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Stochastic reverse logistics network design for waste of electrical and electronic equipment

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ABSTRACT

In recent years, Reverse Logistics has received increasing attentions in supply chain management area. The reasons such as political, economic, green image and social responsibility etc. force firms to develop strategies to their current systems. The aim of this study is to propose a generic Reverse Logistics Network Design model under return quantity, sorting ratio (quality), and transportation cost uncertainties. We present a generic multi-echelon, multi-product and capacity constrained two stage stochastic programing model to take into consideration uncertainties in Reverse Logistics Network Design for a third party waste of electrical and electronic equipment recycling companies to maximize profit. We validated developed model by applying to a real world case study for waste of electrical and electronic equipment recycling firm in Turkey. Sample average approximation method was used to solve the model. Results show that the developed two stage stochastic programming model provides acceptable solutions to make efficient decisions under quantity, quality and transportation cost uncertainties.

1. Introduction

In recent years, product recovery has received growing attention in the world, due to driving factors such as social, environmental, and economic reasons. The factors such as regulation pressure, economic, green image and social responsibility force firms to evolve strategies to their current systems. Many manufacturers have adapted the practice of recovering value from returned products and integrated product recovery activities into their processes (Lee and Dong, 2009). Reverse logistics (RL) is the concept of reusing used products to reduce wastes and to increase an industry's environmental performance (Diabat et al., 2013). In term of sustainability, RL can be defined as a business strategy that acts as the driving force of putting recovery activities in action effectively in order to increase sustainability.

The recovery options in RL are remanufacturing, repairing, refurbishing, cannibalizing, and recycling (Zhou and Wang, 2008). It is widely applicable for the products like computers, vehicle engines, electrical appliances, electronic equipment, copiers, single-use cameras, cellular phones, paper, carpets, plastics, medical equipment, tires, and batteries (Srivastava, 2008a; Sasikumar et al., 2010).

The reason of product return in the supply can be listed such as; manufacturing returns, commercial returns (B2B and B2C), product recalls, warranty returns, service returns, end-of-use returns, end-of-life returns. (De Brito, 2002; Du and Evans, 2008).

Decisions in RL can be taken for long-term such as those about facility location, layout, capacity and design; or medium term such as those related to integrating operations or deciding about which information and communication technologies systems support the return handling or short-term decisions about inventory handling, vehicle routing, remanufacturing scheduling, etc. (Srivastava, 2008b).

Studies in the literature associated with RL have been concluded on different aspects such as network design, return forecasting, economic and environmental performance, lot sizing, vehicle routing, etc. The design of product recovery networks is one of the challenging RL problems (De Brito, 2002; Chanintrakul et al., 2009).

A Reverse Logistics Network Design (RLND) is complicated by the needs for testing and grading of return products, addressing 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 RL networks (Fleischmann et al., 2000). Especially the impact of uncertainty in terms of quantity, quality and

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timing is the most popular issue in RLND (Chanintrakul et al., 2009). Deterministic models for RLND lack the ability to incorporate such uncertainty factors as variances of return amount, timing, and lead time through the network (Lee, 2009). Kall and Wallace (1994) claim that stochastic programming techniques present more flexibility to cope with uncertainty. So, in order to deal with this uncertainty, researchers developed various stochastic models (Ilgin and Gupta, 2010).

The aim of this study is to propose a RLND model under return quantity, quality, and transportation cost uncertainties and solve with a well-known solution algorithm, Sample average approximation (SAA), for Stochastic Programming (SP) problems. We present a multi-stage, multi-echelon, multi-product and capacity constrained two stage stochastic programing model to take into consideration uncertainties in RLND. We validate the developed generic model by applying to a real world case study of waste of electric and the waste of electrical and electronic equipment (WEEE) third party recycling company in Turkey. SAA schema is applied in solution process. The contributions of this paper are as follows: First, this study is the first appliance, in WEEE literature for RLND under uncertain parameters, such as, amount of WEEE, quality of collected WEEE and transportation costs. Second, the RLND network is modeled as a SP model and it is solved by SAA. Third, the proposed model is a generic RLND for third party reverse logistic companies. Lastly, the proposed model is easy and effective to support establishing RLND decisions for managers and decision makers.

In the literature, many researchers showed increasingly interest in the RLND problem. Some of the studies are briefly explained as follows:

Barros et al. (1998) presented a multi-level capacitated facility location problem for sand recycling in the Netherlands. They developed a mixed integer program (MILP) model when the volume and the locations of the demand are uncertain. They determined the optimal number, capacities and locations of the depots and cleaning facilities for recycling sand from construction waste. Krikke et al. (1999) developed a MILP model for a multi-echelon RLND for a copier manufacturer in the Netherlands. Shih (2001) developed a MILP model for design of an optimal collection and recycling system for end-of-life computers and home appliances. Jayaraman et al. (2003) developed an MILP model as a two-echelon capacitated facility location problem with limited collection and refurbishing facilities. Heuristic methods were also developed to solve the model. Min et al. (2006) addressed the multi-echelon RLND problem for product returns and developed a single-objective, nonlinear mixed-integer programming model that determines the optimal number and locations of collecting points as well as centralized return centers while taking the shipping costs, closeness of the collection points and in-transit inventory into consideration. A genetic algorithm is developed to solve the problem. Lu and Bostel (2007) addressed a two-level location problem with three types of facility to be located in a specific reverse logistics system. For this problem, they developed mixed integer programming model, considering simultaneously “forward” and “reverse” flows. They used langrage heuristic to solve the problem. Pati et al. (2008) developed a mixed integer goal programming model. The model addressed the inter-relationship between multiple objectives of a recycled paper distribution network. The objectives were the reverse logistics cost, a non-relevant wastepaper target and a wastepaper recovery target. Du and Evans (2008) presented a bi-objective MILP model for designing a closed-loop logistics network for third-party logistics providers. The objectives of the model are the minimization of total costs and the tardiness.

Kannan et al. (2012) presented a mixed integer linear model for a carbon footprint based RLND. The developed model aims to minimize the costs involved in the reverse logistics network model, and it considers the carbon footprint involved both in transportation and reverse logistics operations (collection) costs. It employs reverse logistics activities to recover used products, hence including the location/transportation decision problem. The presented model is applied to a plastic sector. Achillas et al. (2012) presented multiple objective linear programming (MOLP). The main goal of a MOLP model is the weighted optimization of different objectives. The developed MOLP approach minimizes total logistics costs, consumption of fossil fuel and production of emissions.

The uncertainty is an important characteristic of product recovery (Fleischmann et al., 2000). Design of reverse and closed-loop supply chain networks involves generally high degree of uncertainty, especially associated with quality and quantity of the returned products, as well as the time, delay and location of recovery and redistribution (Chouinard et al., 2008; Ilgin and Gupta, 2010; Pishvaee et al., 2011). The quantity and quality of used products are more difficult to control and estimate (Qin and Ji, 2010). Diabat et al. (2013) developed a multi-echelon reverse logistics network for product returns to minimize the total reverse logistics cost, which consists of renting, inventory carrying, material handling, setup, and shipping costs. In their study, a mixed integer non-linear programming (MINLP) model is developed to find out the number and location of initial collection points and centralized return centers. Two solution approaches, namely genetic algorithm and artificial immune system, are implemented and compared. The usefulness of the proposed model and algorithm are illustrated by an illustrative example.

Listes (2002) presented a generic stochastic model for the design of networks organized in a closed loop system. This model considers one echelon forward network combined with two echelon reverse network. The uncertainty is handled in a stochastic formulation by means of discrete alternative scenarios. Listeş and Dekker (2005) proposed two formulations using stochastic optimization for the network design of recycling sand under demand and supply uncertainties. The first formulation is a two-stage stochastic optimization with locational uncertainty of demand. The second formulation involves both demand and supply uncertainty via a three-stage stochastic optimization model. Listeş (2007) presented a generic stochastic model for the design of integrated real-world RL network. They considered uncertainty under return quantity. The objective is to maximize profit. Decomposition method based on the branch-and-cut known as the integer L-shaped method is developed to solve the problem. Salema et al. (2007) developed a generic reverse logistics network model which includes multi-product management and uncertain product demands and returns. A mixed integer formulation is developed. They solve their model with standard branch-and-bound (BB) techniques rather than using a decomposition method. Chouinard et al. (2008) considered the uncertainties related with recovery, processing and demand volumes in a closed-loop supply chain design problem by developing a stochastic programming model. Sample average approximation-based heuristic is developed to solve the problem. Lee and Dong (2009) considered a stochastic approach for the dynamic RLND under demand and return uncertainties. A two-stage stochastic programming model is developed by which a deterministic model for dynamic RLND can be extended to consider uncertainties. Pishvaee et al. (2009) presented a stochastic programming model for single period, single product, multi-stage integrated forward/Reverse Logistics Network Design to cope with the uncertainty associated with the quantity and quality of returned products, demands and variable costs. First, an efficient deterministic MILP model is developed for integrated logistics network design to avoid the sub-optimality caused by the separate design of the forward and reverse networks. Then the stochastic counterpart of the proposed MILP model is developed by using scenario-based stochastic approach.

