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A Bi-objective Mathematical Model for Closed-loop Supply Chain Network Design Problem

Mehdi Boronoos*[1], Seyed Ali Torabi[2] and Mohammad Mousazadeh[3]

1. School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
2. School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran (satorabi@ut.ac.ir)
3. School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran (mousazadeh@ut.ac.ir)

***Corresponding Author:** *Boronoos, M. (Email: m.boronoos72@ut.ac.ir)*

Abstract– *In this paper, a bi-objective mixed-integer linear optimization model for Closed-loop Supply Chain Network Design Problem (CLSCND) is developed. The proposed model includes both the forward and reverse directions and includes different types of facilities, namely, manufacturing/remanufacturing centers, warehouses, and disassembly centers. The first objective function tried to minimize the total cost of the supply chain, while the second one was aimed at maximizing the responsiveness of the network in both forward and reverse directions, simultaneously. To solve the proposed bi-objective model, an augmented ε-constraint method was implemented by which a set of Pareto-optimal solutions for the problem were generated. An illustrative numerical example is given in the study to show the applicability and efficiency of the presented optimization model.*

Keywords– *Augmented ε-constraint, Integrated forward/reverse supply chain, Multi-objective optimization, Responsiveness.*

I. INTRODUCTION

A Supply Chain (SC) network typically consists of multiple suppliers, manufacturing centers, and distribution centers as well as a number of links between these facilities as the nodes and edges of the network. The goal of the SC can be defined as receiving raw materials, changing them into final goods, and dispatching those final goods to the customer zones (Babazadeh et al., 2013). By considering reverse flows because of environmental issues and resource exhaustion, this definition is further extended. Therefore, the increasing interest in disused goods collection for the recovery of resources is logical (Lee et al., 2009). Generally, the CLSCN includes forward and reverse logistics. In forward logistics, distribution centers dispatch final products to customer zones to meet their demands. In reverse logistics, activities such as disassembling for reuse and disposal or recovery or sorting are carried out. These activities can enhance the service level of customers, increase enterprise competence, provide a green image, and decrease the production costs (Demirel & Gökçen, 2008). Real-world SC network design problems should include multiple objectives to make trade-off analysis possible. Among the proposed objectives, cost minimization and responsiveness maximization are the most desirable ones and the most commonly-used objectives in the forward SCND (Pishvaee et al., 2009). Since end-users, due to the related holding cost, have a tendency to dispose utilized products as soon as possible, responsiveness in the reverse direction is also a significant issue.

The aim of this paper is to present a multi-objective Mixed-Integer Linear Programming (MILP) model for CLSCND, which minimizes the total costs of network design while maximizing the responsiveness of the SCN. The

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developed model simultaneously optimizes forward and reverse networks as well as long-term and mid-term decisions, making the achieved results more applicable to real-world industrial cases.

The remainder of the study is structured as follows: the relevant literature is reviewed in Section II. The definition of the problem and the mathematical formulation are presented in Section III. In Section VI, a numerical example, solution method, and the achieved results are provided. Finally, the conclusions of this study along with some directions for future research are provided in Section V.

