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

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Abstract

This study aims in providing a new approach regarding design of a closed loop supply chain network through emphasizing on the impact of the environmental government policies based on a bi-level mixed integer linear programming model. Government is considered as a leader in the first level and tends to set a collection rate policy which leads to collect more used products in order to ensure a minimum distribution ratio to satisfy a minimum demands. In the second level, 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 used products collection policy. A heuristic algorithm and an adaptive genetic algorithm based on 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 Min-Max regret scenario based robust optimization approach. The results show the necessity of using robust bi-level programming in closed loop supply chain network design under the governmental legislative decisions as a leader-follower configuration.

Keywords: Bi-level programming, Closed-loop supply chain, Government regulations, Genetic algorithm, Robust optimization, Scenario.

1. Introduction

Due to the environmental issues, governmental legal and consumers tendency, closed loop supply chain (CLSC) network design has increasingly gained the interested of the researchers. 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 closed loop supply chain network design. Here we review some of the recent studies that investigate CLSC design. Altmann and 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 uncertain market demand and cost parameters by economical cost and environmental impact considering. Talaei, et al. [4], addressed a multi-product, bi-objective mixed integer linear programming for the CLSC network design under demand and costs parameters uncertainty 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 product with aim to maximize 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 amount of new and remanufactured products. Jeihoonian, et al. [9] developed a two stage stochastic programming model with several type 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 uncetain environment. Mohammed, et al. [11] addressed a 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. Amin, et al. [13] investigated a multi-period closed loop supply chain model by considering cash flow in anu uncertain environment. Farrokh, et al. [14] peoposed a robust fuzzy stochastic programming approach for designig a closed loop supply chain in uncertain environment. Haddadsisakht and Ryan [15] addressed a stochstic closed-loop supply chain design with multiple transportation mode under uncertain carbon tax. Besides, Govindan et al. [16], provided a comprehensive review on most of the reverse logistics and CLSC studies between 2007 and 2013. They clustered and explored gaps of studies based on different aspects like modeling approaches, solution methodologies, uncertainty approaches, type of decision variables and the number of objective functions, product and time period and so on. But they didn't mention to the importance of the governmental and central authority's impact on CLSC design polices and its dealing approaches. Indeed, in the recent years by growing environmental pollutions, collecting used products and decreasing environmental pollutions have become one of the 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 returned products, distribution companies don't have any tendency to establishing collection centers. Therefore, this process doesn't form itself without interpositions of superior organs. As it can be seen, governments try to form this process by setting motivational or compulsory rules such as considering subsidies, tax discounts, penalties, 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 (WEEP) directive 2002/96/EC of the European Parliament and the Council became a European law in 2003, which contains mandatory requirements on collection, recycling and recovery for all types of electrical goods. Toffel [17], reports that the European electrical and electronic equipment industries are bearded 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, industry 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 waste for municipal and industrial sources and makes Environmental Impact Assessment (EIA) mandatory for any major development project that might have adverse impact on the environment [19]. According to the conflict between the aim of the company and government, the best solutions those obtained based on the company standpoint models may not satisfy the government targets. Thus, government as a legislative entity tries to lead company to collect and recover used products using motivational tools. By studying the literature in social aspects such as attention to reduce environmental pollutions and governmental intervention in leading the relevant departments, it can be seen that many researchers tried to formulate these aspects by various mathematical techniques such as economical 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 makers. The first formulation of bi-level programming was proposed by Bracken and McGill [20]. A bi-level programming problem is a special case of multi-level problem with two decision makers, one of whom takes the leader position and the other one whom making decisions subject to the leader's decisions is follower. Amouzegar and Jacobsen [21], proposed a bi-level programming model to provide controls on the transportation and disposal of hazardous waste 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], have proposed a model that government is considered as a policy maker and employ deposit-refund systems as subsidy. Kara and Verter [23], considered the network design problem for dangerous goods transportation as a bi-level integer programing 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 aim to minimize 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 to manufacturers and return ratio due to the environmental protection. Wojanowski et al. [25], have developed a model that government is tended to determine the minimum subsidy that is deposit-refund system for each collected item to ensure the minimum desired collection rate is met. This problem is modeled as a continuous modeling with aim to achieve maximum firm's profit by considering governmental incentive system. Erkut and Gzara [26], have developed a bi-level mixed integer programming to cope the network design problem for hazardous material transportation. A heuristic method that uses to overcome the difficulty of bi-level programming is introduced. de Figueiredo and Mayerle [27], have proposed a minimum cost recycling network design problem with incentive dependent recyclable product collection and required quantity 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 to its complexity. Mitra and Webster [28], analyzed a two-period model of a competition between an original manufacturer and a remanufacturer. In this model, the effect of the government subsidies to promote remanufacturing activity is examined. Plambeck and Wang [29], found that applying the "fee upon disposal" policy motivates manufacturers to design for recyclability. Aksen et al. [30], proposed two supportive and legislative bi-level programming models by considering governmental subsidization cope 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 the paper the government applies reward-penalty mechanism to motivate industry's recycling effort for different CLSCs. Rezapour et al. [33], proposed a bi-level model for closed loop network design by considering 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 in a competitive environmental that market demand is dependent to the price. A summary of related studies based on considering the impact of governmental regulation on SCNDs is displayed in Table 1.

