Scientia Iranica E (2019) 26(6), 3747–3764

Sharif University of Technology
Scientia Iranica
Transactions E: Industrial Engineering
http://scientiairanica.sharif.edu

A robust bi-level programming model for designing a closed-loop supply chain considering government's collection policy

A. Hassanpour[a], J. Bagherinejad[a,*], and M. Bashiri[b,1]

a. *Department of Industrial Engineering, Faculty of Engineering and Technology, Alzahra University, Tehran, P.O. Box 199389373, Iran.*
b. *Department of Industrial Engineering, Faculty of Engineering and Technology, Shahed University, Tehran, P.O. Box 319118651, Iran.*

Received 27 May 2017; received in revised form 13 December 2017; accepted 23 June 2018

KEYWORDS
Bi-level programming;
Closed-loop supply chain;
Government regulations;
Genetic algorithm;
Robust optimization;
Scenario.

Abstract. This study aims to provide a new approach to the design of a closed-loop supply chain network by emphasizing the impact of the government's environmental policies based on a bi-level mixed integer linear programming model. Government is considered as the leader at the first level and tends to set a collection rate policy, which leads to collecting more used products in order to ensure a minimum distribution ratio to satisfy minimum demands. At the second level, the private sector is considered as a follower and tries to maximize its profit by designing its own closed-loop supply chain network according to the government's used products collection policy. A heuristic algorithm and an adaptive genetic algorithm based on the enumeration method are proposed, and their performances are evaluated through computational experiences. The comparison among numerical examples reveals that there is an obvious conflict between the government and CLSC goals. Moreover, it shows that this conflict should be considered and elaborated in uncertain environment by applying the min-max regret scenario based robust optimization approach. The results show the necessity of applying robust bi-level programming to the closed-loop supply chain network design under the governmental legislative decisions as a leader-follower configuration.

© 2019 Sharif University of Technology. All rights reserved.

1. Introduction

Due to environmental issues, governmental laws, and consumers' tendency, Closed-Loop Supply Chain (CLSC) network design has increasingly gained researchers' attention. Thus, closed-loop supply chain has become one of the major research areas over the last decade. A closed-loop supply chain is a complex network of business entities (e.g., suppliers, manufacturers, remanufacturers, distribution and collection centers, recycling and disposal centers, and finally customers), which are involved in the network design. Various studies exist in the field of the closed-loop supply chain network design. In this paper, some of the recent studies that have investigated CLSC design have been reviewed. Altmann and

*. *Corresponding author.*
1. *Present address: School of Strategy and Leadership, Faculty of Business and Law, Coventry University, Coventry, UK.*
E-mail addresses: a.hassanpour1319@gmail.com (A. Hassanpour); jbagheri@alzahra.ac.ir (J. Bagherinejad); Bashiri.m@gmail.com (M. Bashiri)

doi: 10.24200/sci.2018.20609

Bogaschewsky [1] developed a multi-objective robust CLSC network design model under customer demands and return product ratio uncertainty. Zeballos et al. [2] developed a multi-stage stochastic mixed integer linear programming model to design a multi-product, multi-period CLSC network by considering uncertainty in customer demands and amount of raw material. Ma et al. [3] addressed a robust multi-objective CLSC mathematical model under the uncertainty of market demand and cost parameters considering economical cost and environmental impact. Talaei et al. [4] addressed the multi-product, bi-objective mixed integer linear programming for the CLSC network design under the uncertainty of demand and cost parameters based on a robust stochastic programming approach. Giri and Sharma [5] developed a CLSC inventory system with stochastic market demand and random return of used products with the aim of maximizing the total profit of the CLSC. Keyvanshokooh et al. [6] proposed a hybrid robust stochastic mixed integer linear programming model for a multi-period capacitated CLSC network design under uncertain demand and return quantity and transportation costs. Dutta et al. [7] developed a multi-period CLSC recovery-based model under demand and capacity uncertainty to determine optimal buy-back price. Zeballos and Méndez [8] proposed a two-stage stochastic programming model for a multi-product, multi-echelon, and multi-period CLSC to determine the quantity of new and remanufactured products. Jeihoonian et al. [9] developed a two-stage stochastic programming model with several types of recovery options under returned quality uncertainty. Huang et al. [10] proposed a novel genetic algorithm to solve an interval closed-loop supply chain design in uncertain environment. Fareeduddin et al. [11] addressed stochastic multi-period planning of a closed-loop supply chain design under carbon emission regulations. Safaei et al. [12] proposed a robust closed-loop model by considering cardboard recycling under demand uncertainty. Hassanzadeh Amin et al. [13] investigated a multi-period closed-loop supply chain model by considering cash flow in an uncertain environment. Farrokh et al. [14] proposed a robust fuzzy stochastic programming approach for designing a closed-loop supply chain in uncertain environment. Haddadsisakht and Ryan [15] addressed a stochastic closed-loop supply chain design with multiple transportation modes under uncertain carbon tax. Besides, Govindan et al. [16] provided a comprehensive review of most of the reverse logistics and CLSC studies between 2007 and 2013. They clustered and explored gaps of studies based on different aspects such as modeling approaches, solution methodologies, uncertainty approaches, type of decision variables and the number of objective functions, product and time period, etc. However, they did not mention the importance of the impact of governmental and central authority on CLSC design policies and its dealing approaches. Indeed, in recent years, by the growing environmental pollutions, collecting used products and decreasing environmental pollutions have become major challenges of the governments. Since there is no persuasion for customers to return their used products to recovery cycle and because of high costs and, also, high uncertainties in the quantity and quality of the returned products, distribution companies do not have any tendency to establish collection centers. Therefore, this process does not form itself without interpositions of superior organs. As can be seen, governments try to form this process by setting motivational or compulsory rules (such as considering subsidies, tax discounts, and penalties) and applying different policy tools (such as deposit-refund, pay as you throw, technology standards, performance standards, labeling standards, and so on). For instance, the Waste Electrical and Electronic Equipment (WEEE) directive 2002/96/EC of the European Parliament and the Council became a European law in 2003, containing mandatory requirements on collection, recycling, and recovery for all types of electrical goods. Toffel [17] reported that the European electrical and electronic equipment industries bear some of the highest regulatory pressures regarding EOL products. Moreover, the European Union (EU) Waste Framework Directive was developed in order to strengthen waste prevention and recovery in 2008. According to this act, industries and the commercial sector have been made responsible for the recovery of waste. They also have to bear the relative costs [18]. Besides, according to the Nigeria's environmental pollutions, Federal Environmental Protection Agency (FEPA) policies regulate the collection, treatment, and disposal of solid and hazardous wastes for municipal and industrial sources and make Environmental Impact Assessment (EIA) mandatory for any major development projects that might exert adverse impact on the environment [19]. According to the conflict between the aim of the company and that of government, the best solutions obtained based on the company standpoint models may not satisfy governmental objectives and targets. Thus, the government as a legislative entity tries to lead the company to collect and recover used products by using motivational tools. By studying the literature through a social lens such as attention to the reduction of environmental pollutions and governmental intervention in leading relevant departments, it can be seen that many researchers have tried to formulate these aspects by various mathematical techniques such as economic approaches, game theory, and multi-level optimization. Multi-level optimization problems constitute a very important class of problems within a hierarchical structure with more than one decision-maker. The first formulation of bi-level programming was proposed by Bracken and McGill [20]. A bi-level programming problem is a special case of the multi-level problem with two decision-makers, one of whom takes the leader position, and the other one whose decision-making is subject to the leader's decisions is the follower. Amouzegar and Jacobsen [21] proposed a bi-level programming model to provide controls on the transportation and disposal of hazardous wastes by finding the regional planning, treatment capacity, and the cost of waste treatment for regional hazardous waste in the San Francisco Bay area in Northern California. Kulshreshtha and Sarangi [22] proposed a model where government is considered a policy maker that employs deposit-refund systems as a subsidy. Kara and Verter [23] considered the network design problem for the transportation of dangerous goods as a bi-level integer programming problem. Government is considered as a leader aiming to minimize risk by closing certain roads to vehicles carrying hazardous materials, and the carriers are considered as followers who comply with the government's regulations with the aim of minimizing related cost. Sheu et al. [24] proposed a linear multi-objective programming model to improve the performance of a green supply chain. They developed their model by considering governmental subsidies for product recovery in reverse logistics and recycle fees charged upon manufacturers and return ratio due to the environmental protection. Wojanowski et al. [25] developed a model where government tends to determine the minimum subsidy as in a deposit-refund system for each collected item to ensure that the minimum desired collection rate is met. This problem is modeled as continuous modeling with the aim of achieving maximum firm profit by considering governmental incentive system. Erkut and Gzara [26] developed a bi-level mixed integer programming to deal with the network design problem of hazardous material transportation. A heuristic method used to overcome the difficulty of bi-level programming is introduced. De Figueiredo and Mayerle [27] proposed a minimum cost recycling network design problem with incentive-dependent recyclable product collection that requires a number of recycled items per unit time. This problem is modeled as a large bi-level nonlinear mixed integer program, and a three-stage heuristic algorithm is proposed for its complexity. Mitra and Webster [28] analyzed a two-period model of the competition between an original manufacturer and a remanufacturer. In this model, the effect of government subsidies to promote remanufacturing activity is examined. Plambeck and Wang [29] found that applying the "fee upon disposal" policy motivates manufacturers to design recyclability. Aksen et al. [30] proposed two supportive and legislative bi-level programming models by considering governmental subsidization to improve collections. Sheu and Chen [31] proposed a three-stage game theoretic model to analyze the effect of green taxation and subsidization as governmental financial interventions on green supply chain profits and social welfare. A modified Tabu search heuristic method is applied to solve these models. Wang et al. [32] considered responsible sharing in waste electrical and electronic equipment collection. In this case, the government applies a reward-penalty mechanism to motivate industry's recycling effort for different CLSCs. Rezapour et al. [33] proposed a bi-level model for the closed-loop network design by considering internal and external competitions. Strategic reverse network design decisions are made at the first level, and tactical/operational decisions are made at the second level in a competitive environment where market demand is dependent on the price. A summary of related studies based on the impact of governmental regulation on Supply Chain Network Designs (SCNDs) is displayed in Table 1.