II. LITERATURE REVIEW

Designing a reverse SC requires determining the locations and capacities of the facilities and material flows between the stages of SC (Saffar et al., 2015). As the initial studies of reverse SC network design, Krikke et al. (1999) developed an MILP model for a two-stage reverse SC. Sasikumar & Kannan (2008) reviewed the literature on end-of-life (EOL) product recovery in reverse SCs and outlined some future directions for research on these issues. Chen & Chou (2006) formulated a reverse SCND problem as a bi-level model. Min & Ko (2008) presented a Mixed-Integer Programming (MIP) model for a reverse logistics network from the perspective of third-party logistics service providers. Separated design of forward and reverse SC results in sub-optimality. The main reason for this issue is that the forward and reverse SCNDs have a significant influence on the performance of each other. In order to resolve the aforementioned issue, these decisions (i.e., SCND decisions in both directions) should be integrated (Pishvaee et al., 2010). CLSCN model with product recovery, reselling, and waste disposal was proposed by Yun et al. (2016). They developed a mathematical formulation using nonlinear MIP in order to effectively represent the proposed CLSCN model. Ghassemi et al. (2018) presented a bi-objective mathematical model for a CLSCND problem considering remanufacturer subcontractors and supplier selection. Govindan et al. (2017) provided a comprehensive review of studies in the field of SCND and reverse logistics network design under uncertainty. Pishvaee et al. (2010) developed a multi-objective mathematical model for integrated forward/reverse logistics network design to maximize responsiveness and minimize total cost of the network. They also developed a memetic algorithm in order to find a set of non-dominated solutions. In another research, Pishvaee & Torabi (2010) proposed a bi-objective possibilistic MIP model to minimize total delivery tardiness and total costs in the CLSCND. Ramezani et al. (2013) presented a multiple-objective stochastic model for forward/reverse logistics network design to maximize quality, profit, and responsiveness of costumers in the considered logistics network. Fazli-khalaf et al. (2017) developed a bi-objective mathematical model for a reliable green CLSCND. The first Objective Function (OF) was aimed at minimizing total cost and the second one at minimizing harmful gas emissions. Then, the presented bi-objective model was solved using ε-constraint method. Finally, the model was tested using a numerical illustration in the lead-acid battery SC. Ghayebloo et al. (2015) considered disassembly of products and green supplier selection and then, developed a bi-objective MIP model for a forward/reverse SCND. Maximization of profit and greenness were the two OFs addressed in this study. The weighted sum method and ε-constraint method were used to solve the presented optimization model. Ghomi-avili et al. (2018) developed a fuzzy bi-objective bi-level mathematical model for a CLSCND problem. The model tried to maximize profit and minimize CO_2 in the forward and reverse directions, simultaneously. They used ε-constraint method to convert the proposed bi-objective model to a mono-objective one and Karus-Kuhn-Tucker and possibilistic programming approaches were combined to solve the presented model. Tavakkoli-moghaddam et al. (2015) investigated a CLSCND problem and developed a bi-objective model in which total costs as well as pollution production rate, disposal rate, and total defective rate were minimized, simultaneously. Fuzzy possibilistic programming approach was used to transform the uncertain model to its crisp equivalent and the TH approach was used to solve the bi-objective mathematical model. Based on the quality of the returned products, Masoudipour et al. (2017) presented a multi-objective mathematical model for a CLSCND problem. The presented model tried to maximize total profit of the manufacturers and DCs as the first and second OFs, respectively. They solved the bi-objective model using simple weighted sum method. They also investigated the efficiency of the presented model using a case-study in textile industry. In another work, Pazhani et al. (2013) presented an MILP model for a CLSCND problem. Minimizing total costs and maximizing the service efficiency of the hybrid facilities as well as warehouses were the objectives addressed in this study. They used goal programming approach to solve the developed bi-objective model. Talaei et al. (2016) presented an MILP model for a CLSCND problem. Their proposed model tended to minimize total cost and CO_2 emission, simultaneously. Epistemic uncertainty in demand and cost coefficients were considered and a fuzzy programming approach was used to deal with such uncertainty. Then, this model was solved using ε-constraint method and a numerical illustration was utilized to demonstrate the efficiency of the developed model. In another work, Nurjanni et al. (2016) developed a bi-objective mathematical model to concurrently minimize total cost and CO_2 emission in a CLSC. They solved the developed model using weighted Tchebycheff, weighted sum, and augmented weighted Tchebycheff, and demonstrated the benefits and drawbacks of each solution approach. Vahdani & Mohamadi (2017) considered minimization of waiting times in the queue of products and total costs, and developed an optimization-based mathematical model for a CLSND under uncertainty. Khalilpourazari & Arshadi Khamseh (2017) presented an MILP model to design efficient and effective SCN in earthquake. They also investigated the application of the developed model to a real-world case study. Other reviewed papers along with their characteristics are provided in Table I.

As literature review reveals, most of the studies tend to optimize a single objective in terms of minimizing total cost. However, the presented model in this study seeks to make a trade-off analysis between total network costs minimization and maximization of responsiveness in a multi-objective modeling framework. Several authors, e.g., Pishvaee et al. (2010), Talaei et al. (2016), Ghassemi et al. (2018), etc., have used the classic ε-constraint method to solve the multi-objective CLSCND models, which may result in weakly efficient solutions (Mavrotas & Florios, 2013). Furthermore, some authors have used the weighted sum method in which the preferences of the Decision Makers (DMs) are stated before the solution procedure. One of the drawbacks of this approach is that exact quantification and having prior knowledge are so difficult and time-consuming for the DMs. Interested readers for more details on the drawbacks of these approaches can refer to Mavrotas & Florios (2013). Accordingly, in this study, we use an augmented ε-constraint method by which obtaining an efficient solution is guaranteed. It is noteworthy that, to the best of our knowledge, choosing the most desirable solution in the conventional/augmented ε-constraint method highly depends on the preferences of the DM(s). In this study, to overcome this drawback and create a simplified solution selection structure for choosing the optimal solution, a novel procedure is proposed. The description of this method is provided in Section IV.

This paper develops a bi-objective MILP model for a multi-product, multi-echelon CLSCND in which both strategic decisions (i.e., numbers and locations of the facilities) and tactical decisions (i.e., product flows between different layers of the designed SC) are taken simultaneously into account. The developed model includes both the forward and reverse directions and includes different type of facilities, namely manufacturing/remanufacturing centers, warehouse, and Disassembly Centers (DCs). We also provide an illustrative numerical example to validate the applicability and efficiency of the developed model.

