JEB™
Website : www.jeb.co.in
E-mail : editor@jeb.co.in

Journal of Environmental Biology

ISSN: 0254-8704 (Print)
ISSN: 2394-0379 (Online)
CODEN: JEBIDP

Robust reverse logistics network design for the waste of electrical and electronic equipment (WEEE) under recovery uncertainty

Sun Qiang[1*] **and Xing-Zhong Zhou**[2]
[1*]School of Business and Administrator, Liaoning Technical University, Huludao, Liaoning, China
[2]Department of Automotive Engineering, Shandong Huayu University of Technical, Dezhou, Shandong China
*Corresponding Author E-mail: **yantainormal@163.com**

Abstract

The recovery of waste electrical and electronic equipment (WEEE) has become a major issue for solid waste management. Exploring new ways to dispose of WEEE has become mandatory in most of the countries in the world. Reverse logistics which is the backward flows of used product from consumers to producers is an important stage dealing with the WEEE. The reverse logistics network design for WEEE plays an important role in the total cost of recovery system. With this study, taking into account the uncertainty of reverse logistics network operation for WEEE, a robust mixed integer linear programming model for WEEE reverse logistics network was established for handling problem, which was affected by the uncertainty of recovery based on the risk preference coefficient and penalty coefficient deviated from the constraints, that could allow decision-makers to adjust the robust level of the operation system and risk preferences. The calculation and simulation of the model is used for lingo 11.0. The result showed that the robust mixed integer linear programming model was better than the classic model, which had a lower operational risk and could give consideration to the cycles of different circumstances that is effective in inhibiting the uncertainty of reverse logistics system for WEEE.

Publication Info

Paper received:
25 October 2015

Revised received:
27 April 2016

Re-revised received:
05 May 2016

Accepted:
23 June 2016

Key words

Network design, Reverse logistics, Recovery uncertainty, Robust optimization, WEEE

Introduction

With the development of economy and increased in consumption of natural sources, the economic usage and recovery of natural resources for industrialized society have become vital for the sustainability of life. Thus, new ways to reduce consumption of resources need to be investigated (Kilic *et al.,* 2015).

Reverse logistics such as recovery of used products has become more important. One of the important materials considered within reverse logistics is the waste of electrical and electronic equipment (WEEE). Waste electrical and electronic equipment contains more than 1,000 different substances, many of which are toxic for human health and environment, such as lead, mercury, arsenic, chromium, cadmium and plastics (Menikpura *et al.,* 2014)

Emissions resulting from end of life treatment may release hazardous compounds into the environment, such as dioxins and furans. Thus, WEEE requires specific end-of-life treatments to ensure proper recycling or disposal. Reuse, as one important strategy in 3R (Reduce, Reuse, Recovery) principles of waste management, plays an important role to minimize the environmental impacts in Waste Electrical and Electronic Equipment (WEEE) management (Truttmann *et al.,* 2006; Williams *et al.,* 2008; Devoldere *et al.,* 2009).

WEEE such as computers, TV-sets, fridges and cell phones are the fastest growing waste streams in the EU, with some 9 million tones generated in 2005, and expected to grow to more than 12 million tonnes by 2020 (He *et al.,* 2006).

WEEE is a complex mixture of materials and components because of their hazardous content, and if not properly managed, can cause major environmental and health problems. Moreover, the production of modern electronics requires the use of scarce and expensive resources (Alumur *et al.,* 2012). To improve the environmental management of WEEE and to contribute to a circular economy and enhance resource efficiency, the improvement of collection, treatment and recycling of electronics at the end of their life is essential.

The first WEEE Directive (Directive 2002/96/EC) entered into force in February 2003. The Directive provided for the creation of collection schemes where consumers return their WEEE free of charge. These schemes aim to increase the recycling of WEEE and reuse (Darby *et al.,* 2005). In accordance with the Directive 2002/96/EC, the WEEE recovery product categories are classified in Table 1.

High recycling and disposal costs encourage waste electrical and electronic equipment (WEEE) flows out of the developed world and down to the points of lowest-cost disposal. Lowest cost, however, usually means little oversight over the treatment process, assuming that the waste has been treated and not directly dumped into landfills (Wong *et al.,* 2007; Scharnhorst *et al.,* 2007).

Ongondo *et al.* (2011) reported that there are different WEEE management practices in various countries such as Germany, United Kingdom, Switzerland, China, India and Japan. They presented the existing situation of countries regarding the global trends in the quantities and composition of WEEE. There are numerous studies related to the reverse logistics. Studies dealing with the network designs for different sectors include steel industry, recycling of sand, carpets, batteries, tires and paper. Bigum *et al.* (2013) examined the network design for battery recycling options. Krikke (2011) and Srivastava (2008) focused on the remanufacturing of copiers and personal computers. Regarding studies on different sectors, there are good representations of reverse logistics networks.

There are different WEEE management practices in various countries. China has presented the existing situation regarding the global trends in the quantities and composition of WEEE. Table 2 shows that China has constructed a suitable reverse logistics network to reuse the resources for remanufacturing. Domestic enterprises in China has become the body of recovery system with expanding their recycling network and extending the industry chain, which built the “3-bit” recovery system pilot such as recovery site, sorting center and terminal market. The traditional recycling, sorting, processing and handling model are upgrading. But there are still many problems such as low level of organization, no standardization of operational processes, as well as lower coordination of recycling, transport, storage and other issues. The recycling organization has faced many problems such as less market competitiveness and difficulty in management.

