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Optimization of a sustainable closed loop supply chain network design under uncertainty using multi-objective evolutionary algorithms

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A B S T R A C T

Environmental, social and economic concerns have highlighted the importance of closed loop supply chain (CLSC) network design problem according to sustainable development. In addition, the uncertainty in decision elements adds to the complexity of this problem. Hence, this paper aims to propose a fuzzy multi-objective mixed integer linear programming (FMOMILP) model for a multi-echelon and multi-period CLSC network that minimize cost and environmental effects and maximize social impacts, simultaneously. At first, the model is converted into a multi-objective mixed-integer linear programming (MOMILP) model by the weighted average method. Due to NP-hardness of the problem, a non-dominated sorting genetic algorithm-II (NSGA-II) is developed to solve this multi-objective mathematical model. The obtained results are validated with the non-dominated ranking genetic algorithm (NRGA), due to there is no benchmark for this problem. In addition, different numerical instances are presented and analyzed with different measures in order to indicate the efficiency of proposed algorithms. The provided results demonstrate that the proposed NSGA-II algorithm is an adequate tool to solve the multi-objective problem of CLSC network design.

A R T I C L E   I N F O

Keywords:
Closed loop supply chain;
Evolutionary algorithms;
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1. Introduction

Recently, the closed loop supply chain (CLSC) increasingly attracted the attention of researchers and practitioners, due to its potential to increase the original equipment manufacturers profit by including the benefit from the collection and recovery of used products. Therefore, designing CLSC networks is of a major importance for organizations. Companies have been continuously pressured by consumers and regulators to control the impact of their products and operations on the environment. Three issues should be considered simultaneously to achieve the sustainable development. These three considerations are economic, environmental, and social aspects. Integration of economic, environmental, and social considerations in sustainable supply chain development, has been receiving an increased attention from companies and academic communities [1]. While the objective of many studies is minimizing the cost or maximizing the profit in supply chain network design (SCND), minimizing the environmental impact and maximizing the social impact are neglected.

The complexity of sustainable SCND is due to the properties of the objectives which are conflicting, inexpressible, sophisticated, and interpenetrating [2]. The uncertainty in decision elements adds to the complexity of the problem. Since there is an inherent uncertainty in the quantity and quality of returned products in reverse chains, considering the uncertainty is a major issue in sustainable SCND problems [3]. The grouping of above-mentioned uncertainties amplifies the total problem uncertainty. The incomplete information and qualitative nature of social and environmental aspects result in the fuzziness of their coefficients in sustainable SCND problems. To obtain an optimum solution for sustainable SCND it is necessary to consider the issue of uncertainty. Researchers implemented several inexact optimization methods to deal with the uncertainties in problems such as interval programming [4], stochastic programming [5], and fuzzy programming [6]. The fuzzy programming approach is more practical among non-deterministic models with multiple objectives. The expansive nature of CLSC networks design as an NP-hard (nondeterministic polynomial time) problem [7, 8]. Achieving reliable and efficient solutions within a practical time becomes more important when dealing with real industrial problems. Meta-heuristic approaches are commonly used for the NP-hard problems. Therefore, multi-objective meta-heuristic approaches are found suitable for solving the problem of sustainable CLSC network design. To ensure the reliability of the solution, the approach should result in Pareto optimal solutions. Since all objectives cannot be optimized by simultaneously, a set of best solutions for different objectives can be developed. In multi-objective evolutionary algorithms (MOEA) [9], such solution set is called Pareto optimal solution that is presented to the expert to make a decision based on the identified criteria.

Based on aforementioned concerns, this paper develops a fuzzy multi-objective mixed integer linear programming (FMOMILP) Model for the problem of CLSC network design in which three objectives of sustainability are met, simultaneously. This method first deals with the uncertainty and applies the weighted average method [10] to convert FMOMILP model into a multi-objective mixed-integer linear programming (MOMILP). The result is a deterministic model. The CLSC network design problem is recognized as an NP-hard problem. In addition, this kind of problems cannot be solved easily by analytical methods and commercial software for large instances. Hence, a non-dominated sorting genetic algorithm (NSGA-II) algorithm is adopted to find the Pareto front sets for the problem of sustainable CLSC network design. This method is used due to its simplicity and efficiency in comparison to analytical methods and other meta-heuristics algorithms. The NSGA-II is currently one of the most popular MOEAs which is used for different multi-objective problems [11]. The complexity of this algorithm is, at most $O(mn^2)$, where m is a number of objectives and n is population size. One of the other advantages of this algorithm is having an explicit diversity preservation mechanism. For the purpose of validating the results, another Non-dominated ranking genetic algorithm (NRGA) is developed and the results are compared. To demonstrate the efficiency of the method, numerical examples are presented. The validation of results is examined utilizing simple additive weighting and T-test methods based on measures of objective function values, spacing index, number of Pareto solutions, and CPU time index.

The major contributions and advantages that distinguish this study from the previous ones are: (1) the proposed approach considers three pillars of sustainability in supply chain network design; (2)the optimization of the forward supply chain and reverse supply chain is conducted simultaneously, while previous studies considered forward chain networks merely; (3) the study considers the uncertainties involved in different levels of supply chain networks to provide a realistic solution; (4) this study largely includes various stages of a CLSC network to imitate a real case; (5) an integrated framework is proposed by using NSGA-II algorithm to develop Pareto-optimal solutions; (6) the provided results of NSGA-II are validated with NRGA based on different instances.

