Considering chain-to-chain competition on environmental and social concerns in a supply chain network design problem

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1. Introduction

The supply chain network design (SCND) problem has been widely studied as one of the most important issues in supply chain management. In recent years, competitive nature of markets caused researchers to attend the competition issue in their studies. In this research, a multi-objective mathematical model for dynamic and integrated network design of a competitive and sustainable supply chain is presented. In the proposed model, a chain-to-chain competition between two supply chains, who compete on environmental and social concerns, is considered. To solve this competitive model, a two-stage solution approach is introduced. A game theory approach is initially used to determine the equilibrium values for competitive decisions. Then, according to results of the competitive stage and respecting complexity of the proposed model, a Pareto-based multi-objective meta-heuristic algorithm is applied to solve the achieved network design problem. Finally, to evaluate the efficiency of the proposed model and presented solution approach, several generated numerical examples are graphically and statistically studied.

1. Introduction

The supply chain network design (SCND) problem is introduced as one of the main issues in supply chain management (Simchi-Levi, Kaminsky, & Simchi-Levi, 1999). The main purpose of SCND problem is to define an efficient structure for supply chain. This problem has been studied by many researchers, over the last decade. According to the related literature, the network design of a supply chain can be studied in the various following scopes, as shown in Figure 1.

Respecting time horizon for decisions made in the SCND problem, two groups are considered: (i) the strategic SCND problem which focuses only on long-term network design decisions, and (ii) the integrated SCND problem in which short-term decisions are considered in addition to long-term decisions (Melo, Nickel, & Saldanha-da-Gama, 2009). The integrated SCND problem attempts to design the structure of supply chain with respect to its future tactical and operational performance (Shen, 2007). A comprehensive study about different decisions of the SCND problem is presented by Zanjirani Farahani, Rezapour, Drezner, and Fallah (2014) and Govindan, Fattahi, and Keyvanshokooh (2017).

According to the number of strategic periods, the SCND problem is categorized into two groups: (i) static SCND problems in which the structure of a supply chain is determined unchangeably for only one strategic time horizon (Fattahi, Mahootchi, Govindan, & Moattar Huseini, 2015), and (ii) dynamic SCND problem in which multiple strategic periods are considered, so that the strategic decisions can be changed dynamically (Thanh, Bostel, & Péton, 2008).

Regarding logistics of supply chain, they are classified into three categories (Melo et al., 2009): (i) supply chain with forward logistics in which only forward flows in servicing customers are focused on, (ii) supply chain with reverse logistics which concentrates on backward activities such as returning and recovering used products, and (iii) supply chain with both forward and reverse logistics (see e.g. Keyvanshokooh, Ryan, & Kabir, 2016).

The SCND problem can be divided into two groups according to the number of objective functions: (i) single-objective model and (ii) multi-objective model. According to Melo et al. (2009), most researchers of the SCND problem have solely focused on single-objective problems. Moreover, there are a number of researchers who have considered multi-objective SCND problem, so that several concerns are simultaneously investigated in their studies (Zanjirani Farahani et al., 2014). One of the new concepts introduced in the literature of multi-objective SCND problem is sustainability. The purpose of a sustainable SCND problem is to design the structure of a supply chain respecting all economic, environmental and social concerns (Seuring, 2013). Eskandarpour, Dejaz, Miemczyk, and Péton (2015) comprehensively reviewed the sustainable SCND problem.

Finally, according to the competition concept, the literature of SCND problem is categorized into three groups. The first group which contains most researches of this area investigates the network design problem in a monopoly market (Fallah, Eskandari, & Pishvaei, 2015). The second group includes researches that studied inner competition among different members within a supply chain. Finally, the last group includes researches in which chain-to-chain competition among different supply chains are studied. In this group, it is assumed that there are several rival supply chains which operate in similar markets and compete on some competitive issues. A few researchers studied chain-to-chain competition in the literature of the SCND problem (Zanjirani Farahani et al., 2014).

Despite the vast number of researches in the realm of the SCND problem, lack of a comprehensive mathematical...
model with respect to different aspects of the network design problem is still a critical research gap (Zanjirani Farahani et al., 2014). This paper attempts to present a comprehensive multi-objective mathematical model for integrated and dynamic network design of a competitive and sustainable supply chain. The main features of this research are highlighted in Figure 1. Table 1 illustrates the distinction between current research and other similar works.

Furthermore, a novel chain-to-chain competition is addressed in the proposed SCND problem. Although most of the researches relating to the competitive SCND problem, looked into the competition issue from only an economic view, this study approaches the competition by regarding the environmental and social factors, as well. It is supposed that there are two rival supply chains who compete with each other in a perfect competitive market. As a result, the competitors are price-takers and they cannot freely influence the market price. Consequently, the customers face with two substitutable supply chains who have similar selling prices. Therefore, it is assumed that the rival supply chains try to achieve more market share via non-economic competitive factors including environmental and social concerns.

The rest of this research is organized as follows: Section 2 describes problem definition of the current study. Section 3 states the solution approach for the proposed model. In Section 4, several numerical examples are evaluated and finally, the conclusion and future research suggestions are discussed in Section 5.

2. Problem definition

In this paper, dynamic and integrated network design of a new-entrant closed-loop supply chain that competes on sustainability concerns, is investigated. The new-entrant supply chain consists of multiple echelons in its forward and reverse logistics. The configuration of the new-entrant

Table 1. Characteristic of relevant works.

| Reference | Logistics of Supply Chain | Multiple Objective Functions | Sustainability Concern | Number of Periods | Time Horizon of Decisions | Competition Level of Supply Chain |
|-----------|---------------------------|-----------------------------|------------------------|------------------|--------------------------|---------------------------------|
| Ahmadi-Javid and Ghandali (2014) | FL | ✓✓✓✓✓ ✓ | | | | |
| Badri et al. (2013) | FL | ✓✓✓✓✓ ✓ | | | | |
| Bilir, Onsel Ekici, and Ulengin (2017) | FL | ✓✓✓✓✓ ✓ | | | | |
| Dehghanian and Mansour (2009) | RL | ✓✓✓✓✓ ✓ | | | | |
| Dubey, Gunasekaran, and Childe (2015) | F/R L | ✓✓✓✓✓ ✓ | | | | |
| Fallah, Eskandari, and Pishvae (2015) | R/R L | ✓✓✓✓✓ ✓ | | | | |
| Fattahi et al. (2015) | FL | ✓✓✓✓✓ ✓ | | | | |
closed-loop supply chain is shown in Figure 2. In the forward logistics, several manufacturers produce different products using raw materials provided by suppliers and sell them to customer zones. In the reverse logistics, the collection centers collect the used products from customer zones and resell them to material customers.

