A robust leader-follower approach for closed loop supply chain network design considering returns quality levels

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Abstract

This paper aims to assess the effect of governmental policies on a closed loop supply chain network design to achieve the optimum decision level of the collection policies for the government. For this purpose, a robust closed loop supply chain network design model with an incentive strategy for different return quality levels with a bi-level programming approach is proposed. The government will act as a leader in the outer problem and maximize the total collected returned products with different quality levels. A predefined ratio of customer demand should be satisfied as a constraint for the outer problem. In the inner problem, a closed loop supply chain designer is considered as a follower and tries to maximize the supply chain net profit with respect to government regulations. A heuristic method based on enumeration and a solution methodology consisting of particle swarm optimization for the outer problem and a genetic algorithm for the inner problem are proposed. In addition, we investigate the impact of demand uncertainty on government regulations and the closed loop supply chain configuration by a robust optimization approach. Finally, numerical examples are generated to evaluate the performance of the proposed model. The results show the necessity of using bi-level programming and the superiority of the proposed solution methodology compared with the proposed enumeration method in large-size problems.

Keywords: Closed-loop supply chain design, Bi-level programming, Government regulation, Robust optimization, Particle Swarm Optimization, Genetic Algorithm.

1. Introduction

Due to increased environmental concerns, government legislation, and awareness of natural resource limitations, closed loop supply chain network design (CLSCND) has attracted growing attention. A closed loop supply chain (CLSC) includes determining the numbers, locations, and capacities of both forward and reverse facilities (suppliers, production plants, distribution, collection, recovery, and disposal centers) in the network design. The unwillingness of companies to engage in reverse activities in addition to forward activities due to the high costs and also high uncertainties in returned product quality and quantity, make environmental concerns of end-used products one of the most important challenges of governments and lead to the use of motivational and compulsory tools. Of course, governments should carefully consider all the implications of enacting rules and regulations to ensure that they are appropriate for the circumstances and provide benefits enough to the environment. As an example, the Waste Electrical and Electronic Equipment (WEEE) Directive 2002/96/EC of the European Parliament and the Council, which contains mandatory requirements on the collection, recycling, and recovery for all types of electrical goods, is one of the instances of the government regulation (European Parliament and the Council, 2002). Additionally, Germany was the first country that introduced obligatory regulations for the recovery and recycling of sales packaging, which includes paper and paperboard material. The main characteristic of "Ordinance on the Avoidance of Packaging Waste" which came into force in 1991 is an obligation on trade and industry to take back a certain percentage of packaging materials. Italy expressed that a significant increase in paper recovery is possible only if local authorities support selective recovery (Organization for Economic Co-operation and Development, 1994). Moreover, the European Union (EU) Waste Framework Directive was introduced to strengthen waste prevention and recovery, in 2008. According to this act, the industrial and the commercial sectors have been made responsible for waste recovery. They also have to endure the relative costs (European Parliament and Council, 2008). Additionally, according to Nigeria's environmental pollution regulations, Federal Environmental Protection Agency (FEPA) policies regulate the collection, treatment and disposal of solid and hazardous waste for municipal and industrial sources and makes Environmental Impact Assessment (EIA) mandatory for any major development project that might have incompatible impacts on the environment (Chefu N., and E. Akpofure, 2002). Indeed, government as a legislative entity can lead companies to collect and recover used products. Due to the conflict between the aims of government and the supply chain designer, the best solutions obtained based only on the CLSC standpoint may not satisfy government goals. Thus, the government as a legislative entity and central authority tries to make companies collect and recover used products using motivational and compulsory tools. Therefore, a conflict between the government and the designer in reverse logistics makes us formulate a CLSCND problem using a leader-follower model. In this new configuration, the government is considered as a leader in the outer problem with aim of achieving maximum collected returns. Additionally, the government should assure satisfaction of a predefined ratio of customer demand. A CLSC designer also maximizes the supply chain profit with respect to government regulations. In addition, the impact of demand uncertainty on government regulation and the CLSC configuration is investigated by a robust optimization approach. Figure 1 gives the general structure of the proposed problem.

Figure 1: A schematic view of the proposed bi-level closed loop supply chain design problem

The organization of this paper is as follows: The literature review is presented in Section 2. In Section 3, the model definition and formulation of the deterministic and robust counterpart are developed. A heuristic method based on the enumeration and a meta-heuristic algorithm are proposed in Section 4. In Section 5, the computational results are analyzed. Conclusions and suggestions for future research are presented in Sections 6.

2. Literature review

Various strategic and operational aspects of CLSCs have been investigated in recent decades. In this study, it is attempted to propose a new formulation to deal with CLSCND by considering government decision impacts as a superior authority. Moreover, demand uncertainty is considered for the CLSC network configuration. Thus, the focus of the literature survey in this study is on the CLSCND problems in an uncertain environment and leader regulations based on the bi-level programming approach.

2.1.CLSCND under uncertainty

Ignoring the inherent uncertainty in the supply chain parameters can lead to inferior quality and less realistic results. Thus, in most of the recent and relevant studies, a supply chain is designed in an uncertain environment. Uncertainty in demand and return parameters are the most common uncertainties. Altmann and Bogaschewsky (2014), Zeballos, et al. (2014), Ma, et al. (2015), Khatami, et al. (2015), Talaei, et al. (2015), Vahdani and Mohammadi (2015), Giri and Sharma (2016), Giri and Sharma (2016), Keyvanshokooh, et al. (2016), Ma, et al. (2016) and Dutta, et al. (2016) developed various CLSC design models under demand and/or returned product uncertainty. Different approaches to cope with uncertainty exist in the literature and are classified based on their mathematical implementation of the uncertain parameters, such as interval programming, stochastic programming, robust optimization, chaos theory, and fuzzy programming. Zeballos, et al. (2014), Khatami, et al. (2015), Zeballos and Méndez (2017) and Jeihoonian, et al. (2017) developed two-stage stochastic programming models to design a CLSC network by considering multiple scenarios with known occurrence probabilities. Dutta, et al. (2016) developed a multi-period CLSC recovery based model under demand and capacity uncertainty by applying a chance constraint approach. Giri and Sharma (2016) developed a CLSC inventory system with stochastic market demand and a random return of used products with a known probability density function. Moshtagh and Taleizadeh (2017) developed a stochastic integrated manufacturing and remanufacturing CLSC model with a known quality of returned items distribution function. Altmann and Bogaschewsky (2014) and Ma, et al. (2015) applied scenario-based robust optimization approach to cope with both solution and model robustness in CLSC network design. Moreover, some of the recent studies developed hybrid approaches to cope with the uncertainty of different parameters. Vahdani and Mohammadi (2015), Talaei, et al. (2015) and Keyvanshokooh, et al. (2016) developed new hybrid solution approaches based on interval programming, stochastic programming, robust optimization approaches, and fuzzy multi-objective programming to deal with the uncertainty environment of a bi-objective optimization model for CLSCND problems.