2. Literature review

As it was mentioned, the uncertainty of decision variables increases the complexity of CLSC network design problem. There are several approaches to handling the uncertainty of CLSC network design problem. Stochastic programming is one of the methods used. Zeballos *et al.* [12] developed a two-stage scenario-based modeling for designing and planning decisions in a CLSC network. They considered demand and returns as uncertain parameters. A mixed-integer linear stochastic programming model for a single-period multi-product CLSC location problem including multiple plants, collection centers, and demand markets was introduced by Amin and Zhang [13]. In addition, robust programming is recognized as a commonly used method to design supply chain network under uncertainty. For instance, Hasani *et al*. [14] used an interval robust optimization technique to model a strategic CLSC network design. Ramezani *et al*. [15] presented a multi-objective model to design a forward/reverse supply chain network under an uncertain environment. A robust optimization approach was adopted to address the uncertainty of demand and the return rate with them.

Fuzzy programming was applied to accommodate uncertainty in supply chain network design problem. Vahdani *et al*. [16] proposed a bi-objective interval fuzzy possibilistic chance-constraint mixed integer linear programming to solve the CLSC network design. Sherafati and Bashiri [17] proposed a CLSC network design model considering the suitable transportation modes. They employed fuzzy decision variables in the supply chain network design model. Fuzzy programming has the advantages of being more practical and non-deterministic and it measures the degree of satisfaction of each objective functions. The latter feature helps decision makers to select a preferred efficient solution. Although the uncertainty is addressed in the aforementioned studies, they did not consider the environmental and social impacts in designing the supply chain networks. In addition, the proposed models and solution methods in these studies were applied for small cases. CLSC network design problem is identified as a NP-hard problem, for which and analytical methods and commercial software are not able to provide optimal solutions for large problem situations. Therefore meta-heuristics methods are used to solve such problems. Wang and Hsu [18] developed a revised spanning-tree-based genetic algorithm using determinant encoding representation to optimize a generalized CLSC network design. Pishvaee *et al*. [19] introduced simulated annealing algorithm with special neighborhood search mechanisms to solve a MILP model to design a multistage reverse logistics network. Soleimani *et al*. [20] also employed genetic algorithm to solve a CLSC network design problem. A hybrid meta-heuristic algorithm based on GA and PSO was developed by Soleimani and Kannan [8] to solve large-size instances of CLSC network design problem. Khalilpourazari and Mohammadi [21] proposed a novel meta-heuristic algorithm named water cycle algorithm to solve the mathematical model of CLSC network design. Pasandideh *et al*. [11] applied NASGA-II and NRGA algorithms to solve a multi-product multi-period three-echelon supply-chain-network problem. The analysis of literature review reveals the conducted studies in this field have neglected uncertainty and sustainability issues in the proposed models, simultaneously. While several approaches have been employed to deal with uncertainty in problem of CLSC network design, these studies have not taken sustainability concerns into account and they modeled only one objective function (minimize cost). For this reason, in this paper a FMOMILP model which consider all sustainable development objectives are proposed. In addition, a multi-objective evolutionary algorithm called NSGA-II algorithm is employed to solve this model for large problem instances.

3. Problem formulation

Fig. 1 demonstrates the proposed structure of this study for a multi-echelon, multi-period CLSC network. Four layers in the forward logistics, suppliers, producers, distributors, and customer centers have been taken into account. In addition, in the reverse logistics, there are four layers, collection & inspection, disposal, recycling, and repairing centers. These assumptions and limitations are made in the network configuration: (1) Return rates of products from customer centers, the capacity of all facilities, and product demand are fuzzy parameters; (2) The locations of suppliers and customer centers are fixed and predefined; (3) The potential locations of plants, distributors, collection and inspection, disposal, recycling, and repairing centers are known; (4) The flows are only permitted to be shipped between two consecutive stages in forward and reverse logistics. Furthermore, there are no flows between facilities at the same layer; (5) The transportation cost per product from the supplier to the producers is included in the raw material purchasing cost; (6) The transportation cost of products between all layers remains fixed for all the periods; (7) The inspection cost of the returned products is included in the transportation cost from customer zones to collection & inspection centers; (8) The model is single-product; (9) The model is multi-period.

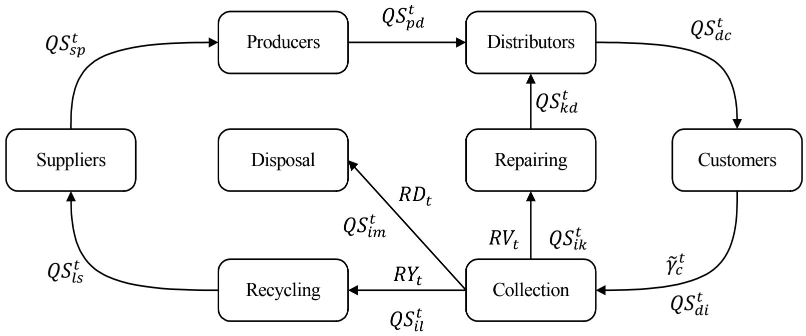

Fig. 1 The network structure of CLSC model

3.1 Objective functions

Three objective functions, minimize cost (Z_1), minimize environmental impacts (Z_2), and maximize social impacts are established for the proposed multi-echelon and multi-period CLSC model. These objective functions are presented by the following equations:

