder facilities, and recycling facilities in the network.

\[
\sum_{i=1}^{I} B_{ikt}^{\omega} + \sum_{j=1}^{J} \delta_{jkt}^{\omega} \leq cap_{kt} e_{kt} \forall \omega, k, t
\]

(21)

Constraints (29) and (30) ensure the harmony of binary variables.

\[
p_{\omega} A_{ikt}^{\omega} B_{ikt}^{\omega} \delta_{jkt}^{\omega} \sum_{k=1}^{K} \gamma_{ikt}^{\omega} \forall \omega, l, t
\]

(31)

Constraints (31) secure the non-negativity of the decision variables.
3.3 Case Study Description and Data Collection

Istanbul is one of the most crucial cities in Turkey due to its great geographical location, flourishing economy, and very skilled labour force. It is the most populous city with 15,067,724 inhabitants [10]. This mega-city consists of 39 districts. In this study, centres of the districts are assumed as ELV sources. There are 52 collection centres, five dismantler facilities, and four shredder facilities that are active and working with the relevant license. Besides, three recycling centres and 29 s-hand markets are located within the different parts of Istanbul [4]. The exact locations of all network entities licensed for the ELV management are provided in Fig. 4.

Data was collected through field studies, interviews with experts from both academy and industry, technical reports, and literature surveys. It is assumed that the opening cost of the dismantler facility is 887,500 ₺ [4, 43] and the opening cost of the shredder facility is 2,500,000 ₺ [24, 27, 44].

It is assumed that collection costs in collection and dismantler centres are 200 ₺ and 100 ₺, respectively [4]. The average weight of an ELV is 1000 kg [29]. The operating costs of each dismantler facility, shredder facility, recycling facility, and landfilling centre are assumed as 980 ₺/ton, 135 ₺/ton, 500 ₺/ton, and 250 ₺/ton, respectively [4, 29, 45]. All cost and price parameters of the model are presented in Tables 2 and 3.

Decomposition components of ELVs are assumed as: ferrous metals (69%), non-ferrous metals (7%), plastics and process polymers (13.5%), tires (4%), glass (3%), textiles (1.3%), fluids (1.2%), and rubber (1%) [46]. The ratio of hulk to ELV after disassembling operations is 81% and the ratio of ASR to hulk is assumed as 18.5%. In this study, material composition rate assumptions are used from the publications in the literature [4, 27]. Table 4 presents the composition rates of ELVs.

Capacities of collection centres, dismantler facilities, shredder facilities, and landfilling centres are considered as 1000 tons/year, 17,600 tons/year, 22,500 tons/year, and 25,000 tons/year, respectively. Capacity assumptions for fluid and tire recycling facilities are 7300 tons/year and battery recycling facilities are 25,000 tons/year [29]. Table 5 presents capacity assumptions for the facilities in the network.

In this model, the estimated amount of ELVs from 2019 to 2028 is generated by a GDP-dependent Gompertz function as the first step [47]. Although the GDP-dependent Gompertz function is a well-known forecasting approach for predicting the amount of ELVs generated in the future, three other forecasting approaches are applied individually and their validities are questioned by calculating their $R^2$, MAPE (Mean Absolute Percentage Error), and MAD (Mean Absolute Deviation) values. These approaches are Moving Average ($m = 3$), Single Exponential Smoothing, Regression Analysis (parameters of GDP, number of accidents in a year, the population of the city for a year, number of registered vehicles in the traffic are used as continuous predictors). These approaches are applied via Minitab 19 Statistical Software. Table 6 presents that the Moving Average has the highest accuracy scores. For this reason, Moving Average is selected for forecasting the number of ELVs generated in Istanbul for the next ten years.

Table 7 presents the estimated amount of ELVs generated in Istanbul from 2019 to 2028.

