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Application of meta-heuristic algorithm for multi-objective optimization of sustainable supply chain uncertainty

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Abstract. In the present research, a multi-objective mathematical model for construction material supply chain design under uncertainty is investigated. The considered supply chain is made up of a primary supplier and a number of projects (i.e., customers) demanding for different construction materials in different periods of time depending on the technical specifications of the demanded product in terms of life time. Moreover, the rate of product loss due to ill-timed transportation affects the respective managerial decisions. However, the most significant issue to address is the presence of uncertainty, for which we used the robust programming method proposed by Bertsimas and Sim. In order to solve the formulated mathematical model, we used epsilon-constraint method and the best-worst method as a multi-criteria decision-making method for small-scale cases, and meta-heuristic algorithms (NSGA-II, PESA, and SPEA) for large-scale problems. According to the obtained numerical results, one can observe that the SPEA algorithm outperformed all other algorithms, making it the optimal choice for addressing real cases. Moreover, a sensitivity analysis on the problem at different levels of the associated uncertainty with the parameters indicated the large impact of the uncertainty on the final outcomes. Results of this model can be used as efficient managerial instruments for optimizing the construction material supply chain design problem in the scope of civil project management.

Keywords. Sustainable construction supply chain; multi-objective optimization; robust programming; best-worst method (BWM); meta-heuristic algorithms.

1. Introduction

During the last decade, many researchers have placed an emphasis on the advantages of supply chain management in construction industry to shed light on improved construction performance and reduced waste generation due to inefficient management and control [1]. The construction industry is among the most versatile and unstable sectors on economy. Dealing with the installation, maintenance, and repair of portable structures, demolition of existing structures, and land development [2], this industry possesses special characteristics which make it distinctive of any other industry. Among others, such characteristics include physical nature and non-transferability of the product, structure of the industry, and cost-intensiveness of construction processes. In this industry, the product is designed and constructed to address the customer's needs as mentioned on the customer's order. This industry is made up of three key elements, namely customer/client, design, and construction. A fundamental problem encountered in the construction industry has been the isolation of these three key elements, as opposed to the establishment of an efficient communication among them. Indeed, lack of an effective communication leads to a situation where the designer fails to comprehend the customer's needs, which end up making the customer dissatisfied with the final product. With its project-oriented and temporary nature, this industry is encountering such problems as the isolation of its different elements, high rate of loss, low productivity, too much cost in terms of time and money, weak communication, lack of harmony among different elements, and the contradictions arose upon delays in performing the projects.

Since late 1980s, the construction industry has witnessed the emergence of a number of initially small and isolated inventions and innovations into the supply chain management. In general, the architecture, engineering and construction industry covers the design of construction supply chain, and repairing and completing the constructed environment [3]. Two main topics are discussed in relation to the construction supply chain: development of retarded efficiency and enhancement of economic weight of the supply chain. Investigations indicate that, the costs of material and workforce are responsible for some 75% of the main contractors' turnover [4]. Adoption of supply chain management can reduce the cost of material and workforce

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procurement and improve the level of productivity and performance in construction industry. For the purpose of this research, the term *supply chain* refers to the determination of the stages through which the construction resources (material, equipment, and personnel) are dispatched from the supply nodes to the construction sites [1]. In the scope of construction, the supply chain has the most to do with programming and guiding separate amounts of material to the construction site with the aim of gathering the input material [5].

The construction supply chain management proposes new approaches for lowering the cost while enhancing the reliability and pace of construction processes. Similar to the manufacturing industries where the supply chain management had resulted in significant cost savings, it can bring about similar advantages to the construction industry, although the construction companies are described as producers of unique products in temporary plants, as opposed to the manufacturing companies [6]. The temporary nature of the projects has acted as a barrier against establishment of long-term relationships, leading to the lack of effective communication across the construction supply chain. The development and maintenance of good relationships with customers and suppliers represent a key factor in successful performance of projects. The construction supply chain management undertakes to coordinate the decisions made across the chain and integrate the business processes and members of the supply chain including client, main contractor, subcontractor, suppliers, etc.

The rest of this research has been organized as follows. Section 2 presents a review on related literature. Section 3 describes the research methodology, and section 4 presents the numerical results. Finally, in section 5 conclusions and recommendations for future research are provided.

2. Literature review

2.1 *Supply chain network design*

In this subsection, some of the most important research works on the design of supply chain network in different fields are briefly introduced.

Tuzkaya *et al* [7] presented a multi-objective model for designing a reverse logistics network based on multi-criteria decision-making (MCDM) methods, namely ANP-FTOPSIS and genetic algorithm (GA), in the so-called white goods industry. Pishvaee *et al* [8] presented a multi-objective fuzzy mathematical programming model for environmental design of supply chain. The objectives considered in this research included the minimization of environmental impacts and costs. Finally, they developed an interactive fuzzy approach to solve the constructed model. Later on, Pishvaee *et al* [9] further introduced a two-objective robust possibilistic programing approach for social supply chain network design. In their research, Badri *et al* [10] presented a mathematical model for a multi-echelon multi-product supply chain network design considering different temporal analyses for tactical and strategic decisions. In order to solve the model, they used a methodology based on Lagrangian relaxation (LR).