$$
\begin{aligned}
&\text{Min} \\
&= \sum_{p}\sum_{t} FC_p\, OP_p^t + \sum_{d}\sum_{t} FC_d\, OD_d^t + \sum_{i}\sum_{t} FC_i\, OI_i^t + \sum_{m}\sum_{t} FC_m\, OM_m^t + \sum_{l}\sum_{t} FC_l\, OL_l^t \\
&+ \sum_{k}\sum_{t} FC_k\, OK_k^t + \sum_{p}\sum_{d}\sum_{t} MC_p^t\, QS_{pd}^t + \sum_{i}\sum_{l}\sum_{t} RC_l^t\, QS_{il}^t + \sum_{k}\sum_{i}\sum_{t} BC_k^t\, QS_{ik}^t \\
&+ \sum_{m}\sum_{i}\sum_{t} DC_m^t\, QS_{im}^t + \sum_{d}\sum_{p}\sum_{t} TC_{pd}\, QS_{pd}^t + \sum_{d}\sum_{c}\sum_{t} TC_{dc}\, QS_{dc}^t + \sum_{c}\sum_{i}\sum_{t} TC_{ci}\, QS_{ci}^t \\
&+ \sum_{i}\sum_{m}\sum_{t} TC_{im}\, QS_{im}^t + \sum_{i}\sum_{l}\sum_{t} TC_{il}\, QS_{il}^t + \sum_{i}\sum_{k}\sum_{t} TC_{ik}\, QS_{ik}^t + \sum_{k}\sum_{d}\sum_{t} TC_{kd}\, QS_{kd}^t \\
&+ \sum_{s}\sum_{p}\sum_{t} TC_{sp}\, QS_{sp}^t
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
&\text{Min } EI \\
&= \sum_{p}\sum_{d}\sum_{t} EIP_p\, QS_{pd}^t + \sum_{i}\sum_{m}\sum_{t} EID_m\, QS_{im}^t + \sum_{s}\sum_{p}\sum_{t} EIS_{sp}\, QS_{sp}^t + \sum_{p}\sum_{d}\sum_{t} EIS_{pd}\, QS_{pd}^t \\
&+ \sum_{d}\sum_{c}\sum_{t} EIS_{dc}\, QS_{dc}^t + \sum_{c}\sum_{i}\sum_{t} EIS_{ci}\, QS_{ci}^t \\
&+ \sum_{i}\sum_{m}\sum_{t} EIS_{im}\, QS_{im}^t + \sum_{i}\sum_{l}\sum_{t} EIS_{il}\, QS_{il}^t + \sum_{i}\sum_{k}\sum_{t} EIS_{ik}\, QS_{ik}^t + \sum_{l}\sum_{s}\sum_{t} EIS_{ls}\, QS_{ls}^t \\
&+ \sum_{k}\sum_{d}\sum_{t} EIS_{kd}\, QS_{kd}^t
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
&\text{Max } SI \\
&= \sum_{p}\sum_{t} FJ_p\, OP_p^t + \sum_{d}\sum_{t} FJ_d\, OD_d^t + \sum_{i}\sum_{t} FJ_i\, OI_i^t + \sum_{m}\sum_{t} FJ_m\, OM_m^t + \sum_{l}\sum_{t} FJ_l\, OL_l^t \\
&+ \sum_{k}\sum_{t} FJ_k\, OK_k^t + \sum_{p}\sum_{d}\sum_{t} VJ_p\, QS_{pd}^t / \widetilde{CP}_p^t + \sum_{d}\sum_{c}\sum_{t} VJ_d\, QS_{dc}^t / \widetilde{CD}_d^t \\
&+ \sum_{c}\sum_{i}\sum_{t} VJ_i\, QS_{ci}^t / \widetilde{CI}_i^t + \sum_{i}\sum_{m}\sum_{t} VJ_m\, QS_{im}^t / \widetilde{CM}_m^t + \sum_{i}\sum_{l}\sum_{t} VJ_l\, QS_{il}^t / \widetilde{CL}_l^t \\
&+ \sum_{i}\sum_{k}\sum_{t} VJ_k\, QS_{ik}^t / \widetilde{CK}_k^t
\end{aligned}
\tag{3}
$$

The first objective function calculates the total cost of the CLSC model. This objective consists of fixed costs of establishing facilities (first six terms), manufacturing, recycling, repairing, and disposal costs (seventh to tenth terms), and transportation costs (eleventh to eighteenth terms). The second function is related to environmental impacts objective function of the CLSC network. The first and second terms are the environmental impacts of producing goods by producers and disposing of returned products by disposal centers. The rest terms in this objective function stand for the environmental impacts of shipping products between facilities. The social impacts of CLSC network design are formulated by the third function. Fixed and variable job opportunities are measures we considered for social impact objective function. In this objective function, the seventh to twelfths terms stand for the created variable jobs.

3.2 Constraints

The following constraints are taking into account:

$$\sum_{p} QS_{sp}^{t} \leq OS_{s}^{t}\, \widetilde{CS}_{s}^{t} \qquad \forall\, s,t \tag{4}$$

$$\sum_{d} QS_{pd}^{t} \leq OP_{p}^{t}\, \widetilde{CP}_{p}^{t} \qquad \forall\, p,t \tag{5}$$

$$\sum_{p} QS_{pd}^{t} + QS_{kd}^{t} \leq OD_{d}^{t}\, \widetilde{CD}_{d}^{t} \qquad \forall\, d,t \tag{6}$$

$$\sum_{c} QS_{ci}^{t} \leq OI_{i}^{t}\, \widetilde{CI}_{i}^{t} \qquad \forall\, i,t \tag{7}$$

$$\sum_{i} QS_{im}^{t} \leq OM_{m}^{t}\, \widetilde{CM}_{m}^{t} \qquad \forall\, m,t \tag{8}$$

$$\sum_{s} QS_{ls}^{t} \leq OL_{l}^{t}\, \widetilde{CL}_{l}^{t} \qquad \forall\, l,t \tag{9}$$