As the promoting process of industrialization and urbanization, resource consumption is increasing but not decreasing. The resource bottleneck has become more prominent, which poses a serious threat to the country's economic security. The collection, storage, transport, treatment and recycling of WEEE, as well as its preparation

Table 1 : Ten WEEE product categories (Grunow *et al.,* 2009)

No.	Category
1	Large household appliances
2	Small household appliances
3	IT and telecommunications equipment
4	Consumer equipment
5	Lighting equipment
6	Electrical and electronic tools
7	Toys, leisure and sports equipment
8	Medical devices
9	Monitoring and control instruments
10	Automatic dispensers

Table 2 : Recovery species of mainly renewable resources (unit: 10^4 tonne)

No.	Category	2009	2010	2011	2012	2013
1	Iron and Steel	7620	8310	9100	8400	8570
2	Non-ferrous metals	361	405	455	530	562
3	Plastic	1000	1200	1350	1600	1366.2
4	Paper	3423	3695	4347	4472	4377
5	Tire	306.9	334.7	329	370.3	375
6	WEEE	280	284.3	370.6	190.7	263.8
7	Automobile	147	276	183	200	276.7
8	Boats and ships	323	187	225.2	255	250

for reuse shall be conducted with an approach to protect the environment and human health and preserving raw materials.

In the present study, a description of the problem and a nominal model of WEEE reverse logistics network and robust optimization approach with numerical examples have been proposed.

Materials and Methods

There are many logistics network design models available for forward logistics network design problem, which has been configured from suppliers to customers through direct and forward flows of goods among production and distribution centers and customers. Melo *et al.* (2009) provided a comprehensive review on the facility location models in the context of strategic supply chain planning. Listes and Dekker (2005) proposed a stochastic mixed integer programming model with several scenarios to design a reverse network. Listes (2008) developed a stochastic model for a network design problem. Salema *et al.* (2007) proposed a stochastic mixed integer programming for multi-product networks to deal with demand uncertainty. Ding *et al.* (2009) developed a stochastic simulation based optimization approach to design a production–distribution network. Lee and Dong (2009) introduced a two stage stochastic programming to take uncertainty into account in a dynamic reverse logistics. Kara and Onut (2010) presented a two-stage stochastic programming model for a paper recycling reverse logistics network design under uncertainty. Pishvaee *et al.* (2009) proposed a scenario-based stochastic programming for an integrated forward–reverse logistics network design under demand, quantity and quality return rate and variable cost uncertainty. El-Sayed et al. (2010) developed a stochastic mixed integer linear programming for designing a forward–reverse logistics under demand uncertainty. They considered a multi-period integrated network including suppliers, facilities and distribution centers in the forward flow and disassembly, and redistribution centers in the reverse flow. Ramezani *et al.* (2013) introduce a multi-objective stochastic model for designing a forward–reverse logistic network, which optimizes three objective functions namely the profit, the customer responsiveness and the quality level.

Robust optimization is a recent methodology for handling problems affected by uncertain data, where no probability distribution is available on the ambiguous parameters. The goal of the robust optimization framework is to obtain a robust solution, which protects the decision maker against adverse realizations of the uncertainty. A specific definition of robustness depends on the modeling of uncertainty, location of uncertainty within the problem and decision-making context. A robust optimization (RO) can be considered as an alternative approach for dealing with the first category of risk in the case where there is no enough historical data to estimate the probability distribution of the uncertain parameters. Ben-Tal and Nemirovski (1998) developed an approach for robust convex optimization that solves the robust counterpart of the uncertain problem. Bertsimas and Sim (2004) contributed to the evolution of robust optimization. RO approaches have been introduced by Mulvey *et al.* (1995). Pishvaee *et al.* (2011) and Hasani *et al.* (2012) that consider RO approach to design robust closed-loop supply chain networks. The objective of cost minimization can be found in most supply chain network design models (Shen, 2006).

Stochastic programming is the most widely accepted tool that is used to design a robust supply chain network. However, limited researches employ robust optimization approach to tackle the existing uncertainties in supply chain network design. For example, Pishvaee *et al.* (2011) and Hasani *et al.* (2012) used a robust optimization approach to design closed-loop logistics networks.

The existing studies just can cope up with one category of risks, while the present study proposes a robust and reliable model for an integrated forward–reverse logistics network design that deals with both types of the supply chain risks. To the best of our knowledge, this is a first attempt for doing so. Furthermore, it is worth pointing out that it is the first study which takes the issue of reliability into account for designing an integrated reverse logistics network. This paper deals with the robust optimization approach for designing a forward–reverse logistics network to cope up

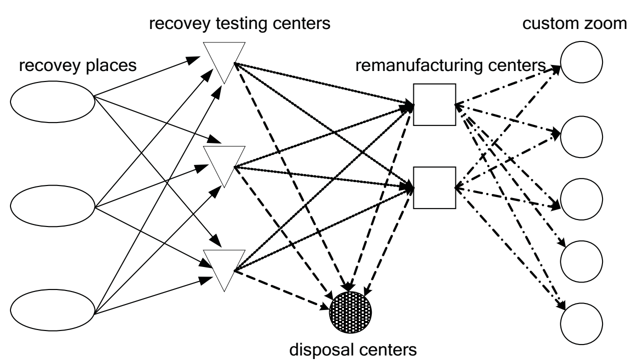

Fig. 1 : WEEE reverse logistics network

with the uncertainty in the customer's demand, the quantity and quality of returned products.

It is necessary to build a multi-million-recycling, focusing on sorting and disassembling, safety transport recovery system satisfying the requirements of WEEE. At this point, few workers have provided the WEEE reverse logistics network design. In order to fill up this gap, a WEEE reverse logistics network was performed based on different scenario each of which is based on different quantities of WEEE. It was determined to minimize the total cost of the system. The network was modeled via a mixed robust integer liner programming which was developed by the generic models in the literature. The model was different from the existing literature for handling problems affected by the uncertainty of recovery based on the risk preference coefficient and penalty coefficient deviated from the constraints, which would allow decision-makers to adjust the robust level of the operation system and risk preferences.

Problem definition : A single period, single product, multi-echelon WEEE reverse logistics network consisting of recovery and remanufacturing as well as disposal centers was considered. Recovery products collected from the recovery places first entered into the recovery testing centers, parts of usefulness were remanufactured in remanufacturing centers, others were disposed off to the disposal centers. At the end, the new products would be sold in the market (Fig.1). This network has several advantages such as saving in costs and pollution reduction. Three flows were taken into account in this study: flows from the recovery places to the recovery testing centers, flows from the recovery testing centers to the remanufacturing centers and the flows from the recovery testing centers to the disposal centers. The goal of WEEE reverse logistics network was to determine the optimal cost, number of recovery testing and disposal centers and optimal quantity of the recovery product flow.