Shankar *et al* [11] investigated a multi-objective optimization problem for a single-product, four-level supply chain, where the objectives were the minimization of transportation and facility location costs and maximization of meeting the customers' demands. They used the MOPSO algorithm for solving the problem. Kanzian *et al* [12] performed a research where they presented a multi-criteria optimization framework along with a model for biomass supply networks. As objectives, this research sought maximum profitability along with minimum CO_2 emission. Wu and Zhang [13] took a look into a supply chain network design problem where the chain was made up of an external source, a set of potential distribution centers, and a set of retailers under uncertain demand for multiple products with the final objective of minimizing the costs incurred to the system. They formulated an integer nonlinear programing model for the problem.

Working on supply chain network design, Sarrafha *et al* [14] presented a bi-objective mixed-integer nonlinear programing model to minimize not only the system costs, but also average delay in delivering the products to distribution centers. They finally had the problem solved using either of three algorithms, namely multi-objective biogeography-based optimization (MOBBO), MOSA, and NSGA-II. Soleimani and Kannan [15] employed the GA and PSO for closed-loop supply chain network design on large-scale networks. Fattahi *et al* [16] presented a mixed-integer linear programing model for designing a multi-echelon, multi-product dynamic supply chain network at a multi-period programing horizon. The formulated model was solved using SA algorithm. In a research, Hasani and Khosrojerdi [17] developed a mixed-integer nonlinear model for designing robust global supply chain network design under uncertainty. In addition, they used a Taguchi-based MA algorithm to solve the model. Chibeles-Martins *et al* [18] presented a new SA-based multi-objective algorithm for solving a mixed-integer linear multi-objective programing model representing the design and planning of a green supply chain. Zohal and Soleimani [19] developed an ACA algorithm to design a closed-loop green supply chain network for the purpose of solving an integer linear programing problem where the objectives were minimization of cost and CO_2 emission.

In another research, Kumar *et al* [20] employed the so-called NSGA-II algorithm for solving a multi-objective problem describing the design of a supply chain network by taking into consideration the social relationships, carbon emission, and associated risks with the supply chain. Fahimnia *et al* [21] presented a mixed-integer nonlinear

Table 1. Reported research on the design of supply chain network design.

Solution method			Problem space				Objective function			
Non-exact			Non-exact							
Meta-heuristic	Heuristic	Exact	Robust	Fuzzy	Possibilistic		MO	SO	Year	Reference
GA						✔	✔		2009	[43]
		Weighted method/Goal programming				✔	✔		2010	[44]
		Goal programming				✔	✔		2010	[45]
		Goal programming				✔	✔		2010	[46]
		Interactive fuzzy approach		✔			✔		2011	[47]
		Interactive fuzzy approach		✔			✔		2012	[8]
		Robust possibilistic programming		✔			✔		2012	[9]
MA						✔	✔		2012	[48]
		ε-constraint				✔	✔		2013	[49]
NSGA-II						✔	✔		2013	[50]
		ε-constraint				✔	✔		2013	[51]
		ε-constraint			✔		✔		2013	[52]
		Interactive fuzzy approach		✔			✔		2014	[53]
PSO/VNS						✔	✔		2014	[54]
NSGA-II/ SPEA2						✔	✔		2014	[55]
		Interactive fuzzy goal programming		✔			✔		2015	[56]
GA/PSO						✔		✔	2015	[15]
MA			✔					✔	2016	[17]
SA						✔	✔		2016	[18]
ACA						✔	✔		2016	[19]
NSGA-II						✔	✔		2017	[20]
GA/SA/ Cross-Entropy						✔	✔		2018	[21]
		Interactive fuzzy approach		✔	✔				2018	[22]
WOA			✔	✔				✔	2019	[23]
		ε-constraint			✔		✔		2019	[24]
NSGA-II/ PESA/ SPEA		ε-constraint	✔				✔		Present research	

model for tactical programming of a green supply chain. Later on, the developed model was solved using three algorithms, namely GA, SA, and cross-entropy algorithms. Upon comparing the results obtained from different algorithms, the SA algorithm was found to be capable of producing better results in shorter time spans. In their research, Tsao *et al* [22] presented a multi-objective programing model for sustainable supply chain network design by taking the maximization of social benefits and minimization of economic burdens and environmental impacts as the objectives. They finally adopted a fuzzy multi-objective possibilistic programing approach to solve the model. Ghahremani-Nahr [23] presented a fuzzy robust mathematical programing model for the design of a closed-loop supply chain network, with the motel then solved using a new algorithm based on the whale optimization algorithm (WOM) to minimize total network costs. Hamdan and Diabat [24] published a research where a two-stage possibilistic programing problem on the supply chain network was discussed. Finally, they used epsilon-constraint method to convert the three-objective problem into a single-objective mixed-integer programming problem.

Table 1 provides a list of some of the most important methods used to solve supply chain network design models.

Given the results of the review on related literature, one can see that various approaches have been followed to the supply chain network design problem. However, considering the complexity and wide scope of the supply chain network problems, most of the research works in recent years have been focused on the application of meta-heuristic algorithms, among which the GA, NSGA-II, PSO, and SA has gained the greatest deals of attention from the researchers.