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Fonseca et al. (2010) presented a comprehensive model for RL planning in which they considered many real-world features such as the existence of multi-echelons, multi-commodities, choices of technology, and uncertainties associated with transportation costs and waste generation. Moreover, they presented a two-stage stochastic dual-objective mixed-integer programming formulation in which strategic decisions are considered in the first stage and tactical and operational decisions in the second. The two objectives considered are the total cost and the total obnoxious effect. El-Sayed et al. (2010) proposed a Stochastic MILP model for integrated logistics network design including demand and return uncertainties. The objective is the total profit maximization. Kara and Onut (2010) developed a two-stage stochastic programming model to determine a long term strategy including optimal facility locations and optimal flow amounts for large scale reverse supply chain network design problem under uncertainty. In this study, the first stage decisions correspond to the location decisions that must be made for opening facilities before the values of the random parameters become known and the second stage decisions correspond to the flow amount decisions through the established network after the values of the random parameters become known.

Gomes et al. (2011) extended the model proposed by Salema et al. (2010) to handle the uncertainty related to the quality of the returned products, which at this stage is modeled by a two-stage scenario-based stochastic approach. Ramezani et al. (2013) proposed a stochastic multi-objective model for forward/reverse logistic network design under a uncertain environment including three echelons in forward direction (i.e., suppliers, plants, and distribution centers) and two echelons in backward direction (i.e., collection centers and disposal centers). They demonstrated a method to evaluate the systematic supply chain configuration maximizing the profit, customer responsiveness, and quality as objectives of the logistic network. The set of Pareto optimal solutions is obtained and also financial risk relevant to them is computed in order to show the tradeoff between objectives. The results give important insight for fostering the decision making process. In their study, uncertainties are associated with quantity of price, production costs, operating costs, collection costs, disposal costs, demands and return rates and are described by the set of scenarios.

Demirel et al. (2014) presented a mixed integer linear programming model for network design including the different actors taking part in end-of-life vehicles (ELVs) recovery system in order to comply with related regulations and manage the recovery of end-of-life vehicles efficiently. The proposed framework is justified by a real case performed in Ankara. They also presented a modeling approach for the projection of car ownership and number of end-of-life vehicles and generated scenario analyzes based on the long-term changing in the number of end-of-life vehicles. Suyabatmaz et al. (2014) presented two hybrid simulation-analytical modeling approaches for the RLND of the third-party logistics. Hatefi and Jolai (2014) proposed a robust and reliable mixed-integer linear programing model for designing an integrated forward–reverse network, which can cope with the parameters' uncertainty in the customer demand, the quantity and quality of returned products and facility disruptions, simultaneously. To present the behavior of the robustness and reliability of the network, numerical examples are conducted. Ferri et al. (2015) proposed a reverse logistics network for the management of municipal solid waste considering the recent legal requirements of the Brazilian Waste Management Policy. The presented mathematical model allows the determination of the number of facilities required for the reverse logistics network, their location, capacities, and waste flows between these facilities. Zhou and Zhou (2015) proposed a nonlinear integer programming model for determining the locations and numbers of recycling stations and plants, in order to minimize the total cost. A case study of selected sites along the Xueyuan Road in Beijing is conducted to illustrate the presented model. Kilic et al. (2015) developed a reverse logistics system for WEEE in Turkey. They used a mixed integer linear programming model in order to provide solutions. Ten scenarios are taken into consideration related to different collection rates. The optimum locations and flows are determined for each scenario via the proposed MILP model. Roghanian and Pazhoheshfar (2014) addressed multi-product, multi-stage reverse logistics network problem for the return products. They presented a probabilistic mixed integer linear programming model for the design of a reverse logistics network to handle the degree of uncertainty in terms of the capacities, demands and quantity of products. To solve the proposed model, priority based genetic algorithm is used. The proposed model is applied to a numerical example. Ene and Öztürk (2015) developed a mathematical programming model for managing reverse flows in end-of-life vehicles' recovery network. The objectives of the proposed model are to maximize revenue and minimize pollution in end of-life product operations.

Table 1 gives an overview of some important models' characteristics. The result of literature review shows clearly that deterministic models commonly ignore uncertainty associated with RLND process; the stochastic models account for the uncertainties in terms of returned products quantity, quality and time. The uncertainty in RL literature is still scarce.

As a result, there are some gap research areas related to RLND such as combining of multiple objectives, multiple commodities, multiple echelons, real life cases and uncertainty. Therefore in this study, we present multi-echelon and multi-product SP for RLND under return product quantity, quality (sorting ratio), and transportation costs.

2. Problem statement and methodology

The RLND problem that is addressed in this paper is an open loop, multi-echelon, multi-product, capacity constrained under return quantity, return quality (sorting ratio) and transportation cost uncertainties. It is known that deterministic programming is unable to handle uncertainties parameters. Therefore stochastic programming is used to cope with the uncertain parameters.

Stochastic Programming (SP) is a framework to model optimization problems which involve uncertain parameters (Bidhandi and Yusuff, 2011). It is assumed that the probability distribution functions of uncertain parameters are known and decision makers optimize the expected value of the objective function (Hosseini and Dullaert, 2011). The most widely applied SP models are two-stage linear and mixed integer linear programs. A two stage SP model is proposed by Birge and Louveaux (1997) that take into account randomness. The first stage variables are those that have to be decided before the actual realization of the uncertain parameters becomes available. Subsequently, once the random events have presented themselves, further design or operational policy improvements can be made by selecting, at a certain cost, the values of the second stage or recourse variables. The objective is to choose the first stage variables in a way that the sum of the first stage costs and the expected value of the random second stage or recourse costs are minimized (Ayvaz and Bolat, 2014).

We present two stage stochastic programming model to determine the number of collecting centers, sorting centers, and recycling centers to maximize the profit. The presented model includes collecting centers, sorting centers, recycling centers, refinery centers, raw material markets, and disposal centers. As shown in Fig. 1, returned products are collected from customer zones which are electronic markets, municipality, electronic distributers etc., and transported to the collecting centers then they are sent to sorting centers in order to preprocessing; it is divided into

Table 1
Review of reverse logistic network design literature.

References	Model	Objectives	Type of network	Number of product	Uncertain parameters
Barros et al. (1998)	MILP	*C*	Open-loop	Multi	–
Krikke et al. (1999)	MILP	*C*	Open-loop	Single	–
Shih (2001)	MIP	*P*	Open-loop	Multi	*RR*
Jayaraman et al. (2003)	MIP	*C*	Open-loop	Single	–
Min et al. (2006)	MINLP	*C*	Open-loop	Single	–
Du and Evans (2008)	MILP	*C, TT*	Close-loop	Multi	–
Pati et al. (2008)	MIGP	*C, NWT, WRT*	Open-loop	Single	*D*
Lu and Bostel (2007)	MIP	*C*	Close-loop	Single	–
Achillas et al. (2012)	MOLP	*C, E, F*	Open-loop	Single	–
Kannan et al. (2012)	MILP	*C*	Close-loop	Single	–
Diabat et al. (2013)	MINLP	*C*	Open-loop	Single	–
Listes (2002)	SMILP	*C*	Close-loop	Single	*D, R*
Listeş and Dekker (2005)	SMILP	*P*	Open-loop	Single	*D, R*
Listeş (2007)	SMILP	*P*	Close-loop	Single	*D, R*
Chouinard et al. (2008)	SMIP	*C*	Close-loop	Multi	*D, Rec, Pro*
Salema et al. (2007)	SMIP	*C*	Close-loop	Multi	*D, TC, R*
Lee and Dong (2009)	SMILP	*C*	Close-loop	Multi	*D, R*
Pishvaee et al. (2009)	SMILP	*C*	Close-loop	Single	*R, Q, VC*
Fonseca et al. (2010)	SMILP	*C, TOE*	Open-loop	Multi	*TC, R*
El-Sayed et al. (2010)	SMILP	*P*	Close-loop	Single	*D, R*
Kara and Onut (2010)	SMILP	*P*	Open-loop	Single	*D, R*
Gomes et al. (2011)	SMILP	*C*	Open-loop	Multi	*Q*
Ramezani et al. (2013)	SMILP	*P, CR, SQ*	Close-loop	Multi	*Pr, PC, OC, CC, DC, D, RR*
Diabat et al. (2013)	MINLP	*C*	Open-loop	Single	–
Demirel et al. (2014)	MILP	*C*	Open-loop	Single	–
Suyabatmaz et al. (2014)	MILP	*C*	Open-loop	Single	*R*
Hatefi and Jolai (2014)	RO	*C*	Close-loop	Single	*D, R, Q*
Ferri et al. (2015)	MILP	*P*	Close-loop	Multi	–
Roghanian and Pazhoheshfar (2014)	PMILP	*C*	Open-loop	Multi	*CAP, D, R*
Zhou and Zhou (2015)	MINLP	*C*	Open-loop	Single	–
Kilic et al. (2015)	MILP	*C*	Open-loop	Multi	–
Ene and Öztürk (2015)	SMILP	*P, Pol*	Open-loop	Single	*R*

MILP: mixed integer linear programming, PMILP: probabilistic mixed integer linear programming, NLP: non linear programming, SMILP: stochastic mixed integer linear programming, MIGP: mixed integer goal programming, MINLP: mixed integer non linear programming, MOLP: multi objectives linear programming, RO: robust optimization, C: cost min., P: profit max., TT: total tardiness min., E: minimize emissions, F: minimize fossil fuel, Pol: pollution min., NWT: a non-relevant wastepaper target, WRT: a wastepaper recovery target, D: demand quantity, R: return quantity, Rec: recovery volumes, Pro: processing volumes, TC: transportation costs, Q: return quality, VC: variable cost, TOE: total obnoxious effect, CR: customer responsiveness, SQ: service quality, Pr: price, PC: production costs, OC: operating costs, CC: collection costs, DC: disposal costs, RR: return rates, CAP: capacity.

recoverable products and scrapped products. The recoverable products are transported to the recycling centers and scrapped products are sent to disposal centers. As a result, recycled materials are sent to raw material markets, some hazardous material are sent to disposal center, and products, which cannot be processing such as gold, are sent to refinery center(s).