Despite the importance of environmental issues and the necessity of considering government's potential impact on sub-organizations' policies, only a few research studies have considered government as a legislative entity and an independent decision-maker in their model and applied a bi-level programming formulation to the CLSC network design. In addition, lack of considering uncertain parameters in the bi-level programming approach can be taken as another research gap. In this paper, decision-making is considered consecutive at two levels by applying a bi-level programming model. Government is considered as the first decision-maker and determines a suitable collection rate to ensure that predetermined customers' demands are satisfied. Besides, private sector as a follower designs its closed-loop supply chain network with the aim of maximizing its net profit subject to the government's policy. The conceptual framework of the proposed model is illustrated in Figure 1.

In addition, since the uncertainty in demand parameter is so probable and effective, min-max regret and min-sum regret scenarios based robust optimization approaches are proposed where the occurrence probability of each scenario is not known.

Compared to the above-mentioned studies, the characteristics of this study are as follows:

- Only a few studies of the existing mathematical models for the optimal design of CLSC networks considered the government as one of the model decision-makers. This study applies a leader-follower modeling framework to consider the government as a legislative decision-maker;
- Most of the relevant studies that have considered the impact of governmental policies on the supply chain design have also considered government

Table 1. Some studies of government regulations considered in the supply chain network design.

References	Field of research (flow type)		Decision making level		Collection regulation		Decision variables			Uncertain parameter(s) and its approach	Solution method
	Reverse	Closed loop/green	One level	Bi-level	Compulsion system	Incentive system	Strategic	Tactical	Operational		
Amouzegar and Jacobsen [21]	✓			✓	✓	✓	✓	✓		—	Heuristic method
Kulshreshtha and Sarangi [22]	✓		✓			✓		✓		—	Game theory approach
Kara and Verter [23]				✓	✓			✓		—	Karush-Kuhn-Tuker conditions
Sheu et al. [24]		✓	✓			✓		✓		—	Pareto-optimal
Wojanowski et al. [25]	✓		✓			✓	✓	✓		—	Game theory approach
Mitra and Webster [28]		✓	✓			✓		✓		—	Nash equilibrium
Erkut and Gzara [26]				✓	✓			✓		—	Heuristic method
de Figueiredo and Mayerle [27]	✓			✓		✓	✓	✓		—	Heuristic method
Sheu and Chen [31]		✓	✓		✓	✓		✓		—	Nash equilibrium
Aksen et al. [30]	✓			✓		✓	✓	✓		Quality of returned products (stochastic approach)	Modified tabu search algorithm
Rezapour et al. [33]		✓		✓			✓	✓	✓	—	Game theory, variational inequality
Wang et al. [32]		✓	✓			✓		✓		—	Backward induction
This study		✓		✓	✓		✓	✓		Demand (min max regret robust approach)	Heuristic method based on enumeration and genetic algorithm

regulation as some parameters in the model. In this study, the impact of governmental regulation on closed-loop supply chain design and customer welfare is investigated through sensitivity analysis of the critical parameters in the bi-level programming configuration;

- Regarding algorithm design, first, the proposed model is solved by the heuristic algorithm based on enumeration and, then, is compared with the adaptive proposed genetic algorithm;

- Since most of the related studies considered the CLSC design in an uncertain environment, the impacts of the demand uncertainty on the governmental regulation and the CLSC configuration are investigated by applying robust optimization approach in this study.

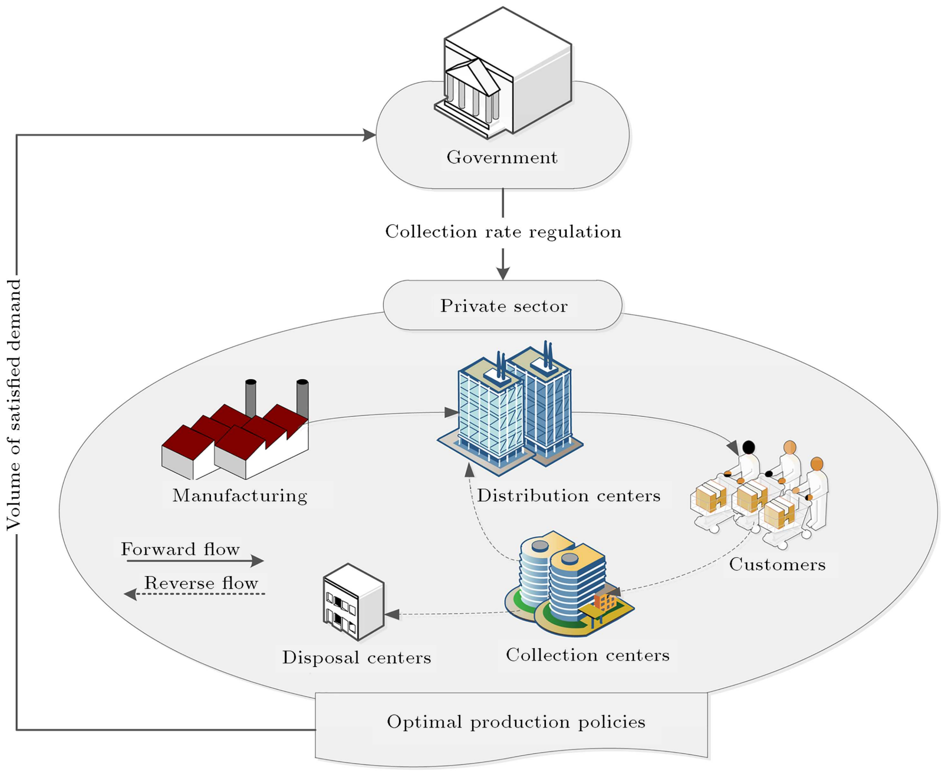

Figure 1. The proposed model configuration.

This paper is organized as follows: Section 2 develops a bi-level programming formulation for the government's legislative problem design with the aim of affecting private sector's policies. A heuristic algorithm and a genetic algorithm based on enumeration are described in Section 3. Computational results are presented in Section 4, and the bi-level proposed model in the presence of uncertainty is provided in Section 5. Then, the numerical analysis of the proposed model with uncertain demands is considered in Section 6. Finally, Section 7 provides a conclusion and suggestions for future research.