It can be concluded that supply chain designers have to deal with uncertainty in the demand parameter while markets have become more competitive, transparent and agile. Thus in this paper, a robust scenario-based CLSC design is developed by considering uncertainty in the demand parameter.

2.2. Governmental regulation on collecting used products

In recent decades, government, as a legislative and authorized entity, has tried to lead organizations to recover and recycle used products as much as possible. In the related literature, this concept is formulated by game theory or multi-level mathematical approaches. Multi-level optimization problems constitute a class of hierarchical structure problems with more than one decision maker.

A bi-level programming problem is a special case of a multi-level problem with two decision makers and was first proposed by Bracken and McGill (1973). In this approach, one of the decision makers takes the leader position and the other one, who makes decisions subject to the leader's decisions, is the follower. The decisions are taken in an independent and sequential way. Here, some of the related studies investigate that governmental regulation in their modeling are reviewed. Amouzegar and Jacobsen (1998) proposed a bi-level programming model to provide controls on the transportation and disposal of hazardous waste in the San Francisco Bay area in Northern California. In this model, the government was treated as a leader to maximize social welfare. A production company was considered a follower to maximize its profit. Kulshreshtha and Sarangi (2001) proposed a model to analyze the impact of an incentive policy based on deposit-refund systems on a company that was involved in recycling product packages. Kara and Verter (2004) considered a bi-level integer programming problem for dangerous goods transportation network design. The government was considered the leader to minimize risk by closing certain roads to vehicles carrying hazardous materials and the carriers are followers. Sheu, et al. (2005) proposed a linear multi-objective programming model by considering governmental subsidies for product recovery, recycle fees charged to manufacturers, and the return ratio due to the environmental protection. Wojanowski, et al. (2007) developed a model in which government tended to determine the minimum subsidy based on a deposit-refund system for each collected item to ensure that the minimum desired collection rate is met. Mitra and Webster (2008) examined the effect of government subsidies to promote remanufacturing activity through a competition between an original manufacturer and a remanufacturer in a two-period model. Erkut and Gzara (2008) investigated a bi-level mixed integer programming model to deal with the network design problem for hazardous material transportation. de Figueiredo and Mayerle (2008) proposed a bi-level nonlinear mixed integer model to minimize the cost of a recycling network design problem with incentive dependent recyclable product collection and required a quantity of recycled items per unit time. Plambeck and Wang (2009) found that applying a "fee upon disposal" policy motivates manufacturers to design for recyclability. Aksen, et al. (2009) proposed two supportive and legislative bi-level programming models by considering governmental subsidization to improve returns collection. Sheu and Chen (2012) analyzed the effect of green taxation and subsidization as governmental financial interventions on green supply chain profits and social welfare by applying a three-stage game theoretic model. Rezapour, et al. (2015) proposed a bi-level model for closed loop network design with price dependent market demand by considering the internal and external competition. Strategic reverse network design decisions are made in the first level and tactical/operational decisions are made in the second level. Wang, et al. (2015) considered responsible sharing in waste electrical and electronic equipment collection by applying a reward-penalty policy to motivate the industry's recycling effort for different CLSCs. Wang, et al. (2017) proposed a closed-loop supply chain design based on a contract design problem for a manufacturer and retailer. The reward-penalty mechanism, as one on of the government interpositions, is considered to motivate the asymmetric closed loop supply chain. Yang and Xiao (2017) developed three game theory-based models to cope with green supply chain problem with governmental interventions under uncertain parameters.

A summary of related studies based on considering the impact of governmental regulation on supply chain network design (SCND) is displayed in Table 1.

Table 1: A summary of some studies related to the SCND considering the government regulations

References	Flow type		Collection Regulation		Authority tool for collection	Decision making level					
						Single level		Bi-level			
	Reverse	Closed loop/ green	Compulsion System	Incentive System		DM*	Objective Function	First DM	Second DM	Leader Objective Function	Follower Objective Function
Amouzegar & Jacobsen (1998)	✓		✓	✓	Taxing schemes	-	-	Central Authority	Firms	Maximize social welfare	Maximize profit
Kulshreshha & sarangi (2001)	✓			✓	Deposit - refund system	Consumer	Maximize consumer's utility	-	-	-	-
Sheu et al. (2005)		✓		✓	Subsidization	Reverse Logistic designer	Maximize profit	-	-	-	-
Wojanowski et al. (2007)	✓			✓	Deposit - refund system	Industrial firms	Maximize profit	-	-	-	-
Mitra & Webster (2008)		✓		✓	Subsidization	Manufacturer and Remanufacturer	Maximize profit	-	-	-	-
Sheu and Chen (2012)		✓	✓	✓	Green taxation and Subsidization	Green supply chain designer	Maximize profit	-	-	-	-
Erkut & Gzara (2008)			✓		Impose certain routes	-	-	Government	Carriers	Minimize the total risk	Minimize cost
Figueiredo & Mayerle (2008)	✓				Financial reward payment	-	-	Recycler	Collector	Minimize cost	Minimize cost
Aksen et al. (2012)	✓			✓	Subsidization	-	-	Government	Reverse Logistic designer	Minimize subsidize per unit	Maximize profit
Wang et al. (2015)		✓		✓	Reward-Penalty Mechanism	CLSC designer	Maximize profit	-	-	-	-
Wang, et al. (2017)		✓		✓	Reward-Penalty Mechanism	-	-	Manufacturer	Retailer	Maximize profit	Maximize profit
Yang and Xiao (2017)		✓		✓	Subsidization	-	-	Manufacturer	Retailer	Maximize profit	Maximize profit
This study		✓	✓		Collection regulation	-	-	Government	CLSC designer	Maximize collection rate	Maximize profit

* DM: Decision Maker

As reported in Table 1, many researchers considered government regulations in their models as a major part of related research. However, most of them considered government regulations as model parameters and analyzed the model sensitivity due to these parameters. However, the government can act as a leader to optimize its regulatory decisions as well as its social welfare and supportive actions, which is considered in this study as a research gap. In addition, a lack of considering the uncertainty parameters in a bi-level programming approach can be taken as another research gap. In this paper, decision making is considered consecutively in two levels by applying a bi-level programming model in which government takes a leader role and a CLSC designer takes a follower position and tries to design a CLSC network according to the government regulations.