4 Results and Discussions

4.1 Computational Results

The scenario-based stochastic optimization model presented above resulted in a problem with 62 blocks of equations, 56 blocks of variables, 1,594,863 non-zero elements, 33,673 single equations, 249,632 single variables, and 99 discrete variables. The model is solved in GAMS 23.5 software and CPLEX is used as the solver. The developed model is solved to optimality on an Intel Core i7 processor within 8.003 CPU seconds.
The formulated model was solved to optimality under seven scenarios (ω = A, B, C, D, E, F, G). The occurrence probability for each scenario (pω) was 0.143. Under this assumption, the objective function attains the value of 185,087,909₺. Figure 5 presents the cost items and revenue in the objective function.

The operational cost has by far the highest proportion as 96.1% of the cost items. The decomposition of this component is depicted in Fig. 6. Its integral parts are dismantling (85%), shredding (9.5%), landfilling (3.2%), and recycling (2.3%) costs.

Figure 7 presents the decomposition of the revenue component. It comprises of profits come from sales of dismantlers to second-hand markets (74%) and sales of shredder facilities to recycling facilities (26%). Dismantler facilities contribute almost three times more than shredder facilities.

According to the obtained results, three out of five dismantler facilities and three out of four shredder facilities must be opened in the period 2019-2028. The total amount of ELVs that must be collected by 34 collection centres are 180,032 tons for ω = A, 229,132 tons for ω = B, 274,942 tons for ω = C, 321,755 tons for ω = D, 356,672 tons for ω = E, 376,904 tons for ω = F, and 406,073 tons for ω = G, respectively (Supplementary Table S1). The rest of ELVs (27,416 tons for ω = A, 34,893 tons for ω = B, 45,660 tons for ω = C, 63,859 tons for ω = D, 77,085 tons for ω = E, 113,431 tons for ω = F, and 140,838 tons for ω = G) needs to be directly transported to the dismantler facilities (Supplementary Table S2). The total amount of ELVs that must be transferred from collection centres to dismantler facilities is 180,032 tons for ω = A, 229,132 tons for ω = B, 274,942 tons for ω = C, 321,755 tons for ω = D, 356,672 tons for ω = E, 376,904 tons for ω = F, and 406,073 tons for ω = G. The rest of ELVs (27,416 tons for ω = A, 34,893 tons for ω = B, 45,660 tons for ω = C, 63,859 tons for ω = D, 77,085 tons for ω = E, 113,431 tons for ω = F, and 140,838 tons for ω = G) must be transported from the last owners to the dismantler facilities (ADCs) directly (Supplementary Table S3).

The optimal result of the mathematical model shows that three dismantler facilities and three shredder facilities must be opened. These facilities must stay open for 10 years continuously. Their locations are depicted in Fig. 8.

Optimal material flows between opened dismantler facilities and shredder facilities for three analyzed scenarios are shown in Supplementary Table S4. Material flows between dismantler facilities, shredder facilities, recycling facilities and landfilling centres are presented in Fig. 9.

Supplementary Table S5 provides material flow details between shredder facilities and landfilling centre. Material flow details between dismantler facilities and fluid recycling...
facilities, tire recycling facilities, and battery recycling facilities are given in Supplementary Tables S6, S7, S8, respectively. Supplementary Tables S9, S10 present optimal material flows between shredder facilities and recycling facilities.

The total amount of reusable parts and components unmounted from ELVs in dismantler facilities and sold to second-hand markets are presented in Supplementary Table S11. Approximately 44% of these parts and components are ferrous, 29% are non-ferrous, 4% are fluids, 1% are batteries, and 22% are classified as other types of materials.

**4.2 Sensitivity Analysis**

A sensitivity analysis checks the reliability and robustness of generated solutions. Previously, the developed scenario-based stochastic optimization model was solved to...
optimality when the occurrence probabilities of seven scenarios ($\omega = A, B, C, D, E, F, G$) were equal. The occurrence probability for each scenario can also be seen as an external modelling parameter. Variation of $p_\omega$ values and investigation of its effect on the components of the objective function (costs and revenue), as well as binary decision variables (for opening dismantler and shredder facilities), provides a comprehensive insight into the optimal solutions for ELV reverse logistics network in Istanbul.