2. Model definition and formulation

2.1. Problem definition

As mentioned before, most of the works reviewed in the literature did not consider government's critical role in company's policies on collecting and recovering used products. As illustrated in Figure 1, a bi-level programming approach is applied to formulate this problem as a leader-follower model where the government is considered as the leader at the first level and tends to collect more used products by determining suitable collection rate denoted by A, while it ensures a minimum distribution ratio denoted by α to satisfy a minimum proportion of customers' demands. It is worth mentioning that A is the government's suitable collection rate and is assumed to be independent of the CLSC's activities. This variable determines a suitable fraction of potential reverses that government tends to collect. On the other hand, a closed-loop supply chain network is considered as a follower and tries to maximize its net profit subject to the government collection policies. In this model, it is assumed that each product user would be willing to return their used products if they received a reasonable incentive or payment from the company. In fact, the amount of incentive payment that a company offers to users is considered the same as the expected value of payments, encouraging users to return their used products. The unit incentive payment is denoted by q. It is supposed that almost $\mu\%$ of the used items will be returned based on the amount of incentive payment. Besides, the collected used products are transported to Collection Centers (CCs); after a quality test, products are divided into recoverable and scrapped categories. Recoverable products are repaired in collection centers, and scrapped products are shipped to disposal centers. Moreover, in the forward network, manufactured products and recovered products are shipped to Distribution Centers (DCs) separately to meet their demands. In addition, since the company will also incur collection-related costs such as opening facilities, transportation costs, and incentive payment to users, it may not be profitable to have a reverse logistics or, in a better situation, to collect all used products. It is clear that the companies will intend to collect the used products if there is high cost saving for each unit. In contrast, in the case of used products with low or minus cost saving, a high-level incentive or regulation should be proposed to achieve environmental objectives. As a result, the proposed model is more suitable for products with low or minus cost saving such that companies are not willing to collect their used products. Therefore, due to the environmental issues, the government should intervene as a superior and a legislative entity to force or motivate companies to collect used products in a supportive or legislative role.

The proposed model is applied in the real world. Some cases of the application of governmental acts and regulation to reverse models in the real world are mentioned as follows:

- The Waste Electrical and Electronic Equipment (WEEE) directive 2002/96/EC of the European Parliament and the Council became a European law in 2003 containing mandatory requirements on collection, recycling, and recovery for all types of electrical goods [17];
- The European Union (EU) Waste Framework Directive was developed in order to strengthen waste prevention and recovery in 2008. According to this act, industry and the commercial sector have been made responsible for the recovery of waste [18];
- Federal Environmental Protection Agency (FEPA) policies regulate the collection, treatment, and disposal of solid and hazardous wastes for municipal and industrial sources due to Nigeria's environmental pollutions [19];
- Germany was the first country to introduce obligatory regulations for the recovery and recycling of sales packaging, including paper and paperboard materials. The main characteristic of "Ordinance on the Avoidance of Packaging Waste", which came into effect in 1991, is an obligation on the part of trade and industry to take back a certain percentage of packaging materials.

2.2. Problem formulation

In this section, a bi-level mixed integer linear programming model formulation is presented. The notations used in the model are described as follows:

Index sets:

I	Set of fixed locations of production centers $i = 1, \cdots, I$
J	Set of candidate locations of distribution centers $j = 1, \cdots, J$
K	Set of customer zones $k = 1, \cdots, K$
L	Set of candidate locations of collection centers $l = 1, \cdots, L$
M	Set of fixed locations of disposal centers $m = 1, \cdots, M$

Parameters:

F_j	Fixed cost for opening distribution center j
F_l	Fixed cost for opening collection center l
C_i	Unit production cost at production center i
C_j	Unit storage cost at distribution center j
C_l	Unit inspection and collection cost at collection center l
C_l^r	Unit recovery cost at collection center l
C_m	Unit disposal cost at disposal center m
$C_{ij}, C_{jk}, C_{kl}, C_{lj}, C_{lm}$	Unit transportation travel cost between a pair of nodes from different sets
d_k	Customer's demands in zone k
α	Minimum ratio of customer's demands that should be satisfied (service level)
β	Recovery ratio of collected used products
$cap_i, cap_j, cap_l, cap_m$	Capacity of each center
p	Price of selling product
q	Incentive price paid to customers for each used product
μ	The fraction of used products returned to the private sector

Decision variables:

A	Proportion of distributed products that should be collected by the private sector
$X_{ij}, X_{jk}, X_{kl}, X_{lj}, X_{lm}$	Quantity of shipped products between a pair of nodes from different sets
Y_j	Binary variable is 1 if a DC opens in site j
Y_l	Binary variable is 1 if a CC opens in site l

The proposed model can be defined as follows:

$$Z_1 = \max A, \tag{1}$$

$$\sum_{j}^{J} \sum_{k}^{K} X_{jk}^{s} \geq \alpha \sum_{k}^{K} d_k, \tag{2}$$

$$0 \leq A \leq 1, \tag{3}$$

$$Z_2 = \max \sum_{j}^{J}\sum_{k}^{K} X_{jk}.p - \sum_{k}^{K}\sum_{l}^{L} X_{kl}.q - \sum_{i}^{I}\sum_{j}^{J}(C_i + C_{ij})X_{ij} - \sum_{j}^{J}\sum_{k}^{K}(C_j + C_{jk})X_{jk} - \sum_{l}^{L}\sum_{k}^{K}(C_l + C_{kl})X_{kl} - \sum_{l}^{L}\sum_{m}^{M}(C_m + C_{lm})X_{lm} - \sum_{l}^{L}\sum_{j}^{J}(C_{lj} + C_l^r)X_{lj} - \sum_{j}^{J} F_j Y_j - \sum_{l}^{L} F_l Y_l, \quad (4)$$

s.t.:

$$\sum_{l}^{L} X_{kl} \geq A \sum_{j}^{J} \mu.X_{jk} \qquad \forall\, k, \qquad (5)$$

$$\sum_{i}^{I} X_{ij} + \sum_{l}^{L} X_{lj} = \sum_{k}^{K} X_{jk} \qquad \forall\, j, \qquad (6)$$

$$\sum_{j}^{J} X_{lj} = \beta \sum_{k}^{K} X_{kl} \qquad \forall\, l, \qquad (7)$$

$$\sum_{m}^{M} X_{lm} = (1-\beta) \sum_{k}^{l} X_{kl} \qquad \forall\, l, \qquad (8)$$

$$\sum_{j}^{J} X_{ij} \leq Cap_i \qquad \forall\, i, \qquad (9)$$

$$\sum_{k}^{K} X_{jk} \leq Y_j Cap_j \qquad \forall\, j, \qquad (10)$$

$$\sum_{k}^{K} X_{kl} \leq Y_l Cap_l \qquad \forall\, l, \qquad (11)$$

$$\sum_{l}^{L} X_{lm} \leq Cap_m \qquad \forall\, m, \qquad (12)$$

$$\sum_{j}^{J} X_{jk} \leq d_k \qquad \forall\, k, \qquad (13)$$

$$X_{ij}, X_{jk}, X_{kl}, X_{lm}, X_{lj} \geq 0 \qquad \forall\, i,j,k,l,m,$$

$$Y_j, Y_l \in \{0,1\} \qquad \forall\, j,l. \qquad (14)$$

The outer problem is represented by Eqs. (1) to (3). Eq. (1) displays the government's objective function, which aims to maximize collection rate A; this variable of the outer problem is constituted as an input parameter for the inner problem. Constraint (2) assures that the desired amount of customers' demands is satisfied by the private sector; Constraint (3) represents the upper and lower levels of governmental decision variable. The inner problem is represented by Eqs. (4) to (14). In this problem, net profit function is maximized, as shown in Eq. (4), which is obtained by subtracting incentive payment and transportation, operational and opening DC and CC facilities costs from the total revenue of selling products to customers. Constraint (5) is the government's legislative constraint on each CLSC, which enforces the CLSC to collect a specific governmental collection rate of distributed products. Eqs. (6) to (8) represent the flow balances for each distribution and collection center. Constraints (9) to (12) ensure capacity restrictions on production, distribution, collection, and disposal centers, respectively. Constraint (13) restricts the number of products that can be distributed to the customers according to the number of demands. Finally, Constraint (14) shows the binary and non-negative restrictions on the decision variables of lower level.