3. Model definition and formulation

3.1. Problem definition

In this paper, a two-echelon CLSCND is proposed in a leader-follower configuration based on a bi-level programming approach. As shown in Figure 1, the CLSC network includes manufacturing, distribution centers (DCs), and demand zones in the forward logistics and contains collection (CCs), recycling, and disposal centers in the reverse logistics. In the reverse logistics model, collected returns are transported to CCs. In these centers, returned products are divided into recoverable and scrapped categories according to their quality type N $(n=1,\dots, N)$. Thus, returned products with higher quality are considered recoverable products and have more probability to be recovered against recycling and disposing. Recoverable products are repaired in CCs and scrapped products are shipped to recycling or disposal centers according to their material type. Recyclable parts are transported to the recycling centers, and the others are shipped to disposal centers. It should be mentioned that CLSC can select a material type during production based on the material recyclability degree. Although new products with more recyclable materials have higher production costs, their returned products have more probability to be recycled and a garner higher selling price in recycling centers. Moreover, in the forward network, manufactured products and recovered products are shipped to distribution centers separately to meet their demands. The CLSC decisions are made according to governmental regulations. Regulations may affect the CLSC feasibility solution space. The government is the leader of the problem, which makes the first decisions, and the CLSC designer takes a follower role and makes its decisions based on the government regulations. The government tends to achieve the most collected returns with different quality levels by setting suitable collection regulations. Additionally, a CLSC network is designed with respect to the government regulations in the second level of the problem.

The model assumptions are as follows:

- Recovered products have the same quality as the new product.
- Used products are divided into N ($n = 1, ..., N$) groups with respect to their quality levels.
- Owners are paid q_n for each returned product unit with quality type n.
- Returned products with higher quality have a higher probability to be recovered instead of recycled or disposed.
- The collection rate of each type of used product is determined by the CLSC designer based on its net profit and leader regulations.
- New products with a higher degree of recyclable materials (w) have higher production costs (C_w) but have a higher probability to be recycled (η_w) as well as higher price p'_w in recycling centers.

Generally, it may not be profitable for companies to have reverse logistics or to collect all used products because of the collection related costs, such as opening reverse facilities, transportation costs, and incentive payments to customers. It means that the amount of each collected item revenue has a direct impact on collection policies. In other words, companies are interested in collecting products with high cost-savings that can be regarded as revenue due to saving production costs. As a result, the proposed model is more suitable for products with low or negative cost savings; while companies are not interested in collecting their used products and governments should intervene, due to the environmental issues, as a superior and legislative entity in a supportive or legislative role to force or motivate companies to collect used products, which leads us to propose a bi-level programming model with regards to considering government decisions about collection rate regulation. In addition, it is reasonable that the government acts as a leader to make steady state decisions against parameter uncertainty. From the literature, demand uncertainty is common in CLSCND problems. Thus, in this paper, demand is considered an uncertain parameter. One of the popular methods in considering a parameter's uncertainty in such cases is deciding based on the worst case. Robust decisions of a leader based on the worst case may impose extra costs to the followers, and it may affect the government's effective performance. Mulvey, et al. (1995) proposed the concept of the robust scenario-based optimization method in operations research for the first time. They offered an approach for the optimization of the objective function in a problem with scenario-based data. In this approach, they used a penalty function, in their non-linear objective function which is the expected value of different scenarios. Their approach is a proper alternative for considering parameter's uncertainty, especially in bi-level programming. Thus, according to Mulvey, et al. (1995) robust scenario-based on the robust model formulation is presented.

3.2. Problem formulation

In this section, a bi-level mixed integer linear programming model formulation is presented. The model indices, variables, and parameters are provided in Table 2.

Table 2: Notations of the proposed model

Indices	
I	Set of fixed locations of production centers, ($i = 1, \dots, I$)
J	Set of potential locations of distribution centers, ($j = 1, \dots, J$)
K	Set of fixed locations of customer, ($k = 1, \dots, K$)
L	Set of potential locations of collection centers, ($l = 1, \dots, L$)
R	Set of fixed locations of recycle centers, ($r = 1, \dots, R$)
M	Set of fixed locations of disposal centers, ($m = 1, \dots, M$)
N	Set of quality types of returned products, ($n = 1, \dots, N$)
W	Set of recyclable material types that is used in production, ($w = 1, \dots, W$)
Decision variables:	
A_n	Proportion of potential returned products with quality type n that should be collected
$X_{ijw}, X_{jkw}, X_{ljw}, X_{lrw}, X_{lmw}$	The flow of batches of product with recyclable material type w between pair of nodes in different levels
X_{klnw}	The flow of batches of used product with quality type n and recyclable material type w between customer k and collection center l
Y_j	Binary variable that is 1 if a DC is opened in site j
Y_l	Binary variable that is 1 if a CC is opened in site l
$diff_s^+$	Positive change variables of the variance cost statement
$diff_s^-$	Negative change variables of the variance cost statement
ε_s^+	Positive deviation for violations of the constraint
ε_s^-	Negative deviation for violations of the constraint
Parameters:	
F_j, F_l	Fixed cost for opening distribution center j and collection center l, respectively
$C_i, C_j, C_l, Cr_{ln}, C_r, C_m, C_w$	Unit production, operating, inspection and collection, recovery, recycling, disposal and added production cost
$C_{ij}, C_{jk}, C_{kl}, C_{lj}, C_{lr}, C_{lm}$	Unit transportation travel cost between pair of nodes from different sets
d_k	Customer demands in zone k
α	Minimum ratio of customer's demands that should be satisfied
μ_n	Minimum ratio of collected distributed products with quality type n
γ_{kn}	The proportion of customers k having used product with quality type n
β_n	Recovery ratio of collected used product with quality type n
η_w	Recycling ratio of unrecoverable returns with recyclable material type w
$Cap_i, Cap_j, Cap_l, Cap_r, Cap_m$	Capacity of each center
p	Price of selling product
p'_w	Price of selling recycled product with recycling material type w
q_n	Incentive price should be paid to customers for each used product with quality type n
λ	optimality robustness coefficient
ω_1	First level model robustness coefficient
ω_2	Second level model robustness coefficient