2.1. Two-stage stochastic programming model

The aim of the RLND is to determine the location of collecting, sorting and recycling centers, and to find the quantity of flow between the network facilities.

The proposed model considers the following assumptions:

- Inventory costs are ignored.
- There is no any safety stock in collecting and recycling centers.
- There are capacity constraints of collecting centers, sorting centers, and recycling centers.
- All costs except transportation cost, and allocation rates of products and materials are known in advance.
- Possible locations of collecting centers, sorting centers, recycling centers and capacities are known.
- Locations of refinery, markets disposal centers are known in advance.

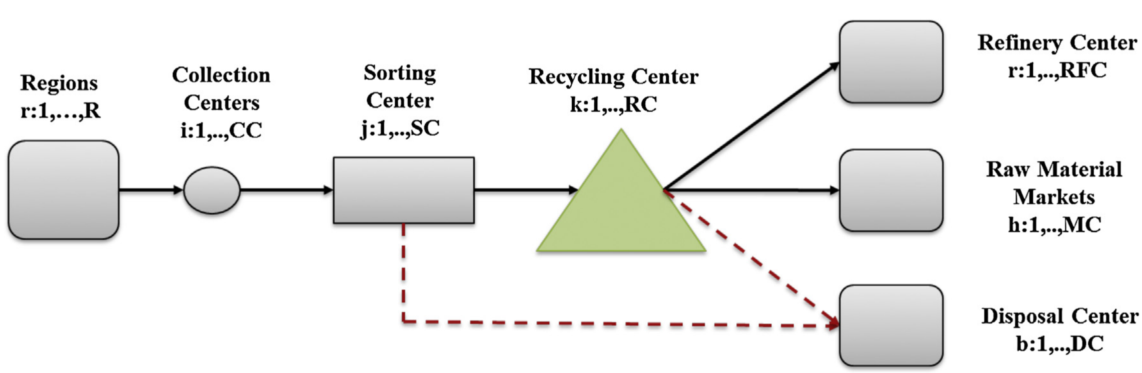

Fig. 1. Presented reverse logistic network.

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For the clearness, for the rest of this study, we will refer to waste as 'product'. According to above descriptions, the stochastic programming model under quantity, quality, and transportation cost uncertainties can be defined and the presented model, which includes the following sets, parameters and decision variables are as follows:

Sets	Indices and superscripts
R: set of regions where waste occurs	r: region index, $r \in R$
CC: set of possible facility locations for collecting processes	i: collecting center index, $i \in CC$
SC: set of possible facility locations for sorting processes	j: sorting center index, $j \in SC$
RC: set of possible facility locations for recycling processes	k: recycling center index, $k \in RC$
RFC: set of refinery locations	rf: refinery index, $rf \in RFC$
MC: set of market locations	h: market index, $h \in MC$
DC: set of facility locations for disposing processes	b: disposal center index, $b \in DC$
Pr: set of products	p: product index, $p \in Pr$
Com: set of commodities	c: commodity index, $c \in Com$
S: set of scenarios	s: scenario index, $s \in S$

Parameters, constants, and coefficients
FCC_i: fixed cost for locating a collecting center at location i, $i \in CC$
FSC_j: fixed cost for locating a sorting center at location j, $j \in SC$
FRC_k: fixed cost for locating a recycling center at location k, $k \in RC$
$tr_{r,i}^{p,s}$: cost of transporting one unit of product p from region r to collecting center i in scenario s, $r \in R$, $i \in CC$, $p \in Pr$, $s \in S$
$tc_{i,j}^{p,s}$: cost of transporting one unit of product p from collecting center i to sorting center j in scenario s, $i \in CC$, $j \in SC$, $p \in Pr$, $s \in S$
$ts_{j,k}^{p,s}$: cost of transporting one unit of product p from sorting center j to recycling center k in scenario s, $j \in SC$, $k \in RC$, $p \in Pr$, $s \in S$
$tsd_{j,b}^{p,s}$: cost of transporting one unit of product p from sorting center j to disposing center b in scenario s, $j \in SC$, $b \in DC$, $p \in Pr$, $s \in S$
$trc_{k,rf}^{p,s}$: cost of transporting one unit of product p from recycling center k to refinery rf in scenario s, $k \in RC$, $rf \in RFC$, $p \in Pr$, $s \in S$
$trcd_{k,b}^{p,s}$: cost of transporting one unit of product p from recycling center k to disposing centre b in scenario s, $k \in RC$, $b \in DC$, $p \in Pr$, $s \in S$
$trcm_{k,h}^{c,s}$: cost of transporting one unit of commodity c from recycling center k to market h in scenario s, $k \in RC$, $h \in MC$, $c \in Com$, $s \in S$
PCC_i^p: processing cost of collecting one unit of product p at collecting center i, $i \in CC$, $p \in Pr$
PSC_j^p: processing cost of sorting one unit of product p at sorting center j, $j \in SC$, $p \in Pr$
PRC_k^p: processing cost of recycling one unit of product p at recycling center k, $k \in RC$, $p \in Pr$
PDC_b^p: processing cost of disposing one unit of product p at disposing center b, $b \in DC$, $p \in Pr$
InP^p: income from one unit of product p, $p \in Pr$
InC^c: income from one unit of commodity c, $c \in Com$
$\Phi_r^{p,s}$: amount of product p occurred at region r in scenario s, $r \in R$, $p \in Pr$, $s \in S$
$a^{p,s}$: percentage of product p that worth to be recycled in scenario s, $p \in Pr$, $s \in S$
ψ^p: percentage of product p that is transported to refinery, $p \in Pr$
Ω^p: percentage of product p that is transported to markets, $p \in Pr$
$\Theta^{c,p}$: percentage of product p that consists commodity c, $c \in Com$, $p \in Pr$
$CapCCi$: capacity of collecting center i, $i \in CC$
$CapSC_j^p$: capacity of sorting center j for product p, $j \in SC$, $p \in Pr$
$CapRC_k^p$: capacity of recycling center k for product p, $k \in RC$, $p \in Pr$
π^s: probability of scenario s, $s \in S$
Decision variables
x_i: 1 if collecting center i is located, 0 otherwise, $i \in CC$
y_j: 1 if sorting center j is located, 0 otherwise, $j \in SC$
z_k: 1 if recycling center k is located, 0 otherwise, $k \in RC$
$w_{i,j}$: 1 if collecting center i is assigned to sorting center j, 0 otherwise, $i \in CC$, $j \in SC$
$\alpha_{r,i}^{p,s}$: amount of product p transported from region r to collected center i in scenario s, $r \in R$, $i \in CC$, $p \in Pr$, $s \in S$
$\beta_{i,j}^{p,s}$: amount of product p transported from collecting center i to sorting center j in scenario s, $i \in CC$, $j \in SC$, $p \in Pr$, $s \in S$
$\gamma_{j,k}^{p,s}$: amount of product p transported from sorting center j to recycling center k in scenario s, $j \in SC$, $k \in RC$, $p \in Pr$, $s \in S$
$\delta_{j,b}^{p,s}$: amount of product p transported from sorting center j to disposing center b in scenario s, $j \in SC$, $b \in DC$, $p \in Pr$, $s \in S$
$\theta_{k,rf}^{p,s}$: amount of product p transported from recycling center k to refinery rf in scenario s, $k \in RC$, $rf \in RFC$, $p \in Pr$, $s \in S$
$\omega_{k,b}^{p,s}$: amount of product p transported from recycling center k to disposing center b in scenario s, $k \in RC$, $b \in DC$, $p \in Pr$, $s \in S$
$\rho_{k,h}^{c,s}$: amount of commodity c transported from recycling center k to market h in scenario s, $k \in RC$, $h \in MC$, $c \in Com$, $s \in S$

We now model our RLND as two-stage stochastic program with recourse. The uncertain parameters in this formulation are the amount of collected WEEE, the quality of collected WEEE and transportation costs.