It is assumed that a rival supply chain exists in the market who produces substitutable products. As a result, a chain-to-chain competition occurs among rival supply chains. In Section 2.3, this competition will be explained in more detail.

Moreover, it is presumed that the structure of new-entrant supply chain can be changed over multiple strategic periods over the planning horizon. Therefore, there is a budget assigned to each strategic period which can be spent to open new facilities. Furthermore, to integrate the tactical performance of the supply chain with strategic network design problem, multiple tactical periods are considered in each strategic timeframe.

The new-entrant supply chain attempts to sustainably design its network with respect to the chain-to-chain competition. Other assumptions of the proposed model are as follows:

- The potential locations for facilities of different echelons are determined.
- The opened facilities in each strategic period cannot be closed.
- The maximum capacity of each facility is already known.
- Shortages can occur in form of lost sales.
- All parameters are deterministic.

### 2.1. Notations

All notation, parameters, and decision variables used in the proposed mathematical model are stated in Table 2.
Table 2. Notations of proposed model.

| Sets | | Sets |
|------|---|---|
| $C$ | Set of potential collection centers ($C$) | $C'$ | Set of material customers ($C'$) |
| $K$ | Set of potential customer zones ($K$) | $M$ | Set of potential manufacturers ($m \in M$) |
| $m \in M$ | Set of strategic periods ($n \in N$) | $n \in N$ | Set of products ($p \in P$) |
| $p \in P$ | Set of raw materials ($P$) | $R$ | Set of rivals supply chains ($R$) |
| $S$ | Set of suppliers ($S$) | $T$ | Set of tactical periods ($T$) |

| Parameters | | Parameters |
|------------|---|---|
| $B_i$ | Budget assigned to strategic period $n$ | $B_{i,p}$ | Buying cost of one unit of product $p$ from supplier $s$ |
| $p'$ | Mean value of all costs spent by supply chain to provide one unit of product $p$ for customer zone $k$ in each period | $Cap_{m}^{max}$ | Maximum installable production capacity of manufacturer $m$ |
| $Cap_{m,c}^{max}$ | Maximum collecting capacity of collection center $c$ | $CC_{k,p}$ | Variable cost of collecting one unit of product $p$ from customer zone $k$ |
| Demand$^{d}_{i,k,p}$ | Potential Demand of customer zone $k$, related to supply chain $r$, for product $p$ in tactical period $t$ of strategic period $n$ | Demand$^{d'}_{i,k,p}$ | Market share of supply chain $r$ in customer zone $k$ for product $p$ in tactical period $t$ of strategic period $n$ |
| $FO_i$ | Fixed cost charged in strategic period $0$, for opening facility $i$ in strategic period $n$ | $FOC_{i}$ | Fixed operating cost of facility $i$ |
| $FOC_{c}$ | Cost coefficient of the green degree per one unit of product $p$ | $PC_{m,p}$ | Variable cost of producing one unit of product $p$ at manufacturer $m$ |
| $PC_{m,p}$ | Selling price of one unit of product $p$, charged by of supply chain $r$, in customer zone $k$ in each period | $PB_{i,k,p}$ | Variable shortage cost of one unit of product $p$ at customer zone $k$ |
| $SV_{c,p}$ | Variable revenue of selling one unit of unrecovered product $p$ to material customer $SV_{c,p}$ | $TC_{i,j,p}$ | Variable cost of transporting one unit of product $p$ between facilities $i$ and $j$ |
| $TC_{i,j,p}$ | Usage rate of production capacity for manufacturer $m$ to produce one unit of product $p$ | $\alpha_{k,p}$ | Self-quality elasticity coefficient of supply chain $r$ in demand function of customer zone $k$ for product $p$ |
| $\alpha_{k,p}$ | Cross-quality elasticity coefficient supply chain $r$ in demand function of customer zone $k$ for product $p$ | $\alpha'_{k,p}$ | Self-eco-friendly elasticity coefficient of supply chain $r$ in acquisition function of customer zone $k$ for product $p$ |
| $\beta'_{k,p}$ | Cross-eco-friendly elasticity coefficient of supply chain $r$ in acquisition function of customer zone $k$ for product $p$ | $\beta_{k,p}$ | Cost coefficient of the quality level per one unit of product $p$ |
| $\rho_{p}$ | Quantity of required raw material$^{*}$, to produce one unit of product $p$ | $\theta_{k,p}$ | Maximum rate of reusable products for product $p$ in customer zone $k$ |

$^{*}$ $CC_{k,p}$, $CC_{s,p}$, $Gr_{k,p}^{n}$ and $Gr_{s,p}^{n}$ are related to new entrant supply chain
2.2. Model formulation

In this sub-section, objective functions of the multi-objective model are described, as well as the corresponding constraints.