3.2.1. Deterministic model

In terms of the above-mentioned notation, the proposed mixed integer, linear, bi-level programming model without any variation of defined parameters can be formulated as follows:

$$Z_1 = \max \sum_{n}^{N} A_n \tag{1}$$

$$\sum_{w} \sum_{j} \sum_{k} X_{jkw} \geq \alpha \sum_{k}^{K} d_k \tag{2}$$

$$\mu_n \leq A_n \leq 1 \qquad \forall n \tag{3}$$

$$Z_2 = \max \sum_{w} \sum_{j} \sum_{k} (p - C_j - C_{jk}) X_{jkw} + \sum_{w} \sum_{l} \sum_{r} (p'_w - C_{lr} - C_r) X_{lrw}$$

$$- \sum_{w} \sum_{i} \sum_{j} (C_w + C_i + C_{ij}) X_{ijw} - \sum_{w} \sum_{n} \sum_{k} \sum_{l} (q_n + C_l + C_{kl} + Cr_{\ln} \beta_n) X_{k \ln w} \tag{4}$$

$$- \sum_{w} \sum_{l} \sum_{m} (C_m + C_{lm}) X_{lmw} - \sum_{w} \sum_{l} \sum_{j} C_{lj} X_{ljw} - \sum_{j} F_j Y_j - \sum_{l} F_l Y_l$$

$s.t:$

$$\sum_{l} X_{k \ln w} \geq A_n \gamma_{kn} \sum_{j} X_{jkw} \qquad \forall n, k, w \tag{5}$$

$$\sum_{w} X_{ijw} + \sum_{l} X_{ljw} = \sum_{k} X_{jkw} \qquad \forall j, w \tag{6}$$

$$\sum_{j} X_{ljw} = \sum_{n} \sum_{k} \beta_n X_{k \ln w} \qquad \forall l, w \tag{7}$$

$$\sum_{r} X_{lrw} = \sum_{n} \sum_{k} \eta_w (1 - \beta_n) X_{k \ln w} \qquad \forall l, w \tag{8}$$

$$\sum_{m} X_{lmw} = \sum_{n} \sum_{k} (1 - \eta_w)(1 - \beta_n) X_{k \ln w} \quad \forall l, w \tag{9}$$

$$\sum_{w} \sum_{j} X_{ijw} \leq Cap_i \quad \forall i \tag{10}$$

$$\sum_{w} \sum_{k} X_{jkw} \leq Y_j Cap_j \qquad \forall j \tag{11}$$

$$\sum_{w}^{W} \sum_{n}^{N} \sum_{k}^{K} X_{k \ln w} \leq Y_l Cap_l \qquad \forall l \tag{12}$$

$$\sum_{w}^{W} \sum_{l}^{L} X_{lrw} \leq Cap_r \qquad \forall r \tag{13}$$

$$\sum_{w} \sum_{l} X_{lmw} \leq Cap_m \qquad \forall m \tag{14}$$

$$\sum_{w} \sum_{j} X_{jkw} \leq d_k \quad \forall k \tag{15}$$

$$X_{ijw}, X_{jkw}, X_{k\ln w}, X_{lmw}, X_{ljw}, X_{lrw} \geq 0 \quad \forall i, j, k, l, m, r, n, w$$
$$Y_j, Y_l \in \{0,1\} \tag{16}$$

Equations (1)-(3) represent the first level model. Equation (1) displays the government objective function, which is to maximize the summation of collection ratios of used products under various quality types. Constraint (2) ensures that the desired proportion of customer demand should be satisfied in the network, and Constraint (3) ensures that at least a minimum collection ratio should be met for each used products quality level. In the second level, CLSC profit is maximized in Equation (4), which is obtained by subtracting incentive payments and transportation, operational, and opening costs from the total revenue of final and recycled products. Constraint (5) is the government legislative constraint and considers the government collecting. Equations (6)-(9) are flow balancing constraints. Constraints (10)-(14) express the capacity restrictions for the production, distribution, collection, recycling, and disposal centers, respectively. Constraint (15) restricts the distributed products according to the number of demands. Finally, variable types are declared in Constraint (16).

3.2.2. Robust counterpart model

According to Mulvey, et al. (1995), in a robust scenario-based model formulation, the robust counterpart of the proposed bi-level model is formulated in Equations (17)-(34). Consider that variables $diff_s^+$ and $diff_s^-$ are change variables of the variance cost statement, and ε_s^+ and ε_s^- are the deviation for violations of the control constraints and transform the formulation to a linear program.

$$Max \quad \sum_{n}^{N} A_n - \omega_1 \sum_{s \in S} P_s \varepsilon_{1s}^- \tag{17}$$

$$\sum_{w}\sum_{j}\sum_{k} X^{s}_{jkw} = \alpha\sum_{k}^{K} d^{s}_{k} + \varepsilon^{+}_{1s} - \varepsilon^{-}_{1s} \qquad \forall s \tag{18}$$

$$\mu_n \le A_n \le 1 \qquad \forall n \tag{19}$$

$$\varepsilon^{+}_{s}, \varepsilon^{-}_{s} \ge 0 \qquad \forall s$$

$$\begin{aligned} Max \quad & \sum_{s\in S} P_s Z_s - \lambda\sum_{s\in S} P_s (diff^{+}_{s} + diff^{-}_{s}) - \omega_2 \sum_{s\in S} P_s [\sum_{k}\sum_{n}\sum_{w} \varepsilon^{-}_{2knws} + \\ & \sum_{w}\sum_{j}(\varepsilon^{+}_{3jws} + \varepsilon^{-}_{3jws}) + \sum_{w}\sum_{l}(\varepsilon^{+}_{4lws} + \varepsilon^{-}_{4lws}) + \sum_{w}\sum_{l}(\varepsilon^{+}_{5lws} + \varepsilon^{-}_{5lws}) + \\ & \sum_{w}\sum_{l}(\varepsilon^{+}_{6lws} + \varepsilon^{-}_{6lws}) + \sum_{i}\varepsilon^{+}_{7is} + \sum_{j}\varepsilon^{+}_{8js} + \sum_{l}\varepsilon^{+}_{9ls} + \sum_{r}\varepsilon^{+}_{10rs} + \sum_{m}\varepsilon^{+}_{11ms} + \sum_{k}\varepsilon^{+}_{12ks}] \end{aligned} \tag{20}$$