Despite the importance of the environmental issues and necessity of considering government's potential impact on sub organizations policies, only a few researches considered government as a legislative entity and independent decision maker in their model and applied a bi-level programing formulation in the CLSC network design. In addition, lack of considering uncertain parameters in bi-level programming approach can be taken as another research gap. In this paper, decision making is considered consecutive and in two levels by applying a bi-level programming model. Government is considered as a first decision maker and determines a suitable collection rate to ensure facing of predetermined satisfied customers' demands. Beside, private sector as a follower designs its closed loop supply chain network with 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 scenario based robust optimization approaches are proposed where 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 government as one of the model decision maker. This study applies a leader-follower modeling framework to consider the government as a legislative decision maker.

- Most of the relevant studies which considered governmental policies impact on the supply chain design, considered government regulation as some parameters in the model. In this study government regulation impacts on closed loop supply chain design and customer welfare are 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 compared with the adaptive proposed genetic algorithm.
- Since most of the related studies considered the CLSC design in an uncertain environment, in this study the impact of the demand uncertainty on the government regulation and the CLSC configuration are investigated by applying robust optimization approach.

This paper has been organized as follows: Section 2 develops a bi-level programming formulation for the government's legislative problem design with aim to affect private sector's policies. A heuristic algorithm and a genetic algorithm based on enumeration are described in the section 3. Computational results are presented in Section 4 and the bi-level proposed model in presence of uncertainty is provided in Section 5. Then 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 didn't consider government's critical role to affect company's policies in 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 a leader in the first level and is tended to collect more used products by determining suitable collection rate that is denoted by A, while ensures a minimum distribution ratio denoted by α to satisfy a minimum proportion of customers' demands. It is worth to be mentioned that A is government's suitable collection rate and is assumed to be independent from the CLSC's activities. This variable determines the suitable fraction of the potential reverses which government tends to be collected. 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, we assume that each product user would be willing to return their used products if they receive a reasonable incentive or payment from the company. In fact, we consider the amount of the incentive payment that company offered to the users is same as the expected value of payments that encourage users to return their used products. The unit incentive payment is denoted by q. We suppose that by this amount incentive payment almost μ% of the used items will be returned. Besides, the collected used products are transported to collection centers (CCs) and 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 the better situation, to collect all used products. It is clear that the companies will intend to collect the used products if there is a high cost saving for each unit, but in contrast in a case of used products with low or minus cost saving, a high level incentive or regulation should be existed to achieve environmental objectives. As a result, the proposed model is more suitable for products with low or minus cost saving that companies are not interested to collect their used products, so due to the environmental issues government should intervene as a superior and legislative entity to force or motivate companies to collect used products in a supportive or legislative role.