Supplementary Table S12 presents the results of the sensitivity analysis. Four additional cases are compared with the base case (equal scenario occurrence probabilities for seven scenarios). Based on Supplementary Table S12, three dismantler facilities and three shredder centres are opened in Istanbul in the base scenario. Despite variations of the amount of ELVs generated ($R_\omega$) for each scenario, four dismantler facilities, and three shredder facilities need to be opened. However, facilities are opened in different locations in Case 4. More detailed, if the optimistic scenarios (smaller amount of ELVs generated) have smaller occurrence probabilities than the pessimistic scenarios (greater amount of ELVs generated), dismantler facilities should be opened in locations 1, 3, 4, 5, and shredder facilities in locations 2, 3, 4. Furthermore, dismantler facilities should be opened in locations 2, 3, 4, 5, and shredder facilities should be opened in locations 1, 3, 4 in Case 4 when the greatest amount of ELVs are generated in the pessimistic scenarios. This reverse logistic network for ELVs in Istanbul differs from the results of the base scenario (partially) depicted in Fig. 8. Figure 10 focuses on the objective variable value and cost items of five scenarios. Not surprisingly, fixed-cost values are the same for Case 1, Case 2, Case 3, and Case 4. Furthermore, cost and revenue items in the objective function do not change significantly with the change in the amount of ELVs generated. The total cost reaches its minimum value in Case 2 and the revenue item reaches its maximum value in Case 4. Supplementary Table S12 and Fig. 10 reveal that changes in the amount of ELVs in optimistic and pessimistic scenarios cause more significant changes in the locations of the facilities opened.

Fig. 9 Material flows between dismantler, shredder, recycling facilities and landfilling centres

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Figure 5 demonstrates that operational cost has the highest rate in the cost items. On the other hand, revenue has a significant impact on the objective value. For this reason, another sensitivity analysis is applied to see the impact of the changes in the operational costs and the selling prices of the components of ELVs on the objective value. In Case 5, the operational costs (dismantling cost, shredding cost, landfilling cost, and recycling cost) decreased by 50%. In Case 6, the selling prices of the materials (ferrous, non-ferrous, fluids, batteries, and others) increased by 100%. Supplementary Table S13 and Fig. 11 establish that the objective value attains negative values when operational costs increased or selling prices increased. For this reason, changes in the operational costs or the selling prices have a crucial impact on the profitability of the ELVs’ recovery network.
Supplementary Table S13 and Fig. 11 prove that the material composition of the ELVs has a crucial effect on the profitability of the supply chain network of ELVs’ recovery. With this motivation, another sensitivity analysis regarding the change in material composition rates of the ELVs sold to the second-hand markets and material suppliers is applied. In Cases 7–11, changes in the rates of materials sold from ADCs to the second-hand markets (ferrous material: $\mu_1$, non-ferrous material: $\mu_2$, fluid: $\mu_3$, battery: $\mu_4$, other materials: $\mu_5$) are analyzed. In Cases 12–14, changes in the rates of materials sold from ADCs to material suppliers (fluid: $\lambda_1$, tyre: $\lambda_2$, battery: $\lambda_3$) are analyzed. In Case 15 and Case 16, changes in the rates of materials sold from shredder centres to the material suppliers (ferrous material: $\gamma_1$, non-ferrous material: $\gamma_2$) are analyzed. Supplementary Table S14 and Fig. 12 represent the results of the sensitivity analysis to the change in the rate of ELVs’ components. The results establish that the objective variable attains its minimum value and revenue attains its maximum value in Case 15. This depicts that rates of ferrous ($\gamma_1$) and non-ferrous ($\gamma_2$) materials sold from the shredder centres to the material suppliers have the most significant impact on the total revenue.