$s.t:$

$$\begin{aligned} Z^{s} = & \sum_{s}\sum_{w}\sum_{j}\sum_{k}(p - C_j - C_{jk}) X^{s}_{jkw} - \sum_{s}\sum_{l}\sum_{r}\sum_{w}(p'_w - C_{lr} - C_r) X^{s}_{lrw} \\ & \sum_{s}\sum_{w}\sum_{i}\sum_{j}(C_w + C_i + C_{ij}) X^{s}_{ijw} - \sum_{s}\sum_{l}\sum_{m}\sum_{w}(C_m + C_{lm}) X^{s}_{lmw} - \\ & \sum_{s}\sum_{w}\sum_{n}\sum_{k}\sum_{l}(q + C_l + C_{kl} + Cr_{\ln}\beta_n) X^{s}_{k\ln w} - \sum_{s}\sum_{w}\sum_{l}\sum_{j} C_{lj} X^{s}_{ljw} \\ & - \sum_{j}^{J} F_j Y_j - \sum_{l}^{L} F_l Y_l \end{aligned} \tag{21}$$

$$Z_s - \sum_{s'} p_{s'} Z_{s'} = diff^{+}_{s} - diff^{-}_{s} \qquad \forall s \tag{22}$$

$$\sum_{l}^{L} X^{s}_{k\ln w} = A_n \gamma_{kn} \sum_{j}^{J} X^{s}_{jkw} + \varepsilon^{+}_{2knws} - \varepsilon^{-}_{2knws} \qquad \forall k, n, w, s \tag{23}$$

$$\sum_{i}^{I} X^{s}_{ijw} + \sum_{l}^{L} X^{s}_{ljw} = \sum_{k}^{K} X^{s}_{jkw} + \varepsilon^{+}_{3jws} - \varepsilon^{-}_{3jws} \qquad \forall j, w, s \tag{24}$$

$$\sum_{j}^{J} X^{s}_{ljw} = \sum_{n}\sum_{k}\beta_n X^{s}_{k\ln w} + \varepsilon^{+}_{4lws} - \varepsilon^{-}_{4lws} \quad \forall l, w, s \tag{25}$$

$$\sum_{r} X^{s}_{lrw} = \sum_{n}\sum_{k}\eta_w (1-\beta_n) X^{s}_{k\ln w} + \varepsilon^{+}_{5lws} - \varepsilon^{-}_{5lws} \quad \forall l, w, s \tag{26}$$

$$\sum_{m} X^{s}_{lmw} = \sum_{n}\sum_{k}(1-\eta_w)(1-\beta_n) X^{s}_{k\ln w} + \varepsilon^{+}_{6lws} - \varepsilon^{-}_{6lws} \qquad \forall l, w, s \tag{27}$$

$$\sum_{w}\sum_{j} X^{s}_{ijw} = Cap_i + \varepsilon^{+}_{7is} - \varepsilon^{-}_{7is} \quad \forall i, s \tag{28}$$

$$\sum_{w}\sum_{k} X^{s}_{jkw} = Y_j Cap_j + \varepsilon^{+}_{8js} - \varepsilon^{-}_{8js} \qquad \forall j, s \tag{29}$$

$$\sum_{w}\sum_{n}\sum_{k} X^{s}_{k\ln w} = Y_l Cap_l + \varepsilon^{+}_{9ls} - \varepsilon^{-}_{9ls} \qquad \forall l, s \tag{30}$$

$$\sum_{w}\sum_{l} X^{s}_{lrw} = Cap_r + \varepsilon^{+}_{10rs} - \varepsilon^{-}_{10rs} \qquad \forall r, s \tag{31}$$

$$\sum_{w}\sum_{l} X^{s}_{lmw} = Cap_m + \varepsilon^{+}_{11ms} - \varepsilon^{-}_{11ms} \qquad \forall m, s \tag{32}$$

$$\sum_w \sum_j X_{jkw}^s = d_k^s + \varepsilon_{12ks}^+ - \varepsilon_{12ks}^- \quad \forall k,s \tag{33}$$

$$\begin{aligned}
&X_{ijw}^s, X_{jkw}^s, X_{k\ln w}^s, X_{lmw}^s, X_{ljw}^s, X_{lrw}^s \geq 0 \quad \forall i,j,k,l,m,s,w,n \\
&\varepsilon_{2knws}^+, \varepsilon_{2knws}^-, \varepsilon_{3jws}^+, \varepsilon_{3jws}^-, \varepsilon_{4lws}^+, \varepsilon_{4lws}^-, \varepsilon_{5lws}^+, \varepsilon_{5lws}^-, \varepsilon_{6lws}^+, \varepsilon_{6lws}^-, \varepsilon_{7is}^+, \varepsilon_{7is}^- \\
&\varepsilon_{8js}^+, \varepsilon_{8js}^-, \varepsilon_{10rs}^+, \varepsilon_{10rs}^-, \varepsilon_{11ms}^+, \varepsilon_{11ms}^-, \varepsilon_{12ks}^+, \varepsilon_{12ks}^- \geq 0 \\
&Y_j, Y_l \in \{0,1\} \quad \forall j,l
\end{aligned} \tag{34}$$

4. Solution methodologies

Moore and Bard (1990) showed that mixed integer bi-level programming models are Np-hard. They also developed a branch and bound method and extended it to solve instances with at most 35 integer decision variables in the outer problem (Bard and Moore, 1990). The restriction of the number of variables in this method indicates that the branch and bound method is not efficient to solve large size instances. Thus, using efficient heuristic and meta-heuristic algorithms is suggested to obtain near-optimal solutions for such instances. In this section, a heuristic algorithm based on enumeration as well as a hybrid particle swarm optimization-genetic algorithm (PSO-GA) are proposed to solve the developed model. The first algorithm will be efficient only in small size instances, while the second one performs well in large size instances, too.