3. Solution methodologies

Moore and Bard [34] showed that mixed integer bi-level programming models are Np-hard. Recent advances have been made concerning exact solutions for the mixed integer bi-level programming, such as cutting plane and decomposition-based solution method; however, their applicability is limited to small-sized instances only. Therefore, it is recommended using heuristic and meta-heuristic algorithms. In this section, at first, a heuristic algorithm is developed based on enumeration; however, since this method is not an efficient technique for large-sized problems, a genetic algorithm has been proposed to solve the developed model.

3.1. Heuristic algorithm based on enumeration

In the proposed model, since the outer problem is a univariate bounded model, the inner problem is only dependent on one variable of the outer problem to obtain the optimal network design. Thus, according to the specific form of the outer problem, the optimum value of the bi-level model in an iterative procedure can be obtained. Therefore, in the initialized iteration, the collection rate is set equal to maximum value, i.e., one, which can be then fixed in the inner problem as a parameter to solve the second-level model. The results of the inner problem are put in the outer problem constraint; in the case of satisfying the minimum demand responded constraint, the final solution of the bi-level model is obtained. Otherwise, collection ratio value (the first-level decision variable) is decreased by a small decrement, and the second level is solved again. This iterative procedure continues until minimum demand responded constraint is satisfied.

3.2. Proposed genetic algorithm for the inner problem

As discussed before, the main idea of solving the proposed bi-level model is based on enumeration regarding the first level variable; now, this study implements a proposed genetic algorithm for solving an inner problem instead of applying commercial solvers to General Algebraic Modeling System (GAMS). Genetic algorithm is an evolutionary search algorithm that uses mechanisms of natural selection and genetics to find optimal or near-optimal solutions to the problems.

3.2.1. Chromosomes

One of the most important components of Genetic Algorithm (GA) is the selection of chromosomes as a solution representation. Attempts have been made to select the best chromosomes in the proposed GA that lead the algorithm to optimal or near-optimal solutions. Since the proposed inner problem is a location-allocation problem, the strategic decisions of the inner problem are considered as chromosomes. In fact, the candidate locations of DCs and CCs are set as binary chromosomes, where each gene indicates one of the candidate locations, and the binary amount of that represents the opening status of its location. The selected chromosome is presented in Figure 2. It is shown that nodes 2, 3, and 4 have been selected as opened distribution centers, while collection centers (nodes (3) and (4)) have been opened.

3.2.2. Initial population and Fitness

A specific number of chromosomes are created randomly as the initial population, and the fitness of each individual is evaluated subsequently. As presented in Section 3, the outer problem has one variable and its value is constituted as an input parameter for the inner problem. Besides, the inner problem is composed of binary and continuous variables that represent strategic and tactical decisions, respectively. As represented in the previous subsection, binary variables are considered as chromosomes of genetic algorithm; thus, to evaluate the fitness of each individual, the value of the continuous variable should be determined. Therefore, at first, X_{jk} (flowing from distribution centers to the customers) and X_{kl} (flowing from customers to collection centers) are determined randomly as the most important flows of the proposed CLSC; the other allocations of X_{lj}, X_{lm}, and X_{ij} are evaluated by greedy algorithm and Vogel's Approximation Method (VAM). Following this procedure, the fitness of each individual can be evaluated. The individuals are sorted based on their fitness to perform the crossover and mutation operators on the best individuals and generate a new individual based on the best chromosomes. The parents and offspring chromosomes are arranged based on the value of the fitness, and the best chromosomes are selected for the next generation according to the population size.

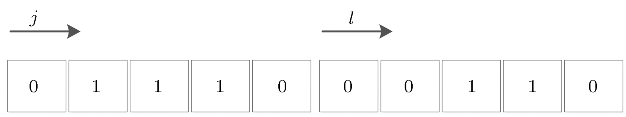

Figure 2. A sample chromosome in the proposed genetic algorithm.

3.2.3. Crossover operator

Crossover is one of the main operators of the genetic algorithm to diversify the search process. This operator merges the genes of two parent's chromosomes and generates two offspring. The crossover point is chosen randomly, and the values of both sides of the chromosomes are exchanged. Accordingly, the one-point crossover is applied, as shown in Figure 3.

3.2.4. Mutation operator

Mutation is one of the other main operators of the genetic algorithm, preventing the algorithm from trapping in local optimum by exploring new solution spaces. This operator is applied to the chromosomes according to the mutation probability. To create an extensive search, the mutation operator is considered as a combination of four different mutation types: general mutation, swap, insertion, and reversion. The general mutation changes the opening status of the random selected gene with a small mutation probability. Swap is applied as the second mutation type; this mutation operator exchanges the values of two random selected genes. Moreover, the insertion mutation removes a randomly selected gene from the string and reinserts it into a different randomly selected gene with insertion probability. Finally, the reversion mutation operator inverts the substring between the two random

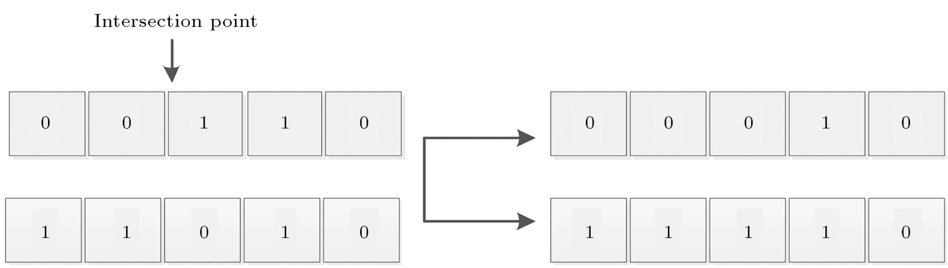

Figure 3. Crossover operation for the proposed model.

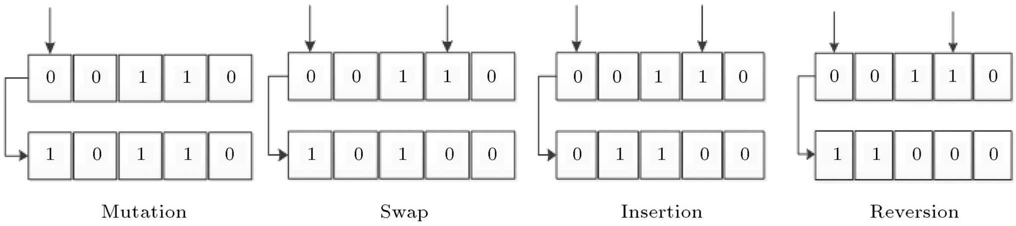

Figure 4. Different applied mutation operators in the proposed algorithm.

```
SET Algorithm Parameters (Population-Size, Iteration-Number, Acceptable-Satisfied Demand-Ratio(α))
SET Collection-Ratio=1
WHILE SatisfiedDemand-Ratio≤Acceptable-SatisfiedDemand-Ratio (α)
        CHOOSE initial population randomly
        FIND the best Flows for each individual based on Greedy Algorithm
        EVALUATE fitness of each individual
        FIND the best fitness and set as P_Best
        FOR j = 1 To Number of generations
                Do Crossover and Mutation Operators to generate P_NEW
                        FIND Best Flows for P_NEW Based on a Greedy Algorithm
                        Evaluate fitness of P_NEW
                        Update P_Best
                SORT Population
                Select Population-Size Best Solution as new population by Elitist
        END FOR
        Report P_Best.P_Best fitness
        EVALUATE Satisfied-Demand-Ratio for P_Best
        Collection-Ratio = Collection-Ratio-0.02
END WHILE
```

Figure 5. Pseudocode of the proposed solution algorithm based on GA.

reversion points. For example, the application of these four operators is illustrated in Figure 4. It is worth mentioning that after defining the location decisions, allocation decisions are determined by the aforementioned procedure.

3.2.5. Selection

To select the next generation chromosomes according to the population size, a selection method should be chosen for the algorithm. Among different possible selection methods, the elite mechanism is applied in this paper. The best chromosomes are selected based on the parents and offspring fitness. The pseudocode of the proposed solution algorithm based on GA is represented in Figure 5.

In addition, the parameters of genetic algorithm, such as population size, rate of crossover and mutation, and maximum generation number, need to be set properly to seek the optimal solution efficiently. These parameters are tuned by Taguchi method.

4. Computational study

To illustrate the applicability of the proposed model, some numerical studies are conducted. The parameter values are generated randomly according to the uniform distributions specified in Table 2.