The capacities of the facilities play a crucial role in the decision-making process of supply chain management. In this section, another sensitivity analysis is applied by focusing on the changes in the capacities of ADCs and shredder centres. Supplementary Table S15 and Fig. 13 present the results of the sensitivity analysis regarding the capacities of the facilities. In Case 17 and Case 18, the capacities of the shredder centres are fixed and the capacities of ADCs are increased.
simultaneously. In Case 19 and Case 20, the capacities of ADCs are fixed and the capacities of shredder centres are increased partially. The results depict that the capacities of the facilities have a direct effect on the number of opened facilities. Furthermore, changes in the capacities of the facilities have an impact on the locations of the facilities. The fixed-cost item and the objective variable attain their minimum values in Case 20 when the capacities of the shredder centres are increased. This result highlights that the changes in the capacities of the shredder centres have a significant effect on the profitability of the supply chain network of ELVs.

### 4.3 Scenario Analysis

In S1, the proposed mathematical model is solved to optimality with seven scenarios \((\omega = A, B, C, D, E, F, G)\) and \(p_\omega\) (occurrence probability for scenario \(\omega\)) is assumed as 0.143 for each scenario. This means, our model was solved with the assumption of equal probability for each scenario. In this section, the impacts of each scenario on the results are analyzed via scenario analysis. For this reason, the mathematical model is solved by assigning 0.000 to each scenario and assigning 0.167 to other scenarios simultaneously. Supplementary Table S16 and Fig. 14 represent the results of the seven scenarios.

Supplementary Table S16 and Fig. 14 establish that the values of the objective variable, operational cost, transportation cost, and revenue decrease linearly in seven scenarios. The objective variable attains its minimum value in SCN7 and the revenue values attain their maximum value in SCN1. However, the fixed-cost value and opened facilities are the same for each scenario. This result highlights that scenario weights have a significant impact on the values of the objective variable items rather than the number and/or locations of the facilities.

Apart from the seven scenarios, another seven scenarios are analyzed. In this section, the occurrence probability of...
each scenario \( (p_w) \) attains 1.000 and the rest of the occurrence probabilities attain zero for each scenario simultaneously. Supplementary Table S17 and Fig. 15 establish the results of the scenario analysis.

Supplementary Table S17 and Fig. 15 establish that the values of the objective variable, operational cost, transportation cost, and revenue increase linearly in seven scenarios. The objective variable attains its minimum value in SCN8 and the revenue values attain their maximum value in SCN14. However, the fixed-cost value and opened facilities are the same for each scenario. This result highlights that pessimistic scenarios tend to provide higher revenue and total cost. Scenario weights have a significant impact on the values of the objective variable items. However, they do not have a significant impact on the number and/or locations of the facilities.

4.4 Facility Utilization

Based on the results of the mathematical model (Base Case), Fig. 16 represents the capacity utilization rates of ADCs and the shredder centres. The facility utilization rates establish that both shredder centres and ADCs are used most effectively in pessimistic scenarios. On the other hand, ADCs are operated more effectively than shredder centres.

5 Conclusions and Managerial Implications

The ELV management problem is recently being paid more attention by researchers from both academic and industrial backgrounds. The latest environmental challenges triggered policymakers to take action, and new legislations are promulgated by both local and global authorities. Multiple players like users, producers, treatment facilities, and municipalities require a cooperative engagement and they are being conferred new responsibilities in the ELV management. The participation of multiple actors in the recycling process of ELVs brings various uncertainties. For this reason, this paper proposes a scenario-based real-life stochastic programming model for optimizing ELV supply chain network management in Istanbul.

Based on the results of the developed mathematical model, the capacities of the facilities are not used effectively. It can be a consequence of lower return rates of ELVs, ill-planned operational capacities, and locations. At this point, policymakers may need to revise legislation to put more pressure on various players in the ELV recycling process in Istanbul. Besides, the operational cost is the most significant cost item in the recycling process of ELVs. The dismantling cost makes by far the highest proportion of operational costs. This shows that the total cost can be efficiently decreased with improvements in dismantling processes. Furthermore, rates of material components of ELVs have a significant impact on the objective variable. This result highlights that improvements in the operational costs and the material components can improve the profitability of the recovery supply chain of ELVs.