Application of the proposed model in the real world:

Some of the application of the governmental acts and regulation on reverse models in real world are mentioned as follows:

- The Waste Electrical and Electronic Equipment (WEEP) directive 2002/96/EC of the European Parliament and the Council became a European law in 2003 contains 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 waste for municipal and industrial sources due to the Nigeria's environmental pollutions [19].
- Germany as the first country 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.

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 $i = 1, ..., I$

J : Set of candidate locations of distribution centers $j = 1, ..., J$

K : Set of customer zones $k = 1, ..., K$

L : Set of candidate locations of collection centers $l = 1, ..., L$

M : Set of fixed locations of disposal centers $m = 1,...,M$

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 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 to pay to customers for each used product

μ: The fraction of used products which returned to the private sector

Decision variables

A : Proportion of distributed product that should be collected by private sector

$X_{ij}, X_{jk}, X_{kl}, X_{lj}, X_{lm}$: Quantity of shipped product between pair of nodes from different sets

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

The proposed model can be defined as follows:

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

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

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

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

$s.t:$

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

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

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

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

$$\sum_{j}^{J} X_{ij} \leq Cap_i \quad \forall i \tag{9}$$

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

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

$$\sum_{l}^{L} X_{lm} \leq Cap_m \ \forall m \tag{12}$$

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

$$X_{ij}, X_{jk}, X_{kl}, X_{lm}, X_{lj} \geq 0 \qquad \forall i, j, k, l, m$$
$$Y_j, Y_l \in \{0,1\} \quad \forall j, l \tag{14}$$

The outer problem is represented by equations (1) to (3). The equation (1) displays the government's objective function which is to maximize the collection rate A, this variable of the outer problem constitute as an input parameter for the inner problem. Constraint (2) assures the desired amount of customers' demands is satisfied by private sector and constraint (3) represents the upper and lower level of governmental decision variable. The inner problem is represented by equations (4) to (14). In this problem net profit function is maximized as shown in equation (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 legislative constraint for each CLSC, which enforces the CLSC to collect a specific governmental collection rate of distributed products. Equations (6) to (8) represent the flow balances for each distribution and collection centers. Constraints (9) to (12) ensure capacity restrictions for production, distribution, collection and disposal centers, respectively. Constraint (13) restricts the amount of products that can be distributed to the customers according to the amount of demands. Finally, constraint (14) shows the binary and non-negative restrictions on lower level decision variables.

3. Solution methodologies

Moore and Bard [34], showed that mixed integer bi-level programming models are Np-hard. There are recent advances in exact solutions for mixed integer bi-level programming such as cutting plane and decompositions based solution method but their applicability is limited for small size instances only. Therefore, using of heuristic and meta-heuristic algorithms is suggested. In this section at first we develop a heuristic algorithm based on enumeration, but since this method is not efficient technique for large size problems, we also proposed a genetic algorithm to solve the developed model.

3.1. Heuristic algorithm based on enumeration

Since in the proposed model, the outer problem is a univariate bounded model, the inner problem is just dependent to one variable of the outer problem to obtain the optimal network design. Thus, according to the specific form of the outer problem, we can obtain optimum value of the bi-level model in an iterative procedure. So in the initialize iteration we set the collection rate equal to maximum value which is one that 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 and in case of satisfying the minimum demand responded constraint, the bi-level model final solution has been 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 to be satisfied.

3.2. Proposed genetic algorithm for the inner problem

As discussed before, the main idea to solve the proposed bi-level model is based on enumeration on the first level variable; now we implement a proposed genetic algorithm for solving inner problem instead of applying commercial solvers on GAMS. Genetic algorithm is an evolutionary search algorithm that uses mechanisms of nature selection and genetics to find optimal or near-optimal solutions of 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. We attempted to select the best chromosomes in the proposed GA that lead the algorithm to the optimal or near-optimal solutions. Since the proposed inner problem is a location-allocation problem, we consider the strategic decisions of the inner problem as chromosomes. In fact, the candidate locations of DCs and CCs are set as binary chromosomes where each gen indicates one of the candidate location and the binary amount of that, represent the opening status of its location. A selected chromosome is presented in Figure 2. It shows that nodes 2, 3 and 4 have been selected as opened distribution centers while 3 and 4 collection centers have been opened.