The following sets parameters and variables are defined to formulate the WEEE reverse logistics network :

Sets

I : potential numbers of recovery centers, indexed by i

J : potential numbers of recovery testing centers, indexed by j

K : potential numbers of remanufacturing centers, indexed by k

M : potential numbers of disposal centers, indexed by m

T : planning horizon, indexed by t

Parameters

C_y^{ij} : unit transportation cost from i reverse place to j testing center

C_f^{ij} : unit other fixed cost from i reverse place to j testing center

d_{ij} : distance from i reverse place to j testing center

C_y^{jk} : unit transportation cost from j testing center to k remanufacturing center

C_f^{jk} : unit other fixed cost from j testing center to k remanufacturing center

d_{jk} : distance from j testing center to k remanufacturing center

C_y^{jm} : unit transportation cost from j testing center to m disposal center

C_f^{jm} : unit other fixed cost from j testing center to m disposal center

d_{jm} : distance from j testing center to m disposal center

C_y^{km} : unit transportation cost from k remanufacturing center to m disposal center

C_f^{km} : unit other fixed cost from k remanufacturing center to m disposal center

d_{km} : distance from k remanufacturing center to m disposal center

α_{ij} : rate of recovery

β_{jk} : rate of remanufacturing

FC_j : fixed cost of recovery center

FC_m : fixed cost of disposal center

p_{ij} : recovery cost per unit

r_{ij} : disposal cost per unit

e_{ij} : equipment running cost per unit

C_I : maximum capacity of testing center

C_C : maximum capacity of remanufacturing center

C_D : maximum capacity of disposal center

Variables

q_{ij} : quantity of recycled WEEE from i recovery place to j testing center

q_{ik} : quantity of reused WEEE from i recovery place to k remanufacturing center

q_{jm} : quantity of disposed WEEE from j testing center to m disposal center

q_{km} : quantity of disposed WEEE from k remanufacturing center to m disposal center

$Y_j \in \{0,1\}$: binary variable equals to 1 if recovery testing center j is open, 0 otherwise

$Y_m \in \{0,1\}$: binary variable equals to 1 if disposal center m is open, 0 otherwise

The objective function of the model was to minimize the total cost of the WEEE reverse logistics network such as fixed opening costs of facilities, recovery and disposal costs, transportation costs and equipment running costs.

$$P(\mathrm{I}):\ minTC = \sum_j FC_j^t \cdot Y_j^t + \sum_m FC_m^t \cdot Y_m^t + \sum_i \sum_j q_{ij}^t \cdot p_{ij}^t + \sum_j \sum_m r_{jm}^t \cdot \left(1-\alpha_{ij}\right) \cdot q_{jm}^t$$
$$+ \sum_k \sum_m r_{jm}^t \cdot \alpha_{ij} \cdot \beta_{jk} \cdot q_{km}^t + \sum_j \sum_k e_{jk}^t \cdot \alpha_{ij} \cdot \beta_{jk} \cdot q_{jk}^t + \sum_i \sum_j \left(C_r^{ij} + C_f^{ij}\right) \cdot d_r^{ij} \cdot q_{ij}$$
$$+ \sum_j \sum_k \left(C_r^{jk} + C_f^{jk}\right) \cdot d_r^{jk} \cdot q_{jk} + \sum_k \sum_m \left(C_r^{km} + C_f^{km}\right) \cdot d_r^{km} \cdot q_{km} + \sum_j \sum_m \left(C_r^{jm} + C_f^{jm}\right) \cdot d_r^{jm} \cdot q_{jm}$$

Subject to:

$$\sum_i \sum_j Y_j^t \cdot q_{ij}^t \le C_I^t \tag{1}$$

$$\sum_j \sum_m Y_m^t \cdot q_{jm}^t + \sum_k \sum_m Y_m^t \cdot q_{km}^t \le C_D^t \tag{2}$$

$$\sum_j \sum_k q_{jk}^t \le C_C^t \tag{3}$$

$$\Phi Y_j \ge C_r^t \tag{4}$$

$$\Phi Y_m \ge C_p^t \tag{5}$$

$$\sum_j q_{ij}^t = q_i^t \tag{6}$$

$$\sum_i \sum_j q_{ij}^t = \sum_j \sum_k q_{jk}^t + \sum_j \sum_m q_{jm}^t \tag{7}$$

$$\sum_i \sum_j \left(1-\alpha_{ij}\right) \cdot q_{ij}^t = \sum_j \sum_m q_{jm}^t \tag{8}$$

$$\sum_i \sum_j \alpha_{ij} \cdot q_{ij}^t = \sum_j \sum_k q_{jk}^t \tag{9}$$

$$\sum_j \sum_k \left(1-\beta_{jk}\right) q_{jk}^t = \sum_k \sum_m q_{km}^t \tag{10}$$

$$Y_j \in \{0,\ 1\},\ j \in J \tag{11}$$

$$Y_m \in \{0,\ 1\},\ m \in M \tag{12}$$

$$q_{ij}, q_{jk}, q_{jm}, q_{km} \ge 0, \forall i \in I, j \in J, k \in K, m \in M \tag{13}$$

The first two terms in the objective function presents the costs of fixed opening of recovery testing centers and disposal centers. The following four terms in the objective function represent the cost of recovery, disposal and equipment running cost. The last four terms in the objective function represent transportation and other fixed cost, i.e., the transportation and other fixed costs from reverse places to testing centers, transportation and other fixed costs from testing centers to remanufacturing centers, transportation and other fixed cost from testing centers to remanufacturing centers, transportation and other fixed costs from remanufacturing centers to disposal centers.