Results of the sensitivity and scenario analyses indicate that changes in the amount of collected ELVs significantly influence the cost items and facility locations. Since the number of vehicles withdrawn from traffic in Istanbul shows uncertain characteristics, decision-makers need to pay extra attention to the capacity and location planning of facilities of the reverse logistic network for ELVs.

This research can be extended in various directions. The primary direction is to use the developed scenario-based stochastic optimization model to examine the effectiveness of ELV management in Istanbul since it could represent the whole of Turkey with its economic and cultural characteristics. Another important direction is to use the model to improve ELV supply chain network management of larger regions such as the whole country. Further works can also try to implement the novel concept of a “socially resilient
supply chain” [48] into the formulated model to design ELV supply chain networks able to timely, eco-efficiently, and cost-effectively recover from social disruption events. Finally, the proposed model is suitable only for ELV management. Its adaptation to some other major waste flows (e.g., electronic waste, construction and demolition waste, etc.) also deserves future research efforts.

**Abbreviations**

Indices

\( l, i \) sources of ELV; \( j = 1, 2, \ldots, J; \) \( j, k \) collection centers; \( j = 1, 2, \ldots, J; k \) dismantler facilities; \( k = 1, 2, \ldots, K; l, \) shredder facilities; \( l = 1, 2, \ldots, L; M, m \) second-hand markets; \( m = 1, 2, \ldots, M; \) \( N, n \) recycling facilities for ferrous and non-ferrous metals; \( n = 1, 2, \ldots, N; P, p \) recycling facilities for fluids; \( p = 1, 2, \ldots, P; R, r \) recycling facilities for tires; \( r = 1, 2, \ldots, R; S, s \) s recycling facilities for batteries; \( s = 1, 2, \ldots, S; U, u \) landfilling centres; \( u = 1, 2, \ldots, U; T, t \) periods; \( t = 1, 2, \ldots, T; \) \( \Omega, \omega \) scenario: \( \omega = 1, 2, \ldots, \Omega \)

Parameters

\( p_{\omega} \): Occurrence probability for scenario \( \omega \) (\( 0 \leq p_{\omega} \leq 1 \)); \( R_{\omega}^{op} \): Amount of ELVs collected from the source \( i \) in period \( t \) and scenario \( \omega \) (ton); \( f_{\omega} \): Facility opening cost for dismantler \( k \) (ton); \( f_{\omega}^{st} \): Facility opening cost for shredder \( l \) (ton); \( c_{\omega}^{dl} \): Dismantling cost at dismantler \( k \) in period \( t \) (ton); \( c_{\omega}^{sc} \): Shredding cost at shredder facility in period \( t \) (ton); \( l_{\omega}^{cap} \): Disposal cost at landfilling centre \( u \) in period \( t \) (ton); \( r_{\omega}^{rc} \): Fluid recycling cost at fluid recycling facility \( p \) in period \( t \) (ton); \( r_{\omega}^{tr} \): Tire recycling cost at tire recycling facility \( r \) in period \( t \) (ton); \( r_{\omega}^{bc} \): Battery recycling cost at battery recycling facility \( s \) in period \( t \) (ton); \( x_{\omega}^{cap} \): The unit selling price of ferrous metal from dismantler facility to second-hand markets in period \( t \) (ton); \( x_{\omega}^{cap} \): The unit selling price of the non-ferrous metal from dismantler facility to second-hand markets in period \( t \) (ton); \( s_{\omega}^{cap} \): The unit selling price of fluid from dismantler facility to second-hand markets in period \( t \) (ton); \( s_{\omega}^{cap} \): The unit selling price of a battery from dismantler facility to second-hand markets in period \( t \) (ton); \( s_{\omega}^{cap} \): The unit selling price of other types of materials (i.e. glass, plastic, textile etc.) from dismantler facility to second-hand markets in period \( t \) (ton); \( c_{\omega}^{dl} \): The unit selling price of ferrous metal from shredder facility to recycling facilities in period \( t \) (ton); \( z_{\omega}^{cap} \): The unit selling price of the non-ferrous metal from shredder facility to recycling facilities in period \( t \) (ton); \( t_{\omega}^{cap} \): Unit transportation cost from ELV source \( i \) to collection centre \( j \) in period \( t \) (ton/m-ton); \( t_{\omega}^{st} \): Unit transportation cost from ELV source \( i \) to dismantler facility \( k \) in period \( t \) (ton/m-ton); \( t_{\omega}^{sc} \): Unit transportation cost from collection centre \( j \) to dismantler facility \( k \) in period \( t \) (ton/m-ton); \( t_{\omega}^{dl} \): Unit transportation cost from dismantler facility \( k \) to shredder facility \( l \) in period \( t \) (ton/m-ton); \( t_{\omega}^{tr} \): Unit transportation cost from dismantler facility \( k \) to fluid recycling facility \( p \) in period \( t \) and scenario \( \omega \) (ton)