In summary, the main distinctive features of this paper, which make it different from the existing papers, are the following:

1. Devising a mathematical model for a CLSCND problem. The model addresses a multi-product SC, which makes the study different from other research. Both strategic and tactical decisions in forward and reverse directions are taken into account, simultaneously.
2. Constructing a novel solution selection procedure, which alleviates the difficulties of choosing the most desirable solution. Noteworthy, choosing the most desirable solution in the conventional/augmented ε-constraint method highly depends on the preferences of the DM(s).
3. Providing a comprehensive literature review.
4. Solving the devised mathematical model using augmented ε-constraint method, which overcomes the drawbacks of the classical ε-constraint method.

F: Forward; R: Reverse; S: Single; M: Multi; C: Cost; P: Profit; G: Greenhouse emission; RE: Responsiveness; EU: Energy Use; FA: Financial Approach; DR: Defective Rate, Disposal Rate; PR: Pollution Rate; WT: Waiting Time; SE:

Service Efficiency; GP: Goal Programming; W: Weighted sum; WT: Weighted Tchebycheff; AWT: Augmented Weighted Tchebycheff; FM: Fuzzy Multi-objective programming; EP: ε-constraint; AEP: Augmented ε-constraint; BD: Benders Decomposition; FM: Fuzzy; H: Heuristic/meta-heuristic; ND: Network Design; TA: Transportation Amount; IL: Inventory Level, PA: Purchasing Amount

Table I. Investigated research papers

Article	*Type of SC*	*Product*	*Period*	*Objective function(s)*	*Solution approach*	*Variable(s)*
Krikke et al. (1999)	R	S	S	C	E	TA,IL
Chen and Chou (2006)	R	S	S	C	E	TA
Min and Ko (2008)	R	M	M	C	H	ND,TA
Demirel and Gökçen (2008)	F,R	M	S	C	E	ND,TA
Fleischmann et al. (2009)	F,R	S	S	C	E	ND,TA
Salema et al. (2009)	F,R	S	M	P	E	ND,TA,IL
Kannan et al. (2010)	F,R	M	M	C	H	TA,PA
Pishvaee et al. (2010)	F,R	S	S	C,Re	H	ND,TA
Özceylan and Paksoy (2013)	F,R	M	M	C	E	ND,TA
Pazhani et al. (2013)	F,R	M	M	C,SE	GP	ND,TA,IL
Ramezani et al. (2014)	F,R	S	M	FA	E	ND,TA,IL
Saffar et al. (2015)	F,R	M	M	C,G	H	ND,TA
Ghayebloo et al. (2015)	F,R	M	S	C,G	EP	ND,TA
Vahdani and Mohamadi (2015)	F,R	M	S	C,WT	H	ND,TA
Tavakkoli-Moghaddam et al. (2015)	F,R	M	M	C,DR,PR	FM	ND,TA
Talaei et al. (2016)	F,R	M	S	C,G	EP	ND, TA
Nurjanni et al. (2016)	F,R	S	S	C,G	W,WT,AWT	ND, TA
Yang et al. (2017)	F,R	S	S	C,G	H	TA,PA
Masoudipour et al. (2017)	F,R	S	S	P	WS	ND, TA
Kadambala et al. (2017)	F,R	S	S	P,EU	H	TA
Fazli-Khalaf et al. (2017)	F,R	S	S	C,G	EP	ND,TA,PA
Ghassemi et al. (2018)	F,R	M	M	P,G	AEP	ND,TA,IL
Haddadsisakht and Ryan (2018)	F,R	S	S	C	BD	ND,TA
Ghomi-Avili et al. (2018)	F,R	S	M	P,G	EP	ND,TA,IL
Our study	F,R	M	S	C,Re	AEP	ND,TA

III. PROBLEM DEFINITION

Fig. (1) illustrates the graphical view of the concerned network, including manufacturing/remanufacturing centers, warehouses, customer zones, and DCs. Also, to transport products (new products, products to be disposed, and products to be remanufactured) from a given echelon to the succeeding one, different types of transportation modes (i.e., road, rail, etc.) exist. In detail, new products (either brand new or remanufactured) are dispatched first from manufacturing/remanufacturing centers to warehouses and then, from warehouses to customer zones to fully satisfy customer demand. Thereafter, the returned units of goods are collected in the DCs and after examination, the products to be remanufactured (recoverable units of products) are shipped to remanufacturing centers while the recycling process is performed on the products to be disposed (scraped units of products) in the DCs. The main decisions to be made by the proposed model consist of the optimal locations of the facilities (manufacturing/remanufacturing centers, warehouses, and DCs), the optimal quantities of produced/remanufactured and disassembled products in manufacturing/remanufacturing centers and DCs, respectively, and the optimal flow of the goods in the network.