Objective function [maximize] = income − (transportation costs between nodes + fixed costs of locating centers + processing costs of collecting, sorting, recycling and disposing)

$$\begin{aligned}
\textbf{Maximize} \quad & \sum_{k\in RC}\sum_{rf\in RFC}\sum_{p\in Pr}\sum_{s\in S}\pi^s\left(\mathrm{In}P^p - trc_{k,rf}^{p,s}\right)\theta_{k,rf}^{p,s} \\
& + \sum_{k\in RC}\sum_{h\in MC}\sum_{c\in Com}\sum_{s\in S}\pi^s\left(\mathrm{In}C^c - trcm_{k,b}^{c,s}\right)\rho_{k,h}^{c,s} \\
& - \sum_{i\in CC} FCC_i x_i - \sum_{j\in SC} FSC_j y_j \\
& - \sum_{k\in FRC} FRC_k z_k - \sum_{r\in R}\sum_{i\in CC}\sum_{p\in Pr}\sum_{s\in S}\pi^s\left(PCC_i^p + tr_{r,i}^{p,s}\right)\alpha_{r,i}^{p,s} \\
& - \sum_{i\in CC}\sum_{j\in SC}\sum_{p\in Pr}\sum_{s\in S}\pi^s\left(PSC_j^p + tc_{i,j}^{p,s}\right)\beta_{i,j}^{p,s} \\
& - \sum_{j\in SC}\sum_{k\in RC}\sum_{p\in Pr}\sum_{s\in S}\pi^s\left(PRC_k^p + ts_{j,k}^{p,s}\right)\gamma_{j,k}^{p,s} \\
& - \sum_{j\in SC}\sum_{b\in DC}\sum_{p\in Pr}\sum_{s\in S}\pi^s\left(PDC_b^p + tsd_{j,b}^{p,s}\right)\delta_{j,b}^{p,s} \\
& - \sum_{k\in RC}\sum_{b\in DC}\sum_{p\in]}\sum_{s\in S}\pi^s\left(PDC_b^p + trcd_{k,b}^{p,s}\right)\omega_{k,b}^{p,s}
\end{aligned} \tag{1}$$

Subject to

$$\sum_{i\in CC}\alpha_{r,i}^{p,s} \le \Phi_r^{p,s} \qquad \forall r\in R,\quad p\in Pr,\quad s\in S \tag{2}$$

$$\beta_{i,j}^{p,s} \le CapSC_j^p w_{i,j} \qquad \forall i\in CC,\quad j\in SC,\quad p\in Pr,\quad s\in S \tag{3}$$

$$\sum_{j\in SC} w_{i,j} \le 1 \qquad \forall i\in CC \tag{4}$$

$$\sum_{j\in SC}\beta_{i,j}^{p,s} = \sum_{r\in R}\alpha_{r,i}^{p,s} \qquad \forall i\in CC,\quad p\in Pr,\quad s\in S \tag{5}$$

$$\sum_{k\in RC}\gamma_{j,k}^{p,s} = \sum_{i\in CC} a^{p,s}\beta_{i,j}^{p,s} \qquad \forall j\in SC,\quad p\in Pr,\quad s\in S \tag{6}$$

$$\sum_{b\in DC}\delta_{j,b}^{p,s} = \sum_{i\in CC}\left(1 - a^{p,s}\right)\beta_{i,j}^{p,s} \qquad \forall j\in SC,\quad p\in Pr,\quad s\in S \tag{7}$$

$$\sum_{h\in MC}\rho_{k,h}^{c,s} = \sum_{j\in SC}\sum_{p\in Pr}\Omega^p\Theta^{c,p}\gamma_{j,k}^{p,s} \qquad \forall k\in RC,\quad c\in Com,\quad s\in S \tag{8}$$

$$\sum_{rf\in RFC}\theta_{k,rf}^{p,s} = \sum_{j\in SC}\Psi^p\gamma_{j,k}^{p,s} \qquad \forall k\in RC,\quad p\in Pr,\quad s\in S \tag{9}$$

$$\sum_{b\in DC}\omega_{k,b}^{p,s} = \sum_{j\in SC}\left(1 - \Omega^p - \Psi^p\right)\gamma_{j,k}^{p,s} \qquad \forall k\in RC,\quad p\in Pr,\quad s\in S \tag{10}$$

$$\sum_{r\in R}\sum_{p\in Pr}\alpha_{r,i}^{p,s} \le CapCC_i x_i \qquad \forall i \in CC, \quad s \in S \tag{11}$$

$$\sum_{i\in CC}\beta_{i,j}^{p,s} \le CapSC_j^p y_j \qquad \forall j \in SC, \quad p \in Pr, \quad s \in S \tag{12}$$

$$\sum_{j\in SC}\gamma_{j,k}^{p,s} \le CapRC_k^p z_k \qquad \forall k \in RC, \quad p \in Pr, \quad s \in S \tag{13}$$

$$x_i, y_j, z_k, w_{i,j} \in \left\{0, 1\right\} \qquad i \in CC, \quad j \in SC, \quad k \in RC \tag{14}$$

$$\alpha_{r,i}^{p,s}, \beta_{i,j}^{p,s}, \gamma_{j,k}^{p,s}, \delta_{j,b}^{p,s}, \theta_{k,rf}^{p,s}, \omega_{k,b}^{p,s}, \rho_{k,h}^{c,s} \ge 0 \qquad r \in R, \quad i \in CC, \quad j \in SC, \quad k \in RC, \quad b \in DC, \quad rf \in RFC, \quad h \in MC, \quad p \in Pr, \quad c \in Com, \quad s \in S \tag{15}$$

The objective function in (1) is the sum of the first stage-costs and the expected second-stage costs and income. The first stage costs represent the costs of opening collecting centers, sorting centers and recycling centers. The second stage costs represent expected total transporting costs, processing costs of collecting, sorting, recycling and disposing, and expected total income from markets and refineries. Constraints (2) prevent that the total transported products to collecting center is less than or equal to the total occurred products in the regions. Constraints (3) are the assignment constraints and prevent any transportation from a collecting center to a sorting center if the specified collecting center is not assigned to that sorting center. Constraints (4) ensure that each collecting center is assigned to at most one sorting center. Constraints (5) equalize the inflow to outflow of products for each collecting center. Constraints (6) and (7) determine the flow from each sorting center to recycling centers and disposing centers, respectively. Constraints (8)–(10) determine the flow from each recycling center to markets, refineries and disposing centers, respectively. Constraints (11)–(13) take care of capacity restrictions for collecting centers, sorting centers and recycling centers, respectively. Constraints (14) and (15) are the non-negativity constraints.

As a solution methodology one of the most known solution algorithm, Sample average approximation (SAA), is used to determine an accurate solution to the problem. SAA method uses exterior sampling and has become a popular technique in solving large-scale SP problems. This is primarily due to its ease of application. It has been shown that the solutions obtained by the SAA converge to the optimal solution when the sample size is sufficiently large (Ahmed and Shapiro, 2002a,b; Aydin and Murat, 2013).

2.2. Sample average approximation (SAA)

Sampling based methods are usually used when the stochastic problem is too large or difficult to solve by exact solution techniques. The objective function is approximated through a random sample of scenarios via the sampling based methods. Typically sampling based approaches are classified into two: Interior sampling and exterior sampling methods (Verweij et al., 2003). In interior sampling methods, sampling is performed inside a chosen algorithm with new (independent) samples generated during the iterative solution process. In the exterior sampling approach, a sample of scenarios is generated from possible realizations, and then deterministic optimization problem is developed from the generated samples and then it is solved. This procedure (generating samples and solving deterministic problems) repeated several times. SAA is one of the exterior type sampling based method and is a Monte Carlo simulation based sampling method, in which the expected value of objective function of stochastic program is approximated by solving the problem for a sample of scenarios. In network models usually parameters such as demand, travel cost, and link costs are uncertain and difficult to forecast accurately (Patil and Ukkusuri, 2011). In this study, we consider quantity, quality, and transportation costs as uncertain, such as transportation cost from a location i.e. collecting center to another i.e. sorting center, and quantity that is transported between centers, etc. SAA can be defined through a number of steps; random samples are generated, a sample average function is applied to the selected random samples to approximate the expected value function.

Some advantages of SAA are listed as following: Ease of numerical implementation, often one can use existing software, good convergence properties, well developed statistical inference (validation and error analysis, stopping rules), easily amendable to variance reduction techniques and ideal for parallel computations (Shapiro, 2004). SAA procedure includes following steps:

Step 1: Generate M independent samples of sizes $i = 1, \ldots, N$, $(\xi^1, \ldots, \xi^N)$. For each sample solve the corresponding SAA problem.

$$\min\left\{c^T y + \frac{1}{N}\sum_{n=1}^{N} Q\left(y, \xi_j^n\right)\right\}$$

v_N^j and $\hat{y}_N^j$ be, respectively, the corresponding optimal objective value and an optimal solution for the samples $j = 1, \ldots, M$.