3.2.2 Initial population and Fitness

A specific number of chromosomes are created randomly as initial population and the fitness of each individual are 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 the strategic and tactical decisions, respectively. As represented in previous subsection, binary variables are considered as chromosomes of genetic algorithm; thus, to evaluate fitness of each individual, the continuous variable's values should be determined. So, at first we determined the X_{jk} (flows from distribution centers to the customers) and X_{kl} (flows from customers to collection centers) that are the most important flows of proposed CLSC randomly and the other allocations of X_{lj}, X_{lm} and X_{ij} evaluated by greedy algorithm and Vogel's approximation method (VAM) idea. After 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 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.

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.

3.2.5 Mutation operator

Mutation is one of the other main operators of the genetic algorithm which prevents 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, we consider the mutation operator as a combination of four different mutation types, general mutation, swap, insertion and reversion. The general mutation changes opening status of the random selected gen 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 random selected gen from the string and reinserts it into a different random selected gen with insertion probability. Finally the reversion mutation operator inverts the substring between the two random reversion points. As an example, the application of these four operators is illustrated in Figure 4. It is worth to mention that after defining of the location decisions allocation decisions are determined by the aforementioned procedure.

3.2.6 Selection

To select 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. Pseudo code 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, maximum generation number need to be set properly to seek the optimal solution efficiently. We tuned these parameters by using 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 uniform distributions specified in Table 2.

As mentioned before, we applied Taguchi method to set four major parameters to get 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 heuristic enumeration method applying the GAMS 23.5 software and by the proposed genetic algorithm coded in the MATLAB 2012 in a pc with following configurations; core (TM) i5 computer with 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 comparing to the heuristic algorithm in both accuracy and computational time for large sized instances. Computation times of mentioned algorithms have been compared graphically in Figure 6 as well.

5. An extension of the problem to consider uncertainty

As discussed before, there is an uncertainty of demands in real cases which can affect on the CLSC network designs. Review of CLSC network design with leader and follower configuration confirms that most of previous studies assume that the design parameters are deterministic. Thus, the proposed model by considering uncertain demands is developed and some solution approaches are applied 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 in 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 mentioned types two approaches are considered as following:

5.2.1 Min-Sum regret based bi-level programming

As mentioned before, government as a legislative and supportive entity is responsible about global pollution issues, customer's satisfaction and creating a secure and competitive market for private sectors. Moreover as the government policies have a direct effect on the private sector decisions, the government 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 which is denoted by A_s^* and Z_s^* for government and private sector, respectively where the set of scenarios is denoted by $s = 1, 2, ..., S$ and also 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 , X_{lj}^s , which are the amount 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:

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

$$\sum_{j}^{J}\sum_{k}^{K} X_{jk}^{s} \geq \alpha \sum_{k}^{K} d_k^s \qquad \forall s \tag{16}$$

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

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

$s.t:$

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

$$\sum_{l}^{L} X_{kl}^{s} \geq A \sum_{j}^{J} X_{jk}^{s} \qquad \forall k, s \tag{20}$$

$$\sum_{i}^{I} X_{ij}^{s} + \sum_{l}^{L} X_{lj}^{s} = \sum_{k}^{K} X_{jk}^{s} \qquad \forall j, s \tag{21}$$

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

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

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

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

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

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

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

$$X_{ij}^{s}, X_{jk}^{s}, X_{kl}^{s}, X_{lm}^{s}, X_{lj}^{s} \geq 0 \qquad \forall i, j, k, l, m, s$$
$$Y_j, Y_l \in \{0,1\} \qquad \forall j, l \tag{29}$$