### 2.2.1. Objective Functions (OF)

Equation (1) indicates the economic objective function by which total profit of the new-entrant supply chain is maximized with respect to costs of establishing new facilities, buying raw materials, producing products, providing quality and eco-friendly levels for products, occurring shortage, collecting used products, transporting goods among facilities, and selling collected products to material customers.

\[
\text{Max } OF_1 = \sum_{m \in N} \sum_{t \in T} \sum_{k \in M} \sum_{c \in C} \sum_{p \in P} PR_{k,p}^n t f_{m,k,p}^n \]

Subject to:

\[
- \sum_{m \in N} \sum_{t \in T} \sum_{c \in C} \sum_{p \in P} BC_{c,p} f_{s,m,p}^n
\]

\[
- \sum_{n \in N} \sum_{t \in T} \sum_{m \in M} \sum_{k \in K} \sum_{c \in C} \sum_{p \in P} PC_{n,m,k,p}^n
\]

\[
- \sum_{n \in N} \sum_{t \in T} \sum_{k \in K} \sum_{p \in P} SC_{k,p}^n
\]

\[\text{Subject to: } (1)\]

In recent years, many researchers have considered eco-friendly objective functions due to the prevalent environmental concerns (Seuring, 2013; Zhu & He, 2016). Accordingly, the second objective function of this study aims to maximize green degree of the products. Equation (2) calculates green degree of the products produced by the new-entrant supply chain for customer zones.

\[
\text{Max } OF_2 = \sum_{n \in N} \sum_{t \in T} \sum_{k \in K} \sum_{c \in C} \sum_{p \in P} GR_{k,p}^n OK_{k,p}^n \]

In the related literature, the social responsibility aiming to meet global willingness has been widely addressed (Dolgoff & Feldstein, 1980). In this research, the customers’ dissatisfaction is accounted to calculate social responsibility of the new-entrant supply chain. This dissatisfaction is the difference between the quality that customers are willing to receive and the quality that they practically receive. Equation (3) is developed to optimize the social responsibility by minimizing total dissatisfaction of served customer zones.

\[
\text{Min } OF_3 = \sum_{n \in N} \sum_{t \in T} \sum_{k \in K} \sum_{c \in C} \sum_{p \in P} (1 - Q_{k,p}^n)^t OK_{k,p}^n \]

### 2.2.2. Constraints

\[
\sum_{n \in N} f_{s,m,p}^n = \sum_{k \in K} \sum_{p \in P} \rho_{p}^n f_{m,k,p}^n \quad \forall m, p, n > 0, t
\]

\[
C_{m,k,p}^n = f_{m,k,p}^n \forall m, k, p, n > 0, t
\]

\[
\sum_{m \in M} f_{m,k,p}^n \leq OK_{k,p}^n Dem_{k,p}^n \quad \forall p, k, n > 0, t
\]

\[
\sum_{m \in M} f_{m,k,p}^n \leq OK_{k,p}^n Dem_{k,p}^n \quad \forall p, k, n > 0, t
\]

\[
\sum_{c \in C} f_{k,c,p}^n \leq \theta_{k,p} \sum_{m \in M} f_{m,k,p}^n
\]

\[
OM_{m}^n \geq OM_{m}^{n-1} \quad \forall m, n > 0
\]

\[
OC_{c}^n \geq OC_{c}^{n-1} \quad \forall c, n > 0
\]

\[
\sum_{m \in M} FO_{m}^{n+1} (OM_{m}^{n+1} - OM_{m}^{n}) + \sum_{c \in C} FO_{c}^{n+1} (OC_{c}^{n+1} - OC_{c}^{n}) \leq B^n
\]

\[
\sum_{k \in K} \sum_{p \in P} f_{m,k,p}^n \leq Cap_{m}^n OM_{m}^n \forall m, n > 0, t
\]

\[
\sum_{k \in K} \sum_{c \in C} \sum_{p \in P} f_{k,c,p}^n \leq OC_{c}^n Cap_{c}^{\max} \quad \forall c, n > 0, t
\]

\[
OM_{m}^n, OC_{c}^n, OK_{k,p}^n \in \{0, 1\}, \quad Q_{k,p}^n, f_{m,k,p}^n, f_{k,c,p}^n, S_{c,p}^n \geq 0
\]

Equation (4) ensures that the manufacturers receive sufficient raw materials to produce the products. Equation (5) assures that the manufacturers transport all the products to the customer zones. Equation (6) states that in each period, the products provided by supply chain for each customer zone is less than the market share of that customer zone. Moreover, it assures that the products can only be transported to the customer zones for which the supply chain is servicing. Equation (7) guarantees that for each customer zone in each period, the market share equals sum of the products delivered to that customer zone and the shortage occurs there. Equation (8) limits the amount of products, returned from each customer zone, to the satisfied market share of that customer zone with respect to the maximum reusable rate. Equation (9) ensures that each collection center sells all products collected from the customer zones. Equations (10) and (11) confirm that the activated facilities cannot be closed in the next strategic periods. Equation (12) limits costs of opening facilities to the assigned budget for each strategic period. Equations (13) and (14) express the capacity limitation for the facilities. Finally, Eq. (15) indicates the decision variables.
2.3. Competition of supply chain

The chain-to-chain competition between new-entrant and existing supply chains is described in this sub-section. Considering the competition on environmental and social responsibility, it is presumed that for each supply chain the demand function depends linearly to the following factors:

(1) Green degree of the products
(2) Quality level of the products

Actually, selling prices of the products are supposed to be given. According to Li and Li (2016), this assumption is practical and rational. It is observed that in many markets the customer zones are attracted by supply chains which care more about non-economic factors. Nowadays, most firms compete on factors beyond price, such as brand, eco-friendly level, social responsibility, etc (Dolgo & Feldstein, 1980).

Based on the chain-to-chain competition among new-entrant and existing supply chains, the demand function for each supply chain can be formulated by Eq. (16).

\[
Dem_{r,k,p}^{n,t} = Demand_{r,k,p}^{n,t} + \alpha_{r,k,p}Qu_{r,k,p}^{n,t} - \alpha_{r,k,p}Qu_{r,k,p}^{n,t} + \beta_{r,k,p}Gr_{r,k,p}^{n,t} - \beta_{r,k,p}Gr_{r,k,p}^{n,t}
\]

(16)

where \(Dem_{r,k,p}^{n,t} = Demand_{r,k,p}^{n,t} + \alpha_{r,k,p}Qu_{r,k,p}^{n,t} - \alpha_{r,k,p}Qu_{r,k,p}^{n,t} + \beta_{r,k,p}Gr_{r,k,p}^{n,t} - \beta_{r,k,p}Gr_{r,k,p}^{n,t}\) and \(Dem_{r,k,p}^{n,t} = Demand_{r,k,p}^{n,t} + \alpha_{r,k,p}Qu_{r,k,p}^{n,t} - \alpha_{r,k,p}Qu_{r,k,p}^{n,t} + \beta_{r,k,p}Gr_{r,k,p}^{n,t} - \beta_{r,k,p}Gr_{r,k,p}^{n,t}\) indicate the quality levels, \(Qu_{r,k,p}^{n,t}\) and \(Qu_{r,k,p}^{n,t}\) show the greenness levels for supply chain \(r\) and its rival supply chain \(Gr_{r,k,p}^{n,t}\), respectively.