Step 2: Calculate the statistical lower bound based on the average optimal objective value obtained from samples $j = 1, \ldots, M$ in step1.

$$\bar{v}_{N,M} := \frac{1}{M}\sum_{J=1}^{M} v_N^j$$

Then the variance of this estimate can be estimated as:

$$\sigma_{\bar{v}_{N,M}}^2 := \frac{1}{(M-1)M}\sum_{j=1}^{M}\left(v_N^j - \bar{v}_{N,M}\right)^2$$

Step 3: Choice a feasible solution $\bar{y}$ among those obtained in step 1. Estimate the value of the objective function with a sample of size N', much larger than N, by solving

$$\tilde{f}_{N'}(\bar{y}) := c^T \bar{y} + \frac{1}{N'}\sum_{n=1}^{N'} Q\left(\bar{y}, \xi^n\right)$$

The value of $\tilde{f}_{N'}(\bar{y})$, is an estimated upper bound of the "true" problem objective function. Then the variance of this estimate can be estimated as:

$$\sigma_{N'}^2(\bar{y}) := \frac{1}{(N'-1)N'}\sum_{n=1}^{N'}\left(c^T\bar{y} + Q\left(\bar{y}, \xi^n\right) - \tilde{f}_{N'}(\bar{y})\right)^2$$

Step 4: Calculate an estimate of the optimality gap of the solution $\bar{y}$:

$$\mathrm{gap}_{N,M,N'}(\bar{y}) = \tilde{f}_{N'}(\bar{y}) - \bar{v}_{N,M}$$

The variance of this estimate can be estimated as:

$$\sigma_{\mathrm{gap}}^2 = \sigma_{N'}^2(\bar{y}) + \sigma_{\bar{v}_{N,M}}^2$$

The confidence interval for the optimality gap is then calculated as following.

$$\tilde{f}_{N'}(\bar{y}) - \bar{v}_{N,M} + z_\alpha\left(\sigma_{N'}^2(\bar{y}) + \sigma_{\bar{v}_{N,M}}^2\right)^{1/2}$$

with $Z_\alpha := \Phi^{-1}(1-\alpha)$ where $\Phi(z)$ is the cumulative distribution function of the standard normal distribution.

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When the estimated gap is judged as unreasonable, additional samples or increased sample size N must be tested (Chouinard et al., 2008). Note that quality of a solution to stochastic programming based sampling methods depends on several criteria such as, sample size, convergence rate, and stopping rules (criterion). Bayraksan and Morton (2009) in their tutorial introduced a procedure that shapes an interval estimator on the optimality gap of a certain solution. They provide methods reducing the variance and computational effort of the estimator they introduced. Also, they discussed ways to increase sample size without hurting computational effort in a smart way what they call "sequential sampling procedure". Researches similar to the sequential sampling procedure are done both in simulation and statistics (Chow and Robbins, 1965; Law and Kelton, 1982).

If the decision variables are continuous, it has been proven that an optimal solution of the SAA problem provides exact solution of the true problem with probability approaching to one exponentially fast as N increases (Shapiro and Homem-de-Mello, 2000; Ahmed and Shapiro, 2002a,b). Many studies are conducted to determine the required sample size. Kleywegt et al. (2002) applied the SAA method to stochastic discrete optimization problems, i.e., knapsack problem. They noted that the complexity of the SAA methods usually increases exponentially, at least linearly, in terms of sample size selected. Selecting the sample size is needed to consider the tradeoff between the bounds on the optimality gap and the quality of an optimal solution of a SAA problem and the computational performance. They expressed that selecting sample size should dynamically change depending on the previous results that are computed and the more proficient gap estimator of the approximated value function improves the performance of SAA method applied to the algorithm.

Problem definition and methodology that is used in this study is presented schematically as in Fig. 2.

3. Case study and data acquisition

Recycled WEEE is a very valuable material for Turkey and it is noted that the collection rates of WEEE increases fast in the last decade. It is difficult to obtain statistical data of WEEE utilization and recycling rates. In this study, proposed general RLND model is applied with the data of the waste electrical and electronic equipment collecting and recycling facility which operates in İzmit-Turkey. It is one of the biggest WEEE recycling companies in Turkey.

The company plans to develop a new RL network considering already functioning system to lead the market. The company has a limited process centers: such as collecting, sorting and recycling centers. The constructed network is a type of multi echelon and it has several steps: E-wastes are collected from regions, including distributors, original equipment manufacturers, and municipalities. In this study, region refers to a city or a district where waste occurs. In total 28 cities are selected as regions and are as follows: Adana, Afyon, Ankara, Antalya, Aydın, Balıkesir, Bursa, Çanakkale, Diyarbakır, Edirne, Erzurum, Eskişehir, İstanbul, İzmir, İzmit, Kırıkkale, Konya, Kütahya, Manisa, Mersin, Muğla, Niğde, Sakarya, Samsun, Tekirdağ, Trabzon, Yalova, and Zonguldak. Even though there are ten types of WEEE based on European Commission WEEE Directive (EC, 2003), in this study only four types of E-waste are considered because other six types of E-waste are not collected at an adequate amount in Turkey. These four types are large household appliances, IT and telecommunications equipment, lighting equipment and Small household appliances, respectively. In collecting centers waste is collected based on its type as specified above.

In this study, ten possible locations are considered as collecting centers and are as follows: Adana, Ankara, Antalya, Bursa, Eskişehir, Istanbul, Izmir, Izmit, Sakarya, and Tekirdag. Waste is transported from collecting centers to sorting centers in order to eliminate invaluable parts. There are seven potential sorting centers, Antalya, Erzurum, Gaziantep, Kayseri, Kocaeli, Tekirdağ, and Zonguldak, respectively. Lastly, five cities are considered as possible locations to build recycling center(s). These cities are: Adana, Ankara, Izmir, Kocaeli, and Samsun. Since the company already has a functioning disposing center and no further disposing center are needed, the management of the company decided not to change the disposing center's location. The disposing center is located in Gebze/Kocaeli. Also, the company sends the recycled products to Bursa, as a market. After recycling process some raw materials (commodities) are acquired. These commodities, i.e., gold, are sent to refinery where is located in Belgium, because the companies in Turkey do not have required license for recycling such metals. Potential facility sites are shown in Fig. 3.

The flow of the WEEE for Turkey through the network is shown in Fig. 4.

In this study, the data is acquired as following. The data is analyzed for 44 monthly time periods for four different types of waste which is collected from 28 regions. Based on our statistical analysis we concluded that the data fits exponential distribution for all types of products with different mean (λ) values: 211.1 for product 1, 1300.5 for product 2, 52.8 for product 3 and 158.3 for product 4. The parameter $\Phi_r^{p,s}$ (amount of product p occurred at region r in scenario s) is randomly generated from exponential distributions for each product, region and scenario. Please note that the SAA requires the equal occurrence probability for scenarios. Thus, each scenario is taken with the same probability occurrence and $\sum_{s\in S}\pi^s = 1$. The amount of waste is the first uncertain parameter in the model. In addition, two different uncertain parameters are considered, such as the quality of waste and the transportation cost. The quality of the waste is related to the percentage of the waste that is recyclable. This percentage is determined during the sorting process. During the sorting process the invaluable part $(1 - a^{p,s}, p \in Pr, s \in S)$ of the waste is sent to disposal center and the rest of the waste $(a^{p,s})$ is sent to recycling centers. The $a^{p,s}$ determines the percentage of the valuable waste that is sent to recycling centers. Based on the information gathered from the company's historical data, $a^{p,s}$ is randomly generated from uniform distribution which ranges from 0.8 to 0.9. Furthermore, the transportation costs are randomly generated from uniform distribution which ranges from 0.64 $ and 1.0 $ per kilometer per ton of waste.

The data related to distances in terms of km between regions and collecting centers, collecting centers and sorting centers, sorting centers and recycling centers and recycling centers and market, disposing center and refinery are presented in Appendices A1, A2, A3, and A4, respectively. The distance data are obtained from the General Directorate of Highways of Turkey (www.kgm.gov.tr).

3.1. Results and analysis

The calculations are carried out on a Windows 7 Home Premium, running Intel(R) Core(TM) i7-3612QM with 2.10 GHz processor and 12 GB RAM. The solution scheme is implemented in IBM Ilog CPLEX and MATLAB (R2010b) is used for statistical calculations.

We choose to solve the problem with three different sizes of replications: M = 5, 10 and 20 SAA problems. For the SAA problems, we use sample sizes of N = 20, 40, 60 and 100 scenarios. Each SAA problem is solved to optimality. The best feasible solution of SAA is then stored as a candidate solution for evaluation in the reference sample. The size of the reference sample is set to N' = 1000 scenarios.