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, so the decision making is done considering the worst case. The robust bi-level model by applying Min-Max regret approach can be formulated 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 to mention 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 approaches is compared in terms of the feasibility and changes in value of 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. As government strategy and locating 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 the fixed decisions, feasibility and both player benefits are examined considering occurrence of all possible scenarios. Actually, since the proposed model has a bi-level nature, uncertainty has more impacts on the obtained value and of course the feasibility of the model compared with the classic single level CLSC network design. The necessity analysis results are presented in Table 6. It shows that ignoring of demand uncertainties will due to infeasibility or private sector loss, so it means that uncertainty should be considered in the proposed CLSC design problem. Actually, despite 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 goal are not achieved and 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 in dealing with uncertain parameters. In this approach, we replace each demand parameter 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 expected value approach results are better than deterministic approach, but infeasibility and private sector's loss is existed too. Expected value approach leads government to take a more conservative decision to decrease the infeasibility risk.

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

In both approaches, the strategic decisions are made to respond to all possible scenarios. While in the second approach there is the least risk during the decision making. The results are presented in Table 8 and Table 9, respectively.

Due to constraint (16), the robust results are certainly feasible. As it can be seen in Table 9 and Table 9 by applying these approaches, government takes a more conservative decision to remove the infeasibility risk. Therefore, private sector's benefit is almost more than the deterministic and expected value approaches counterparts as a result of less collection rate. But as a result of Table 8, Min-Sum regret approach couldn't achieve to a feasible solution to satisfy entire specified rate of customers' demands for all of the scenarios in instances 2 and 6.

As government is a legislative entity and its decisions have a direct effect on the private sector decisions, clearly government should make its decisions as robust as possible. As proven that, if government's decisions have more fluctuation and freedom, private sector will lost more benefit. Thus, as it can be seen, although in Min-Max regret robust optimization approach, government's policy is less than the other approaches but this approach ensures the feasibility of the model under each possible scenario and government doesn't need to change its policy after scenario occurrence. And private sector's benefit is almost better than the other approaches. The comparison between average private sector's benefit that obtained from each scenario occurrence 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 network design problem under the governmental legislative decisions as a leader-follower configuration. Indeed, the government as a leader wants to set a highest used product collection rate policy with ensuring of achieving at least a predefined satisfied demand rate. On the other hand, the private sector as a follower sets its CLSC design to determine the distribution and collection centers location among a set of candidate sites and to obtain the highest net profit subject to the government regulation. A heuristic and a genetic algorithms based on enumeration were proposed for the model. Numerical examples were randomly generated and used to test and evaluate the solution approaches efficiency. Computational results showed that proposed genetic algorithm can obtain near optimal solution in large scale instances in a reasonable time comparing with the enumeration approach. Besides, a Min-Max regret and Min-Sum regret based bi-level programming approaches were proposed for incorporating uncertainty of demands. The numerical comparisons confirm their necessity as well as their efficiency. Considering of other parameters uncertainty in the proposed model is suggested as a future study. Also using of other stochastic and robust approaches in the bi-level programming can be considered as another future work direction.

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Table1. Some studies of government regulations consideration 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 (1998)	✓			✓	✓	✓	✓	✓		-	Heuristic Method
Kulshreshtha and Sarangi (2001)	✓		✓			✓		✓		-	Game theory approach
Kara and Verter (2004)				✓	✓			✓		-	Karush-Kuhn-Tuker conditions
Sheu et al. (2005)		✓	✓			✓		✓		-	Pareto-Optimal
Wojanowski et al. (2007)	✓		✓			✓	✓	✓		-	Game theory approach
Mitra and Webster (2008)		✓	✓			✓		✓		-	Nash equilibrium
Erkut and Gzara (2008)				✓	✓			✓		-	Heuristic Method
de Figueiredo and Mayerle (2008)	✓			✓		✓	✓	✓		-	Heuristic Method
Sheu and Chen (2012)		✓	✓		✓	✓		✓		-	Nash equilibrium
Aksen et al. (2009)	✓			✓		✓	✓	✓		Quality of returned products (Stochastic approach)	Modified Tabu Search Algorithm
Rezapour et al. (2015)		✓		✓			✓	✓	✓	-	Game theory, Variational Inequality
Wang et al. (2015)		✓	✓			✓		✓		-	Backward induction
This study		✓		✓	✓		✓	✓		Demand (Min max regret robust approach)	Heuristic Method based on Enumeration and Genetic Algorithm