4.1. Heuristic algorithm based on enumeration

As mentioned before, the outer problem has *n* variables and just one constraint without any dependency on its variables. Thus, the optimal value of the proposed bi-level model can be obtained in an iterative procedure by fixing these *n* variables in the inner problem and solving it. In the first iteration, the maximum collection rate amounts are set to one. Then the optimum results of the inner problem are put in the outer problem constraint. During an iterative procedure, one of the collection ratio values is decreased by a small decrement (ε) and the second level is solved again. This iterative procedure continues until all the permutations ($\prod_n (\frac{1-\mu_n}{\varepsilon})$ iterations) of the first level variables are tested. All solutions which satisfy the constraint mentioned will be gathered as final solution candidates. The final optimal solution, which lead to the highest leader objective function, will be obtained from the candidate solutions.

4.2. Particle Swarm Optimization- Genetic algorithm

Since the number of iterations of the proposed heuristic enumeration algorithm is dependent on the number of returned product quality types (*n*), for a large number of these parameters, it does not work efficiently. Thus, particle swarm optimization (PSO) is implemented for solving the outer problem. Moreover, a genetic algorithm (GA) is applied for solving the mixed integer inner problem. Eberhart and Kennedy (1995) developed the PSO evolutionary algorithm. PSO initializes a population of random solutions in a specific number and tries to find near-optimal solutions. In this algorithm, particles move through the problem space by following other particles. Here, the outer problem variables (A_n) are considered particles of the proposed PSO algorithm in case of feasibility. Then, the GA is implemented to solve the inner problem according to the outer problem variables. GA is one of the most popular meta-heuristic algorithms and was developed by Holland ((1992). Each proposed binary chromosome determines the locations of DC and CC facilities among candidate locations. Other flow variables are determined by a greedy heuristic algorithm for each chromosome. Parents and populations for the next generation are selected by the elitist strategy. The pseudo code of the proposed PSO-GA for solving the proposed bi-level model is represented in Figure 2:

Figure 2: Pseudo code of the proposed PSO-GA to solve the bi-level model

It should also be noted that the GA and the PSO parameters are tuned using the Taguchi method to find the near optimal solution efficiently based on SN ratio. Taguchi is a common method for tuning algorithm parameters which is used in previous papers (Shukla, et al. (2010), Alizadeh Afrouzy, et al. (2016), Sahebjamnia, et al. (2018), Yadegari, et al. (2019)).

5. Computational results

In order to validate the proposed model, some numerical examples in small, medium and large size instances were generated randomly. The parameter values are presented in Table 3. All of the costs and prices are based on Cents (¢).

Table 3: Parameters generation scheme for the computational study

Parameter	Value	Parameter	Value
d_k	~Uniform (300,700)	$Cr_{\ln}, C_r$ (¢)	~Uniform (250,350)
C_{ab} (¢)	~Uniform (20,2000)	p (¢)	~Uniform (4000,10000)
F_j, F_l (¢)	~Uniform (50000,200000)	p'_w (¢)	~Uniform (2000,5000)
C_i (¢)	~Uniform (500,600)	β_n, η_w	~Uniform (0.3,1)
C_j, C_l, C_m (¢)	~Uniform (200,250)	μ_n	=0.2

As mentioned in Section 1, Directive 2002/96/EC of the European Parliament and of the Council on Waste Electrical and Electronic Equipment was introduced. Similar to the concept of this paper, this directive was established to reduce the quantity of waste for disposal and save natural resources, by reusing, recycling, composting, and recovering energy from waste and recognized that the choice of options in any particular case must consider environmental and economic effects. This directive also encouraged producers to integrate recycled material into new equipment.

5.1. Necessity of applying a Bi-level programming approach to the proposed model

In this section, the necessity of applying a Bi-level programming approach in the proposed CLSC model is studied by comparing the results of the proposed model both using and not using a bi-level programming approach in terms of “responded demand ratio” and “CLSC profit to capture 50 percent of the responded demand”. Despite incorporating the using bi-level programming model in the not using bi-level programming approach, leader decisions, which are set by the government without any mathematical analysis, are constituted as input parameters for the CLSC design problem. The results are reported in Table 4. It is worth mentioning that the government decision variance and the fluctuation in its decision making gradually increase. Note that if a bi-level programming approach applied, the government can analyze various decisions and set a reasonable collection policy that satisfied the predefined responded demand. On the other hand, if the government does not apply a bi-level programming approach and makes its decision without mathematical analysis, the government may be forced to change its decisions to obtain the desired responded demand. Thus, these changes may lead to a loss for both players; government and CLSC.

Table 4: Results of government decision making in using or non-using bi-level programming approach by considering $\alpha = 0.5$

Decision making status	AGDV*	Government Strategy			CLSC Strategy		
		$\sum_{n}^{N} A_n$	α	**Responded demand**	**Number of opened DC**	**Number of opened CC**	**CLSC profit (¢)**
With applying Bi-level programming	-	0.85	0.6	0.4	2	1	1204482.59
Without applying Bi-level programming	low	1	0.4	0.6	1	1	1282421.95
		0.7	0.6	0.4	2	1	2195579.14
		0.85	0.54	0.46	2	1	487268.43
	Mid	1	0.4	0.6	1	1	1282421.95
		0.6	0.6	0.4	2	1	2448805.54
		0.85	0.54	0.46	2	1	416252.31
	high	1	0.4	0.6	1	1	1282421.95
		0.5	0.8	0.2	3	1	3400214.43
		0.85	0.8	0.2	3	2	-1.51984

* Assumed government decisions variance

As shown in Table 4, CLSC's optimal solutions are declared gradually by incremental changes in the government decision in cases with low-, mid-, and high-government decision variance. On the other hand, in recent decision-making situations, government loses the chance of checking out all of the possible states and it is possible that government loses the optimal collection rate and the CLSC designer, as a follower, decides subject to the government policies. Although DC and CC location decisions are strategic decisions, CLSC cannot change these decisions according to government decision changes. Thus, it is strongly possible that the previous decisions of the CLSC designer will not be optimal in the new situation and as a result, the CLSC will bear the exorbitant costs of opening non-optimal locations. Indeed, private sector loss increases when the government has greater decision variance. Thus, the differences between the results of decision making by using and not-using a bi-level programming approach increases when the robustness of government decision making decreases. Figure 3 presents the results of CLSC benefit in using and not-using a bi-level programming approach to satisfy at least 50 percent of the demands.