A single scenario sub problem has 1.725 decision variables while 92 of them are binary and 621 constraints. The accumulated

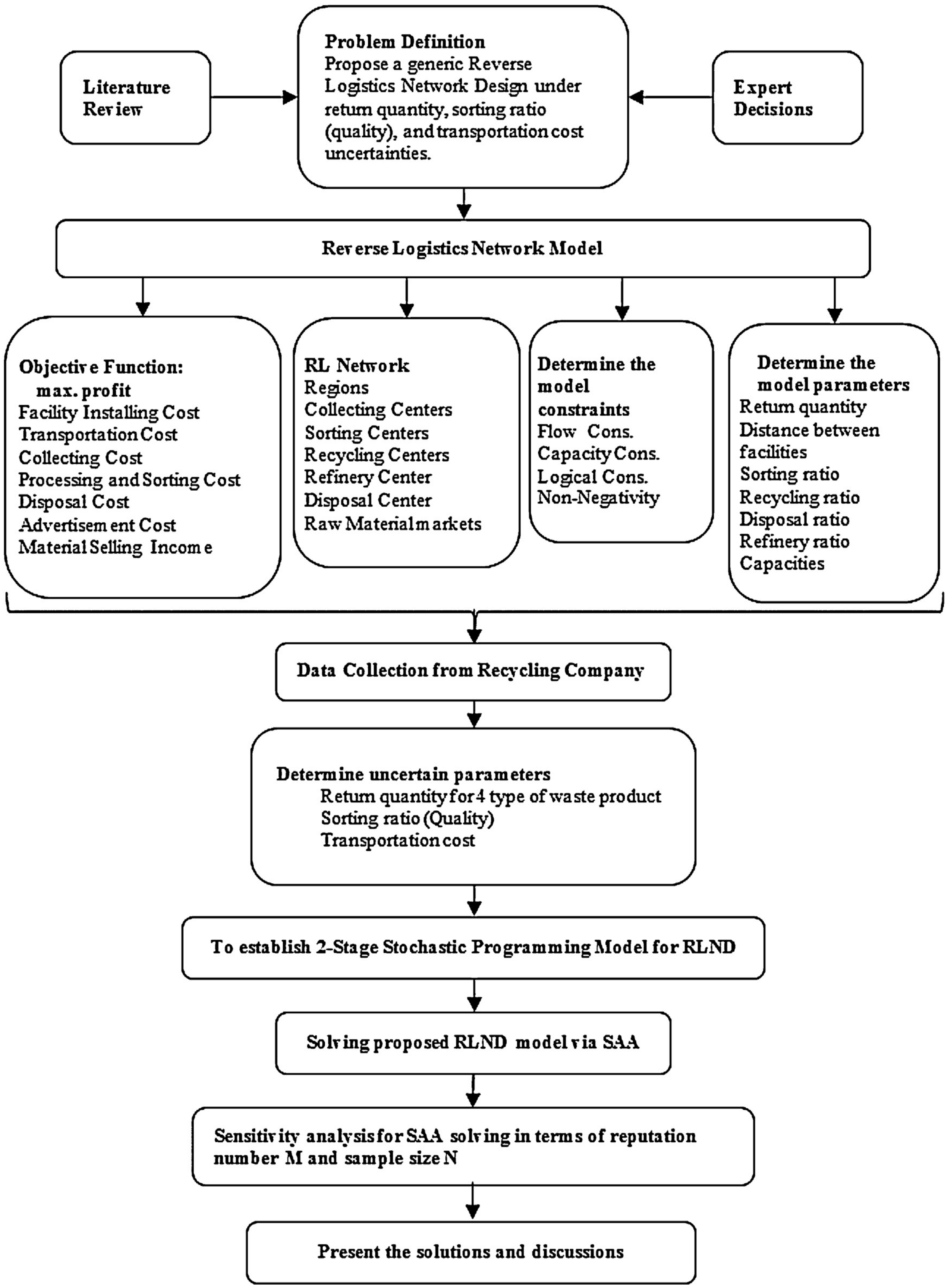

Fig. 2. Schematically representation of model.

problems with 20 scenarios have 32.752 decision variables and 12.230 constraints. Further, accumulated problems with 40, 60 and 100 scenarios have 65.412, 98.072 and 163.392 decision variables, whilst, 24.450, 36.670 and 61.110 constraints, consecutively.

Testing a given first-stage solution in the reference sample provides a statistical upper bound on the optimal objective function value of the original problem. For the accumulated problem instances, the average of *M* optimal objective function values of the SAA problems provides the statistical lower bound on the objective function value of the original problem.

The statistical lower and upper bounds and the best solutions and performances of the best solutions in the reference sample are presented in Table 2. The first and second columns in Table 2 show number of replications and sample sizes, respectively. The third and fourth columns show average of the objective function values and standard deviation of the upper bound while the fifth and

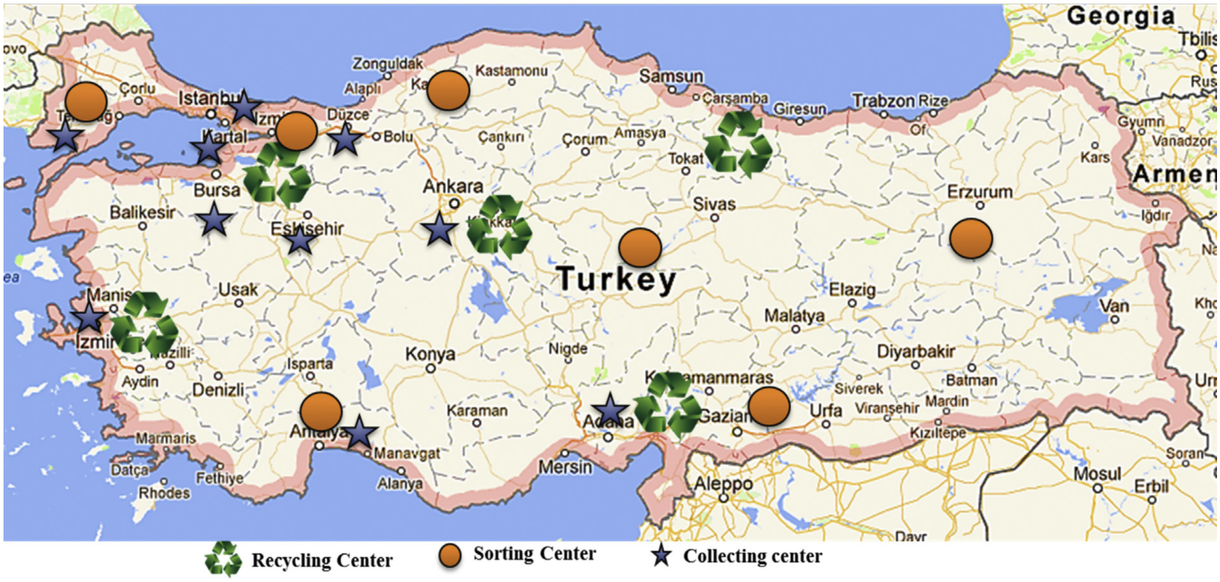

Fig. 3. Potential facility sites for RLND.

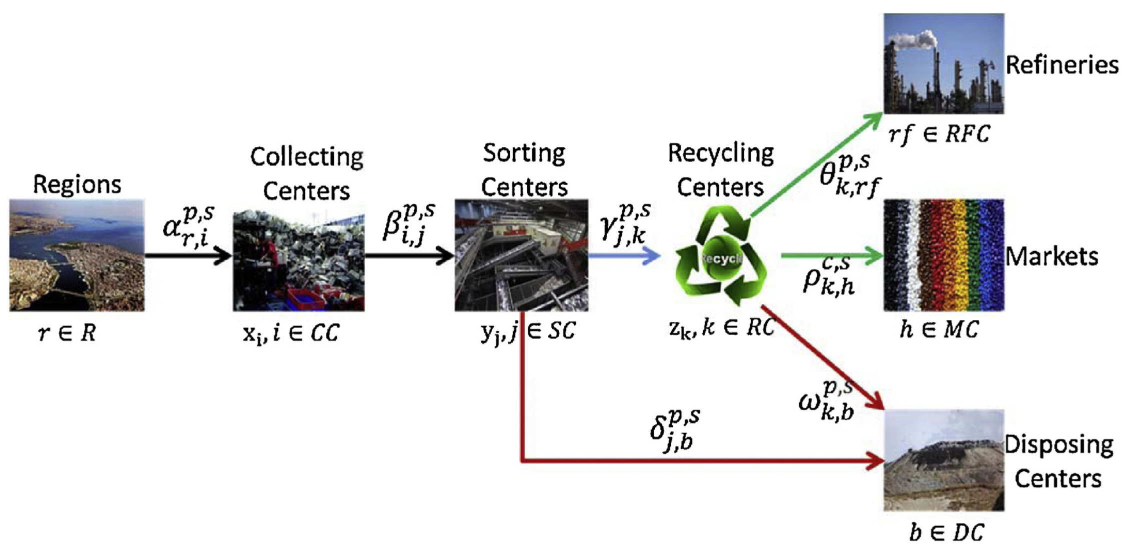

Fig. 4. Network and decision variables of RLND.