2.2 *Construction supply chain network design*

The construction research on supply chain is a relatively new direction that appeared since mid-1990s. The construction supply chain includes the entire chain of construction processes from the initial order placement by the customer/client to the design, construction, maintenance, and final demolition stages. From another point of view, the construction supply chain is contributed by organizations and firms such as the client, the designer, the main contractor, subcontractors, consultants, and suppliers. The construction supply chain refers to a network of organizations and the relationships among them, including the information flow, materials and services flow, and capital flow among different members of the construction supply chain. In a research, Erik Eriksson [25] attempted to improve the coordination and performance of construction supply chain to achieve short-term business goals and attain long-term competitive advantages. Cheng *et al* [26] presented a service-oriented framework to obtain an integrated construction supply chain. Meng *et al* [27] studied the characteristics of construction industry and developed a maturity model to measure and improve the relationships among key partners along the construction supply chain. Irizarry *et al* [1] reported a research wherein an integrated GIS-BIM-based model was presented; the model could visually demonstrate the flow of materials, availability of resources, and map of the supply chain. In the research by Wibowo and Sholeh [28], supply chain performance was analyzed in road construction projects. This examination was practiced using the supply chain operations references (SCOR) model, as a key performance index, that was calculated via analytical hierarchy process (AHP). Among similar research works, one may refer to the Refs. [29, 30]. In general, a review on related literature indicates the lack of a comprehensive investigation on the design of construction supply chain network based on programing models using heuristic and meta-heuristic methodologies. Therefore, the present research is an attempt to address this research gap.

3. Problem description

The present research presents a three-objective model for the design of a bi-level construction supply chain established between the construction material supply center and the construction workshops. Along this chain, the construction material supply center serves as the supplier, and the construction workshops are considered as demanders. Accordingly, the flow of materials is always from the material supply center toward the construction workshops. However, when it comes to the procurement of special materials with a particular technical life time, cross connections must be established among the construction workshops, so as to address the existing demands appropriately. Moreover, even for the construction materials with no such life time limitations, the concept of safety stock is adopted to establish an appropriate atmosphere for addressing possible deficiencies in different periods. Another important topic discussed in this research is that, if the construction workshops store too much material in their stock, there are chances that some of the materials lose their technical properties. At the other end of the spectrum, shortage of the material may end up interrupting the significant construction operations, thereby increasing the rate of loss.

To the best of our knowledge, there are very few research works on construction material supply chain design under uncertainty. Therefore, application of robust programing can be referred to as an outstanding innovation offered by this research. Moreover, consideration of the loss rate and incorporation of the concept of safety stock represent other novelty aspects of the present study. Another novelty of this study is the possibility of cross transfers among the construction workshops, which not only lowers the overall level of deficiencies, but also indirectly generates some profit for the members of the chain.

In the model presented in this work, the focus has been on the investigation of construction material supply chain considering the loss rate, cross transfers, and safety stocks. Some of the most important assumptions in the presented model are as follows:

- Capacities of the construction material supply center and construction site are limited.
- Construction materials can be separated into well-defined groups in terms of different technical specifications.
- In general, the construction materials are dispatched to the construction workshops for in this project according to the so-called “first-in, first-out” (FIFO) policy, wherein the oldest units in the stock are dispatched if there is a demand for construction material.
- The demand for construction material is identical in the construction material supply center and the construction workshops.
- The costs of loss are different between the construction material supply center and the construction workshops as the end users of the material.
- A network can be established across the construction workshops to reduce the rate of loss and possible deficiencies.

Mathematical model

$$MinZ1 = \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g TDem_{jt}^{rmgl} \times TCost_j + \sum_m \sum_t \sum_r BLvL_t^{rm} \times HCost + \sum_j \sum_m \sum_t \sum_r ILvL_{jt}^{rm} \times HCost + \sum_r \sum_m \sum_j \sum_t Por_{jt}^{rm} \times Dem_{jt}^m \times PCost_{jt}^m + \sum_t WCost^b \times EM_t + \sum_j \sum_t WCost^h \times EMH_{jt} + \sum_j \sum_t \sum_m BCost \times \left(UCD_{jt}^{Frm} + UCD_{jt}^{Om}\right) + \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g SeV_{jt}^{rmgl} \times Stock_{jt}^{rmgl} + \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g \sum_{j'} TrV_{jj't}^{rmgl} \times TCost_{jj't}^{rmgl} \tag{1}$$

$$MinZ2 = \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g TrT_j TDem_{jt}^{rmgl} + \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g \sum_{j'} TrV_{jj't}^{rmgl} \times TrsT_{jj'} \tag{2}$$

$$MinZ3 = \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g EnT_j TDem_{jt}^{rmgl} + \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g \sum_{j'} TrV_{jj't}^{rmgl} \times ENsT_{jj'} \tag{3}$$

$$\sum_r^{Subject\ to} Por_{jt}^{rm} \le 1 \quad \forall mjt \tag{4}$$

$$\sum_m \sum_r ILvL_{jt}^{rm} \le Capacity_j \quad \forall jt \tag{5}$$

$$\sum_{r=2}^{3} DV_{jt}^{rm} = \sum_{r=2}^{3} \sum_{l=1}^{4} \sum_g TDem_{it}^{rmgl} \times PR^{gml} + \sum_{r=2}^{3} \sum_{l=1}^{4} \sum_g \sum_{j' \ne j} \sum_{t' \le t} TrV_{jj't'}^{r-1mgl} - \sum_{r=2}^{3} \sum_{l=1}^{4} \sum_g \sum_{j' \ne j} TrV_{jj't}^{rmgl} + UCD_{jt}^{Frm} \quad \forall mjt = 1,\ldots,3 \tag{6}$$