Figure 3: Comparing the CLCS profit in order to different government decision changes variances

5.2. Robustness consideration in CLSCND problem

As illustrated in the previous subsection, the government decision should not be changed because it imposes large costs to the followers. This case is more important when we face some uncertainties in operational levels parameters. In order to evaluate the proposed bi-level model under uncertainty, different scenarios are generated and presented in Table 5. The third scenario (base-case) is similar to the deterministic demands considered in the first instance in Table 6.

Table 5: Product demands of each demand zone under different scenarios

Scenarios	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8	d_9	d_{10}	Probability
Scenario 1	378	737	540	726	385	405	495	572	342	440	0.15
Scenario 2	462	603	660	594	350	495	550	468	418	360	0.15
Base-case	420	670	600	660	350	450	550	520	380	400	0.4
Scenario 4	462	670	540	660	315	450	605	572	342	360	0.15
Scenario 5	378	737	600	726	315	405	495	520	380	400	0.15

Robust optimization, as presented by Mulvey, et al. (1995) 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 set. The optimal solution provided by a robust optimization model is called robust if it remains close to the optimal when changing parameters. This is solution robustness. Robust optimization is looking for a solution that is less sensitive to varying input data (optimality robustness) and remains feasible in the possible set of uncertain scenarios (model robustness). As discussed before, in this paper the government is considered a legislative entity that makes its decisions as the first decision maker of the proposed bi-level model, and its decisions affect the CLSC designer decisions directly. The government is also interested in assuring that its planned decisions will be met, so different large values of ω_2 (3000, 5000, 7000, 10000) were analyzed with a fixed value of ω_1 (5). Results of the proposed bi-level robust model for different values of variance cost (λ) and penalty infeasibility weighting factors (ω_1, ω_2) are presented in Figure 4.

Figure 4: CLSC profit for different variance cost and penalty infeasibility weighting factors in α=0.6

As is shown in Figure 4, by applying more penalty to the second level infeasibility (ω_2) and more variance cost (λ), the CLSC designer makes more conservative decisions and achieves less benefit. Thus, for large values of these parameters, the highest model robustness is obtained.

Also, Mulvey, et al. (1995) pointed out that stochastic optimization is appropriate for problems under uncertainty where decisions can be adjusted easily as a reaction to changing conditions, while robust optimization is suitable for problems with a high degree of uncertainty where a risk-averse decision maker is not able to change a decision once it is fixed. Figure 5 summarizes the comparative statistics between the solution of a two-stage stochastic programming (Two-stage SP) formulation of the proposed bi-level model with the robust optimization model (robust OM) obtained for a particular set of the parameters ($\lambda = 0.5$,$\omega_1 = 5$, and $\omega_2 = 10000$).

Figure 5: Comparison of the robust OM and two stage SP in (a) expected profits and (b) variance of profits

As reported in Figure 5, in comparing robust optimization and two-stage stochastic programming solutions, the robust approach achieves more optimality robustness despite less expected benefit than stochastic programming. Indeed, robust optimization variance is less than the two-stage stochastic programming; thus, it has more optimality robustness, but the expected profit value is dependent on the infeasibility penalty. Clearly, for a high infeasibility penalty, the model robustness of both robust and stochastic approaches are the same and, as a result, robust optimization achieves less variance.

5.3. Proposed algorithm performance

In this section, to compare the performance of the proposed PSO-GA algorithm, all instances are solved by the heuristic enumeration method by using the CPLEX solver on GAMS 23.5. The hybrid PSO-GA algorithm is run in MATLAB 2012 on a computer with 2.40 GHz core (TM) i5

CPU and 4.00 GB RAM. The computational results are reported in Table 6. The proposed algorithm was evaluated by comparing the CPU time and its gap with the enumeration method. The gap is calculated using the following equation.

$$\text{Gap}=\frac{\textbf{CLSC's profit}(\textbf{enumeration})-\textbf{CLSC's profit}\ (\textbf{PSO}-\textbf{GA})}{\textbf{CLSC's profit}(\textbf{enumeration})}$$

Table 6: Heuristic and meta-heuristic results for the proposed bi-level programming model

Instance (I,J,K,L,R,M,N,W)	α	**Heuristic method based on enumeration**						**PSO-GA**						**Gap**
		$\sum_n A_n$	A_1	A_2	A_3	**CLSC's profit (¢)**	**CPU time**	$\sum_n A_n$	A_1	A_2	A_3	**CLSC's profit (¢)**	**CPU time**	
	0.6	0.85	0.65	0.2	-	1204482.59	0:01:53	0.85	0.65	0.2	-	1189300.21	0:11:13	0.01
	0.4	1.25	1	0.25	-	425921.67	0:01:53	1.25	1	0.25	-	406736.38	0:07:22	0.04
	0.2	1.25	1	0.25	-	425921.67	0:01:53	1.25	1	0.25	-	406736.38	0:06:47	0.04
(3,10,20,10,2,2,2,2)	0.8	1.05	0.35	0.7	-	2754821.65	0:02:11	1.05	0.35	0.6	-	2745026.7	0:24:36	0.01
	0.6	1.05	0.35	0.7	-	2754821.65	0:02:11	1.05	0.35	0.6	-	2745026.7	0:26:02	0.01
	0.4	1.25	0.25	1	-	1423405.35	0:02:11	1.25	0.25	1	-	1401445.52	0:16:29	0.02
	0.2	1.35	0.35	1	-	341687.72	0:02:11	1.35	0.35	1	-	321517.02	0:09:17	0.01
(5,20,60,20,2,2,2,2)	0.8	0.9	0.2	0.7	-	39422710	0:19:54	0.9	0.2	0.7	-	37182516	1:42:26	0.02
	0.6	1.1	0.2	0.9	-	19391500	0:19:54	1.1	0.2	0.9	-	19380617	1:32:17	0.001
	0.4	1.25	0.25	1	-	9354862.5	0:19:54	1.25	0.25	1	-	9334551.9	1:12:45	0.01
	0.2	1.35	0.35	1	-	3092284.25	0:19:54	1.35	0.35	1	-	3083147.1	0:57:26	0.001
(5,30,80,30,3,3,2,2)	0.8	0.75	0.25	0.5	-	35606530	0:36:57	0.75	0.25	0.5	-	31211521	2:27:05	0.03
	0.6	0.85	0.2	0.65	-	26936500	0:36:57	0.85	0.2	0.65	-	25965237	2:12:45	0.01
	0.4	1	0.2	0.8	-	13061170	0:36:57	1	0.2	0.8	-	12122813	1:46:19	0.02
	0.2	1.1	0.2	0.9	-	7874744.38	0:36:57	1.1	0.2	0.9	-	7524164.6	1:37:28	0.01
(8,32,90,32,3,3,3,3)	0.8	0.8	0.2	0.2	0.4	61075780	3:57:22	0.8	0.2	0.2	0.4	59085691	4:37:57	0.02
	0.6	1.1	0.2	0.2	0.7	28306230	3:57:22	1.1	0.2	0.2	0.7	26307136	4:03:16	0.02
	0.4	1.3	0.2	0.9	0.2	15261380	3:57:22	1.3	0.2	0.9	0.2	12673960	3:45:28	0.02
	0.2	1.5	0.2	0.6	0.7	2554039.53	3:57:22	1.5	0.2	0.6	0.7	2261172.7	3:26:13	0.01
(8,35,100,35,4,4,3,3)	0.8	0.7	0.2	0.2	0.3	63437610	6:43:12	0.7	0.2	0.2	0.3	60568141	5:18:23	0.04
	0.6	0.8	0.2	0.2	0.4	31239770	6:43:12	0.8	0.2	0.2	0.4	28188163	5:04:17	0.05
	0.4	1.1	0.2	0.3	0.6	22344190	6:43:12	1.1	0.2	0.3	0.6	20219820	5:01:22	0.01