As mentioned before, Taguchi method is applied to set four major parameters to obtain better results. The first one is the number of generations, and others are the population size, the crossover, and mutation rates. The instances are solved by the heuristic enumeration method in the GAMS 23.5 software and by the proposed genetic algorithm coded in MATLAB

Table 2. Parameter values of problem instances.

Parameter	Value	Parameter	Value
d_k	~Uniform (300, 700)	C_j	~Uniform (300, 400)
C_{ab}	~Uniform (20, 2000)	C_l	~Uniform (200, 250)
F_j	~Uniform (50000, 200000)	C_l^r	~Uniform (250, 350)
F_l	~Uniform (50000, 200000)	C_m	~Uniform (200, 250)
C_i	~Uniform (500, 600)	(β, μ)	$= (0.7, 0.8)$

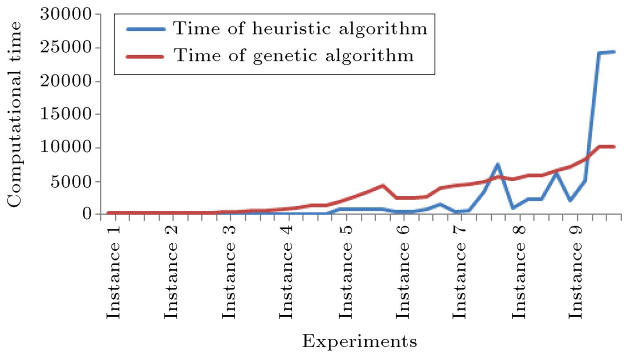

Figure 6. Comparison of heuristic and genetic algorithms in terms of time.

2012 in a PC with the following configurations: core (TM) i5, 2.40 GHz CPU, and 4.00 GB RAM. The results are reported in Table 3.

According to the reported results in Table 3, the proposed genetic algorithm has acceptable performance compared to the heuristic algorithm in terms of both accuracy and computational time for large-sized instances. Computation times of the mentioned algorithms are compared graphically in Figure 6, too.

5. An extension of the problem to consider uncertainty

As discussed before, there is uncertainty of demands in real cases that can affect the CLSC network designs. Review of CLSC network design with leader and follower configuration confirms the assumption of most previous studies that design parameters are deterministic. Thus, by considering uncertain demands, the proposed model is developed, and some solution approaches are applied in order to analyze it.

5.1. Expected value approach

In order to deal with uncertain demands in the proposed model, Expected Value (EV) approach is applied as one of the first simple approaches to solving this type of problems when there are different scenarios without their occurrence probabilities. In fact, in this approach, each uncertain parameter is replaced by the expected value of the parameter in different scenarios.

5.2. Robust bi-level programming

There are two types of robust approaches. In the first type, the robustness is defined for the variations, while, in the second one, the decision is made based on the worst case scenario. To consider both of the mentioned types, two approaches are considered as follows.

5.2.1. Min-sum regret based bi-level programming

As mentioned before, the government as a legislative and supportive entity is responsible for global pollution issues, customer satisfaction, and creation of a secure and competitive market for private sectors. Moreover, as the government policies have a direct effect on the private sector decisions, the government's policies should be as robust and reliable as possible. In the proposed min-sum regret approach, the main goal is to minimize the summation of deviations of the robust solution from the optimal solutions of each scenario denoted by A_s^* and Z_s^* for the government and private sector, respectively, where the set of scenarios is denoted by $s = 1, 2, \cdots, S$; in addition, parameter d_k^s is defined as customer's demand of zone k under scenario s. In order to formulate the bi-level CLSCND under uncertainty, new variables that should be taken after the realization of the scenarios are defined as X_{ij}^s, X_{jk}^s, X_{kl}^s, X_{lm}^s, and X_{lj}^s, which are the quantity of products and used products that are shipped in the forward and reverse logistics under scenario s, respectively. Thus, the robust bi-level model can be formulated as follows:

$$\min \quad |A - A_1^*| + |A - A_2^*| + \cdots + |A - A_s^*|, \tag{15}$$

$$\sum_j^J \sum_k^K X_{jk}^s \geq \alpha \sum_k^K d_k^s \qquad \forall\ s, \tag{16}$$

$$0 \leq A \leq 1, \tag{17}$$

$$\min \quad |Z - Z_1^*| + |Z - Z_2^*| + \cdots + |Z - Z_s^*|, \tag{18}$$

s.t.:

$$\begin{aligned} Z_2^s = &\sum_s \sum_j \sum_k X_{jk}^s.p - \sum_s \sum_k \sum_l X_{kl}^s.q \\ &- \sum_s \sum_i \sum_j (C_i + C_{ij}) X_{ij}^s \\ &- \sum_s \sum_j \sum_k (C_j + C_{jk}) X_{jk}^s \\ &- \sum_s \sum_l \sum_k (C_l + C_{kl}) X_{kl}^s \\ &- \sum_s \sum_l \sum_m (C_m + C_{lm}) X_{lm}^s \\ &- \sum_s \sum_l \sum_j (C_{lj} + C_l^r) X_{lj}^s - \sum_j^J F_j Y_j \\ &- \sum_l^L F_l Y_l, \end{aligned} \tag{19}$$

$$\sum_l^L X_{kl}^s \geq A \sum_j^J X_{jk}^s \qquad \forall\ k, s, \tag{20}$$

$$\sum_i^I X_{ij}^s + \sum_l^L X_{lj}^s = \sum_k^K X_{jk}^s \qquad \forall\ j, s, \tag{21}$$

Table 3. Heuristic and meta-heuristic results of the proposed bi-level programming model.

Instance (I, J, K, L, M)	α	Heuristic method based on enumeration			Genetic algorithm			Gap
		A	Private sector's profit	CPU time	A	Private sector's profit	CPU time	
(2, 5, 10, 5, 1)	0.8	0.58	1512133.94	0:00:05	0.58	1512133.94	0:04:59	0
	0.6	0.66	707019.78	0:00:05	0.66	707019.78	0:03:09	0
	0.4	0.74	156371.06	0:00:04	0.74	152428.47	0:02:37	0.025
	0.2	0.74	156371.06	0:00:04	0.74	152428.47	0:02:37	0.025
(3, 10, 20, 10,2)	0.8	0.74	7681946.39	0:00:07	0.74	7645352.97	0:05:32	0.004
	0.6	0.86	1006000.14	0:00:04	0.86	962723.68	0:03:08	0.04
	0.4	0.86	1006000.14	0:00:05	0.86	962723.68	0:03:04	0.04
	0.2	0.88	142122.76	0:00:05	0.88	139828.82	0:02:54	0.01
(3, 15, 40, 15, 2)	0.8	0.56	17253730	0:00:08	0.56	17175350.33	0:11:52	0.005
	0.6	0.6	10286420	0:00:11	0.6	10197593.93	0:11:24	0.009
	0.4	0.66	2750120.21	0:00:10	0.66	2704139.49	0:08:12	0.02
	0.2	0.7	53093.41	0:00:07	0.7	52139.72	0:07:46	0.02
(5, 30, 80, 30, 3)	0.8	0.58	19190240	0:00:47	0.58	19182231.36	0:21:51	0.0004
	0.6	0.58	19190240	0:00:47	0.58	19182231.36	0:21:51	0.0004
	0.4	0.62	7779105.1	0:00:38	0.62	7687329.4	0:18:12	0.01
	0.2	0.66	1144279.3	0:00:26	0.66	1121922.77	0:14:34	0.02
(10, 50, 150, 50, 5)	0.8	0.46	100336800	0:14:37	0.46	98112967.2	1:14:16	0.02
	0.6	0.52	57850130	0:14:27	0.52	55896113.11	0:57:22	0.03
	0.4	0.6	19742350	0:13:44	0.6	18747260.3	0:43:36	0.05
	0.2	0.64	6713536.8	0:13:36	0.64	6256236.6	0:31:27	0.07
(12,60, 220, 60, 5)	0.8	0.62	91797100	0:26:04	0.62	84834093.48	1:06:51	0.07
	0.6	0.7	23515353	0:14:26	0.7	21543777.41	0:44:26	0.08
	0.4	0.72	12876980	0:08:23	0.72	11687940	0:41:13	0.09
	0.2	0.72	12876980	0:08:23	0.72	11687940	0:41:13	0.09
(15,80, 320, 80, 6)	0.8	0.6	118869100	2:55:56	0.6	109889217.4	1:33:27	0.08
	0.6	0.64	71912280	0:58:40	0.64	70664293.6	1:23:41	0.02
	0.4	0.68	31552570	0:10:46	0.68	29767058.1	1:16:14	0.06
	0.2	0.7	15734629	0:06:55	0.7	14832441.9	1:11:32	0.06
(17, 100, 420, 100, 8)	0.8	0.64	113683300	0:45:12	0.64	120783129.2	1:49:28	0.06
	0.6	0.66	76017570	0:36:05	0.66	74241162.7	1:39:17	0.02
	0.4	0.66	76017570	0:36:05	0.66	74241162.7	1:39:17	0.02
	0.2	0.7	29632390	0:07:42	0.7	26725529.3	1:27:42	0.1
(20, 120, 520, 120, 10)	0.8	0.76	65144947	6:45:14	0.76	58511938.7	2:48:26	0.11
	0.6	0.76	65144947	6:45:14	0.76	58511938.7	2:48:26	0.11
	0.4	0.78	27835720	1:04:01	0.78	25614811.6	2:17:51	0.08
	0.2	0.8	7585857	0:26:42	0.8	7152773.3	1:58:19	0.06