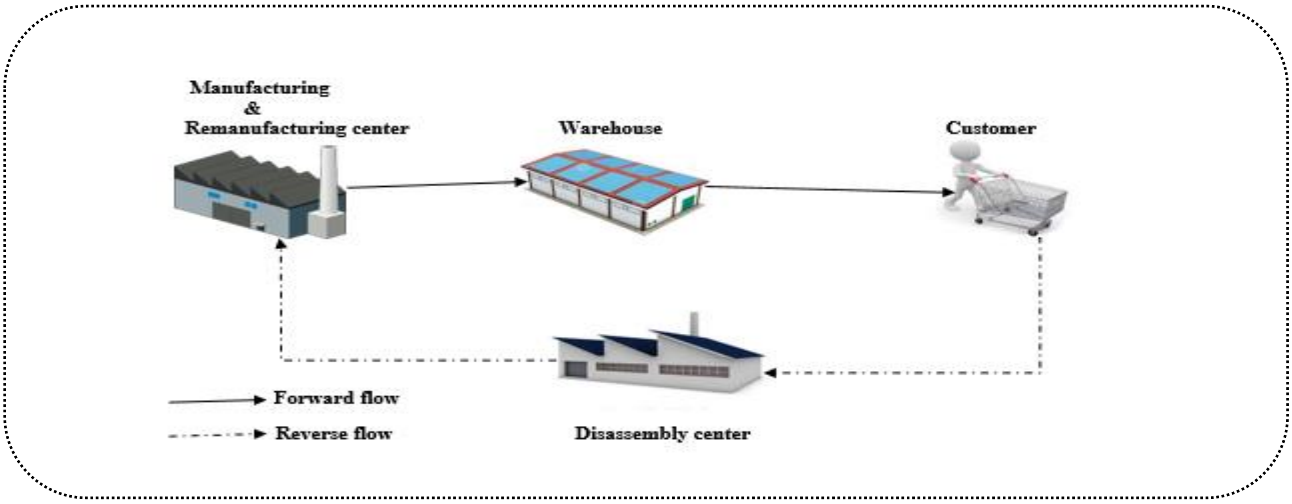

Figure 1. Structure of the concerned closed-loop SC

The indices, parameters, and decision variables used to mathematically formulate the CLSND problem are as follows:

Sets	
$p \in P$	index of products
$f \in F$	index of candidate locations for opening manufacturing/remanufacturing centers
$w \in W$	index of potential locations for opening warehouses
$c \in C$	index of fixed locations of end-users
$i \in I$	index of candidate locations for opening DCs
$l \in L$	index of transportation modes

Parameters	
d_{cp}	demand of end-user *c* for product *p*
t^1_{pfwl}	unit shipment cost of each unit of product *p* from manufacturing/remanufacturing center *f* to warehouse *w* using transportation mode *l*
t^2_{pwcl}	unit shipment cost of each unit of product *p* from warehouse *w* to end-user *c* using transportation mode *l*
t^3_{pcil}	unit shipment cost of each unit of product *p* from end-user *c* to Dc *i* using transportation mode *l*
t^4_{pifl}	unit shipment cost of each unit of product *p* from DC *i* to manufacturing/remanufacturing center *f* using transportation mode *l*

f_f^1	fixed establishment cost of manufacturing/remanufacturing center *f*
f_w^2	fixed establishment cost of warehouse *w*
f_i^3	fixed establishment cost of DC *i*
v_{pf}^1	unit variable production cost of a unit of product *p* in the manufacturing center *f*
v_{pw}^2	unit variable cost of handling a unit of product *p* in the warehouse *w*
v_{pc}^3	unit variable cost of collecting a unit of product *p* from customer *c*
v_{pi}^4	unit variable cost of disassembling a unit of product *p* in the DC *i*
v_{pf}^5	unit variable remanufacturing cost of a unit of product *p* in the remanufacturing center *f*
h_f^1	production capacity of manufacturing center *f*
h_w^2	processing capacity of warehouse *w*
h_i^3	disassembling capacity of DC *i*
h_f^4	remanufacturing capacity of manufacturing/remanufacturing center *f*
α	minimum percentage of unit of products that are collected to be disposed from an end-user
α'	minimum percentage of units of products to be remanufactured and dispatched from a DC
dt_{wcl}	delivery time from warehouse *w* to end-user *c* through transportation mode *l*
ct_{cil}	collection time from end-user *c* to DC *i* through transportation mode *l*
Res_f	expected delivery time in the forward direction
Res_r	expected delivery time in the reverse direction
d_{fcp}	$=\{w\,/dt_{wcl} \le \mathrm{Res}_f\}$
d_{rcp}	$=\{i\,/ct_{cil} \le \mathrm{Res}_r\}$
ρ	importance weight for the responsiveness in the forward direction
$1-\rho$	importance weight for the responsiveness in the reverse direction