	0.2	1.4	0.2	0.5	0.7	6255912.67	6:43:12	1.4	0.2	0.5	0.7	6018231.12	4:56:12	0.01

According to the results in Table 6, the proposed PSO-GA method has acceptable performance compared to the enumeration method in terms of solution quality and CPU time. The algorithms are compared according to the computational time, which is depicted in Figure 6. It is worth mentioning that the CPU time of the enumeration method is strongly dependent on the number of returned quality types.

Figure 6: A comparison of two algorithms considering the computational time

5.4. Model performance and managerial insights

To evaluate the performance of the proposed model, the sensitivity of each returned quality type (q_n) to the incentive price is examined. The selected instances for analyzing are listed in Table 7. The incentive prices of Instance (4) are used as a base-case for the analysis. Different instances with a 10% increase and decrease in incentive price parameters have been generated. Due to the increase of the network costs, the CLSC designer tends to collect returned products with lower quality types by increasing incentive price. Figure 7 (a) shows the model sensitivity in terms of collection rate on incentive price changes. It shows the model validity as well.

Table 7: Model sensitivity analysis on the q_n parameter in $\alpha = 0.6$

Instances	**Changes in q_n**			$\sum_n^N A_n$	A_1	A_2	**CLSC Profit** (¢)	**Amount of collected products with quality *n***	
	q_1	q_2	$q_1 - q_2$					High quality $n=1$	low quality $n=2$
1	3061.3	2795.1	266.2	0.7	0.2	0.5	1487265.62	342.4	644
2	2783	2541	242	0.7	0.2	0.5	1746195.94	342.4	644
3	2530	2310	220	0.75	0.5	0.25	1347999.4	883	558.5
4 (Base-case)	2300	2100	200	0.85	0.65	0.2	1204482.59	750.1	369.2
5	2070	1890	180	0.9	0.7	0.2	1319925.8	807.8	369.2
6	1863	1701	162	1	0.8	0.2	1322198.57	923.2	369.2

7	1676.7	1531	145.8	1.05	0.85	0.2	1460527.95	980.9	369.2

Analytical sensitivity of added production costs is also related to the degree of recyclable materials (C_w) and the price of recycled product (p'_w) parameter will lead to worthy managerial results for both the government and CLSC designer. Thus, changes in C_w and p'_w parameters are considered as other sensitivity analysis. The results are illustrated in Figure 7(b) and Figure 7(c), respectively.

Figure 7: Model sensitivity analysis on parameters of q_n , C_w and p'_w

According to aforementioned sensitivity analysis, some managerial insights can be obtained and are mentioned as follows:

If the government, in a supportive role, implements incentive mechanisms, such as a subsidy, tax discount, or purchasing insurance, then the CLSC designer will tend to use recyclable and environmentally-friendly materials in production. The government can reach this purpose by reducing the CLSC costs in recyclable production or assuring that the recycling products can be sold in the recycle market. For example, according to reports in the Official Journal of the European Union, the establishment of the WEEE directive and giving responsibility to producers encourages them to design and produce electrical and electronic equipment which take into full account and facilitates their repair, possible upgrading, reuse, disassembly, and recycling. according to the Ylä-Mella, et al. (2014) study, WEEE collection rates in 2012 were 12 kg/inhab./year, in Finland, 16 kg/inhab./year, in Sweden, and 27 kg/ inhab./year, in Norway, despite their sparsely populated nature.

6. Conclusion

In this study, a bi-level programming approach was proposed to formulate a CLSCND with different returned product qualities under the governmental legislative decisions in a leader-follower configuration. The government was treated as a leader and tended to achieve the highest returns for collection regulation that ensures predefined satisfied demands. A CLSC designer was a follower with the aim of maximizing its net profit subject to the government regulation. A heuristic method based on enumeration and a solution methodology consists of PSO for the outer problem and a GA for the inner problem were proposed. Numerical examples were randomly generated and used to evaluate the solution method efficiency. Computational results showed that the proposed PSO-GA can obtain near optimal solution in large scale instances in a reasonable time compared with the enumeration approach. Additionally, the necessity of applying a bi-level programming approach and the sensitivity of the proposed model to the critical parameters were examined, and the results showed that the necessity of using a bi-level approach is increased when the government has not made steady-state decisions. Thus, a robust scenario-based optimization approach was proposed for incorporating demand uncertainty. A different robust analysis in each level, separately or simultaneously, can be considered for a future study. Using other stochastic and robust approaches in the bi-level programming can also be considered as another direction for future work.

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