Constraints (1)-(3) impose the capacity restrictions on the recovery testing centers, disposal centers and remanufacturing facilities. Constraints (4) and (5) refers to the binary and their corresponding restrictions. Constraints (6)-(10) balance the flow of recovery, recovery testing, remanufacturing centers and disposal centers which could be fully or partially satisfied. Since the objective function was a type of minimization, this inequality constraint set would be satisfied for the equality status at optima. Constraints (11) and (12) specify that Y_j and Y_m are binary variables. Constraint (13) ensures that all decision variables were not-negative.

Robust optimization model for WEEE reverse logistics network

Framework of robust optimization model : Robust optimization is one of the predominant approaches in solving linear optimization problems with uncertain data. The first step in this direction was taken by Soyster (1973), El-Ghaoui and Lebret (1997). Then, it was further developed by Ben-Tal and Nemirovski (1998, 1999, 2000), El-Ghaoui et al. (1998), Bertsimas and Sim (2004). Robust optimization is able to tackle the decision makers favored risk aversion or service-level function and has yielded a series of solutions that are progressively less sensitive to realizations of the data in a scenario. The optimal solution provided by a robust optimization model is called robust if it remains "close" to the optimal if input data change. This is regarded as solution robustness. A solution is called robust if it is "almost" feasible for small changes in the input data. This is regarded as model robustness. Robust optimization integrates a goal-programming formulation with a scenario-based description of input data. The model generates a series of solutions that are progressively less sensitive to realizations of input data from a set of scenarios. Robust optimization includes two distinct constraints: a structural constrain and a control constrain. Structural constrain are formulated following the concept of linear programming and its input data are free of any noise, while control constrain are taken as an auxiliary constrain influenced by noisy data. The framework of robust optimization approach is briefly described as follows:

The primary optimization LP model is as follows:

$$Min\, c^T x + d^T y$$

Subject to:

$$Ax = b \qquad (14)$$

$$Bx + Cy = e \qquad (15)$$

$$x, y \geq 0 \qquad (16)$$

where, x is the vector of decision variables and y is the vector of control variables. Constrain (14) is the structural constraint whose coefficients are deterministic and free of noise. Constrain (15) is the control constraint whose coefficients are random and subject to noise. Constrain (16) ensures non-negative vectors. The problems formulated by robust optimization involves a set of scenarios $\Omega = \{1, 2, ..., S\}$. Under each scenario $s \in \Omega$, the coefficients associated with the control constraint will become $\{d_s, B_s, C_s, e_s\}$ with fixed probability p_s of scenario ξ, which represents the probability that scenario s happens and has $\sum_{s=1}^{s} p_s = 1$. The optimal solution of this model would be robust with respect to optimality if it remains "close" to optimality for any realization of the scenario $s \in \Omega$. This is termed as solution robustness. The solution is also robust with respect to feasibility if it remains "almost" feasible for any realization of s. This is termed model robustness.

The scenario based robust optimization approach is as follows:

$$Min\, \sigma(x, y_1, y_2, ..., y_s) + \omega\rho\,(\eta_1, \eta_2, ..., \eta_s)$$

Subject to :

$$Ax = b \qquad (17)$$

$$B_s x + C_s y_s + \eta_s = e_s \qquad (18)$$

$$x, y_s, \eta_s, \geq 0,\ \forall s \in \Omega \qquad (19)$$

There are two terms in the objective function: the first represents solution robustness and the second represents model robustness weighted by ω. The aim of this model was to balance the trade off between solution robustness and model robustness. The second term in the objective function $\rho(\eta_1, \eta_2, ..., \eta_s)$ is a feasibility penalty function, which was used to penalize violations of control constraints under some of the scenarios. The violation of control constrain means that the infeasible solution to a problem under some of the scenarios is obtained. Using the weight ω, the trade-off between solution robustness measured from the first term $\sigma(\bullet)$ and model robustness measured from the penalty term $\rho(\bullet)$ can be modeled under the multi-criteria decision-making process. For instance, if $\omega = 0$, the objective is to minimize the term $\sigma(\bullet)$ and the solution may be infeasible; while if ω is assigned to be sufficiently large, the term $\rho(\bullet)$ dominates the objective and results in a higher cost (Leung *et al,* 2007).

The appropriate form of $\sigma(\bullet)$ and $\rho(\bullet)$ can be referred to Mulvey *et al.* (1995), Mulvey and Ruszczynski (1995) and Yu and Li (2000). The term $\rho(\eta_1, \eta_2, ..., \eta_s)$ proposed by Mulvey *et al.* (1995) is the mean value of $\sigma(\bullet)$ plus a constant λ times the variance:

$$\sigma(x, y_1, y_2, \ldots, y_s) = \sum_{s\in\Omega} p_s \xi_s + \lambda \sum_{s\in\Omega} p_s \left(\xi_s - \sum_{s\in\Omega} p_{s'} \xi_{s'}\right)^2 \qquad (20)$$

However, the expression in (20) involves a complicated term $\sum_{s\in\Omega} p_s \left(\xi_s - \sum_{s\in\Omega} p_{s'} \xi_{s'}\right)^2$ because it generates quadratic forms in formulation. Yu and Li (2000) pointed out that to minimize objective (20) the robust optimization model requires a great deal of computation. They proposed a formulation for $\sigma(x, y_1, y_2, ..., y_s)$ in place of (20) which is as follows:

$$\sigma(x, y_1, y_2, \ldots, y_s) = \sum_{s\in\Omega} p_s \xi_s + \lambda \sum_{s\in\Omega} p_s \left|\xi_s - \sum_{s\in\Omega} p_{s'} \xi_{s'}\right|$$

Yu and Li (2000) proposed an efficient method that was initiated by Li (1996) who presented numerous formulations to solve goal-programming problems. The framework of Yu and Li's model was designed to minimize the objective function in the following form:

$$Min\ \ z=\sum_{s\in\Omega}p_s\xi_s+\lambda\sum_{s\in\Omega}p_s\left[\left(\xi_s-\sum_{s'\in\Omega}p_{s'}\xi_{s'}\right)+2\theta_s\right]$$