$$\sum_{r=4}^{U} DV_{jt}^{rm} = \sum_{r=4}^{U} \sum_{l=1}^{8} \sum_g TDem_{it}^{rmgl} \times PR^{gml} + \sum_{r=4}^{U} \sum_{l=1}^{8} \sum_g \sum_{t' \le t} SeV_{jt'}^{r-1mgl} - \sum_{r=4}^{U} \sum_{l=1}^{8} \sum_g SeV_{jt}^{rmgl} + UCD_{jt}^{Om} \quad \forall mjt = 3\ldots T \tag{7}$$

$$ILvL_{jt}^{1m} = RM_{jt}^m - TDem_{jt}^{1gm1} \times PR^{gm1} \quad \forall jmt \tag{8}$$

$$\sum_{r=2}^{3} ILvL_{jt}^{rm} = \sum_{r=2}^{3} ILvL_{jt-1}^{r-1m} + \sum_{r=2}^{3} Por_{jt}^{rm} \times Dem_{jt}^m - \sum_{r=2}^{3} \sum_{l=1}^{6} \sum_g TDem_{jt}^{rmgl} \times PR^{mgl} - \sum_{r=2}^{3} \sum_{l=1}^{4} \sum_g \sum_{j' \ne j} TrV_{j'jt}^{rmgl} \quad \forall t = 1\ldots 3mj \tag{9}$$

$$\sum_{r=4}^{U} ILvL_{jt}^{rm} = \sum_{r=4}^{U} ILvL_{jt-1}^{r-1m} + \sum_{r=4}^{U} Por_{jt}^{rm} \times Dem_{jt}^m - \sum_{r=4}^{U} \sum_{l=1}^{8} \sum_g TDem_{jt}^{rmgl} \times PR^{mgl} + \sum_{r=4}^{U} \sum_{l=1}^{8} \sum_g SeV_{jt-1}^{r-1mgl} \quad \forall t = 3\ldots Tmj \tag{10}$$

$$Por_{jt}^{rm} \le M \times X_t^r \quad \forall tjrm \tag{11}$$

$$BLvL_{t-1}^{rm} \le M \times \left(1 - X_t^r\right) \quad \forall mrt \tag{12}$$

$$X_t^r \le X_t^{r+1} \quad \forall rt \tag{13}$$

$$EM_{tr} = \sum_m BLvL_t^{rm} \quad \forall tr = U \tag{14}$$

$$EMH_{jrt} = \sum_m ILvL_{jt}^{rm} \quad \forall tjr = U \tag{15}$$

$$ILvL_{jt}^{rm} = 0 \quad \forall rjmt = 1 \tag{16}$$

$$BLvL_t^{rm} = 0 \quad \forall rmt = 1 \tag{17}$$

$$SeV_{jj't}^{rmgl} = 0 \quad \forall rmgljj't = 1 \tag{18}$$

$$\sum_{r=2}^{3} \sum_{l=1}^{4} \sum_g \sum_{j' \ne j} TrV_{jj't}^{rmgl} \le UCD_{jt}^{Frm} \quad \forall mjt = 1\ldots 3 \tag{19}$$

$$\sum_{l=1}^{4}\sum_{g}\sum_{j'\neq j} TrV_{jj't}^{rmgl} \leq ILvL_{jt}^{rm} \qquad \forall r \leq 3mjt \tag{20}$$

$$\sum_{r=2}^{3}\sum_{l=1}^{4}\sum_{g}\sum_{m} TrV_{jj't}^{rmgl} \leq MPO_{jj't} \qquad \forall j \neq j' \tag{21}$$

$$\begin{aligned} &Por_{jt}^{rm} \geq 0 \\ &TDem_{jt}^{rmgl} SeV_{jt}^{rmgl} TrV_{jj't}^{rmgl} ILvL_{jt}^{rm} BLvL_{t}^{rm} \in Integer \\ &UCD_{jt}^{Frm} UCD_{jt}^{Om} EM_{tr} EMH_{jrt} RM_{jt}^{m} \in Integer \\ &X_{t}^{r} \in \{01\} \end{aligned} \tag{22}$$

The initial objective function of the problem attempts to minimize total system costs. These include the cost of transportation per unit construction material from the construction material supply center to construction workshops, stock maintenance cost, demand fulfillment cost, waste management cost, deficiency costs, stock-related costs, and costs of cross transfers among construction workshops. The second objective function seeks to minimize the total time spent to transport the construction material from the main supply center to the construction workshops. Finally, the third objective function ensures minimal environmental impact due to transportation of construction material among centers at different levels of the chain.