Decision Variables

\( FC \): Total fixed cost (ton); \( TC \): Total transportation cost (ton/m-ton); \( OC \): Total operational cost (ton); \( RV \): Total revenue (ton/m-ton)

\( A^{op} \): Amount of ELV transferred from ELV source \( i \) to collection centre \( j \) in scenario \( \omega \); \( B^{op} \): Amount of ELV transferred from ELV source \( i \) to dismantler facility \( k \) in period \( t \) and scenario \( \omega \); \( \lambda^{op} \): Amount of ELV transferred from collection centre \( j \) to dismantler facility \( k \) in period \( t \); \( \lambda^{tr} \): Amount of ELV transferred from dismantler facility \( k \) to shredder facility \( l \) in period \( t \) and scenario \( \omega \); \( \lambda^{tr} \): Amount of non-reusable fluid transferred from dismantler facility \( k \) to fluid recycling facility \( p \) in period \( t \) and scenario \( \omega \); \( \lambda^{tr} \): Amount of non-reusable tire transferred from dismantler facility \( k \) to fluid recycling facility \( p \) in period \( t \) and scenario \( \omega \).
facility $k$ to tire recycling facility $r$ in period $t$ and scenario $\omega$;
$U_{kr}^{\omega}$: Amount of non-reusable battery transferred from dismantler facility $k$ to battery recycling facility $r$ in period $t$ and scenario $\omega$; $Q_{k1m}^{\omega}$: Amount of ferrous metal transferred from dismantler facility $k$ to second-hand market $m$ in period $t$ and scenario $\omega$; $Q_{k2m}^{\omega}$: Amount of ferrous metal transferred from dismantler facility $k$ to shredder facility $l$ in period $t$ and scenario $\omega$; $P_{k1m}^{\omega}$: Amount of non-ferrous metal transferred from dismantler facility $k$ to second-hand market $m$ in period $t$ and scenario $\omega$; $P_{k2m}^{\omega}$: Amount of non-ferrous metal transferred from shredder facility $l$ to recycling facility $n$ in period $t$ and scenario $\omega$; $e_{k}$: Binary decision variable for opening dismantler facility $k$; $e_{l}$: Binary decision variable for opening shredder facility $l$ in period $t$; $e_{nt}$: Binary decision variable for opening shredder facility $l$ in period $t$ and scenario $\omega$.

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Data Availability The data that support the findings of this study are available.

Code Availability The data that support the findings of this study are available upon request.

Declarations

Conflict of Interest The authors declare no competing interests.