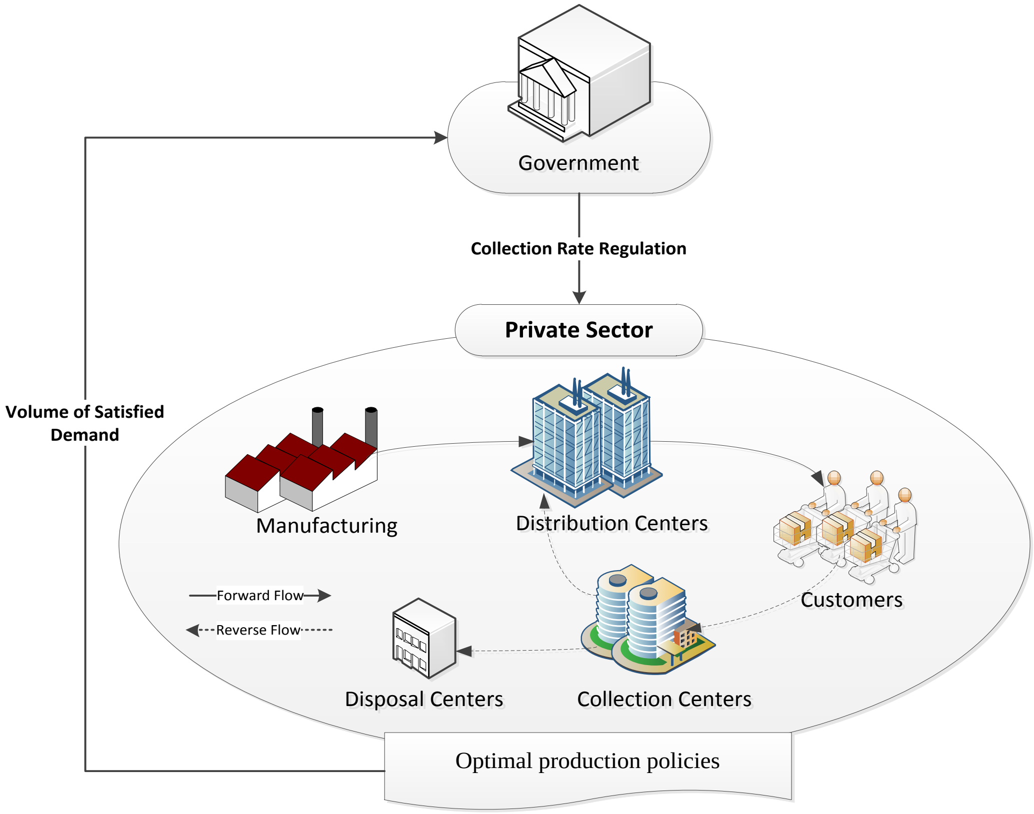

Figure 1. Proposed model configuration

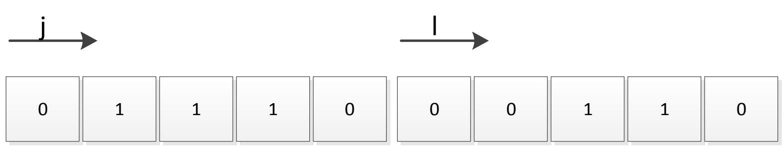

Figure 2. A sample chromosome in the proposed Genetic algorithm

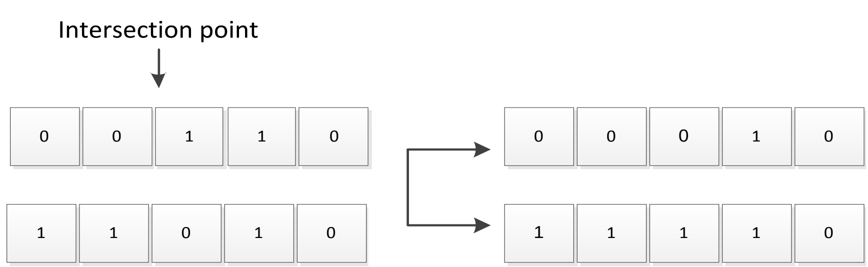

Figure3. Crossover operation for the proposed model

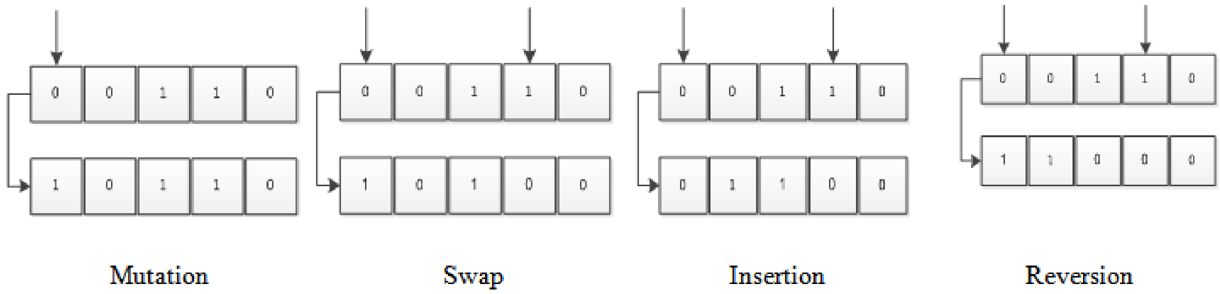

Figure 4. Different applied mutation operators in the proposed algorithm

```
SET Algorithm Parameters(Population − Size, Iteration − Number, Acceptable − SatisfideDemand − 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 fittness 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. Pseudo code of the proposed solution algorithm based on GA

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)

Table3. Heuristic and meta-heuristic results for 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