$$\sum_{s} QS_{sp}^{t} = \sum_{d} QS_{pd}^{t} \qquad \forall\, p,t \tag{10}$$

$$\sum_{k} QS_{kd}^{t} + \sum_{p} QS_{pd}^{t} = \sum_{c} QS_{dc}^{t} \qquad \forall\, d,t \tag{11}$$

$$\sum_{c} QS_{ci}^{t} = \sum_{m} QS_{im}^{t} + \sum_{l} QS_{il}^{t} + \sum_{k} QS_{ik}^{t} \qquad \forall\, i,t \tag{12}$$

$$\sum_{l} QS_{il}^{t} = \sum_{c} QS_{ci}^{t}\, RY_{t} \qquad \forall\, i,t \tag{13}$$

$$\sum_{i} QS_{il}^{t} = \sum_{s} QS_{ls}^{t} \qquad \forall\, l,t \tag{14}$$

$$\sum_{k} QS_{ik}^{t} = \sum_{c} QS_{ci}^{t}\, RV_{t} \qquad \forall\, i,t \tag{15}$$

$$\sum_{i} QS_{ik}^{t} = \sum_{d} QS_{kd}^{t} \qquad \forall\, k,t \tag{16}$$

$$\sum_{m} QS_{im}^{t} = \sum_{c} QS_{ci}^{t}\, RD_{t} \qquad \forall\, i,t \tag{17}$$

$$\sum_{d} QS_{dc}^{t} = \widetilde{DE}_{c}^{t} \qquad \forall\, c,t \tag{18}$$

$$\sum_{i} QS_{ci}^{t} = \widetilde{DE}_{c}^{t} * \tilde{\gamma}_{c}^{t} \qquad \forall\, c,t \tag{19}$$

$$\sum_{s} OS_{s}^{t} \leq S \qquad \forall\, t \tag{20}$$

$$\sum_{p} OP_{p}^{t} \leq P \qquad \forall\, t \tag{21}$$

$$\sum_{d} OD_{d}^{t} \leq D \qquad \forall\, t \tag{22}$$

$$\sum_{i} OI_{i}^{t} \leq I \qquad \forall\, t \tag{23}$$

$$\sum_{m} OM_{m}^{t} \leq M \qquad \forall\, t \tag{24}$$

$$\sum_{l} OL_{l}^{t} \leq L \qquad \forall\, t \tag{25}$$

$$\sum_{k} OK_{k}^{t} \leq K \qquad \forall\, t \tag{26}$$

$$QS_{sp}^{t}, QS_{pd}^{t}, QS_{dc}^{t}, QS_{ci}^{t}, QS_{im}^{t}, QS_{il}^{t}, QS_{ik}^{t}, QS_{ls}^{t}, QS_{kd}^{t} \geq 0 \quad \forall i,j,k,l,m,p,t,c,d \tag{27}$$

$$OS_{s}^{t}, OP_{p}^{t}, OD_{d}^{t}, OI_{i}^{t}, OM_{m}^{t}, OL_{l}^{t}, OK_{k}^{t} \in \{0,1\} \qquad \forall i,k,l,m,p,s,t,d \tag{28}$$

Constraints Eqs. 4 to 9 are capacity constraints. Constraints Eqs. 4, 5, 9 control output capacity of suppliers, producers, and recycling centers in each period respectively. Constraints Eqs. 6 to 8 control input capacity of distributors, collection and inspection centers, and disposal centers in each period respectively. Constraints Eqs. 10 to 17 are balance constraints which guarantee the flow entering to utilities are equal to sum of the flow existing from utilities. Constraints Eqs. 10 to 12 are balance constraints of producers, distributors, and collection & inspection centers respectively. Constraints Eqs. 13 and 14 are balance constraints of recycling centers. Constraints Eqs. 15 and 16 are balance constraints of repairing centers. Constraint Eq. 17 is balance constraint of disposal centers. Constraint Eq. 18 ensures that all customer demands should be met in customer centers. Constraint Eq. 19 shows the amount of returned products which are collected from customer centers. Constraints Eqs. 19 to 26 limit the maximum number of allowable locations. Constraints Eqs. 27 and 28 represent the non-negativity and integrality of variables.

4. Auxiliary MOMILP

As seen from the proposed model for CLSC network design in section 3, fuzzy parameters are employed in objective functions and constraints. For this reason, to solve this model, it should be firstly changed to deterministic model. Hence, the weighted average method [10] is implemented to convert the proposed FMOMILP model into an equivalent auxiliary crisp multiple objective mixed integer linear programming (MOMILP) model. This process is done by the following steps:

Step 1: Strategy for fuzzy objectives

Finding an ideal solution is not guaranteed for the proposed model due to used fuzzy coefficients for the objective function of Social Impacts (*SI*) (Eq. 3). Several approaches are proposed to obtain compromise solutions when there are fuzzy objective functions [10]. The proposed approach by Lai and Hwang [10] has less restrictive assumptions in comparison with other methods and practically is easy in order to use. Hence, the approach of Lai and Hwang is employed to deal with fuzzy objective functions in this study. For this aim, an auxiliary MOMILP model is provided with three objective functions to convert the fuzzy objective function of *SI* to precise one. The triangular possibility distributions are taken into account for fuzzy parameters of this objective function. Based on the proposed approach by Lai and Hwang [10], the fuzzy objective function, maximize *SI*, is converted into minimize (${SI_s}^m$-${SI_s}^p$) (Z_3), maximize ${SI_s}^m$ (Z_4), and maximize (${SI_s}^o$-${SI_s}^m$) (Z_5). The new crisp objective functions are modeled by following equations:

$$\begin{aligned}
&\text{Min } (SI^m - SI^p) = Z_3 \\
&= \sum_p \sum_t FJ_p\, OP_p^t + \sum_d \sum_t FJ_d\, OD_d^t + \sum_i \sum_t FJ_i\, OI_i^t + \sum_m \sum_t FJ_m\, OM_m^t + \sum_l \sum_t FJ_l\, OL_l^t \\
&+ \sum_k \sum_t FJ_k\, OK_k^t + \sum_p \sum_d \sum_t VJ_p\, QS_{pd}^t /(CP_p^{t,m} - CP_p^{t,p}) + \sum_d \sum_c \sum_t VJ_d\, QS_{dc}^t /(CD_d^{t,m} - CD_d^{t,p}) \\
&+ \sum_c \sum_i \sum_t VJ_i\, QS_{ci}^t /(CI_i^{t,m} - CI_i^{t,p}) + \sum_i \sum_m \sum_t VJ_m\, QS_{im}^t /(CM_m^{t,m} - CM_m^{t,p}) \\
&+ \sum_i \sum_l \sum_t VJ_l\, QS_{il}^t /(CL_l^{t,m} - CL_l^{t,p}) + \sum_i \sum_k \sum_t VJ_k\, QS_{ik}^t /(CK_k^{t,m} - CK_k^{t,p})
\end{aligned} \tag{29}$$

$$\begin{aligned}
&\text{Max } SI^m = Z_4 \\
&= \sum_p \sum_t FJ_p\, OP_p^t + \sum_d \sum_t FJ_d\, OD_d^t + \sum_i \sum_t FJ_i\, OI_i^t + \sum_m \sum_t FJ_m\, OM_m^t + \sum_l \sum_t FJ_l\, OL_l^t \\
&+ \sum_k \sum_t FJ_k\, OK_k^t + \sum_p \sum_d \sum_t VJ_p\, QS_{pd}^t /CP_p^{t,m} + \sum_d \sum_c \sum_t VJ_d\, QS_{dc}^t /CP_d^{t,m} \\
&+ \sum_c \sum_i \sum_t VJ_i\, QS_{ci}^t /CI_i^{t,m} + \sum_i \sum_m \sum_t VJ_m\, QS_{im}^t /CM_m^{t,m} + \sum_i \sum_l \sum_t VJ_l\, QS_{il}^t /CL_l^{t,m} \\
&+ \sum_i \sum_k \sum_t VJ_k\, QS_{ik}^t /CK_k^{t,m}
\end{aligned} \tag{30}$$

$$\text{Max}\,(SI^o - SI^m) = Z_5$$
$$= \sum_p \sum_t FJ_p\, OP_p^t + \sum_d \sum_t FJ_d\, OD_d^t + \sum_i \sum_t FJ_i\, OI_i^t + \sum_m \sum_t FJ_m\, OM_m^t + \sum_l \sum_t FJ_l\, OL_l^t$$
$$+ \sum_k \sum_t FJ_k\, OK_k^t + \sum_p \sum_d \sum_t VJ_p\, QS_{pd}^t / (CP_p^{t,o} - CP_p^{t,m}) + \sum_d \sum_c \sum_t VJ_d\, QS_{dc}^t / (CD_d^{t,o} - CD_d^{t,m}) \quad (31)$$
$$+ \sum_c \sum_i \sum_t VJ_i\, QS_{ci}^t / (CI_i^{t,o} - CI_i^{t,m}) + \sum_i \sum_m \sum_t VJ_m\, QS_{im}^t / (CI_m^{t,o} - CI_m^{t,m})$$
$$+ \sum_i \sum_l \sum_t VJ_l\, QS_{il}^t / (CI_l^{t,o} - CI_l^{t,m}) + \sum_i \sum_k \sum_t VJ_k\, QS_{ik}^t / (CK_k^{t,o} - CK_k^{t,m})$$

Step 2: Strategy for fuzzy constraints

In this study, the pattern of triangular distribution is implemented to demonstrate all of the fuzzy numbers in constraints. The simplicity and flexibility of the fuzzy arithmetic operations are the main reason to employ triangular fuzzy numbers in this study [10]. Triangular patterns provide decision makers to define fuzzy numbers in three prominent data points: the most pessimistic value and the optimistic value with possibility degree of 0, and the most likely value with possibility degree of 1. The triangular fuzzy numbers membership functions as linear, which makes it computationally efficient by having a simple formulation in comparing to nonlinear distributions constructions.

A triangular distribution of $\widetilde{CS}_s^t$ consists of: (1) the most pessimistic value ($CS_s^{t,p}$) – it has a very low probability (possibility degree 0) of belonging to the set of accessible values; (2) the most possible value ($CS_s^{t,m}$) – it has a very high probability (possibility degree 1) of belongings to the set of accessible values; (3) the most optimistic value ($CS_s^{t,o}$) – it has a very low probability (possibility degree 0) of belonging to the set of available values [22]. Recalling constraint Eq. 4 from the original FMOMILP model formulated in Section 3 considers situations in which supplier capacity, $\widetilde{CS}_s^t$, is a triangular fuzzy number with most and least likely values. In this study, the weighted average method is applied to convert fuzzy numbers (such as $\widetilde{CS}_s^t$) into a crisp number. Taking considerations β as the minimum acceptable membership level, the corresponding auxiliary crisp inequality of constraint Eq. 4 can be represented as follows:

$$\sum_p QS_{sp}^t \leq OS_s^t\,(W_1 CS_{s,\beta}^{t,p} + W_2 CS_{s,\beta}^{t,m} + W_3 CS_{s,\beta}^{t,o}) \qquad \forall\, s,t \quad (32)$$

Similarly, the corresponding auxiliary crisp inequalities of constraints Eqs. 5 to 9 and Eqs. 18 to 19 are obtained regarding β as the minimum acceptable membership level.