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References

1. International Organization of Motor Vehicle Manufacturers (OICA). (2020). World motor vehicle production by country and type. http://www.oica.net/category/production-statistics/2019-statistics/ (accessed 2022 Jan 24).
2. Simic, V. (2015). Fuzzy risk explicit interval linear programming model for end-of-life vehicle recycling planning in the EU. Waste Management, 35, 265–282. https://doi.org/10.1016/j.wasman.2014.09.013
3. Xia, X., Li, J., Tian, H., Zhou, Z., Li, H., Tian, G., & Chu, J. (2016). The construction and cost-benefit analysis of end-of-life vehicle disassembly plant: A typical case in China. Clean Technologies and Environmental Policy, 18(8), 2663–2675. https://doi.org/10.1007/s10098-016-1185-0
4. Kuşakçı, A. O., Ayvaz, B., Cin, E., & Aydın, N. (2019). Optimization of reverse logistics network of End of Life Vehicles under fuzzy supply: A case study for Istanbul Metropolitan Area. Journal of Cleaner Production, 215, 1036–1051. https://doi.org/10.1016/j.jclepro.2019.01.090
5. Turkish Statistics Institute (TUİK). (2020). Road motor vehicles, December 2019. http://www.turkstat.gov.tr/PreHaberBultenleri.do?id=33648 (accessed 2022 Jan 24).
6. Turkish Statistics Institute (TUİK). (2019a). Number of road motor vehicles withdrawn during the year by Classification of Statistical Region Units Level 1. http://www.turkstat.gov.tr/PreTablo.do?alt_id=1051 (accessed 2022 Jan 24).
7. Karagoz, S., Deveci, M., Simic, V., Aydin, N., & Bolukbas, U. (2020). A novel intuitionistic fuzzy MCDM-based CODAS approach for locating an authorized dismantling center: A case study of Istanbul. Waste Management & Research, 38(6), 660–672. https://doi.org/10.1177/0734242X19899729
8. Fleischmann, M., Krikke, H. R., Dekker, R., & Flapper, S. D. P. (2000). A characterisation of logistics networks for product recovery. Omega, 28(6), 653–666. https://doi.org/10.1016/S0305-0483(00)00022-0
9. Ayvaz, B., Bolat, B., & Aydın, N. (2015). Stochastic reverse logistics network design for waste of electrical and electronic equipment. Resources, Conservation and Recycling, 104, 391-404. https://doi.org/10.1016/j.resconrec.2015.07.006
10. Turkish Statistics Institute. (TUİK) (2019b). Population of provinces by years. http://www.turkstat.gov.tr/UstMenu.do?metot=metotlistem (accessed 2022 Jan 24).
11. Karagoz, S., Aydin, N., & Simic, V. (2020). End-of-life vehicle management: A comprehensive review. Journal of Material Cycles and Waste Management, 22(2), 416–442. https://doi.org/10.1007/s10613-019-00945-y
12. Ahn, H., Keilen, J., & Søren, R. (2005). Recovery network design for end-of-life vehicles. Research Methodologies in Supply Chain Management, 555-570. https://doi.org/10.1007/3-7908-1636-1_36
13. 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. https://doi.org/10.1016/j.ejor.2005.01.016
14. Mansour, S., & Zarei, M. (2008). A multi-period reverse logistics optimisation model for end-of-life vehicles recovery based on EU Directive. International Journal of Computer Integrated Manufacturing, 21(7), 764–777. https://doi.org/10.1080/09511920701685325
46. Wong, Y. C., Al-Obaidi, K. M., & Mahyuddin, N. (2018). Recycling of end-of-life vehicles (ELVs) for building products: Concept of processing framework from automotive to construction industries in Malaysia. *Journal of Cleaner Production, 190*, 285–302. https://doi.org/10.1016/j.jclepro.2018.04.145

47. Dargay, J., Gately, D. (1999). Income's effect on car and vehicle ownership, worldwide: 1960–2015. *Transportation Research Part A: Policy and Practice 33*(2), 101-138. https://doi.org/10.1016/S0965-8564(98)00026-3

48. Dabic-Miletic, S., Simic, V., & Karagoz, S. (2021). End-of-life tire management: A critical review. *Environmental Science and Pollution Research, 28*, 68053–68070. https://doi.org/10.1007/s11356-021-16263-6

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