Decision variables

x_f^1	a binary variable equal to 1 if a manufacturing/remanufacturing center is established at potential location *f* and 0 otherwise
x_w^2	a binary variable equal to 1 if a warehouse is established at potential location *w* and 0 otherwise
x_i^3	a binary variable equal to 1 if a DC is opened at potential location *i* and 0 otherwise
q_{pfwl}	amount of units of product *p* sent from manufacturing/remanufacturing center *f* to warehouse *w* through transportation mode *l*
u_{pwcl}	amount of units of product *p* sent from warehouse *w* to end-user *c* through transportation mode *l*
w_{pcil}	amount of units of product *p* collected from end-user *c* and sent to DC *i* through transportation mode *l*
y_{pifl}	amount of units of product *p* (to be remanufactured) sent from DC *i* to manufacturing/remanufacturing center *f* through transportation mode *l*

Using the abovementioned notation, the developed MILP model for the CLSCND problem can be formulated as follows:

$$\min f_1 = TFC + TVC + TTC \tag{1}$$

$$TFC = \sum_{f} f_f^1 x_f^1 + \sum_{w} f_w^2 x_w^2 + \sum_{i} f_i^3 x_i^3 \tag{1a}$$

$$TVC = \sum_{p,f,w,l} v_{pf}^1 q_{pfwl} + \sum_{p,w,c,l} v_{pw}^2 u_{pwcl} + \sum_{p,c,i,l} v_{pc}^3 w_{pcil} + \sum_{p,i,c,l} v_{pi}^4 w_{pcil} + \sum_{p,i,f,l} v_{pf}^5 y_{pifl} \tag{1b}$$

$$TTC = \sum_{p,f,w,l} t_{pfwl}^1 q_{pfwl} + \sum_{p,w,c,l} t_{pwcl}^2 u_{pwcl} + \sum_{p,c,i,l} t_{pcil}^3 w_{pcil} + \sum_{p,i,f,l} t_{pifl}^4 y_{pifl} \tag{1c}$$

OF (1) consists of Total Fixed Cost (TFC), Total Variable Cost (TVC), and Total Transportation Cost (TTC).

$$\max\ f_2 = \rho\left(\left(\sum_{p,c,l}\sum_{w\in d_{fcp}} u_{pwcl}\right)\Big/\left(\sum_{c,p} d_{cp}\right)\right) + (1-\rho)\left(\left(\sum_{p,c,l}\sum_{i\in d_{rcp}} w_{pcil}\right)\Big/\left(\sum_{c,p}\alpha'.d_{cp}\right)\right) \tag{2}$$

The second OF tries to maximize the responsiveness in the both forward (first sentence) and reverse (second sentence) directions, simultaneously. This OF is adopted from Pishvaee et al. (2010) and its value is bounded between zero and one. In fact, the second OF has been derived from the fact that customers are likely to receive products from distribution centers or warehouses at the lowest possible delivery time. The same can be stated about the collection of products by DCs. In other words, the use of the second OF will result in establishing warehouses from which delivery time, as well as DCs in which collection time, is lower than the expectations of the customers. This will lead to an increase in the responsiveness of the SC.

$$\sum_{p,w,l} q_{pfwl} \le h_f^1 x_f^1 \qquad \forall f \tag{3a}$$

$$\sum_{p,f,l} q_{pfwl} \le h_w^2 x_w^2 \qquad \forall w \tag{3b}$$

$$\sum_{c,l} u_{pwcl} \le \sum_{f,l} q_{pfwl} \qquad \forall p,w \tag{3c}$$

$$\sum_{p,c,l} w_{pcil} \le h_i^3 x_i^3 \qquad \forall i \tag{3d}$$

$$\sum_{p,i,l} y_{pifl} \le h_f^4 x_f^1 \qquad \forall f \tag{3e}$$

Constraints (3a-e) are capacity constraints of the manufacturing centers, warehouses, DCs, and remanufacturing centers, respectively. Constraint (3a) states that the total number of units of products that are sent from a manufacturing center to any warehouse using any transportation mode should be equal to or less than the capacity of the respective manufacturing center. Constraint (3b) indicates that the total number of units of goods that are entered into a warehouse from any manufacturing/remanufacturing center through any transportation mode should be equal to or less than the capacity of the respective warehouse. Constraint (3c) ensures that the total quantity of each product that is sent from a warehouse to any customer zone in a given time period should be equal to or less than the total number of each product entered from any manufacturing/remanufacturing center into the respective warehouse. Constraint (3d) implies that the total number of units of product that should be dismantled and collected in a DC from any customer and through any transportation option should be equal to or less than the capacity of the corresponding DC. Constraint (3e) determines that the total number of units of products that are sent to a remanufacturing center from any DC through any transportation option should be equal to or less than the remanufacturing capacity of the respective manufacturing/remanufacturing center.