Subject to :

$$\xi_s-\sum_{s\in\Omega}p_s\xi_s+\theta_s\geq 0 \tag{21}$$

$$\theta_s\geq 0 \tag{22}$$

If $\xi_s-\sum_{s\in\Omega}p_s\xi_s\geq 0$, then $\theta_s=0$ and

$$z=\sum_{s\in\Omega}p_s\xi_s+\lambda\sum_{s\in\Omega}p_s\left(\xi_s-\sum_{s'\in\Omega}p_{s'}\xi_{s'}\right).$$

On the other hand, if $\xi_s-\sum_{s\in\Omega}p_s\xi_s<0$,

then $\theta_s=\sum_{s\in\Omega}p_s\xi_s-\xi_s$ and

$$z=\sum_{s\in\Omega}p_s\xi_s+\lambda\sum_{s\in\Omega}p_s\left(\sum_{s'\in\Omega}p_{s'}\xi_{s'}-\xi_s\right).$$

The proposed robust optimization model : In this study we defined $\{q_{ij}, q_{jk}, q_{jm}, q_{km}\}$ scenario based uncertain $\{q^s_{ijt}, q^s_{jkt}, q^s_{jmt}, q^s_{kmt}\}$. In this paper, an absolute penalized form has been used for obtaining the solution robustness measurement in objective function. The developed robust optimization model for the mentioned problem can be stated as follows:

The first and second terms in objective function are the mean value and variance of total costs respectively, and they measure solution robustness. The third term in objective function measures the model robustness with regards to infeasibility associated with control constraints (23) under scenario ξ.

Results and Discussion

Computational results : Some computational experiments were performed to evaluate the robustness and effectiveness of the model in generating robust production plan, in which some parameters are scenario based uncertainty. A data set was generated from a real reverse logistics enterprise, which was used as a real-world industrial case to illustrate the applicability of proposed robust optimization model for practical problems.

Considering a WEEE reverse logistics network with six periods, five recovery centers, two remanufacturing centers, four recovery testing centers and three disposal centers were selected. Some of the parameters in the numerical examples were determined as follows: $\alpha_{ij}=\beta_{jk}=0.7$, $p_{ij}=100$, $r_{jm}=150$, $e_{jk}=120$. There are four scenarios with

$$Min\ \ z=\sum_t\sum_{s\in S}p_s\xi_s+\lambda\sum_t\sum_{s\in S}p_s\left[\left(\xi_s-\sum_{s'\in S}p_{s'}\xi_{s'}\right)+2\theta_s\right]+\sum_t\sum_{s\in S}p_s\sum_i\sum_j\omega_{ijs}\delta_{ijs}$$

$$\xi_s=\sum_t\sum_j FC^t_j\cdot Y^t_j+\sum_t\sum_m FC^t_m\cdot Y^t_m+\sum_t\sum_i\sum_j q^t_{ijs}\cdot p^t_{ij}+\sum_t\sum_j\sum_m r^t_{jm}\cdot\left(1-\alpha_{ij}\right)\cdot q^t_{jms}$$

$$+\sum_t\sum_k\sum_m r^t_{jm}\cdot\alpha_{ij}\cdot\beta_{jk}\cdot q^t_{kms}+\sum_t\sum_j\sum_k e^t_{jk}\cdot\alpha_{ij}\cdot\beta_{jk}\cdot q^t_{jks}+\sum_t\sum_i\sum_j\left(C^{ijt}_r+C^{ijt}_f\right)\cdot d^{ijt}_r\cdot q^t_{ijs}$$

$$+\sum_t\sum_j\sum_k\left(C^{jkt}_r+C^{jkt}_f\right)\cdot d^{jkt}_r\cdot q^t_{jks}+\sum_t\sum_k\sum_m\left(C^{kmt}_r+C^{kmt}_f\right)\cdot d^{kmt}_r\cdot q^t_{kms}+\sum_t\sum_j\sum_m\left(C^{jmt}_r+C^{jmt}_f\right)\cdot d^{jmt}_r\cdot q^t_{jms}$$

$$\xi_s-\sum_{s\in S}p_s\xi_s+\theta_s\geq 0 \tag{23}$$

$$\theta_s\geq 0,\forall s\in\Omega \tag{24}$$

$$q^t_{ijs},q^t_{jks},q^t_{jms},q^t_{kms}\geq 0\qquad \forall i\in I,j\in J,k\in K,m\in M,t\in T \tag{25}$$

with constraint (1)–(13).

0.2, 0.25, 0.35, 0.2 probabilities. The other data related to this real-word practical problem are given in Tables 3-11. At the beginning of horizon, inventory and back-order of products were considered as zero.

All computations were run using the branch and bound algorithm accessed via LINGO 12.0 on a PC with Windows XP (Professional SP3), Intel Core 2 Duo (Core i7-4510U, 2 M Cache, 2.80 GHz) using 1 GB memory of RAM.

The computational results are shown from Tables 12 and 17. Table 12 shows the optimal solutions found for the numerical example under certain mixed integer liner programming model and uncertain robust mixed integer liner programming model. Table 13 to 16 shows the robust optimal solutions such as q_{ij}, q_{ik}, q_{jm} and q_{km}. Table 17 shows the location of recovery testing centers and disposal centers in every period under robust model.

Trade-off between solution robustness and model robustness : Trade-off between solution robustness and model robustness can be estimated using ω in the objective function. As mentioned before, robust optimization approach allows for infeasibility in the control constrain by means of penalties. δ_{ijs} is equal to z due to a minimization of objectives, hence no production was suggested in the optimal plan. The total loss attained its highest value, and obviously this plan cannot be adopted. Therefore, it is necessary to evaluate the proposed robust optimization model with various ω on a practical production planning problem. Trade-off feasibility with cost is illustrated in Fig. 2. As the value of ω increased, the expected total costs representing solution robustness increased exponentially, and the expected total loss representing model robustness dropped. This means that for larger values of ω, the solution obtained was approaching 'almost' feasible for any realization of scenario n through payment of more total cost. Moreover, the expected total loss would eventually drop to zero with an increase in value of ω.