5. Used methods

Two approaches can be followed solving complicated multi-objective optimization problems using evolutionary algorithms two approaches. In the first approach, a multi-objective problem is turned into a single-objective problem. The second approach first creates multiple best (Pareto optimal) solutions for each objective and then finds the best solution among them. The first approach, uses some multi-criteria decision making algorithm to transfer the problem into a single objective one [23]. Methods such as GA, simulated annealing (SA), imperialist competition algorithm (ICA), harmony search algorithm (HAS), and particle swarm optimization (PSO) can be used in this stage [24]. In the second approach multi-objective evolutionary algorithms (MOEA), such as non-dominated sorting genetic algorithm (NSGA-II), non-dominated ranking genetic algorithm (NRGA), and multi-objective particle swarm optimization (MOPSO), can be used to arrive at the solution set [25]. MOEAs are preferred over SOEAs due to the speed of simulation; single simulation run is required to reach a solution. Diversity and convergence distinguish the MOEAs from single-objective optimization algorithms. Diversity maintains the variety within the Pareto-optimal set solutions, while convergence aims at directing the solutions to the optimal Pareto set [24]. In this section, a multi-objective evolutionary algorithm (MOEA) is presented, among the MOEAs, the non-dominated sorting genetic algorithm (NSGA-II) is preferred. NSGA-II is commonly used for similar problems. To validate the results, since no benchmark algorithms are available, this study applies a different GA based algorithm called non-dominated ranking genetic algorithm (NRGA).

5.1. NSGA II

The NSGA II developed by Deb *et al*. [24], is an extension of the non-dominated sorting genetic algorithm (NSGA), [26, 27], in which an extra sorting criterion was introduced. Both algorithms are developed to deal with multi-objective optimization problems and both use Goldberg's non-domination criterion to rank the solutions. NSGA uses a fitness sharing parameter to control the diversity of solutions and is found to be highly sensitive to this parameter. Therefore in NSGA II the crowding distance parameter which is a second-order sorting criterion is used that improves the efficiency of this method. The detailed description of NSGA-II is as follow. First, it generates a mating pool with binary tournament selection. Second, all the members go through a mutation and crossover processes. Third, a larger population is generated by merging the old solutions with the newly generated solutions. Forth, the population is sorted based on the members' rank and crowding distances. Finally, selected members that are sorted higher are kept and the rest are deleted. The previous steps are repeated until the stopping condition is met. The final non-dominated members create the Pareto frontier set for the multi-objective optimization problem.

5.2. NRGA

The non-dominated ranking genetic algorithm (NRGA) is a commonly used MOEA algorithm that is developed to deal with multi-objective optimization problems with creating a Pareto front optimal set. NRGA mechanism is similar to NSGA-II except for the step in which the older members merge with the new generation in the mating pool. The selection process of old members is developed in NRGA to integrate the Pareto based population-ranking algorithm with ranked-based roulette wheel (RBRW) selection process [28].

5.3. Generic operators for GA-based algorithms

Chromosome representation

In a genetic algorithm, a chromosome consist of a series of genes that are arranged sequentially where genes represent decision variables. In this paper, the matrix format is employed to represent the chromosome. Based on the proposed CLSC network structure, nine connections are defined to connect the utilities in this network. To produce each chromosome nine linear programming problems are solved. For instance, a network with 3 suppliers and 4 producers, is defined by a 3 × 4 dimension matrix. Fig. 2 displays a graphical representation of the chromosome.

	P_1	P_2	P_3	P_4
S_1	200	200	150	100
S_2	300	150	200	100
S_3	200	100	150	200

Fig. 2 Chromosome representation

Selection strategy

The selection strategy in NSGA-II uses fast non-dominated sorting, density estimation, and crowded comparison operators [24]. To classify the members in non- domination levels the fast non-dominated sorting operator is used. To find the density of solutions around a specific member in the population, the density estimation operator is used. And finally, to ensure that members are selected from a uniform Pareto front the crowded comparison operator is applied [24]. The binary tournament selection strategy is applied based on the described operators to find the solutions. In this process, the rank and crowding distance of each member is considered for the selection.

Crossover

Crossover operations in NSGA-II ensure that the new population is created by inheriting the good genes from the parents for the purpose of improving the chromosome. Commonly used crossover operators are single-point, two-point, and multiple-point operators. However there are other methods for cross over operation such as partially mapped crossover (PMX), ordered crossover (OX), cycle crossover (CX), and arithmetic crossover. In this research, the arithmetic crossover operator is used. This method combines the parent chromosomes linearly to create the new generation using Eqs. 33 and 34 [27].

$$\text{Offspring 1} = \alpha \times \text{parent 1} + (1-\alpha) \times \text{parent 2} \tag{33}$$

$$\text{Offspring 2} = (1-\alpha) \times \text{parent 1} + \alpha \times \text{parent 2} \tag{34}$$

where $0 < \alpha < 1$. The chance of crossing the parents is indicated by P_c and it is considered high for values above 80 %.

Mutation

Mutation happens after the crossover operation in NSGA-II. The purpose of this step is to create diversity in the newly generated populations. Therefore, moving from the parent generation to the new generation, the mutation operator searches the new solution space for including the solutions. This operator selects a chromosome and randomly chooses some genes and changes their values. The probability of this change is the mutation probability, P_m. There are several mutation operators, such as scramble mutation, random resetting mutation, and inversion mutation.