$$\sum_{w,l} u_{pwcl} = d_{cp} \qquad \forall c, p \tag{4}$$

Constraint (4) guarantees that the demand by each end-user for each product is fully satisfied.

$$\sum_{i,l} w_{pcil} = \alpha d_{cp} \qquad \forall c, p \tag{5a}$$

$$\sum_{f,l} y_{pifl} = \alpha' \sum_{c,l} w_{pcil} \qquad \forall i, p \tag{5b}$$

Constraints (5a) and (5b) address the reverse flow constraints. Constraint (5a) indicates that a certain percentage of each end-user demand for each product is sent to DCs using different transportation modes. Constraint (5b) states that in each DC, a certain percentage of each product is dispatched to manufacturing/remanufacturing centers using different transportation modes.

$$q_{pfwl}, u_{pwcl}, w_{pcil}, y_{pifl} \geq 0 \qquad \forall p, f, w, c, i \tag{6a}$$

$$x_f^1, x_w^2, x_i^3 \in \{0,1\} \qquad \forall f, w, i \tag{6b}$$

Finally, constraints (6a) and (6b) show the types of the decision variables.

IV. APPLICATION: NUMERICAL EXAMPLE

In this section, a numerical example is presented to show the applicability and practicability of the proposed model. Some model parameters are reported in Table II. The given mathematical model was coded and solved using GAMS 24.8.2 software on a Core i7 personal computer with 6.00 GB RAM.

Table II. Values of the model parameters

Parameter	***Value***	***Parameter***	***Value***
d_{cp}	Uniform(80,140)	f_f^1	Uniform(450000,800000)
t_{pfwl}^1, t_{pwcl}^2, t_{pcil}^3, t_{pifl}^4	Uniform(6,12)	f_w^2	Uniform(250000,600000)
$\lvert P\rvert=2, \lvert F\rvert=6, \lvert W\rvert=6$	$\lvert C\rvert=10, \lvert I\rvert=6, \lvert L\rvert=2$	f_i^3	Uniform(180000,240000)
v_{pf}^1	Uniform(20,22)	v_{pw}^2	Uniform(2,4)
v_{pc}^3	Uniform(5,7)	v_{pi}^4	Uniform(6,8)
v_{pf}^5	Uniform(11,13)	h_f^1	Uniform(60000,80000);
h_w^2	Uniform(5000,6000)	h_i^3	Uniform(18000,24000)
α	0.3	α'	0.7
dt_{wcl}	Uniform(5,8)	ct_{cil}	Uniform(5,8)
Res_f	Uniform(5,8)	Res_r	Uniform(5,8)
ρ	0.5		

A. Solution approach

Multi-Attribute Decision Making (MADM) and Multi-Objective Decision Making (MODM) problems are two branches of Multi-Criteria Decision Making (MCDM) problems. Conflicting criteria and objectives are the common characteristics of these problems, in which improving one criterion/objective results in deteriorating one or more criteria/objectives. In MODM problems, the Pareto-optimal solutions, i.e., the solutions that cannot be improved in one objective without worsening their performance in the other objective(s), are replaced with single-optimal solutions. Several approaches ranging from priori, post priori, and progressive methods have been proposed in the literature. The ε-constraint method is one of these methods, which has several advantages and has progressively been used to solve the abovementioned types of problems. Recently, Mavrotas & Florios (2013) introduced the augmented ε-constraint method in which the ranges of OFs were determined using lexicographic optimization. It was proven that this approach avoided inefficient solutions and generated only efficient ones.

In this paper, an augmented ε-constraint method is used to solve the multi-objective mathematical model. The formulation of this model based on the presented method can be written as follows:

$$\max\left(f_1(x)+eps\times\left(s_2/r_2+10^{-1}\times s_3/r_3+...+10^{-(p-2)}\times s_p/r_p\right)\right)$$

s.t:

$$\begin{aligned} & f_2(x)-s_2=e_2 \\ & f_3(x)-s_3=e_3 \\ & ... \\ & f_p(x)-s_p=e_p \end{aligned} \tag{7}$$

where p represents the number of OFs. $e_2, e_3, ...e_p$ are the parameters for the Right-Hand Side (RHS) values. $s_2, s_3, ...s_p$ are the surplus variables of the constrained OFs. eps is a small number usually between 10^{-3} and 10^{-6}. It should be noted that s_i / r_i, in which r_i is the range of the ith OF, is utilized in the second sentence of the OF instead of s_i to prevent any scaling problem. Noteworthy, r_i can be derived using:

$$r_i = f_i^{\max} - f_i^{\min} \tag{8}$$

After obtaining r_i for all OFs through Eq. (8), the ranges of p-1 OFs using $(q_2-1)...(q_p-1)$ intermediate equidistant grid points are divided to $q_2...q_p$ equal intervals and the achieved single-objective mathematical model will be solved using all combinations of the RHS values of the constrained OFs. Among the achieved solutions, the DM chooses the most preferred one based on the specific preference of application (Du et al., 2014; Mavrotas, 2009).