The constraint (4) ensures that the ratio of maximum demand for the construction material with r^{th} technical specification to the delivered amount of that construction material to the j^{th} construction workshop in the t^{th} period of time is equal to one for the maximal group. Constraint (5) ensures that the level of inventory of the construction materials in construction workshops will never exceed the stock capacity. Constraints (6) and (7) indicate the numbers of construction materials of the f^{th} group used to fulfill the demand raised by g^{th} group in the t^{th} period of time with l^{th} order of preference. These constraints evaluate the cross transfers between construction workshops to provide priority construction material during allowed periods (the periods during which the existing construction material are recognized as priority materials. Constraint (6) ensures the allocation of priority and compatible construction material, while constraint (7) calculates the safety stock level for non-priority materials. Since the safety stock level is retained by storing construction material in different periods of time, then this model uses the safety stock for non-priority construction materials only. Equations (8)-(10) represent inventory balance constraints and tend to update the inventories of construction materials in the construction workshops at the end of each period based on technical specifications of the materials and the group to which those belong. Accordingly, constraint (8) links the construction materials from selected centers at construction workshops to daily inventories. Constraints (11)-(13) set forth the FIFO policy. In addition, these constraints imply that the inventory with a particular characteristic cannot be allocated to a customer when older units of the same group are still available. Constraints (14) and (15) identify the number of expired units at the main center and construction workshops. Constraints (16) and (17) imply zero initial inventory at the main center and construction workshops. Constraint (18) ensures zero stock at the initial period. Constraint (19) sets that the amount of construction material cross-transferred among the construction workshops during a given period of time shall never exceed the level of deficiency in that period. Constraint (20) ensures that amount of construction material cross-transferred among the construction workshops during a given period of time shall never exceed the level of inventory at the respective construction workshops. Constraint (21) guarantees that a cross-transfer between construction workshops is possible only when the required connections are in place. Finally, constraint (22) defines the domain of the variables considered in this problem.

3.1 *Mathematical model of the research under uncertainty conditions*

Given that evaluation of exact values of parameters is extremely difficult and sometimes impossible in many real-world cases, it seems necessary to consider the uncertainty when investigating the input data that impose large impacts on providing appropriate level of service. For the purpose of this research, two parameters are associated with significant levels of uncertainty, namely costs of loss at the main center and construction workshops. Therefore, in order to employ the presented model efficiently, these parameters are considered in an interval form, as follows:

$$WCost^{b} = \left[\overline{WCost^{b}} - W\widehat{Cost}^{b}\,\overline{WCost^{b}} + W\widehat{Cost}^{b}\right]$$
$$WCost^{h} = \left[\overline{WCost^{h}} - W\widehat{Cost}^{h}\,\overline{WCost^{h}} + W\widehat{Cost}^{h}\right]$$

where $\overline{WCost^{b}}$ and $\overline{WCost^{b}}$ refer to the average estimated levels and $W\widehat{Cost}^{b}$ and $W\widehat{Cost}^{h}$ indicate the respective estimation errors. However, in response to the existing conditions and in order to present an approach to make these interval variations, the robust programming approach introduced in Ref. [31] was employed. Structure of this approach is described in the following.

3.2 *Robust programming approach*

For the purpose of the specific problem considered in this research, let $WCost^{b} = \left[\overline{WCost^{b}} - W\widehat{Cost}^{b}\,\overline{WCost^{b}} + W\widehat{Cost}^{b}\right]$ and $WCost^{h} = \left[\overline{WCost^{h}} - W\widehat{Cost}^{h}\,\overline{WCost^{h}} + W\widehat{Cost}^{h}\right]$ define the level of uncertainty in general.

Moreover, assume that the term (Jr) represents the $WCost^h$ s for which $WCost^b WCost^h > 0$. Accordingly, it can be written that $Jr = \{WCost^b WCost^h > 0\}$. In order to control the level of uncertainty in converging to the final solution, the parameter Γ_1 is used as the robustness parameter. Located in between $[0|Jr|]$ and $[0|Ir|]$, this parameter may not necessary take an integer value. The central role of this parameter is to determine the number of coefficients that are at their maximum values (worst possible condition). Indeed, at all time, Γ_1 and Γ_2 of the coefficients $W\widehat{Cost}^h W\widehat{Cost}^b > 0$ are at their maximum values, with the rest of the parameters in the sets Jr and Ir being multiplied by the coefficients $\Gamma_1 - \Gamma_1$ and Γ_2 and their variable values (in the range of $WCost^b = \left[\overline{WCost^b} - W\widehat{Cost}^b \overline{WCost^b} + W\widehat{Cost}^b\right]$ and $WCost^h = \left[\overline{WCost^h} - W\widehat{Cost}^h \overline{WCost^h} + W\widehat{Cost}^h\right]$. Therefore, in terms of structure, the problem is changed to the followings:

Model 2

$$
\begin{aligned}
\min Z_1 = & \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g TDem_{jt}^{rmgl} \times TCost_j \\
& + \sum_m \sum_t \sum_r BLvL_t^{rm} \times HCost \\
& + \sum_j \sum_m \sum_t \sum_r ILvL_{jt}^{rm} \times HCost \\
& + \sum_r \sum_m \sum_j \sum_t Por_{jt}^{rm} \times Dem_{jt}^m \times PCost_{jt}^m \\
& + \sum_j \sum_t \sum_m BCost \times \left(UCD_{jt}^{Frm} + UCD_{jt}^{Om}\right) \\
& + \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g SeV_{jt}^{rmgl} \times Stock_{jt}^{rmgl} \\
& + \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g \sum_{j'} TrV_{jj't}^{rmgl} \times TCost_{jj't}^{rmgl} \\
& + \sum_t \overline{WCost^b} \times EM_t \\
& + \sum_j \sum_t \overline{WCost^h} \times EMH_{jt} \\
& + \max_{\left\{\substack{S: S \subseteq J|S| \leq \Gamma \\ (t_t) \in \frac{J}{S}}\right\}} \left(\sum_t W\widehat{Cost}^b \times EM_t - (\Gamma_1 - \Gamma_1) W\widehat{Cost}^b EM_{t_t}\right) \\
& + \max_{\left\{\substack{S: S \subseteq J|S| \leq \Gamma \\ (t_t) \in \frac{J}{S}}\right\}} \left(\sum_t W\widehat{Cost}^h \times EMH_t - (\Gamma_2 - \Gamma_2) W\widehat{Cost}^h EMH_{t_t}\right)
\end{aligned}
$$