Robust optimization was used to obtain a robust solution against the fluctuation of uncertain parameters in future. At the beginning of planning horizon some parameters were uncertain, and just in the execution time of the plan the oriented values of uncertain parameters were determined. The real state of system with really occurred parameters during execution time was determined to demonstrate the robustness of the proposed model. For this purpose, we simulate some possible real scenarios that may occur after executing the production plan in future. Ten random occurrence were considered for uncertain parameters and total cost of each instance was computed for the production plans obtained by robust mixed-integer linear programming model and primary mixed-integer linear programming model.

The total costs obtained by the primary model yielded a series of solutions that were less sensitive to realizations of uncertain data. In other words, violation of results obtained by the robust optimization model was less than primary model. In fact, the values of total cost for robust model was closer to each other than the values for primary model. The curve of total cost in proposed method followed a more robust trend but fluctuation in curve of total cost for primary approach was too high. This problem indicates that the proposed approach was efficient for any system and the robustness of solution was important in addition to total cost of WEEE reverse logistics. Moreover, for such systems having a solution with minimum total cost is not adequate, but the fluctuation in real scenarios in future would be low.

The recovery of used WEEE materials is an essential field. Depending on the importance of this issue, several studies have been performed in recent years. Reverse logistics dealing with the backward flows in a recovery system has become very important. WEEE reverse logistics is a logistic activity composed of recycling, remanufacturing, reusing, waste disposal and repair processes, which can be used for recovery materials by reverse logistics network and can be enhanced for survival and development of environment.

In this paper a robust and reliable mixed-integer linear programming model for designing a WEEE reverse network has been proposed, which can cope up with the parameters' uncertainty and facility locations simultaneously. The parameters' uncertainty, which is considered in quantity of recycled, reused and disposed WEEE, is modeled using the robust optimization approach. The computational results show that the proposed robust model is more practical for handling uncertain parameters in WEEE reverse logistics. The trade off between optimality and infeasibility was used for obtaining robust solution based on the opinion of decision-makers. Furthermore, the results obtained by the robust model indicate the violation of results obtained by the robust optimization model are less than primary model and closer to each other than the values for primary model. Moreover, the total costs obtained by the robust model are

Table 3 : Quantity of recovery from recovery center

recovery center	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
1	1200	1420	1000	1200	1040	1550
2	1050	1200	900	1050	950	1400
3	1300	1500	1230	1300	1200	1600
4	1500	1700	1200	1500	1100	2000
5	1800	2100	1650	1800	1500	2300

Table 4 : Fixed cost if disposal center is open

Disposal center	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
1	12	10	14	15	16	17
2	10	17	20	22	24	26
3	8.5	10.5	11	18	25	32

Table 5 : Cost from recovery center to recovery testing center

Recovery center	Cost	Recovery testing center			
		1	2	3	4
1	Unit transportation cost	35	40	45	50
	Unit other fixed cost	45	50	55	60
	Distance	35	400	380	420
2	Unit transportation cost	30	40	50	60
	Unit other fixed cost	50	55	50	45
	Distance	260	60	105	50
3	Unit transportation cost	40	45	37	40
	Unit other fixed cost	44	67	80	20
	Distance	300	145	210	165
4	Unit transportation cost	50	50	50	50
	Unit other fixed cost	50	65	70	58
	Distance	75	100	85	230
5	Unit transportation cost	47	50	53	55
	Unit other fixed cost	80	66	43	50
	Distance	240	100	88	150

Table 6 : Cost from recovery testing center to disposal center

Recovery testing center	Cost	Disposal center		
		1	2	3
1	Unit transportation cost	45	50	55
	Unit other fixed cost	55	60	65
	Distance	204	150	180
2	Unit transportation cost	50	60	70
	Unit other fixed cost	50	45	50
	Distance	75	100	25
3	Unit transportation cost	37	40	50
	Unit other fixed cost	80	20	56
	Distance	145	75	100
4	Unit transportation cost	56	60	65
	Unit other fixed cost	70	58	60
	Distance	250	300	145

Table 7 : Fixed cost if recovery testing center is open

Recovery testing center	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
1	10	12	14	16	18	20
2	5.4	8	8.5	10	14	18
3	8	14	18	18	22	26
4	14	6	15	20	25	29

Table 8 : Quantity of recovery data under different scenarios for recovery center

Period	Scenario	Recovery center				
		1	2	3	4	5
Period 1	0.2	900	850	1150	1200	600
	0.25	1000	960	1230	1240	750
	0.35	1050	970	1370	1360	730
	0.2	1130	1050	1300	1270	820
Period 2	0.2	920	880	1200	1240	650
	0.25	1020	930	1350	1340	700
	0.35	1120	980	1450	1380	720
	0.2	1300	1030	1500	1400	750
Period 3	0.2	960	900	1230	1250	700
	0.25	1100	960	1280	1320	740
	0.35	1290	1030	1360	1390	800
	0.2	1400	1100	1400	1490	800
Period 4	0.2	1000	950	1200	1200	720
	0.25	1200	1050	1300	1250	790
	0.35	1400	1150	1400	1300	840
	0.2	1600	1000	1490	1300	800
Period 5	0.2	1200	960	1000	1200	830
	0.25	1260	970	960	1160	900
	0.35	1270	980	1040	1080	970
	0.2	1380	990	1200	1100	970
Period 6	0.2	1150	1300	1100	1350	890
	0.25	1100	1360	1200	1100	940
	0.35	1150	1250	1050	1350	900
	0.2	1200	1400	1000	1250	1030

Table 9 : Cost from recovery testing center to remanufacturing center

Recovery testing center	Cost	Remanufacturing center	
		1	2
1	Unit transportation cost	35	40
	Unit other fixed cost	45	50
	Distance	100	85
2	Unit transportation cost	30	40
	Unit other fixed cost	50	55
	Distance	210	150
3	Unit transportation cost	40	45
	Unit other fixed cost	44	67
	Distance	200	95
4	Unit transportation cost	50	50
	Unit other fixed cost	50	65
	Distance	103	55