6. Results and discussion

For the purpose of verifying the proposed meta-heuristic algorithms in this study, experiments with different properties are designed. Nine designed experiments are different in size and are categorized as small, medium, and large size problems. The parameters in each problem are set by randomly assigning values from a uniform distribution with lower and upper limits. Tables 1 and 2 present the experiments and their assigned properties.

Table 1 Generated experiments

	S	P	D	C	I	K	L	M	T
	3	2	3	4	3	2	2	2	6
Small	4	2	2	5	2	2	2	2	6
	2	3	3	4	3	2	3	3	6
	8	8	5	10	7	5	5	5	6
Medium	7	9	6	8	5	6	6	6	6
	9	8	8	8	6	6	5	5	6
	15	15	10	20	10	8	8	8	6
Large	20	15	15	25	10	8	8	10	6
	15	20	10	20	8	10	10	8	6

Table 2 The sources of random parameters of CLSC

Parameter	Range	Parameter	Range
$\widetilde{CS}_s^t, \widetilde{CP}_p^t, \widetilde{CD}_d^t, \widetilde{CI}_i^t, \widetilde{CM}_m^t, \widetilde{CL}_l^t, \widetilde{CK}_k^t$	[2,000 , 4,000]	$FC_d, FC_i, FC_m, FC_l, FC_k$	[30,000 , 60,000]
$TC_{pd}, TC_{dc}, TC_{ci}, TC_{im}, TC_{il}, TC_{ik}, TC_{ls}, TC_{kd}$	[3, 10]	$EIS_{sp}, EIS_{pd}, EIS_{dc}, EIS_{ci}, EIS_{im}, EIS_{il}, EIS_{ik}, EIS_{ls}, EIS_{kd}, EID_m, EIP_p$	[10, 30]
TC_{sp}	[30, 50]	MC_p^t	[150, 200]
$FJ_p, FJ_d, FJ_i, FJ_m, FJ_l, FJ_k$	[5, 10]	DC_m^t, RC_l^t, BC_k^t	[20, 40]
$VJ_p, VJ_d, VJ_i, VJ_m, VJ_l, VJ_k$	[0.4 , 0.6]	$\widetilde{DE}_c^t$	[400, 700]
$\tilde{\gamma}_c^t$	[0.5 , 0.8]		

In addition, for the proposed meta-heuristic algorithms a set of parameters are taken into account; the population number is 100, the generation number is 200, the crossover probability is 0.9, the mutation probability is 0.05. These parameters are chosen empirically based on a trial and error method. All computational work was accomplished on a personal computer (32-bit operating system, 2.53 GHz CPU, and 4.00 GB).

There are various metrics to assess the performance of MOEAs. This study applies three commonly used metrics for this purpose:

Spacing Index

This index takes the non-dominated vectors and calculates the variance of the distance of neighboring solutions [27].

$$SI = \sum_{i=1}^{|n|} \frac{|d_i - \bar{d}|}{|n|} \tag{35}$$

with, $d_i = min \sqrt{\sum_{m=1}^{5}(f_m^i - f_m^k)}$ and $\bar{d} = \sum_{i=1}^{n} \frac{d_i}{|n|}$, where $\bar{d}$ indicates all averages of distances and n indicates the Pareto set solutions, f represents the objective function values. Accordingly, $|n|$ represents the cardinality of n, and the number of objectives is presented by m.

Number of Pareto Solution (NPI) Index

The *NPI* index measures how many Pareto solutions are found by each algorithm.

CPUTI (CPU Time Index)

Measuring the speed of an algorithm with this index is in terms of CPU time needed to find the Pareto-optimal solution.

The NSGA-II and NRGA algorithms are compared based on Z_1, Z_2, Z_3, Z_4, Z_5, *SI*, *NPI*, and *CPUTI* indexes. In every run, the algorithm finds a set of Pareto-optimal solutions. The objective functions are compared by taking the minimum values for Z_1, Z_2, and Z_3, and the maximum values for Z_4, Z_5. Table 3 presents the results of the 9 experiments by NSGA-II and NRGA.

Table 3 The NSGA II and NRGA results

		Z_1	Z_2	Z_3	Z_4	Z_5	*SI*	*NPI*	*CPUTI*
NSGA-II	Small	24,611,010	1,575,001	469	449	453	72	8	207
		25,192,232	1,513,117	497	471	469	96	12	205
		24,817,245	1,561,114	475	445	455	536	7	209
	Medium	73,934,328	4,027,728	1,185	1,109	1,173	409	5	267
		71,819,429	4,011,342	1,019	1,022	1,135	382	13	270
		71,127,814	4,203,279	1,195	1,127	1,163	331	10	275
	Large	152,596,807	8,813,690	2,213	2,077	2,193	2,032	7	327
		175,133,714	8,019,370	2,291	2,113	2,348	1,467	6	320
		178,715,402	8,113,098	2,301	2,193	2,285	487	11	344
NRGA	Small	24,856,211	1,517,229	477	475	451	315	5	331
		24,975,107	1,575,348	491	460	452	319	27	278
		25,134,429	1,631,459	475	452	451	471	3	261
	Medium	74,257,191	4,301,475	1,282	1,187	1,159	212	7	315
		72,517,734	4,157,209	1,122	1,016	1,105	330	5	291
		71,039,875	4,076,342	1,031	1,173	1,183	112	5	297
	Large	155,375,108	7,955,179	2,347	1,952	2,017	767	3	512
		175,917,335	8,245,341	2,375	2,025	2,015	2,027	12	447
		177,009,375	8,279,351	2,410	2,001	2,255	1,103	10	420

Table 4 The p-values of the t-tests on the equality of performance measures

	Z_1	Z_2	Z_3	Z_4	Z_5	*SI*	*NPI*	*CPUTI*
P-value	0.398	0.926	0.227	0.343	0.129	0.928	0.927	0.002

The T-test is selected to examine the hypothesis as a common approach to test the equality of two populations based on parameters. The considered hypothesis for this test is, there is no significant difference between the results obtained by NSGA-II and NRGA for the same experiments. The t-test result does not reject the hypothesis and shows that there is no significant difference between the two test results (Table 4). The P-value is found to be beyond the condition of this test which requires the significance level of α = 0.05. Therefore, the NSGA-II results are considered to be validated by comparing to those of NRGA.