s.t.

$$\tag{23}$$

Objective functions (2) and (3) and all constraints (4)–(22).

Considering the structure of the changed objective functions and the explanations presented so far, it is evident that if $\Gamma_1 = |Jr|$ and $\Gamma_2 = |Ir|$, then the presented robust programing model is consistent with the robust programing approach presented by Soyster (considering the worst cases). Moreover, if $\Gamma_1 = 0$ and $\Gamma_2 = 0$, then the model accepts no uncertainty and the presented robust programming model is consistent with the primary (certain) model. Efficiency of this method in obtaining solutions for different values is merely marginal. However, upon small modifications to the structure of Model 2 while using the fundamental concepts of operational research, it can be proved that the Model 2 represents a linear programing problem.

Theorem *The presented Model 2 is consistent with the following linear programing model.*

Model 3

$$
\begin{aligned}
\min Z_1 = & \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g TDem_{jt}^{rmgl} \times TCost_j \\
& + \sum_m \sum_t \sum_r BLvL_t^{rm} \\
& \times HCost + \sum_j \sum_m \sum_t \sum_r ILvL_{jt}^{rm} \times HCost \\
& + \sum_r \sum_m \sum_j \sum_t Por_{jt}^{rm} \times Dem_{jt}^m \\
& \times PCost_{jt}^m + \sum_j \sum_t \sum_m BCost \times \left(UCD_{jt}^{Frm} + UCD_{jt}^{Om}\right) \\
& + \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g SeV_{jt}^{rmgl} \times Stock_{jt}^{rmgl} \\
& + \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g \sum_{j'} TrV_{jj't}^{rmgl} \times TCost_{jj't}^{rmgl} \\
& + \sum_t \overline{\mathrm{WCostb}} \times EM_t \\
& + \sum_j \sum_t \overline{WCost^h} \times EMH_{jt} + \Gamma_1 U_1 + U1 + \Gamma_2 U_2 + U2
\end{aligned}
$$

s.t.

$$\tag{24}$$

$$\sum_t \overline{WCost^b} \times EM_t + U_1 + U1 \geq 0 \tag{25}$$

$$U1 \geq 0 \tag{26}$$

$$U_1 \geq 0 \tag{27}$$

$$\sum_j \sum_t \overline{WCost^h} \times EMH_{jt} + U_2 + U2 \geq 0 \tag{28}$$

$$U2 \geq 0 \tag{29}$$

$$U_2 \geq 0 \tag{30}$$

Proof In order to prove this lemma, one can convert the objective functions of the Model 2 to their linear forms by defining the variables Z1 and Z2 in such a way that $Z1 \leq \Gamma_1$ and $Z2 \leq \Gamma_2$. It must be noted that $0 \leq Z1_{jtn} Z2_{jtmr} \leq 1$.

Model 4

$$\min Z_1 = \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g TDem_{jt}^{rmgl} \times TCost_j + \sum_m \sum_t \sum_r BLvL_t^{rm} \times HCost + \sum_j \sum_m \sum_t \sum_r ILvL_{jt}^{rm} \times HCost + \sum_r \sum_m \sum_j \sum_t Por_{jt}^{rm} \times Dem_{jt}^{m} \times PCost_{jt}^{m} + \sum_j \sum_t \sum_m BCost \times \left(UCD_{jt}^{Frm} + UCD_{jt}^{Om}\right) + \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g SeV_{jt}^{rmgl} \times Stock_{jt}^{rmgl} + \sum_j \sum_t \sum_m \sum_r \sum_l \sum_g \sum_{j'} TrV_{jj't}^{rmgl} \times TCost_{jj't}^{rmgl} + \sum_t \widehat{WCost^b} \times EM_t \times Z1 + \sum_j \sum_t \widehat{WCosth} \times EMH_{jt} \times Z2$$

s.t.

$$\tag{31}$$

$$Z1 \le \Gamma_1 \tag{32}$$

$$Z2 \le \Gamma_2 \tag{33}$$

In an optimal case, it is obvious that the problem must have a total of Γ_1 variables Z1 = 1, Γ_2 variables Z2 = 1, one variable $Z1 = \Gamma_1 - \Gamma_1$, and one variable $Z2 = \Gamma_2 - \Gamma_2$, which corresponds to the nonlinear part of the objective functions in Model 4. Applying the dual theorem for the EMH_{jt} and EM_t gives:

Model 5

$$Min(\Gamma_1 U_1) + (U1) + (\Gamma_2 U_2) + (U2) \quad s.t. \tag{34}$$

$$\sum_t \overline{WCost^b} \times EM_t + U_1 + U1 \ge 0 \tag{35}$$

$$U1 \ge 0 \tag{36}$$

$$U_1 \ge 0 \tag{37}$$

$$\sum_j \sum_t \overline{WCost^h} \times EMH_{jt} + U_2 + U2 \ge 0 \tag{38}$$

$$U2 \ge 0 \tag{39}$$

$$U_2 \ge 0 \tag{40}$$

This theorem can be proved by combining Model 5 with the initial model.