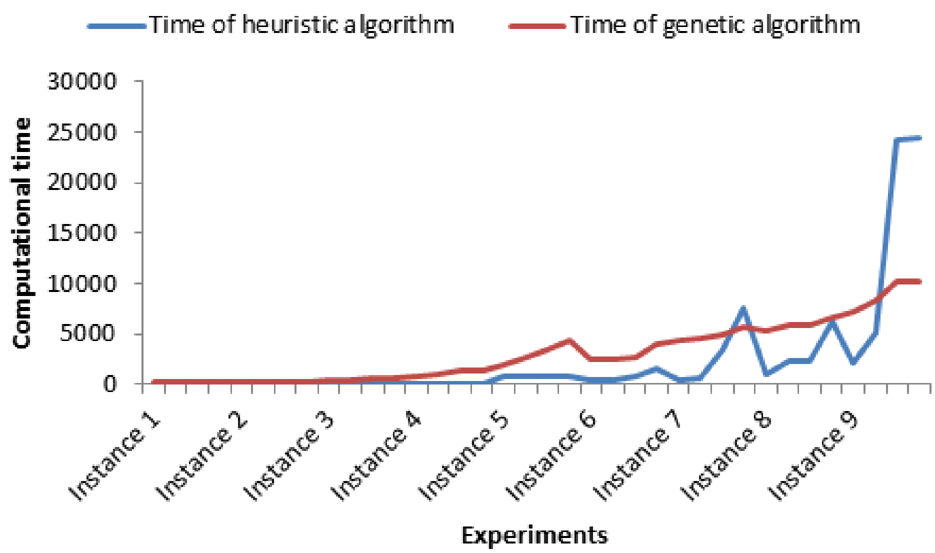

Figure 6. Comparing heuristic and genetic algorithms in term of time

Table4. 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

Table5. The result of bi-level programming with deterministic parameters

	Deterministic approach			
Scenario1	Government Strategy	Private Sector's profit	DC opened locations	CC opened locations
	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

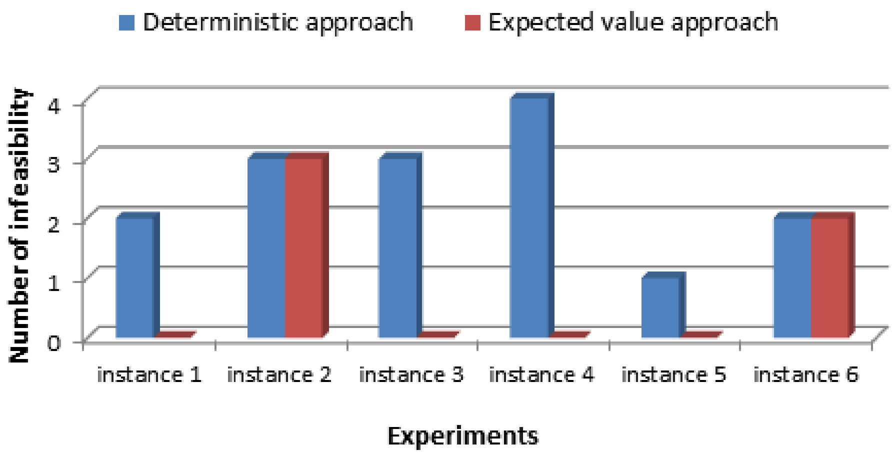

Figure 7. Comparison between the EV and deterministic approaches in number of infeasible cases

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

	Min-Sum regrets robust approach							
	Government Strategy	**Objective function**		**Private Sector's profit**				
		Level1	Level2	Scenario1	Scenario2	Scenario3	Scenario4	Scenario5
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							