Moreover, producing green products to attract more market share imposes an extra cost on each supply chain (Ghosh & Shah, 2012). According to Yan and Pen (2009), this cost is assumed to be a quadratic function of the green level, as formulated by \(Gr_{r,k,p}^{n,t}\). Furthermore, higher quality levels need more cost (Giri, Roy, & Maiti, 2017). In this study, \(g_{t}^{n,t} = (Gr_{r,k,p}^{n,t})^2\) is used to formulate this fixed quality cost. As a result, the profit function of each supply chain is calculated using Eq. (17).

\[
\Pi_{r,k,p}^{n,t} = PR_{r,k,p}^{n,t} - C_{r,k,p}^{n,t} Dem_{r,k,p}^{n,t} - \eta_{t} Qu_{r,k,p}^{n,t}^2 - g_{t} (Gr_{r,k,p}^{n,t})^2
\]

(17)

Note that \(C_{r,k,p}^{n,t}\) is the average operational cost, calculated based on the possible structures for each supply chain. Furthermore, \(Gr_{r,k,p}^{n,t}\) depends on only the economical expenditures. In other words, it is independent of environmental and social costs spent by each supply chain to improve its competitive advantage.

3. Solution approach

The solution approach of the proposed model consists of the following two steps. Figure 3 indicates the proposed solution approach. Initially, the competitive part of the model, described in sub-Section 2.3, is solved. Then, substituting the outputs of the competitive part into the model of sub-Section 2.2, the meta-heuristic algorithm is used to solve the SCND model. Two steps of the solution approach are explained in detail by the following subsections.

3.1. Competitive step

As mentioned in Section 2.3, it is assumed that there is an existing supply chain in addition to the new-entrant supply chain. These two supply chains have to compete on both quality level and green degree of their products to seize more market share in each customer zone.

In the first step, the competitive variables are defined. In this manner, a game theory approach is used by which the equilibrium values of quality level and green degree are achieved. According to simultaneous competition between supply chains (players), Nash equilibrium is calculated for the SCND model. The solution approach of the proposed model consists of the following two steps.

Stage 1: Chain to Chain Competition

- Quality Variable
  - Quality levels
  - Green levels

Game Theory Approach

Stage 2: Sustainable SCND

- Decision Variables
  - Location
  - Quantity of production
  - Supplier selection
  - Flow of goods
  - Shortage

Meta-Heuristic Algorithm

\[\frac{\partial \Pi_{r,k,p}^{n,t}}{\partial Qu_{r,k,p}^{n,t}} = \alpha_{r,k,p} (PR_{r,k,p}^{n,t} - C_{r,k,p}^{n,t}) - 2\eta_{t} Qu_{r,k,p}^{n,t} \]

(18)

\[\frac{\partial \Pi_{r,k,p}^{n,t}}{\partial Gr_{r,k,p}^{n,t}} = \beta_{r,k,p} (PR_{r,k,p}^{n,t} - C_{r,k,p}^{n,t}) - 2g_{t} Gr_{r,k,p}^{n,t} \]

(19)

\[\frac{\partial^2 \Pi_{r,k,p}^{n,t}}{\partial Qu_{r,k,p}^{n,t}^2} = -2\eta_{t} \]

(20)

\[\frac{\partial^2 \Pi_{r,k,p}^{n,t}}{\partial Qu_{r,k,p}^{n,t} \partial Gr_{r,k,p}^{n,t}} = 0 \]

(21)

\[\frac{\partial^2 \Pi_{r,k,p}^{n,t}}{\partial Gr_{r,k,p}^{n,t}^2} = -2g_{t} \]

(22)
\[
\frac{\partial^2 \Pi_{r,k,p}^{n,t}}{\partial G_{r,k,p}^{n,t} \partial Q_{r,k,p}^{n,t}} = 0
\]  

(23)

The Hessian matrix is calculated using Eq. (24).

\[
H = \begin{bmatrix}
-2\eta_p & 0 \\
0 & -2g_p
\end{bmatrix}
\]  

(24)

Since the Hessian matrix is negative definite (det(H) > 0), the profit function is concave. Consequently, the optimal values of the quality level and green degree are calculated by setting the first-order partial derivations to zero, as formulated by Eqs. (25) and (26).

\[
\frac{\partial \Pi_{r,k,p}^{n,t}}{\partial Q_{r,k,p}^{n,t}} = \alpha_{r,k,p} \left( P R_{r,k,p}^{n,t} - C_{r,k,p}^{n,t} \right) - 2\eta_p Q_{r,k,p}^{n,t} = 0
\]  

(25)

\[
\frac{\partial \Pi_{r,k,p}^{n,t}}{\partial G_{r,k,p}^{n,t}} = \beta_{r,k,p} \left( P R_{r,k,p}^{n,t} - C_{r,k,p}^{n,t} \right) - 2g_p G_{r,k,p}^{n,t} = 0
\]  

(26)

Therefore, optimal values of the quality level and green degree are calculated using Eqs. (27) and (28).

\[
Q_{r,k,p}^{n,t} = \frac{\alpha_{r,k,p}}{2\eta_p} \left( P R_{r,k,p}^{n,t} - C_{r,k,p}^{n,t} \right)
\]  

(27)

\[
G_{r,k,p}^{n,t} = \frac{\beta_{r,k,p}}{2g_p} \left( P R_{r,k,p}^{n,t} - C_{r,k,p}^{n,t} \right)
\]  

(28)

Finally, these optimal values and the corresponding market share are substituted in the proposed model, stated in Eqs. (1)–(15).

### 3.2. Sustainable network design step

Substituting optimal values of competitive stage in the proposed model leads to a MILP model which is known as a NP-hard problem (Badri, Bashiri, & Hejazi, 2013). According to complexity of the proposed multi-objective model and the conflict among different objective functions, multi-objective meta-heuristic algorithms are used in this research.