3.3 *Solution method*

Given the NP-Hard nature of the supply chain design problem, we used the CPLEX 12.1 solver with epsilon-constrained method for solving the formulated mathematical model on small-scale problems. When it came to numerical examples of larger scales, meta-heuristic algorithms were developed based on NSGA-II, PESA, and SPEA. An important issue with meta-heuristic algorithms is to design an appropriate way of expressing the solutions reasonably. For this purpose, the algebraic structure of representing the solutions and proposed algorithms is presented in Sections 1.2.1–1.2.4.

3.3a *Solution representation structure*: The most important step in the design of a meta-heuristic algorithm is to design the representation of solutions in the form of chromosomes and initial population. The following figure presents a schematic view of the coding scheme used in this research. This solution representation is composed of five main parts. In the first part, a $R \times T$ matrix is generated with randomly assigned elements ranging between 0 and 1. This matrix is used to initialize the X variable. In order to convert the values in the range of 0 – 1 to the binary values of 0 or 1, firstly, all elements of the matrix were increased by 0.5 followed by taking the bracket of the resultant values. In this way, some of the values would turn into 0 while the remaining ones turned to 1. According to the presented model, random initialization of this matrix may not lead to unreasonable solution.

	1	2	···	T
1	0.2	0.1	···	0.4
⋮	⋮	⋮	⋮	⋮
R	0.8	0.5	···	0.9

The second part of the solution representation includes a $R \times M \times J \times T$ matrix populated by randomly generated values in the range of 0–1. Given that this matrix is used to initialize the Por_{jt}^{rm} variable, then the numbers produced in this matrix can be used directly, obviously without generating unreasonable solutions.

			T	
	F	J	0.4	0.3
R		J	0.7	0.1
	F	J	0.6	0.2
		J	0.1	0.8

The third part of the solution representation adopts a $R \times M \times G \times L \times J \times T$ matrix for which initialization, numbers in the range of 0–1 are generated on a random

```
Initialize Population
Generate N feasiable solution and insert into Population
While Stopping criteria not met Do
Generate ChildPopulation of Size N
Select Parents from Population
Create Children from Parents
Mutate Children
Repare Solution using repair mechanism
Merge Population and ChildPopulation with size 2N
For each individual in CurrentPopulation Do
Assign rank based on Pareto-Fast non-dominates sort
end
Generate sets of non-dominated vector along PF_known
Loop (inside) by adding solution to next generation of Population starting from the best front
Until N solution found and determine crowding distance between points on each front
end
Report results
```

Figure 1. Pseudo-code of the multi-objective genetic algorithm.

basis. This matrix is used to initialize the $TDem_{jt}^{rmgl}$ variable. For this purpose, randomly generated numbers are multiplied by the demand parameter to produce a final value. Accordingly, no unreasonable solution may possibly be produced. The following figures demonstrates the structure of this matrix (figure 1).

				T			
				J		J	
R	F	G	L	0.1	0.4	0.3	0.4
			L	0.2	0.7	0.3	0.7
		G	L	0.9	0.1	0.6	0.7
			L	0.9	0.7	0.6	0.7
	F	G	L	0.2	0.7	0.3	0.1
			L	0.1	0.1	0.3	0.7
		G	L	0.9	0.7	0.6	0.7
			L	0.2	0.7	0.3	0.1

Finally, the fourth part of solution representation produces a $R \times M \times G \times L \times J \times J \times T$ matrix populated by elements with values ranging between 0 and 1. This matrix is used to initialize the TrV_{jt}^{rmgl} variable, and given the structure of this variable, these values can be directly used, similar to the previous case.

T										T	T
								J	J	J	J
				J′	J′	J′	J′	J′	J′	J′	J′
R	F	G	L	0.1	0.4	0.3	0.4	0.4	0.1	0.4	0.4
			L	0.2	0.7	0.3	0.7	0.7	0.2	0.7	0.7
		G	L	0.9	0.1	0.6	0.7	0.1	0.9	0.1	0.7
			L	0.9	0.7	0.6	0.7	0.7	0.9	0.7	0.7
	F	G	L	0.2	0.7	0.3	0.7	0.7	0.2	0.7	0.7
			L	0.9	0.1	0.6	0.7	0.1	0.9	0.1	0.7
		G	L	0.9	0.7	0.6	0.7	0.7	0.9	0.7	0.7
			L	0.2	0.7	0.3	0.1	0.7	0.2	0.7	0.1

In the final part of solution representation, a $R \times M \times G \times L \times J \times T$ matrix is used to initialize the SeV_{jt}^{rmgl} variable. Similar to the third and fourth parts, the values in this atrix can be used without producing unreasonable solutions.