Table9. Min-Max regret based bi-level programming results

	Min-Max regret robust approach							
	Government Strategy	**Objective function**		**Private Sector's profit**				
		Level1	Level2	Scenario1	Scenario2	Scenario3	Scenario4	Scenario5
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

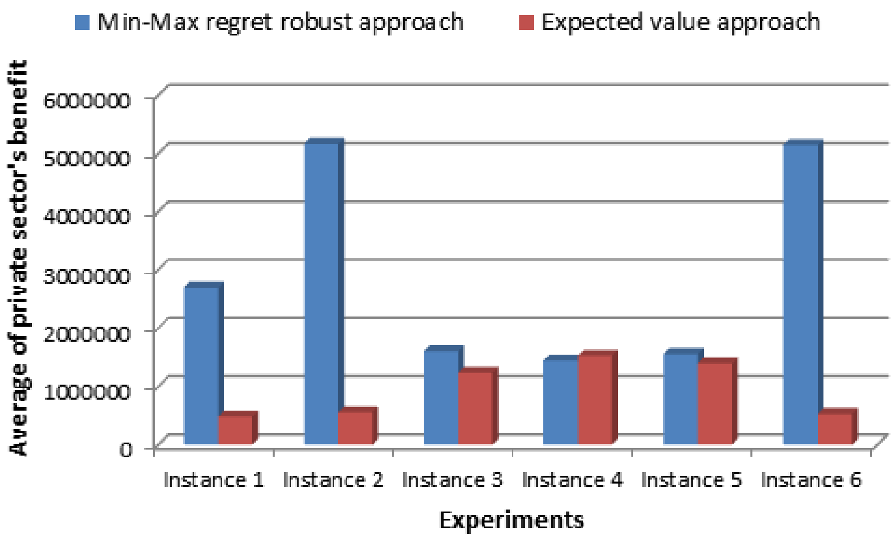

Figure 8. Comparison between the EV and Min-Max regret approaches in private sector's benefit

Biographies

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Atefeh Hassanpour received her BS degree in Industrial Engineering from KNT University and MS degree in Industrial Engineering from Alzahra University and she is Ph.D. candidate in KNT University, right now. Her main research interests include: optimization, SCM, exact and meta-heuristics algorithms.

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