Over last decades, meta-heuristic algorithms are vastly used in the literature to solve multi-objective problems. In this type of the problems, there are several objective functions including \( OF(\tilde{x}) = [OF_1(\tilde{x}), ..., OF_m(\tilde{x})] \) and constraints such as \( OF(\tilde{x}) = [OF_1(\tilde{x}), ..., OF_m(\tilde{x})] \), where \( g_i(\tilde{x}) \leq 0, \quad i = 1, 2, ..., c, \quad \tilde{x} \in X \) is the solution vector and \( g_i(\tilde{x}) \leq 0, \quad i = 1, 2, ..., c, \quad \tilde{x} \in X \) is the feasible region. The conflict among objective functions leads to domination concept. In a maximization form, the domination of solution \( \tilde{a} \) to solution \( \tilde{b} \) is defined as follows:

\[
OF_i(\tilde{a}) \geq OF_i(\tilde{b}), \quad \forall i = 1, 2, \cdots, m
\]

\[
\exists i \in \{1, 2, ..., m\} : OF_i(\tilde{a}) > OF_i(\tilde{b})
\]

It should be noted that the Pareto fronts include solutions which cannot dominate each other. The efficiency of the different solutions of a Pareto front can be evaluated by their diversity and convergence (Deb, Pratap, Agarwal, & Meyarivan, 2002).

In this paper, a Pareto-based multi-objective imperialist competitive algorithm (MOICA) is used to solve the proposed complex model. In order to evaluate performance of the proposed algorithm, a non-dominated sorting genetic algorithm is used, too. Furthermore, for a more clear comparison between the proposed meta-heuristic algorithms, an exact method based on the e-constraint technique is used, as well. The following sub-sections describe MOICA, NSGA-II and augmented e-constraint method.

#### 3.2.1. Multi-objective imperialist competitive algorithm

The imperialist competitive algorithm (ICA) is one of the well-known population-based meta-heuristic algorithms, inspired by imperialism phenomenon. Atashpaz-Gargari and Lucas (2007) introduced this algorithm to solve the single-objective problems. The efficiency and success of this algorithm for single-objective problems have encouraged many researchers to apply the multi-objective version of this algorithm for multi-objective problems. Enayatifar, Yousef, Abdullah, and Darus (2013) developed the multi-objective imperialist competitive algorithm for the first time.

In this study, a Pareto-based MOICA is used to solve the proposed multi-objective model. The steps of the proposed MOICA are as follows:

**Step 1: Initializing the empires**

The first step of MOICA is creating \( N_{pop} \) countries (solution). In this study, each solution is a vector with \( M + C \) cells (number of manufacturers and CCs). The value of each cell indicates the strategic period in which the corresponding facility is activated. Zero value indicates that the facility remains closed during the planning horizon. According to these values, the other decision variables for each solution will be randomly generated. Figure 4 shows the solution representation for the proposed algorithm.

After the initialization of \( N_{pop} \) countries, \( N_{imp} \) of the more powerful countries are chosen as imperialists for whom the other countries are colonies. According to Enayatifar et al. (2013), assigning colonies to the imperialists depends on the power of each imperialist which is defined based on two following criteria:

- Rank of each country which is calculated based on the fast non-dominated sorting (FNDS) technique and consideration of all objective functions
- Merit of each country compared to countries with the same rank which is calculated by using Sigma method (Eq. (29)).

Accordingly, the power of each country is formulated using Eq. (29):

**Figure 4. Solution representation.**
\[ power_n = \frac{1}{D} \sum_{j=1}^{D} \frac{OF_j(n)}{\sum_{i=1}^{N_{col}(C)} OF_i(i)} (\text{Rank}(C) - 1) \times D \]  

(29)

where \( D \) is the number of objective functions, \( OF_j(i) \) is the value of the \( j \)th objective function for country \( i \) and \( OF_j(i) \) is the number of countries in rank \( C \).

The number of colonies for each imperialist (\( NC \)) is simply calculated by Eq. (30):

\[ NC_n = \text{round}(p_n N_{col}) \]  

(30)

where \( NC_n = \text{round}(p_n N_{col}) \), indicates the imperialists power ratio.

**Step 2: Moving the colonies toward their imperialist**

In this step, it is assumed that the colonies move toward their imperialist. The movement of each colony is formulated using Eq. (31). Also, it is presumed that a deviation can occur during this movement, which is formulated by Eq. (32).

\[ x \sim U(0, \beta \times d) \]  

(31)

\[ \theta \sim U(-\gamma, \gamma) \]  

(32)

where \( U(\cdot) \) is a random variable with the Uniform distribution function, \( d \) indicates the distance between each colony and its imperialist, \( \beta \) and \( \beta \) are parameters.

**Step 3: Exchanging position of imperialist and colony**

If a colony reaches a better position than its imperialist, their position will be exchanged. In other words, this colony should be considered as the new imperialist of corresponding empire.

**Step 4: Computing the total cost of all empires**

The total cost of each empire is calculated with respect to total costs of its imperialist and colonies, as formulated by Eq. (33).

\[ TC_n = \text{Cost(imperialist)} + \zeta \text{mean(Colony)} \]  

(33)

where \( TC_n = \text{Cost(imperialist)} + \zeta \text{mean(Colony)} \) is a parameter of MOICA.

**Step 5: Imperialist competition**

In this step, a competition occurs between empires to seize the weakest colony of the weakest empire. The normalized power of each empire (\( NTC_n \)) is calculated using Eq. (34).

\[ NTC_n = TC_n - \max(TC_n) \]  

(34)

**Step 6: Eliminating the powerless empires**

If an empire loses all its colonies, it should be eliminated and the competition will be continued between the other empires.

**Stop condition**

If only one empire remains in the competition, the algorithm stops. Of course, in the proposed algorithm the maximum number of iterations is used as another stop criterion. The pseudo code of the proposed MOICA is indicated in Figure 5.

### 3.2.2. Non-dominated sorting genetic algorithm

One of the most common meta-heuristic algorithms used in the literature of multi-objective optimization problems is the non-dominated sorting genetic algorithm (NSGA). This population-based algorithm introduced by Srinivas and Deb (1995) is developed version of the genetic algorithm. The weaknesses of NSGA encouraged Deb et al. (2002) to present NSGA-II which is widely used to solve multi-objective problems.