B. Implementation

As discussed in the previous section, an augmented ε-constraint method is used to solve the multi-objective mathematical model. To this end, we first construct the pay-off table using lexicographic optimization. Accordingly, we consider the first OF (Obj_1) and obtain its optimal value (f_1*=z_1) without considering the second OF. Then, we optimize the second OF (Obj_2) while the first OF is moved to the constraints with an RHS value equal to f_1*. This procedure is repeated for the second OF. The constructed pay-off table is provided in Table III. Afterwards, we divide the rage of the second OF to 10 equal intervals and then, each sub-problem is solved to obtain the optimal solution. The achieved results are provided in Table III.

Table III. Constructed pay-off table

OF	*Type*	*Obj_1**	*Obj_2**
Obj_1	Min	3484399.97	3861005.36
Obj_2	Max	0.14	0.70

C. Results

Fig. (2) illustrates that the responsiveness and total costs are in conflict with each other as a decrease in the first OF results in a decrease in the second one and vice versa. As depicted in Fig. (2), the first OF seeks to build a centralized network to minimize total cost, while the second OF is aimed at building a decentralized network in order to maximize responsiveness. Also, Table IV demonstrates the locations selected for establishing facilities as well as the values of the first and second OFs in 10 augmented ε-constraint iterations. On the other hand, Table IV reveals that the optimum value of the first OF is 3484399.97 and manufacturing/remanufacturing centers 1, 4, and 6; warehouses 1, 2, and 3; and DCs 3 and 6 are selected. Also, the optimum value of the second OF is 0.70 and manufacturing/remanufacturing centers 1, 4, and 6; warehouses 1, 2, 3, and 5; and DCs 5 and 6 are selected. It is worth noting that if DM tends to minimize the first OF, the first solution (i.e., the first solution in augmented ε-constraint iterations) with minimum total cost and minimum responsiveness is selected while, if the DM's preference is toward maximizing the second OF, the last solution (i.e., the 11^{th} solution in augmented ε-constraint iterations) with maximum responsiveness and maximum total cost is selected.

As illustrated in Table IV, lower TC can be achieved with smaller number of established facilities, but by decreasing the degrees of responsiveness. On the other hand, to increase responsiveness, a larger network with more established facilities will be needed. Table V (total cost components) shows that the TFC has the maximum proportion of the total cost. The table also shows that the TFC increases significantly when a new facility is open (10.27% for a new warehouse) and network changes in the ninth ε-constraint iteration.

Table IV. Results of the augmented ε-constraint method

NO.	*Value of the first OF*	*Value of the second OF*	*Opened factory*	*Opened warehouse*	*Opened DC*
1	3484399.97	0.14	1,4,6	1,2,3	3,6
2	3484505.42	0.20	1,4,6	1,2,3	3,6
3	3484718.69	0.25	1,4,6	1,2,3	3,6
4	3484963.26	0.31	1,4,6	1,2,3	3,6
5	3485292.72	0.37	1,4,6	1,2,3	3,6
6	3485755.60	0.42	1,4,6	1,2,3	3,6
7	3486652.88	0.48	1,4,6	1,2,3	3,6
8	3487864.34	0.53	1,4,6	1,2,3	3,6
9	3494237.05	0.59	1,4,6	1,2,3	3,5
10	3853099.30	0.64	1,4,6	1,2,3,5	3,6
11	3861005.36	0.70	1,4,6	1,2,3,5	5,6

Table V. Total cost components (percentage)