Table 10 : Cost from remanufacturing center to disposal center

Remanufacturing center	Cost	Disposal center		
		1	2	3
1	Unit transportation cost	37	80	56
	Unit other fixed cost	55	60	65
	Distance	95	200	145
2	Unit transportation cost	70	53	43
	Unit other fixed cost	40	37	48
	Distance	162	84	57

Table 11 : Capacity of facilities

Capacity	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
C_I	8500	8500	9000	9500	10000	10000
C_C	6600	6600	7000	7000	8000	8000
C_D	8000	8000	8200	8100	8000	8000

Table 12 : Computational results of the numerical example

Mixed integer liner programming model		Robust mixed integer liner programming model	
Local optimal solution found		Local optimal solution found	
Objective value :	0.7278915E+09	Objective value :	0.5869794E+09
Objective bound :	0.7278915E+09	Objective bound :	0.5869794E+09
Infeasibilities :	0.5587935E-08	Infeasibilities :	0.9546056E-07
Extended solver steps :	0	Extended solver steps :	0
Total solver iterations :	11	Total solver iterations :	57

Table 13 : Quantity from recovery testing centers to remanufacturing centers in every period of robust model

recovery testing center	remanufacturing center	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
1	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
2	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
3	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
4	1	0	0	0	0	0	0
	2	4795	5544	4186	4795	4053	6195

Table 14 : Quantity from recovery centers to recovery testing centers in every period of robust model

recovery center	recovery testing center	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
1	1	1200	1420	1000	1200	1040	1550
	2	0	0	0	0	0	0
	3	0	0	0	0	0	0
	4	0	0	0	0	0	0
2	1	0	0	0	0	0	0
	2	1050	1200	900	1050	950	1400
	3	0	0	0	0	0	0
	4	0	0	0	0	0	0
3	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
	3	0	0	0	0	0	0
	4	1300	1500	1230	1300	1200	1600
4	1	1500	1700	1200	1500	1100	2000
	2	0	0	0	0	0	0
	3	0	0	0	0	0	0
	4	0	0	0	0	0	0
5	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
	3	1800	2100	1650	1800	1500	2300
	4	0	0	0	0	0	0

Table 15 : Quantity from recovery testing centers to disposal center in every period of robust model

recovery testing center	disposal center	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
1	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
	3	0	0	0	0	0	0
2	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
	3	2055	2376	1794	2055	1737	2655
3	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
	3	0	0	0	0	0	0
4	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
	3	0	0	0	0	0	0

Table 16 : Quantity from remanufacturing centers to disposal centers in every period of robust model

remanufacturing center	disposal center	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
1	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
	3	0	0	0	0	0	0
2	1	0	0	0	0	0	0
	2	0	0	0	0	0	0
	3	1438.5	1663.2	1255.8	1438.5	1215.9	1858.5

Table 17 : Facilities location in every period of robust model

		Period 1	Period 2	Period 3	Period 4	Period 5	Period 6
Recovery testing center	1						
	2	Y		Y	Y	Y	Y
	3						
	4		Y				
Disposal center	1		Y		Y	Y	Y
	2						
	3	Y		Y			

Table 18 : Total costs (10^8) obtained by robust and primary models for the scenarios with probabilities 0.2, 0.25, 0.35, 0.2

occurrences	1	2	3	4	5	6	7	8	9	10
Robust model	5.34	5.69	6.05	6.38	5.28	5.50	5.09	6.25	4.45	5.07
Primary model	6.11	6.26	6.82	6.90	5.95	6.08	5.74	6.88	4.99	6.13

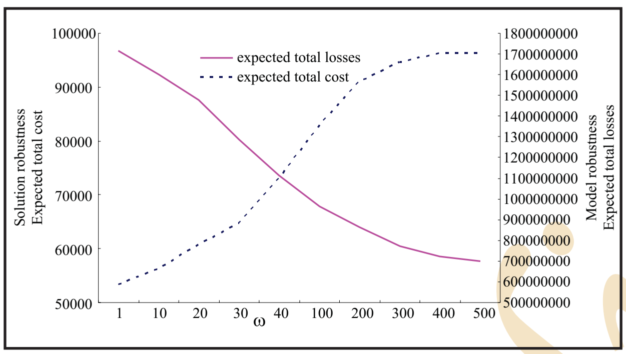

Fig. 2 : Trade off between expected total costs and expected total losses

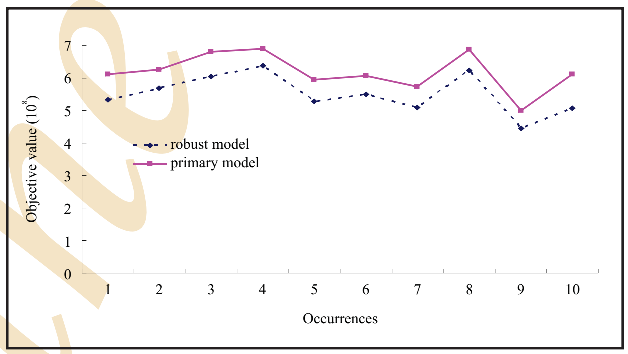

Fig. 3 : Comparison of total costs between robust and primary models for the scenarios with probabilities 0.2, 0.25, 0.35, 0.2

more sensitive to realizations of the uncertain data than the primary model. It is believed that the model can provide a credible and effective methodology for WEEE reverse logistics network design in an uncertain environment.

However, there is still much room for improvement for the proposed model. First, real data from other companies can be used to validate the model. Second, sensitivity analysis on the value of weight in the objective function may be conducted to test the trade off between solution robustness and model robustness. Above all, extending the model to formulate the other reverse logistics network such as papers, woods and irons may be interesting.

References

Alumur, S.A., S. Nickel, G.F. Saldanha, V. Verter : Multi-period reverse logistics network design. *Euro. J. Operati. Res.*, **220**, 67-78 (2012).

Ben-Tal, A. and A. Nemirovski: Robust convex optimization. *Mathem. Operat. Res.*, **23**, 769–805 (1998).

Ben-Tal, A. and A. Nemirovski: Robust solutions to uncertain programs. *Operat. Res. Lett.*, **25**, 1–13 (1999).