Table 2
Solutions, statistical lower and upper bound of the SAA problems with $N' = 1000$.

						Best solution			
		Upper bound		Lower bound		Collecting centers	Sorting centers	Recycling centers	
M	*N*	Average	σ (UB)	Average	σ (LB)				Objective
5	20	1.425.276	6.286	1.406.662	84.128	2, 5, 6, 8, 9, 10	5, 6, 7	2, 4	1.426.028
	40	1.424.187	7.243	1.412.373	74.575	2, 4,7, 8, 9, 10	5, 6, 7	2, 4	1.427.831
	60	1.426.125	6.034	1.410.959	74.973	2, 8, 9, 10	5, 6, 7	2, 4	1.429.352
	100	1.426.638	5.823	1.437.073	59.203	2, 3, 4, 6, 8, 9, 10	1, 5, 6, 7	2, 3, 4	1.429.464
10	20	1.424.789	6.124	1.440.859	91.118	2, 5, 6, 8, 9, 10	5, 6, 7	2, 4	1.426.028
	40	1.423.336	6.257	1.412.737	79.399	2, 4, 7, 8, 9, 10	5, 6, 7	2, 4	1.427.831
	60	1.426.533	2.881	1.425.921	69.212	2, 3, 4, 6, 8, 9, 10	1, 5, 6, 7	2, 3, 4	1.429.464
	100	1.425.607	2.639	1.435.860	64.271	2, 3, 8, 9, 10	1, 5, 6, 7	2, 3, 4	1.431.764
20	20	1.424.116	5.923	1.446.223	75.954	2, 5, 6, 8, 9, 10	5, 6, 7	2, 4	1.426.028
	40	1.425.727	3.106	1.411.103	72.600	2, 6, 8, 9, 10	5, 6, 7	2, 4	1.427.946
	60	1.427.399	2.295	1.417.800	69.316	2, 3, 4, 6, 8, 9, 10	1, 5, 6, 7	2, 3, 4	1.429.464
	100	1.427.228	2.350	1.427.048	68.388	2, 3, 8, 9, 10	1, 5, 6, 7	2, 3, 4	1.431.764

Table 3
Average optimality gap and confidence interval.

		Average optimality gap			90%Confidence interval			
M	*N*	Gap	%	σ (gap)	Min	%	Max	%
5	20	18.614	1.32	42.191	−43.196	−3.07	80.424	5.72
	40	11.814	0.84	37.424	−43.011	−3.05	66.640	4.72
	60	15.166	1.07	37.628	−39.959	−2.83	70.290	4.98
	100	−10.435	−0.73	29.780	−54.062	−3.76	33.192	2.31
10	20	−16.070	−1.12	30.542	−60.813	−4.22	28.674	1.99
	40	10.599	0.75	26.657	−28.454	−2.01	49.651	3.51
	60	612	0.04	23.283	−33.497	−2.35	34.721	2.43
	100	−10.253	−0.71	21.694	−42.034	−2.93	21.528	1.50
20	20	−22.107	−1.53	17.739	−48.095	−3.33	3.880	0.27
	40	14.625	1.04	16.998	−10.278	−0.73	39.528	2.80
	60	9.600	0.68	16.239	−14.191	−1.00	33.390	2.36
	100	180	0.01	16.017	−23.284	−1.63	23.644	1.66

sixth columns show these values for the lower bound. Columns 7–9 present the best solutions while the last column shows the performance of the best solutions in the reference sample. First, we note that the upper bound improved with the incremental in sample size and the number of replications. Further, the improvement is more significant when the sample size increased. Second, standard deviation is getting narrower simultaneously with the improvement in upper bound. We can see the same improvement in standard deviation of the lower bound as well. Third, we note that the more or the less number of opened facilities do not mean the better performance in the reference sample. The solution that gives the best performance, i.e. 1.431.764, in the reference sample is opening the collecting centers 2, 3, 8, 9, 10, sorting centers 1, 5, 6, 7 and recycling centers 2, 3, 4.

In Table 3, we present the estimator for the optimality gap as well as the upper and lower limit of the 90% confidence interval for the best solution by solving the SAA problems with different number of replications and sample sizes. The estimator for the optimality gap is calculated by subtracting the lower bound form the upper bound. The confidence interval for the optimality gap gets tighter as we enlarge the number of replications and the sample sizes of SAA problems. This mostly occurs due to a smaller variance of the lower bound. Therefore, increasing the number of replications but mostly the sample size, gives us a better guarantee regarding how close we are to the optimal solution of the original problem. Based on the results, the optimality gap indicated that the solutions found by the SAA procedure are sufficient to be used in a real life appliance.

We note that the average CPU-time for small size, i.e. N = 20, 40 SAA problems are less than 45 seconds, while CPU-time for medium sample size, i.e. N = 60, varied between 2 and 3 min and for bigger sample size, i.e. N = 100, varies between 7 and 8 min. It is clear that CPU time increased exponentially as we increased the sample size. Calculating the performance of a given first stage solution in the reference sample required approximately 2 min of CPU time.

One of the goals of solving numerous replications and sample sizes by SAA method is to find good candidates for the first stage solutions to be evaluated in the reference sample. The solution(s) with the best performance in the reference sample is reported and this solution can be considered in designing the RLND of the company. The upper bound from these solutions do not vary a lot, but the best upper bounds are obtained from the cases which used 100 scenarios in the SAA samples, regardless from the number of replications.

Furthermore, uncertainty is one of another challenge that is faced in real world applications. The approaches that handle uncertainty help researchers to get accurate results with the real world applications. In real world, parameters are not always known; although, in deterministic optimization programming, parameters are assumed certain. On the other hand, stochastic programming methodologies deal with uncertain parameter by incorporating different possible scenarios in the model infrastructure. The model developed in this study considered three types uncertainties while determining the optimal solution and these uncertainties are: amount of WEEE in system, the quality of collected WEEE and the transportation costs between nodes.

The results show that our solution approach produces good first stage solutions as candidate solutions to be tested in reference sample. We noted that our solution scheme was capable of finding good solutions even with small sized SAA problems. Increasing the sample size develops the lower bound on the optimal function value; consequently the quality guarantee on the optimality is improved. Higher sample size guarantee the quality of the solutions, whilst multiple replications help the solution approach to find more candidate first stage solutions to be tested in the reference sample. Fig. 5(a) and (b) present the average objective function value and standard deviation on upper bound, respectively. As seen in Fig. 5, usually higher average objective function values (a) and tighter standard deviations (b) are obtained with higher sample sizes. Another observation could be that higher number of

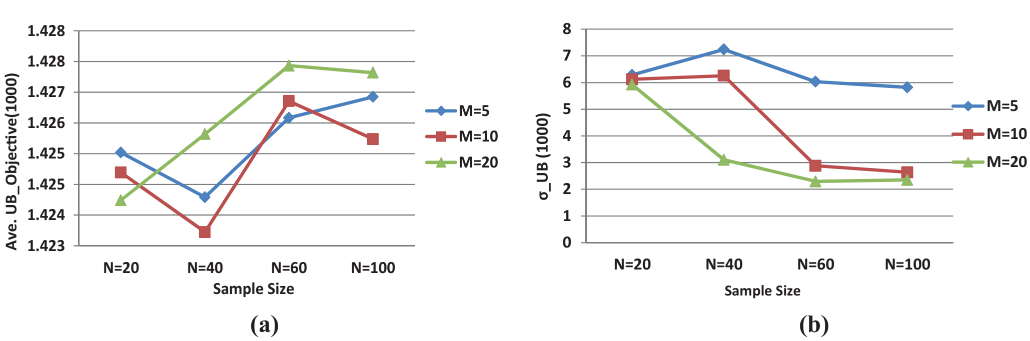

Fig. 5. Average objective function values and standard deviations on upper bound.

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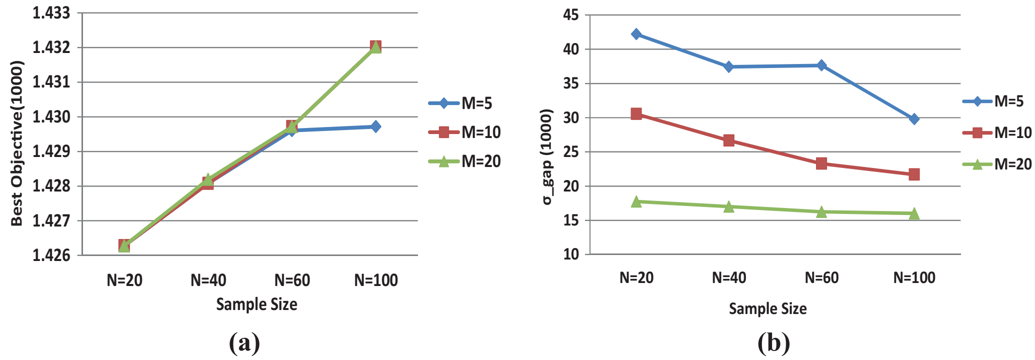

Fig. 6. Best objective function values and standard deviation on the optimality gap.