$$\sum_{j}^{J} X_{lj}^{s} = \beta \sum_{k}^{K} X_{kl}^{s} \qquad \forall\ l, s, \tag{22}$$

$$\sum_{m}^{M} X_{lm}^{s} = (1-\beta) \sum_{k}^{l} X_{kl}^{s} \qquad \forall\ l, s, \tag{23}$$

$$\sum_{j}^{J} X_{ij}^{s} \leq Cap_i \qquad \forall\ i, s, \tag{24}$$

$$\sum_{k}^{K} X_{jk}^{s} \leq Y_j Cap_j \qquad \forall\ j, s, \tag{25}$$

$$\sum_{k}^{K} X_{kl}^{s} \leq Y_l Cap_l \qquad \forall\ l, s, \tag{26}$$

$$\sum_{l}^{L} X_{lm}^{s} \leq Cap_m \qquad \forall\ m, s, \tag{27}$$

$$\sum_{j}^{J} X_{jk}^{s} \leq d_k^s \qquad \forall\ k, s, \tag{28}$$

$$X_{ij}^{s}, X_{jk}^{s}, X_{kl}^{s}, X_{lm}^{s}, X_{lj}^{s} \geq 0 \qquad \forall\ i, j, k, l, m, s,$$

$$Y_j, Y_l \in \{0, 1\} \qquad \forall\ j, l, \tag{29}$$

The aforementioned heuristic enumeration solution approach is used to solve the presented model; however, some changes have been implemented because of the objective function configuration.

5.2.2. Min-max regret based bi-level programming

By applying min-max regret approach, a decision is made with the least risk; therefore, the decision-making is done considering the worst case. The robust bi-level model can be formulated by applying min-max regret approach as follows:

$$\min \quad \max(|A - A_s^*|), \tag{30}$$

$$(16), (17),$$

$$\min \quad \max(|Z - Z_s^*|), \tag{31}$$

$$(19) - (29).$$

Again, the heuristic enumeration method is used to solve the proposed bi-level programming. It is worth mentioning that, in spite of the previous problem, all possible values of the first level variable should be considered during the search algorithm.

6. Uncertainty analysis of the proposed model

In order to evaluate the proposed bi-level model under uncertainty, some numerical examples are generated and illustrated in Table 4. The first scenario of each instance (base-case) is similar to the deterministic demands considered in Section 5. The optimum solution of each instance based on each proposed uncertainty approach is compared in terms of the feasibility and changes in value of the first and second level objective functions with respect to the base case scenario.

At first, the necessity of using uncertainty approaches in the proposed model is examined. Since the government's strategy and location of facilities are strategic decisions, these variables are fixed in the proposed model. Their values were obtained from the base case in $\alpha = 0.6$, as reported in Table 5. Thus, based on fixed decisions, both feasibility and player benefits are examined considering the occurrence of all possible scenarios. Actually, since the proposed model has a bi-level nature, uncertainty has higher impacts on the obtained value; of course, the feasibility of the model is compared with that of the classic single-level CLSC network design. The necessity analysis results are presented in Table 6. It is shown that ignoring of demand uncertainties will result in infeasibility or private sector loss, meaning that uncertainty should be considered in the proposed CLSC design problem. Actually, although the government strategy should support and facilitate private sector's production cycle processes and provide welfare and satisfaction for customers, it can be seen that, in almost all of the experiments, both of these main goals are not achieved and that decision-making without uncertainty approaches leads to customers dissatisfaction or private sectors loss.

6.1. Applying uncertainty approaches

In order to deal with uncertain environment, expected value approach, min-sum regret based and min-max regret based bi-level programming approaches are applied.

6.1.1. Results of the expected value approach

As mentioned before, expected value approach is one of the simplest approaches to uncertain parameters. In this approach, each demand parameter is replaced by the expected value of the parameter in different scenarios. The results are reported in Table 7.

The achieved results of strategic decisions by the mentioned approach were fixed in the model, and the model feasibility and players' objectives were calculated for each scenario. It was compared with the number of infeasibilities in Table 6. A comparison between them is shown in Figure 7. Although the results of expected value approach are better than those of deterministic approach, infeasibility and private sector loss exist, too. The expected value approach encourages governments to make a more conservative decision so as to decrease the infeasibility risk.

Table 4. Product demands of each region under different scenarios.

	Scenarios	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Instance 1	Scenario 1	420	670	600	660	350	450	550	520	380	400
	Scenario 2	470	720	650	590	400	500	600	560	400	600
	Scenario 3	380	600	500	580	280	530	480	600	420	460
	Scenario 4	600	720	700	800	400	500	600	570	560	550
	Scenario 5	300	420	390	720	200	350	400	400	300	320
Instance 2	Scenario 1	420	670	600	660	350	450	550	520	380	400
	Scenario 2	600	800	700	500	500	520	600	450	500	200
	Scenario 3	500	700	500	650	450	500	570	500	500	300
	Scenario 4	450	750	700	600	400	470	520	550	400	350
	Scenario 5	280	400	400	500	200	320	350	380	250	250
Instance 3	Scenario 1	420	670	600	660	350	450	550	520	380	400
	Scenario 2	500	350	420	450	550	420	350	420	550	620
	Scenario 3	650	700	800	750	520	300	650	700	540	550
	Scenario 4	470	800	640	710	450	470	500	550	450	430
	Scenario 5	500	600	570	720	470	500	450	650	350	470
Instance 4	Scenario 1	420	670	600	660	350	450	550	520	380	400
	Scenario 2	670	300	350	750	700	600	720	300	550	630
	Scenario 3	350	600	630	450	420	380	750	650	600	550
	Scenario 4	500	750	700	500	450	510	500	700	500	450
	Scenario 5	480	700	650	700	300	520	480	480	450	350
Instance 5	Scenario 1	420	670	600	660	350	450	550	520	380	400
	Scenario 2	200	950	300	800	700	650	800	250	650	700
	Scenario 3	300	800	350	300	450	300	700	670	500	460
	Scenario 4	550	450	300	750	500	250	400	300	550	500
	Scenario 5	500	400	700	570	300	500	500	600	300	300
Instance 6	Scenario 1	420	670	600	660	350	450	550	520	380	400
	Scenario 2	600	950	220	300	700	700	800	350	650	700
	Scenario 3	250	500	800	400	900	300	850	750	510	510
	Scenario 4	400	500	400	700	200	300	100	400	700	350
	Scenario 5	250	200	300	200	250	310	250	250	450	300

Table 5. Result of bi-level programming with deterministic parameters.

	Deterministic approach			
	Government strategy	**Private sector's profit**	**DC opened locations**	**CC opened locations**
Scenario 1	0.66	707019.778	1, 4	1

Table 6. Necessity of considering the proposed uncertainty approach.