In this research, to evaluate performance of the proposed MOICA algorithm, a NSGA-II approach is used. It is notable that the crossover operator of NSGA-II is defined based on the Uniform crossover operator introduced by Haupt and Haupt (2004) and the binary tournament selection method is also applied as the selection strategy.

The pseudo code of the proposed NSGA-II is indicated in Figure 5, too.

---

**Pseudocode for MOICA**

Begin
- Initialize \( N_{pop} \) countries (Step 1)
- Determine power of countries
  - Perform fast non-dominated sorting (FNDS)
  - Calculate crowding distance (CD)
- Configure the empires
  - Assigning the colonies to imperialists
While Iteration<Max_Iteration (Stop condition)
- Move colonies to empires (Step 2)
  - If a colony dominated its imperialist (Step 3)
    - Exchange the position of colony and imperialist
End if
- Calculate total cost of empires (Step 4)
  - Perform fast non-dominated sorting (FNDS)
  - Calculate crowding distance (CD)
- Preform imperialist competition (Step 5)
  - Competition among empires to seize the weakest colony of the weakest empire
    - Eliminates empires without colony (Step 6)
      - If there is only one empire
        - Stop
End if
End While
End

**Pseudocode for NSGA-II**

Begin
- Initialize population (P)
- Evaluate population
  - Perform fast non-dominated sorting (FNDS)
  - Calculate crowding distance (CD)
While Generation<Max_Generation (Stop condition)
  - Perform crossover operator (P)
    - Select parents
      - Perform binary tournament selection
    - Create Childs based on selected parents
    - Perform mutation operator (P)
      - Select parent
        - Perform binary tournament selection
        - Create Childs based on selected parent
    - Combine populations (\( P = P_1 \cup P_2 \cup P_3 \))
  - Elitism on population (P)
    - Perform fast non-dominated sorting (FNDS)
    - Calculate crowding distance (CD)
End While
End

Figure 5. Pseudo code of proposed algorithms.
3.2.3. Augmented e-constraint method

To compare efficiency of the proposed algorithms more accurately, an augmented e-constraint method is used to solve the sustainable SCND problem. This method developed by Mavrotas (2009) is one of the well-known mathematical programming techniques for solving multi-objective models. According to this technique, the multi-objective problem is reformulated as a single-objective model. Equation (35) indicates reformulation of the achieved sustainable SCND problem.

\[
\begin{align*}
    \text{max } & z_{e\text{-constraint}} = OF_1(x) + \delta \left( \frac{sl_2}{\text{Range}_2} + \frac{sl_3}{\text{Range}_3} \right) \\
    \text{s.t. } & OF_2(x) - sl_2 = e_2 \\
    & OF_3(x) + sl_3 = e_3 \\
    & sl_i \geq 0 \\
    \text{Constraints} (4) - (15)
\end{align*}
\]

where \(OF_i(x)\) indicates the \(i\)th objective function regarding solution \(x\), \(OF_i(x)\) is a small number among \(10^{-3}\) and \(10^{-6}\) parameter, \(e_i\) indicates the epsilon value for \(i\)th objective function added to constraints, \(e_i\) is the slack (surplus) variable related to the minimization (maximization) objective functions added to constraints, \(\text{Range}_i\) is the range of variations for \(i\)th objective function which can be reached via lexicography method (Mavrotas, 2009).

### Table 3. Characteristics of test problems.

| Problem No. | S | M | K | C | C' | P' | P | N | T |
|-------------|---|---|---|---|----|----|---|---|---|
| P1          | 2 | 2 | 2 | 1 | 1  | 2  | 2 | 2 | 3 |
| P2          | 3 | 2 | 3 | 2 | 1  | 3  | 2 | 3 | 3 |
| P3          | 5 | 3 | 4 | 3 | 1  | 3  | 3 | 3 | 3 |
| P4          | 6 | 4 | 5 | 4 | 2  | 5  | 4 | 3 | 3 |
| P5          | 8 | 6 | 8 | 5 | 2  | 8  | 5 | 4 | 4 |
| P6          | 10| 7 | 10| 6 | 3  | 10 | 6 | 4 | 4 |
| P7          | 12| 9 | 13| 7 | 4  | 12 | 8 | 5 | 4 |
| P8          | 15| 10| 15| 9 | 5  | 15 | 10| 5 | 4 |
| P9          | 18| 13| 18| 10| 7  | 18 | 12| 5 | 4 |
| P10         | 20| 15| 20| 13| 8  | 20 | 15| 5 | 4 |

### Table 4. The average values of competitive decision variables.

| Problem No. | Supply chain | Gr | Qu | Dem | II |
|-------------|--------------|----|----|-----|----|
| P1          | New entrant SC | 15.4286 | 0.63 | 682  | 977,532 |
|             | Existing SC   | 17.1429 | 0.74 | 1137 | 165,121  |
| P2          | New entrant SC | 16.2857 | 0.78 | 947  | 136,773  |
|             | Existing SC   | 17.1429 | 0.77 | 865  | 124,574  |
| P3          | New entrant SC | 19.2857 | 0.69 | 1086 | 157,372  |
|             | Existing SC   | 17.5714 | 0.80 | 1012 | 146,489  |
| P4          | New entrant SC | 15.85  | 0.66 | 907  | 131,241  |
|             | Existing SC   | 15.42  | 0.72 | 852  | 115,647  |
| P5          | New entrant SC | 19.28  | 0.83 | 1347 | 196,073  |
|             | Existing SC   | 15.42  | 0.72 | 674  | 96,482   |
| P6          | New entrant SC | 15.42  | 0.64 | 764  | 109,924  |
|             | Existing SC   | 16.28  | 0.85 | 1020 | 147,843  |
| P7          | New entrant SC | 18.42  | 0.64 | 1037 | 150,432  |
|             | Existing SC   | 17.57  | 0.66 | 897  | 129,643  |
| P8          | New entrant SC | 17.57  | 0.73 | 1026 | 148,823  |
|             | Existing SC   | 16.71  | 0.72 | 857  | 123,623  |
| P9          | New entrant SC | 18.00  | 0.88 | 1221 | 177,634  |
|             | Existing SC   | 16.28  | 0.88 | 914  | 131,844  |