Fig. 7. Opened facilities.

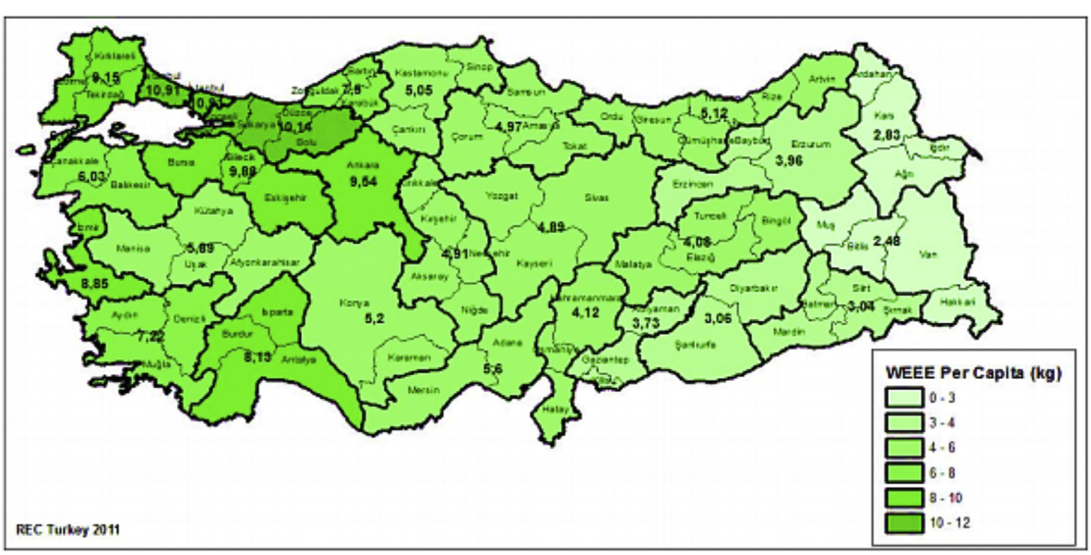

Fig. 8. WEEE amount—Turkey (2011).

replications did not guarantee better average objective function values but the narrower standard deviations.

As seen in Fig. 6(a), although, increasing the number of replications mostly do not help in finding better solution, it helped when $N = 100$. However, we can conclude that increasing the number of replications reduces the gap on optimality by a lot, as seen in Fig. 6(b). Lastly, based on the results in Fig. 6, we note that increasing sample sizes improves the solution found and the optimality gap especially when fewer replications are considered. Working with higher sample sizes provides better solutions with less optimality gap but CPU-time increases. Therefore a tradeoff between gathering better solutions and CPU times occurs for the managers and researchers.

According to the analysis the best solution is to open collecting centers 2, 3, 8, 9, 10 sorting centers 1, 5, 6, 7 and recycling centers 2, 3, 4 as shown in Fig. 7.

Comparing to the Regulatory Impact Assessment of EU Waste Electrical and Electronic Equipment (REC Turkey, 2011) report, the results are relevant, as presented in Fig. 8. WEEE production in Turkey (Fig. 8) supports the optimal solution presented in Fig. 7.

Consequently, the results show that the proposed method provides reliable solutions with a 90% confidence interval under uncertainties in RLND network design for decision makers.

4. Conclusions

In recent years, RL has received more attentions from companies in order to have sustainable process due to the economic, political, and environmental reasons. Today's WEEE generation increases each day and this causes air and environment pollution. Fortunately, the number of companies which realize the importance of recycling increases as well. Thus, modeling reverse supply-chain networks is required more than ever. Above all, developing sustainable networks in reverse logistics has become a fundamental concern due to the environmental issues.

For the reason that companies face pressures from stakeholders and governmental regulations, they need to recycle as much as a specific percentage of their annual production. Therefore, in practice, creating a sustainable RL network becomes a mandatory, especially when there are many uncertainties, i.e., quality of WEEE, costs etc., in the system.

To conserve resources, reusing, remanufacturing and recycling are the three of the most important processes, and reverse supply chain starts with these activities. However, all companies do not have chance to develop a RL network due to budged and operational capability constraints. Thus, a need of third party RL network occurs. This paper mainly focuses on developing a generic reverse logistics network for a third party recycling company.

In this study, a two-stage stochastic profit maximization RLND problem, which is a quite new technique for reverse supply network, with a real case study in WEEE recycling industry is presented. The mathematical formulation of the problem can be employed to any supply chain network design that comprises of multi echelons. It is also probable to adapt the model to a single echelon networks. The specific goal is to determine optimal locations for collecting, sorting and recycling centers and to determine the transportation of waste amounts between nodes in a RLND problem.

The contributions of this paper are as follows: First, this study is the first appliance, in WEEE literature for RLND network design under uncertain parameters, such as, amount of WEEE, quality of collected WEEE and transportation costs. Second, the RLND network is modeled as a SP model and it is solved by SAA. Third, the proposed model is a generic RLND for third party reverse logistic companies. Lastly, the proposed model is easy and effective to support establishing RLND decisions for managers and decision makers.

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Appendix A.

Distances between regions and collecting centers (km).

City	Region	Adana 1	Ankara 2	Antalya 3	Bursa 4	Eskişehir 5	Istanbul 6	Izmir 7	Izmit 8	Sakarya 9	Tekirdağ 10
Adana	1	5	490	558	837	686	939	900	828	791	1071
Afyon	2	573	256	292	273	144	454	327	343	306	586
Ankara	3	490	5	544	384	233	453	579	342	305	585
Antalya	4	558	544	5	537	424	718	444	607	570	850
Aydın	5	883	598	342	445	478	684	126	573	604	630
Balıkesir	6	897	533	505	151	300	390	176	279	310	380
Bursa	7	837	384	537	5	151	243	325	132	159	375
Çanakkale	8	1097	655	705	271	422	320	326	399	430	188
Diyarbakır	9	522	910	1080	1283	1132	1363	1422	1252	1215	1495
Edirne	10	1169	683	913	419	554	230	534	341	378	140
Erzurum	11	808	874	1251	1239	1107	1228	1453	1117	1080	1360
Eskişehir	12	686	233	424	151	5	324	411	213	176	456
İstanbul	13	939	453	718	243	324	5	564	111	148	132
İzmir	14	900	579	444	325	411	564	5	453	484	506
İzmit	15	828	342	607	132	213	111	453	5	37	243
Kırıkkale	16	475	75	567	459	308	528	654	417	380	660
Konya	17	356	258	322	487	336	660	550	549	512	792
Kütahya	18	673	311	364	173	78	354	333	243	206	486
Manisa	19	884	563	428	290	395	529	35	418	449	511
Mersin	20	69	483	489	829	678	932	892	821	784	1064
Muğla	21	869	620	311	544	500	783	225	672	636	729
Niğde	22	205	348	544	717	566	797	786	686	649	929
Sakarya	23	791	305	570	159	176	148	484	37	5	280
Samsun	24	729	414	906	745	647	734	993	623	586	866
Tekirdağ	25	1071	585	850	375	456	132	506	243	280	5
Trabzon	26	852	747	1236	1078	980	1067	1326	956	919	1199
Yalova	27	893	407	605	69	211	176	390	65	102	308
Zonguldak	28	754	268	753	342	359	331	667	220	183	463

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Appendix B.

Distances between collecting centers and sorting centers (km).

City	Collecting center	Antalya 1	Erzurum 2	Gaziantep 3	Kayseri 4	Kocaeli 5	Tekirdağ 6	Zonguldak 7
Adana	1	558	808	209	333	828	1071	754
Ankara	2	544	874	671	318	342	585	268
Antalya	3	5	1251	767	618	607	850	753
Bursa	4	537	1239	1044	691	132	375	342
Eskişehir	5	424	1107	893	540	213	456	359
Istanbul	6	718	1228	1124	771	111	132	331
Izmir	7	444	1453	1109	848	453	506	667
Izmit	8	607	1117	1013	660	5	243	220
Sakarya	9	570	1080	976	623	37	280	183
Tekirdağ	10	850	1360	1256	903	243	5	463

Appendix C.

Distance between sorting centers and recycling and disposing center (s) (km).

City	Sorting center	Adana 1	Ankara 2	Izmir 3	Kocaeli 4	Samsun 5	Gebze 1
Antalya	1	558	544	444	607	906	619
Erzurum	2	808	874	1453	1117	562	1.129
Gaziantep	3	209	671	1109	1013	725	1.025
Kayseri	4	333	318	848	660	453	672
Kocaeli	5	828	342	453	5	623	17
Tekirdağ	6	1071	585	506	243	866	255
Zonguldak	7	754	268	667	220	549	232

Appendix D.

Distance between recycling centers and market, disposing center and refinery (km).

City	Recycling center	Bursa	Gebze	Belgium
Adana	1	837	840	2125
Ankara	2	384	354	2125
Izmir	3	325	465	2125
Kocaeli	4	132	12	2125
Samsun	5	745	635	2125

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