Ben-Tal, A. and A. Nemirovski: Robust solutions of linear programming problems contaminated with uncertain data. *Mathemat. Progra.*, **88**, 411–424 (2000).

Bertsimas, D. and M. Sim: The price of robustness. *Operat. Res.*, **52**, 35–53 (2004).

Darby, L. and L. Obara: Household recycling behavior and attitudes towards the disposal of small electrical and electronic equipment. *Resources, Conservation and Recycling*, **44**, 17–35 (2005).

Devoldere, T., B. Willems and J.R. Dewulf: The eco-efficiency of reuse centers critically explored – the washing machine case. *Inter. J. Sust. Manuf.*, **1**, 265-285 (2009).

Ding, H., L. Benyoucef and X. Xie: Stochastic multi-objective production-distribution network design using simulation based optimization. *Inter. J. Prod. Res.*, **47**, 479–505 (2009).

Ghaoui, E. and L.H. Lebret: Robust solutions to least-square problems to uncertain data matrices. *SIAM J. Mat. Anal. App.*, **18**,1035–1064 (1997).

Ghaou, E., L.F. Oustry and H. Lebret: Robust solutions to uncertain semi-definite programs. *SIAM J. Optimiz.*, **9**, 33–52 (1998).

Grunow, M. and C. Gobbi: Designing the reverse network for WEEE in Denmark. *CIRP Ann. Manuf. Technol.*, **58**, 391-394 (2009).

Hasani, A., S.H. Zegordi and E. Nikbakhsh: Robust closed-loop supply chain network design for perishable goods in agile manufacturing under uncertainty. *Inter. J. Prod. Res.*, **50**, 4649–4669 (2012).

He, W., G. Li, X. Ma, H. Wang, J. Huang and M. Xu: WEEE recovery strategies and the WEEE treatment status in China. *J. Hazar. Mat.*, **B136**, 502–512 (2006)

Kara, S.S. and S. Onut: A two-stage stochastic and robust programming approach to strategic planning of a reverse supply network: the case of paper recycling. *Exp. Systems with Appl.*, **37**, 6129–6137 (2010).

Kilic, H.S., U. Cebeci and M.B. Ayhan: Reverse logistics system design for the waste of electrical and electronic equipment (WEEE) in Turkey. *Reso., Conser. Recycl.*, **95**, 120-132 (2015).

Lee, D. and M. Dong: Dynamic network design for reverse logistics operations under uncertainty. *Transpor. Rese. Part E*, **45**, 61–71 (2009).

Leung, S.C.H., S.O.S. Tsang, W.L. Ng, Y. Wu: A robust optimization model for multi-site production planning problem in an uncertain environment. *Euro. J. Operat. Res.*, **181**, 224–238 (2007).

Listes, O. and R. Dekker: A stochastic approach to a case study for product recovery network design. *Euro. J. Operat. Res.*, **160**, 268–287 (2005).

Listes, O.: A generic stochastic model for supply-and-return network design. *Comp. Oper. Res.*, **34**, 417–442 (2008).

Melo, M.T., S. Nickel and F. Saldanha-da-Gama: Facility location and supply chain management – A review. *Europ. J. Operat. Res.*, **196**, 401- 412 (2009).

Menikpura, S.N.M., A. Santo and Y. Hotta: Assessing the climate co-benefits from Waste Electrical and Electronic Equipment (WEEE) recycling in Japan. *J. Clean Prod.*, **74**, 183-190 (2014).

Mulvey, J.M., R.J. Vanderbei and S.A. Zenios: Robust optimization of large-scale systems. *Oper. Res.*, **43**, 264–281 (1995).

Pishvaee, M.S., F. Jolai and J. Razmi: A stochastic optimization model for integrated forward/reverse logistics network design. *J. Manuf. Syst.*, **28**,107–114 (2009).

Pishvaee, M.S., M. Rabbani and S.A. Torabi: A robust optimization approach to closed-loop supply chain network design under uncertainty. *App. Mathe. Mod.*, **35**, 637–649 (2011).

Ramezani, M., M. Bashiri and M.R. Tavakkoli: A new multi-objective stochastic model for a forward/reverse logistic network design with responsiveness and quality level. *App. Math. Mod.*, **37**, 328–344 (2013).

Salema, M.G., A.P. Barbosa Povoa and A.Q. Novais: An optimization model for the design of a capacitated multi-product reverse logistics network with uncertainty. *Euro. J. Oper. Res.*, **179**, 1063–1077 (2007).

Sayed, E., N. Afia and A. El-Kharbotly: A stochastic model for forward–reverse logistics network design under risk. *Comp. Ind. Engg.*, **58**, 423–431 (2010).

Scharnhorst, W., C. Ludwig, J. Wochele and O. Jolliet: Heavy metal partitioning from electronic scrap during thermal End-of-Life treatment. *Sci. Total Environ.*, **373**, 576-584 (2007).

Shen, Z.: A profit-maximizing supply chain network design model with demand choice flexibility. *Oper. Res. Lett.*, **34**, 673–682 (2006).

Soyster, A.L.: Convex programming with set-inclusive constraints and applications to inexact linear programming. *Oper. Res.*, **21**, 1154–1157 (1973).

Truttmann, N. and H. Rechberger: Contribution to resource conservation by reuse of electrical and electronic household appliances. *Res., Conser. Recyc.*, **48**, 249-262 (2006).

Williams, E., R. Kahhat, B. Allenby, E. Kavazanjian, J. Kim and M. Xu: Environmental, social, and economic implications of global reuse and recycling of personal computers. *Environ. Sci. Technol.*, **42**, 6446-6454 (2008).

Wong, M., S. Wu, W. Deng, X. Yu, Q. Luo, A. Leung, C. Wong, W. Luksemburg and A. Wong: Export of toxic chemical sea review of the case of uncontrolled electronic-waste recycling. *Environ. Pollut.*, **149**, 131-140 (2007).

Yu, C.S. and H.L. Li : A robust optimization model for stochastic logistic problems. *Inter. J. Prod. Econ.*, **64**, 385–397 (2000).