		Private sector's profit	α	Status
Instance 1	Scenario 2	759518.39	0.54	Infeasible
	Scenario 3	701551.07	0.62	Private sector's loss
	Scenario 4	766291.07	0.5	Infeasible
	Scenario 5	484513.51	0.79	Private sector's loss
Instance 2	Scenario 2	753443.9	0.55	Infeasible
	Scenario 3	736489.53	0.58	Infeasible
	Scenario 4	719073.84	0.58	Infeasible
	Scenario 5	408969.11	0.9	Private sector's loss
Instance 3	Scenario 2	771811.92	0.65	—
	Scenario 3	780216.05	0.48	Infeasible
	Scenario 4	743973.25	0.54	Infeasible
	Scenario 5	761737.47	0.57	Infeasible
Instance 4	Scenario 2	800974.09	0.53	Infeasible
	Scenario 3	725567.32	0.56	Infeasible
	Scenario 4	756395.88	0.54	Infeasible
	Scenario 5	706257.93	0.58	Infeasible
Instance 5	Scenario 2	791667.58	0.5	Infeasible
	Scenario 3	702160.27	0.62	Private sector's loss
	Scenario 4	740467.66	0.65	—
	Scenario 5	678321.17	0.64	Private sector's loss
Instance 6	Scenario 2	800621.52	0.5	Infeasible
	Scenario 3	808494.91	0.52	Infeasible
	Scenario 4	610341.69	0.74	Private sector's loss
	Scenario 5	–295677.34	1	Private sector's loss

Table 7. Expected value approach results.

	Expected Value approach			
	Government strategy	**Private sector's profit**	**DC opened locations**	**CC opened locations**
Instance 1	0.58	1481113.03	4, 5	5
Instance 2	0.66	702844.38	4, 1	1
Instance 3	0.58	1542083.23	4, 5	5
Instance 4	0.58	1542478.07	4, 5	5
Instance 5	0.58	1493508.35	1, 2, 3, 4	5
Instance 6	0.66	752439.42	3, 4	1

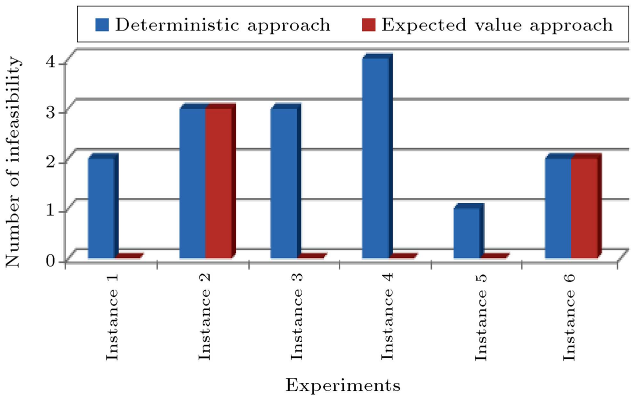

Figure 7. Comparison between the EV and deterministic approaches in a number of infeasible cases.

6.1.2. Results of min-sum and min-max regret-based bi-level programming

In both approaches, strategic decisions are made to respond to all possible scenarios. Of note, the second approach is subject to the least risk during decision-making. The results are presented in Tables 8 and 9, respectively.

Due to Constraint (16), the robust results are certainly feasible. As can be seen in Table 8 and Table 9, by applying these approaches, the government makes a more conservative decision to remove the infeasibility risk. Therefore, the private sector's benefit is almost more than the private sectors' benefit to which deterministic and expected value approaches have been applied as a result of less collection rate. However, based on Table 8, min-sum regret approach could not achieve a feasible solution to satisfy the entire specified rate of customers' demands for all of the scenarios in Instances 2 and 6.

Since the government is a legislative entity and its decisions have a direct effect on the private sector decisions, the government should clearly make its decisions as robust as possible. It is proven that if the government's decisions have more fluctuations and freedom, the private sector will lose more benefit. Thus, as can be seen, although government's policy is less than the other approaches in min-max regret robust optimization approach, this approach ensures the feasibility of the model under each possible scenario and government does not need to change its policy after scenario occurrence. In addition, the private sector's benefit is almost better than the other approaches. The comparison between the average private sector's benefits obtained from each scenario occurring in various instances is illustrated in Figure 8.

7. Conclusion

In this study, a bi-level programming approach was proposed to formulate a closed-loop supply chain net-

Table 8. Min-sum regret based bi-level programming results.

	Min-sum regrets robust approach							
	Government strategy	Objective function		Private sector's profit				
		Level 1	Level 2	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Instance 1	0.4	1.08	2897773.36	4126827.62	4126827.62	4126827.62	4126827.62	4126827.62
Instance 2	Infeasible							
Instance 3	0.54	0.36	1059190.04	1860483.14	1901518.17	1937028.46	1889169.71	1903591.72
Instance 4	0.58	0.14	487681.09	1503894.96	1433863.32	1503894.96	1503894.96	1503894.96
Instance 5	0.56	0.4	544692.882	1618969.81	1662131.32	1627453.01	1624091.05	1618158.17
Instance 6	Infeasible							

Table 9. Min-max regret based bi-level programming results.

	Min-max regret robust approach							
	Government strategy	Objective function		Private sector's profit				
		Level 1	Level 2	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Instance 1	0.48	0.18	857155.03	3234867.29	2517939.2	2387321.08	3156467.42	2190931.84
Instance 2	0.3	0.44	1478936.38	5606885.45	5652555.33	5604666.39	5593408.39	3373995.21
Instance 3	0.56	0.1	256006.53	1614735.02	1507088.28	1710399.77	1587925.22	1581600.91
Instance 4	0.58	0.08	142233.01	1369890.93	1599047.22	1446041.64	1449317.46	1361661.95
Instance 5	0.56	0.1	184530.03	1618969.81	1663246.15	1579400.7	1477601.29	1433628.14
Instance 6	0.24	0.5	2873170.1	7352204.07	6584499.87	5882054.12	4366172.55	1536294.08

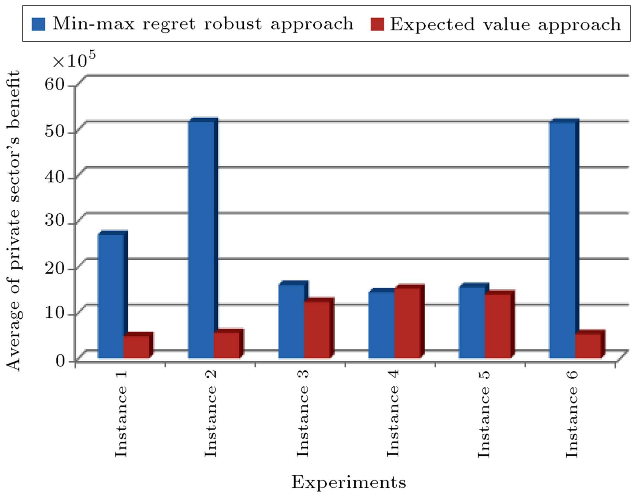

Figure 8. Comparison between the EV and min-max regret approaches in private sector's benefit.

work design problem under the governmental legislative decisions as a leader-follower configuration. Indeed, the government as the leader seeks to set the widely used product collection rate policy by ensuring the achievement of at least a predefined satisfied demand rate. On the other hand, the private sector as a follower sets its CLSC design to determine the location of distribution and collection centers among a set of candidate sites and to obtain the highest net profit subject to the government regulation. Heuristic and genetic algorithms based on enumeration were proposed for the model. Numerical examples were randomly generated and used to test and evaluate efficiency of the solution approaches. Computational results showed that the proposed genetic algorithm could obtain a near-optimal solution in large-scale instances in a reasonable amount of time, compared with the enumeration approach. Besides, a min-max regret and min-sum regret based bi-level programming approaches were proposed to incorporate uncertainty of demands. The numerical comparisons confirm their necessity as well as their efficiency. Considering the uncertainty of other parameters in the proposed model is suggested as for a future study. Moreover, the application of other stochastic and robust approaches to bi-level programming can be considered as another future work direction.

References

1. Altmann, M. and Bogaschewsky, R. "An environmentally conscious robust closed-loop supply chain design", *Journal of Business Economics*, **84**, pp. 613-637 (2014).

2. Zeballos, L.J., Méndez, C.A., Barbosa-Povoa, A.P., and Novais, A.Q. "Multi-period design and planning of closed-loop supply chains with uncertain supply and demand", *Computers & Chemical Engineering*, **66**, pp. 151-164 (2014).