NO.	*Value of the first OF*	*TFC*	*TVC*	*TTC*
1	3484399.97	3343110.286 (95.94%)	99885.082 (2.86%)	41404.599 (1.18%)
2	3484505.42	3343110.286 (95.94%)	99894.556 (2.86%)	41500.579 (1.19%)
3	3484718.69	3343110.286 (95.93%)	100000.633 (2.86%)	41607.772 (1.19%)
4	3484963.26	3343110.286 (95.93%)	100145.809 (2.87%)	41707.162 (1.19%)
5	3485292.72	3343110.286 (95.92%)	100248.630 (2.87%)	41933.803 (1.20%)
6	3485755.60	3343110.286 (95.90%)	100163.396 (2.87%)	42481.913 (1.21%)
7	3486652.88	3343110.286 (95.88%)	100165.517 (2.87%)	43377.081 (1.24%)
8	3487864.34	3343110.286 (95.84%)	100216.593 (2.87%)	44537.460 (1.27%)
9	3494237.05	3348155.716 (95.81%)	100515.377 (2.87%)	45565.958 (1.30%)
10	3853099.30	3706878.728 (96.20%)	100254.435 (2.60%)	45966.136 (1.19%)
11	3861005.36	3714536.510 (96.20%)	100462.041 (2.60%)	46006.805 (1.19%)

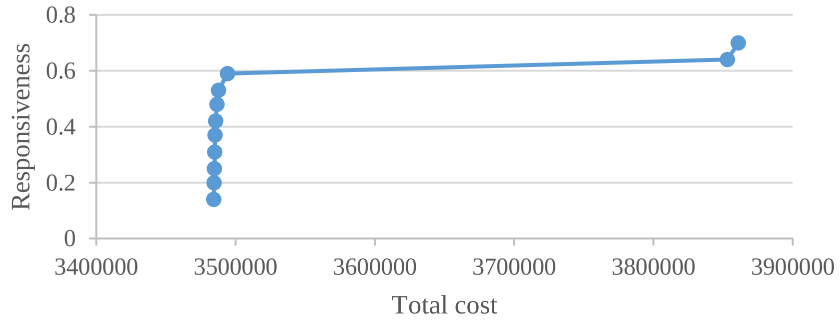

Figure 2. Pareto front of the concerned problem

In the ε-constraint/augmented ε-constraint method, choosing the optimal solution highly depends on the preferences of the DM(s). In this study, to overcome this drawback and create a simplified structure for choosing the optimal solution, the following procedure is proposed. For this purpose, we first create the utility function for each OF considered in this study. The utility functions for minimization and maximization OFs can be defined as follows.

$$UF_1 = \frac{MaxObj_1 - Obj_1}{MaxObj_1 - MinObj_1} \tag{9}$$

$$UF_2 = \frac{Obj_2 - MinObj_2}{MaxObj_2 - MinObj_2} \tag{10}$$

Table VI shows the values of utility functions for the first and second OFs.

Table VI. Utility function of the first and second OF

No.	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*

UF_1	1	0.99972	0.999154	0.998504	0.997629	0.996400	0.994018	0.990801	0.973880	0.020993	0
UF_2	0	0.107143	0.196429	0.303571	0.410714	0.500000	0.607143	0.696429	0.803571	0.892857	1

At the second step of the presented procedure, we calculate the utility of each of the solutions obtained in each iteration of the augmented ε-constraint method. To this end, we consider a certain weight for each solution achieved in each iteration of the method. In this paper, for simplicity, the weight of each OF is considered equal to 0.5. The desirability of the solutions is given in the following table.

Table VII. Utility function of each solution obtained in each augmented iteration

No.	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
UF	0.5	0.553431	0.597791	0.651038	0.704172	0.748200	0.800580	0.843615	0.888726	0.456925	0.5

As shown in Table VII, the 9th solution, which has the maximum desirability, is selected. Also, the values of the first and second OFs are 3494237.05 and 0.59, respectively, and manufacturing/remanufacturing centers 1, 4, and 6; warehouses 1, 2, and 3; and DCs 3 and 5 are selected.

V. CONCLUSION AND FUTURE WORK

In this paper, a bi-objective MILP model for a multi-product, multi-echelon CLSCND in which both strategic and tactical decisions are taken into account, simultaneously, is presented. The first OF tried to minimize the total cost of the SC, while the second one was aimed at maximizing the responsiveness of the network in both forward and reverse directions, simultaneously. A numerical example was presented to illustrate efficiency and applicability of the proposed model. A set of Pareto-optimal solutions was generated by using the augmented ε-constraint method, which encompassed a trade-off between objectives. The achieved results revealed that the total costs and responsiveness OFs were in conflict as the former objective was aimed at building a centralized network while the latter was aimed at building a decentralized network. Moreover, in this study, we tailored a simplified solution selection algorithm for choosing the most desirable solution among different achieved efficient Pareto solutions.

Extending the presented model by considering other echelons (e.g., suppliers and collection centers), taking into account uncertainty in parameters (e.g., demand of customers, fixed and variable costs, quality of the product), using different uncertainty handling approaches (e.g., stochastic programming, fuzzy mathematical programming, and robust optimization approach), applying the proposed mathematical model and the tailored solution selection procedure to a real case study, and using/developing a heuristic or metaheuristic algorithm (especially in large-size problems) are some research directions that can be paved in future studies.

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