### Table 5. Algorithm parameter ranges along with values of algorithms parameters.

| Multi-Objective Algorithms | Algorithm Parameters | Parameter Levels |
|----------------------------|----------------------|-----------------|
| MOICA                     | Number of Population | 20 30 40        |
|                           | Number of Imperialist| 5 10 15         |
|                           | A random Variable    | 1 2 3           |
|                           | Deviation from Original Direction | 0.5 0.6 0.7 |
|                           | Influence Coefficient of Colonies | 0.05 0.1 0.2 |
|                           | Maximum generation   | 50 100 200      |
| NSGA-II                   | Number of Population | 20 25 30        |
|                           | Crossover Probability| 0.5 0.55 0.6   |
|                           | Mutation Probability | 0.35 0.4 0.45   |
|                           | Maximum Number of Generation | 50 75 100 |

### 4. Numerical study

To evaluate the proposed model and solution approach, several numerical examples are used. The experiments are implemented on 10 test problems with the main characteristics presented in Table 3. The other parameters of the model are generated randomly based on the Uniform distribution functions with reasonable range.
To solve the proposed competitive SCND model, first, the competitive stage is solved. In this step, the equilibrium values of green degrees, quality levels and market share are simply determined by using the game theory approach, as stated in Section 3.1. Table 4 indicates the average values of these competitive decision variables regarding different customer zones and time periods.

In the second step, the determined competitive decision variables are substituted in the proposed model. Accordingly, a MILP model for sustainable network design problem is achieved. Finally, two meta-heuristic algorithms (stated in Section 3.2) are used to solve the resulted MILP model.

It is notable that to adjust parameter of the meta-heuristic algorithms, the Taguchi method is used. This method attempts to determine the level of parameters respecting signal to noise ratio (Range), so that the noise effect is minimized. Accordingly, different levels for parameters associated with the proposed algorithms are presented in Table 5. Using Minitab software, the L9 and L27 designs are implemented for NSGA-II and MOICA, respectively. To avoid uncertainty, each problem is solved ten times using both algorithms and finally, the average values are reported. The effect plot of the signal to noise ratio for both algorithms are presented in Figure 6. The efficient level for each parameter is highlighted in Table 5.

Moreover, to compare performance of the MOICA and NSGA-II, the following multi-objective measures are applied, based on Rahmati, Hajipour, and Niaki (2013).

Computational (CPU) time which measures the running time of getting near optimum solutions

Number of solutions (NOS) which indicates the number of Pareto solutions in optimal front (larger NOS indicates higher quality of Pareto front).

Diversity which evaluates how the Pareto solutions are distributed on the Pareto front (Zitzler & Thiele, 1998).

Mean ideal distance (MID) which is measured regarding an ideal point (Zitzler & Thiele, 1998). Smaller value of MID is desired.

Spacing which calculates the standard deviation of distance among Pareto solutions. Smaller value of spacing is desired (Zitzler, 1999).

Both meta-heuristic algorithms are applied for all test problems. The proposed meta-heuristic algorithms are coded in MATLAB and the experiments are implemented on a 2 GHz laptop with 4 GB RAM. Table 6 indicates the abovementioned multi-objective metrics for all test problems.

To evaluate the efficiency of both algorithms and compare the results with an exact method, an augmented e-constraint method is used, as described in Section 3.2.3. It should be noted that all the problems are first reformulated by Eq. (35), and then the achieved single-objective models are solved using GAMS in which CPLEX solver is set. Moreover, for each test problem, the economic objective function is considered as the main objective function of the e-constraint method and the environmental and social concerns are added to the constraints. Furthermore, three different levels are considered for epsilons (ε) of environmental and social objective functions. In Table 6, the objective function values associated with the optimal solution, are reported for each test problem. It is observed in Table 6 that GAMS software led to no optimal solution for two last large-scale problems over 10,000 seconds, while meta-heuristic algorithms achieved several solutions for these problems in a short rational time.

Moreover, the analysis of variance (ANOVA) test is implemented to compare MOICA and NSGA-II algorithms, statistically. The results of ANOVA test is illustrated in Table 7 and the individual value plots of ANOVA test are indicated in Figure 7. It is observed that both algorithms are comparable with respect to the MID and time metrics. The MOICA is better than NSGA-II with respect to the NOS, while NSGA-II shows better performance in terms of the spacing and diversity metrics.

Furthermore, Figure 8 represents the graphical comparison of all multi-objective metrics for 10 test problems which confirm the aforementioned results. It is observed that both algorithms perform similarly with respect to the MID and time metrics. Although MOICA shows better performance against NSGA-II for large-scale problems, both algorithms could reach acceptable solutions in a rational time (less than 6000 seconds). With respect to the

Table 6. Multi-objective metrics computed for five proposed Pareto-based meta-heuristics.

| Algorithms | Metrics | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|------------|---------|---|---|---|---|---|---|---|---|---|----|
| NSGA-II    | Spacing | 4.70E-01 | 6.61E-01 | 1.08E+00 | 8.22E-01 | 7.46E-01 | 7.97E-01 | 5.30E-01 | 8.35E-01 | 6.04E-01 | 7.45E-01 |
|            | MID     | 9.43E-01 | 1.06E-00 | 1.00E+00 | 1.14E+00 | 1.81E+00 | 2.23E+00 | 1.37E+00 | 1.91E+00 | 2.20E+00 | 2.01E+00 |
|            | Diversity | 1.86E+03 | 3.27E+03 | 4.52E+03 | 2.02E+03 | 2.08E+03 | 1.23E+04 | 1.49E+04 | 1.79E+04 | 3.37E+03 | 2.13E+04 |
|            | NOS     | 6 | 6 | 8 | 4 | 8 | 6 | 5 | 12 | 10 | 16 |
|            | Time    | 8.75E+01 | 2.07E+02 | 2.87E+02 | 4.21E+02 | 5.36E+02 | 6.29E+02 | 1.82E+03 | 1.40E+03 | 1.72E+03 | 6.08E+03 |
| MOICA      | Spacing | 2.25E+00 | 2.00E+00 | 1.22E+00 | 1.34E+00 | 2.84E+00 | 1.67E+00 | 1.87E+00 | 2.16E+00 | 3.17E+00 | 2.70E+00 |
|            | MID     | 1.37E+00 | 1.40E+00 | 1.28E+00 | 1.62E+00 | 1.13E+00 | 1.37E+00 | 1.47E+00 | 1.96E+00 | 2.33E+00 | 1.35E+00 |
|            | Diversity | 2.88E+01 | 3.13E+01 | 2.77E+01 | 3.14E+01 | 2.42E+01 | 4.68E+01 | 6.58E+01 | 4.50E+01 | 7.32E+01 | 3.19E+04 |
|            | NOS     | 8 | 11 | 12 | 10 | 19 | 16 | 9 | 16 | 18 | 19 |
|            | Time    | 1.44E+02 | 2.70E+02 | 2.32E+02 | 4.05E+02 | 6.05E+02 | 4.73E+02 | 9.45E+02 | 1.33E+03 | 1.60E+03 | 3.72E+03 |