3. Ma, R., Yao, L., Jin, M., Ren, P., Lv, Z. "Robust environmental closed-loop supply chain design under uncertainty", *Chaos, Solitons & Fractals*, **89**, pp. 195-202 (2015).

4. Talaei, M., Farhang Moghaddam, B., Pishvaee, M.S., Bozorgi-Amiri, A., and Gholamnejad, S. "A robust fuzzy optimization model for carbon-efficient closed-loop supply chain network design problem: A numerical illustration in electronics industry", *Journal of Cleaner Production*, **113**, pp. 662-673 (2015).

5. Giri, B.C. and Sharma, S. "Optimal production policy for a closed-loop hybrid system with uncertain demand and return under supply disruption", *Journal of Cleaner Production*, **112**, pp. 2015-2028 (2016).

6. Keyvanshokooh, E., Ryan, S.M., and Kabir, E. "Hybrid robust and stochastic optimization for closed-loop supply chain network design using accelerated benders decomposition", *European Journal of Operational Research*, **249**, pp.76-92 (2016).

7. Dutta, P., Das, D., Schultmann, F., and Fröhling, M. "Design and planning of a closed-loop supply chain with three way recovery and buy-back offer", *Journal of Cleaner Production*, **135**, pp. 604-619 (2016).

8. Zeballos, L.J. and Méndez, C.A. "Chapter 16 - managing risk in the design of product and closed-loop supply chain structure", In *Computer Aided Chemical Engineering*, Eds.: Mario R. Eden Mariano Martín and G. Chemmangattuvalappil Nishanth, **39**, pp. 443-474 (2017).

9. Jeihoonian, M., Kazemi Zanjani, M., and Gendreau, M. "Closed-loop supply chain network design under uncertain quality status: case of durable products", *International Journal of Production Economics*, **183**, pp. 470-486 (2017).

10. Huang, M., Yi, P., Guo, L., and Shi, T. "A modal interval based genetic algorithm for closed-loop supply chain network design under uncertainty", *IFAC-PapersOnLine*, **49**, pp. 616-621 (2016).

11. Fareeduddin, M., Shokri, Z., Adnan, H., and Mujahid, N. "Multi-period planning of closed-loop supply chain with carbon policies under uncertainty", *Transportation Research Part D: Transport and Environment*, **51**, pp. 146-172 (2017).

12. Safaei, A.S., Roozbeh, A., and Paydar, M.M. "A robust optimization model for the design of a cardboard closed-loop supply chain", *Journal of Cleaner Production*, **166**, pp. 1154-1168 (2017).

13. Hassanzadeh Amin, S., Zhang, G., and Akhtar, P. "Effects of uncertainty on a tire closed-loop supply chain network", *Expert Systems with Applications*, **73**, pp. 82-91 (2017).

14. Farrokh, M., Azar, A., Jandaghi, G., and Ahmadi, E. "A novel robust fuzzy stochastic programming for closed loop supply chain network design under hybrid uncertainty", *Fuzzy Sets and Systems*, **341**, pp. 69-91 (2017).

15. Haddadsisakht, A. and Ryan, S.M. "Closed-loop supply chain network design with multiple transportation modes under stochastic demand and uncertain carbon tax", *International Journal of Production Economics*, **195**, pp. 118-131 (2018).

16. Govindan, K., Soleimani, H., and Kannan, D. "Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future", *European Journal of Operational Research*, **240**(3), pp. 603-626 (2015).

17. Toffel, M.W. "Strategic management of product recovery", *California Management Review*, **46**(2), pp. 120-141 (2004).

18. European Parliament and council "Directive 2008/98/EC of the European parliament and of the council of 19 November 2008 on waste and repealing certain directives", (2008). ELI: http://data,europa.eu/eli/2008/98/oj

19. Echefu, N. and Akpofure, E. "Environmental impact assessment in Nigeria: Regulatory background and procedural framework", *UNEP EIA Training Resource Manual* (2002).

20. Bracken, J. and McGill, J.T. "Mathematical programs with optimization problems in the constraints", *Operations Research*, **21**(1), pp. 37-44 (1973).

21. Amouzegar, M.A. and Jacobsen, S.E. "A decision support system for regional hazardous waste management alternatives", *Advances in Decision Sciences*, **2**(1), pp. 23-50 (1998).

22. Kulshreshtha, P. and Sarangi, S. ""No return, no refund": an analysis of deposit-refund systems", *Journal of Economic Behavior & Organization*, **46**(4), pp. 379-394 (2001).

23. Kara, B.Y. and Verter, V. "Designing a road network for hazardous materials transportation", *Transportation Science*, **38**(2), pp. 188-196 (2004).

24. Sheu, J.-B., Chou, Y.-H., and Hu, C.-C. "An integrated logistics operational model for green-supply chain management", *Transportation Research Part E: Logistics and Transportation Review*, **41**(4), pp. 287-313 (2005).

25. Wojanowski, R., Verter, V., and Boyaci, T. "Retail-collection network design under deposit-refund", *Computers & Operations Research*, **34**(2), pp. 324-345 (2007).

26. Erkut, E. and Gzara, F. "Solving the hazmat transport network design problem", *Computers & Operations Research*, **35**(7), pp. 2234-2247 (2008).

27. de Figueiredo, J.N. and Mayerle, S.F. "Designing minimum-cost recycling collection networks with required throughput", *Transportation Research Part E: Logistics and Transportation Review*, **44**(5), pp. 731-752 (2008).

28. Mitra, S. and Webster, S. "Competition in remanufacturing and the effects of government subsidies", *International Journal of Production Economics*, **111**(2), pp. 287-298 (2008).

29. Plambeck, E. and Wang, Q. "Effects of e-waste regulation on new product introduction", *Management Science*, **55**(3), pp. 333-347 (2009).

30. Aksen, D., Aras, N., and Karaarslan, A.G. "Design and analysis of government subsidized collection systems for incentive-dependent returns", *International Journal of Production Economics*, **119**(2), pp. 308-327 (2009).

31. Sheu, J.-B. and Chen, Y.J. "Impact of government financial intervention on competition among green supply chains", *International Journal of Production Economics*, **138**(1), pp. 201-213 (2012).

32. Wang, W., Zhang, Y., Zhang, K., Bai, T., and Shang, J. "Reward-penalty mechanism for closed-loop supply chains under responsibility-sharing and different power structures", *International Journal of Production Economics*, **170**, pp. 178-190 (2015).

33. Rezapour, S., Farahani, R.Z., Fahimnia, B., Govindan, K., and Mansouri, Y. "Competitive closed-loop supply chain network design with price-dependent demands", *Journal of Cleaner Production*, **93**, pp. 251-272 (2015).

34. Moore, J.T. and Bard, J.F. "The mixed integer linear bilevel programming problem", *Operations Research*, **38**(5), pp. 911-921 (1990).

Biographies

Atefeh Hassanpour received her BS and MS degrees in Industrial Engineering from KNT University and Alzahra University, respectively. She is a PhD Candidate in KNT University right now. Her main research interests include optimization, SCM, and exact and meta-heuristics algorithms.

Jafar Bagherinejad received his PhD degree from Bradford University, UK (1997) and is an Associate Professor of the Industrial Engineering Department, Faculty of Engineering and Technology, Alzahra University, Tehran, Iran. His research interest areas are location-allocation problems including queuing models, queueing systems, project management and control, especially in scheduling problems, quality management, control and quality systems, and innovation and technology engineering and engineering management. He gained professional experience during his various positions as the Dean of Engineering and Technology Faculty, Alzahra University, 2000-2007; the Head of Industrial Engineering Department, 2011-2015; teaching at Industrial Engineering Department since 2000 for undergraduate and postgraduate students in the Industrial Engineering and Information Technology Management programs. Further, he has several papers published in the national and international journals and some books that have been published in Iran.

Mahdi Bashiri is a Professor of Industrial Engineering at Shahed University. He holds a BSc in Industrial Engineering from Iran University of Science and Technology and obtained his MSc and PhD from Tarbiat Modarres University. He is a recipient of the 2013 young national top scientist award from the Academy of Sciences of the Islamic Republic of Iran. He serves as the Editor-in-Chief of Journal of Quality Engineering and Production Optimization published in Iran and an editorial board member of some reputable academic journals. His research interests are facilities planning, stochastic optimization, meta-heuristics, and multi-response optimization. He published one book and more than 190 papers in reputable academic journals and conferences.