The validation of results is further examined using the simple additive weighting (SAW) introduced by Hwang and Yoon [23] is an MADM method that is used for this purpose. The SAW as a second method can help to determine which of the NSGA-II or NRGA have a better result. Table 5 illustrates the SAW evaluation of these algorithms which suggests the superiority of NSGA-II for all problem indices. However, the results from NRGA are satisfactory. Therefore it can be concluded that while both NSGA-II and NRGA provide valid and satisfactory results for SCN problem, the NSGA-II is superior compared to NRGA.

Table 5 The results of SAW method

Small			Medium			Large		
NSGA-II	NRGA	Prefer	NSGA-II	NRGA	Prefer	NSGA-II	NRGA	Prefer
0.9885	0.8059	NSGA-II	0.8958	0.9615	NRGA	0.9100	0.8564	NSGA-II
0.9279	0.8674	NSGA-II	0.9829	0.8929	NSGA-II	0.9375	0.8986	NSGA-II
0.9829	0.8956	NSGA-II	0.8891	0.9282	NRGA	0.9988	0.8754	NSGA-II

7. Conclusion

In this study, an FMOMILP model for a CLSC network design problem was developed. Three objective functions of sustainability that minimize costs and environmental impacts and maximize social impacts, were considered simultaneously. The FMOMILP model was converted into a deterministic MOMILP model by using the weighted average method. As the model developed in this study was hard to be solved analytically, a multi-objective genetic algorithm based on NSGA-II algorithm was developed to find Pareto fronts. Since there was no benchmark for this problem, the obtained results were validated with NRGA. Nine random examples with different sizes of small, medium, and large were provided to demonstrate the efficiency of the proposed algorithms. In addition, these eight performance measures (Z_1, Z_2, Z_3, Z_4, Z_5, SI, NPI, and $CPUTI$) were employed to compare the performance of these algorithms. Two-sample tests were implemented to compare the differences between the eight performance measures for these two algorithms. SAW method was also used to determine which method is more preferable. The provided results showed the NSGA II algorithm had better performance than NRGA. However, there were no significant differences between performance measures. Several ways can be suggested to extend this study. At first, it is suggested implementing other meta-heuristic algorithms such as multi-objective particle swarm optimization. Second, using other mutation and crossover operators are also recommended. The implementation of the proposed model and solution approach to a real industrial case would also be a considerable extension of this study.

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Appendix 1: Notations, parameters and decision variables

s: Suppliers, *p*: Plants, *d*: Distributors, *c*: Customer centers, *i*: Collection and inspection centers, *k*: Repairing centers, *l*: Recycling centers, *m*: Disposal centers, *t*: Periods

$\widetilde{CS}_{\gamma}^{t}$: Capacity of utilities $\gamma \in \{s, p, d, i, m, l, k\}$ at time period t

FC_{γ}: Fixed cost of opening utilities $\gamma \in \{p, d, i, m, l, k\}$

FJ_{γ}: The number of fixed job opportunities created by establishing utilities $\gamma \in \{p, d, i, m, l, k\}$

VJ_{γ}: The number of variable job opportunities created by establishing utilities $\gamma \in \{p, d, i, m, l, k\}$

$TC_{sp}, TC_{pd}, TC_{dc}, TC_{ci}, TC_{im}, TC_{il}, TC_{ik}, TC_{ls}, TC_{kd}$: Transportation cost a product from between utilities

$EIS_{sp}, EIS_{pd}, EIS_{dc}, EIS_{ci}, EIS_{im}, EIS_{il}, EIS_{ik}, EIS_{ls}, EIS_{kd}$: Environmental impacts of shipping a product between utilities

EIP_{p}: Environmental impacts of producing at plant p

EID_{m}: Environmental impacts of disposing at disposal center m

MC_{p}^{t}: Manufacturing cost at plant p at time period t

DC_{m}^{t}: Disposal cost at disposal center m at time period t

RC_{l}^{t}: Recycling cost at recycling center *l* at time period t

BC_{k}^{t}: Repairing cost at repairing center *k* at time period t

$\widetilde{DE}_{c}^{t}$: Demand of customer center *c* at time period t

RY_{t}: Recycling ratio at time period t

RV_{t}: Repairing ratio at time period t

RD_{t}: Disposal ratio at time period t

$\tilde{\gamma}_{c}^{t}$: Reverse ratio at time period t

$O\gamma_{\gamma}^{t}$: 1 if facility $\gamma \in \{s, p, d, i, m, l, k\}$ is to be established at time period t; 0 otherwise

$QS_{sp}^{t}, QS_{pd}^{t}, QS_{dc}^{t}, QS_{ci}^{t}, QS_{im}^{t}, QS_{il}^{t}, QS_{ik}^{t}, QS_{ls}^{t}, QS_{kd}^{t}$: Quantity shipped between utilities