e-constraint Method

OF1: 543,862 899,190 1,200,783 1,639,545 11,983,158 13,051,601 17,178,347 22,092,351 NA*

OF2: 301.3 464.32 710.02 983.44 1,258,255 1,604,320 2,024,311 2,501,494

OF3: 2.05 3.87 12.72 13.63 26.92 28.49 32.83 45.17

* Not Available

Table 7. The P-values of the analysis of variance comparison test.

| Metrics name | P-value | Test results | Rank* |
|--------------|---------|--------------|-------|
| Spacing      | 0       | Null hypothesis is rejected | MOICA < NSGA-II |
| MID          | 0.867   | Null hypothesis is not rejected | MOICA ~ NSGA-II |
| Diversity    | 0.147   | Null hypothesis is not rejected | MOICA < NSGA-II |
| NOS          | 0.001   | Null hypothesis is not rejected | MOICA > NSGA-II |
| Time         | 0.588   | Null hypothesis is not rejected | MOICA ~ NSGA-II |

* Bigger is better
diversity and spacing metrics, NSGA-II outperforms MOICA. According to the NOS metric, it is observed in Figure 8 that MOICA is significantly better than NSGA-II which means the number of solutions achieved by MOICA is more than NSGA-II. Therefore, the decision maker has more options to decide.

Additionally, for test problem 7, the optimal Pareto front of both algorithms is illustrated in Figure 9. Moreover, the objective functions of all Pareto solutions for test problem 7 are reported in Table 8. It is observed that MOICA resulted in solutions which cannot be dominated by the results of NSGA-II. However, the solutions of NSGA-II are

| Solution No. | MOICA | NSGA-II | MOICA | NSGA-II | MOICA | NSGA-II | MOICA | NSGA-II |
|--------------|-------|---------|-------|---------|-------|---------|-------|---------|
| 1            | 16,119,091.02 | 1891.76 | 31.02 | 16,324,202.79 | 1832.91 | 34.58 | 3     |
| 2            | 16,334,273.55 | 1946.36 | 37.40 | 16,222,759.63 | 1853.46 | 48.73 | 2, 3, 5, 8, 9 |
| 3            | 16,362,784.37 | 1932.86 | 31.33 | 16,523,392.60 | 1996.06 | 51.47 | 8, 9  |
| 4            | 16,353,035.01 | 2019.86 | 53.73 | 15,708,676.42 | 1915.56 | 33.71 | 3     |
| 5            | 16,271,615.22 | 1952.56 | 35.42 | 16,490,994.81 | 1877.86 | 49.88 | 3, 8, 9 |
| 6            | 16,531,661.30 | 2035.96 | 54.93 |                   |         |       |       |
| 7            | 16,372,022.97 | 2012.16 | 52.53 |                   |         |       |       |
| 8            | 16,805,488.00 | 1903.32 | 36.22 |                   |         |       |       |
| 9            | 17,112,912.00 | 2005.61 | 42.58 |                   |         |       |       |

Figure 7. Individual value plots of ANOVA test.

Table 8. Pareto solutions of problem no. 7 along with non-domination analysis.
dominated by at least one solution of MOICA. For example, result no. 5 of NSGA-II is dominated by results no. 3, 8, and 9 of MOICA. Furthermore, Figure 9 illustrates the percentage of Pareto solutions of each algorithm which are dominated by the optimal solution achieved by GAMS, for all test problem. As an example, for test problem 7, except results no. 1, 3 and 6 achieved by MOICA, all the other solutions are dominated by the optimal solution achieved by GAMS. Also, all the solutions achieved by NSGA-II for test problem 7 (100%) are dominated by the optimal solution of GAMS. Accordingly, it is clear that MOICA normally indicates a better performance than NSGA-II. Indeed,
MOICA results in more solutions on its Pareto fronts compared to NSGA-II algorithm (larger NOS based on Table 6). On the other hand, the number of solutions dominated by the optimal solution achieved by GAMS is less in MOICA (based on Figure 10). Hence, it seems that the MOICA can be efficiently used to solve the proposed model.

5. Conclusion

This research presented a multi-objective model for dynamic and integrated network design of a new-entrant competitive supply chain. This supply chain attempted to simultaneously achieve sustainability concerns. To develop a more realistic model, it was assumed that the market is competitive respecting the greenness and social responsibility factors. As a result, a chain-to-chain competition occurred among the new-entrant supply chain and an existing supply chain. Therefore, both rival supply chains had to compete on environmental and social concerns. To solve the proposed model, a two-stage solution approach was presented. First, the competitive stage of the model was solved using a game theory approach. Then the outputs of the competitive stage were substituted and the network design stage was solved using Pareto-based MOICA and NSGA-II. Finally, several numerical examples were studied to evaluate the results of the proposed solution approach.

Since the chain-to-chain competition on sustainability concerns was focused in this paper, environmental and social concerns were considered as competitive factors. This model can be extended from the economic competitive factors such as pricing decisions. For the sake of simplicity it was assumed that all parameters of the SCND problem are deterministic. Therefore, the consideration of uncertainty in the proposed model can lead to more reliable results.

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