T							T
						J	J
R	F	G	L	0.1	0.4	0.3	0.4
			L	0.2	0.7	0.3	0.7
		G	L	0.9	0.1	0.6	0.7
			L	0.9	0.7	0.6	0.7
	F	G	L	0.2	0.7	0.3	0.1
			L	0.1	0.1	0.3	0.7
		G	L	0.9	0.7	0.6	0.7
			L	0.2	0.7	0.3	0.1

Therefore, all of the solutions produced in the five parts are presented in the form of the following general matrix:

$$[[R \times M \times J \times T], [R \times M \times J \times T], [R \times M \times G \times L \times J \times T], [R \times M \times G \times L \times J \times J \times T], [R \times M \times G \times L \times J \times T]]$$

It should be noted that, other variables of the research will be initialized appropriately in equations corresponding to the constraints of the problem considering the variables initialized on the above paragraphs.

3.3b *Structure of the proposed NSGA-II algorithm*: The NSGA-II algorithm is one of the most popular and powerful algorithms for solving multi-objective optimization problems with proven efficiency in solving various problems. In an attempt to address the shortcomings of the initial version of this algorithm, Deb *et al* developed a second version of a bi-objective GA wherein not only the quality of solutions, but also versatility of the Pareto-optimal solutions were taken into consideration. This algorithm follows two principle criteria in relation to the solutions: first, high-quality solutions are selected, and if there are two solutions at the same level of quality, the more regular solution is selected, i.e. the quality possesses the highest priority, followed by regularity. The NSGA-II algorithm goes through two known phases. The first phases adopts the ranking criterion and dominance concept, while the second phase, which deals with the regularity, uses the crowding distance. In the first phase, the solutions are ranked by calculating two values, namely the number of times a given solution is dominated and the set of solutions over which the considered solution dominates. In order to compute these two parameters, it is necessary to compare all solutions to one another. If there is any solution that is dominated for zero times, such solutions are non-dominated ones and provide approximations of the Pareto front [32].

3.3c. *SPEA-II algorithm*: The SPEA and SPEA-II are efficient algorithms that use an external archive to store the non-dominated solutions found during the search by the algorithm. The SPEA suffered from weaknesses in the calculation of strength and fitness values. Moreover, it lacked a secondary criterion for comparing non-dominated solutions. As such, Ref. [33] proposed a second version of this algorithm wherein the mentioned weaknesses were addressed. The working framework of the SPEA-II algorithm is described in the following: where, N_E: Maximum size of the archive of the non-dominated solutions, E, N_F: Population size, K: Density calculation parameter, $K = \sqrt{N_E + N_F}$.

Step 1. Generate an initial population of solutions, P_0, and set $E_0 = \emptyset$.
Step 2. Calculate a fitness value for each solution i in the set $P_t \cup E_t$, as follows.

Sub-step 2.1. Begin with calculating the raw fitness value of the solution i via Equation (41):

$$R(i) = \sum_{j \in P_t} s(j), \forall j > i \in P_t \tag{41}$$

where the inequality $j > i$implies that solution j dominates the solution i. Moreover, the parameter s (i) indicates the strength of the solution in terms of the number of solutions dominated by the solution i.
Sub-step 2.2. Calculate the density of the solution i via Equation (42).

$$D(i) = \frac{1}{\sigma_i^k + 2}, \forall i \in P_t \tag{42}$$

where σ_i^k denotes the distance between the solution i and the k^{th} neighborhood around it.
Sub-step 2.3. Finally, sum up the raw fitness value and the density of solution i to obtain total fitness value for the solution.

$$F(i) = R(i) + D(i), \forall i \in P_t \tag{43}$$

Step 3. Copy all non-dominated solutions in the set $P_t \cup E_t$ into the E_{+1}. Accordingly, either of two cases may arise:

Case 1: If $|E_{t+1}| > N_E$, then a total of $|E_{t+1}| - N_E$ solutions are eliminated via iterative elimination of solutions based on the σ^k criterion. That is, the solution at minimum distance (σ^k) to other solutions shall be eliminated first. In the meantime, if more than one solution exhibit the minimum distance, one may proceed to identify the second smallest distance and go on until the redundant solutions are eliminated (this criterion sets the scene to remove the solutions that are too similar or close to one another, which impose no significant impact on the density of solutions).

Case 2: If $|E_{t+1}| \leq N_E$, then a total of $N_E - |E_{t+1}|$ dominated solutions are moved from the set $P_t \cup E_t$ into the E_{+1} according to their fitness values.

Step 4. Should the stopping criterion is met, the algorithm comes to stop and returns the solutions in E_{t+1}.
Step 5. Select the parents from the set E_{t+1} via the dual competition method.
Step 6. Apply the crossover and mutation operators onto the parents to generate N_p offsprings. Copt the offsprings into the set P_{t+1} and add 1 to the counter value $(t = t + 1)$ before going back to **Step 2**.

It is worth noting that the procedures used for crossover and mutation operators were the same as those used for the NSGA-II.

3.3d *PESA-II algorithm:* The second version of the Pareto envelope-based selection algorithm (PESA-II) is among the most well-known multi-objective algorithms where the GA functions are used to generate new solutions. Introduced in Ref. [34], the initial version of this algorithm suffered from weaknesses in the selection procedure, and this was why a second improved version of the algorithm was proposed in 2001: PESA-II. Various steps of the PESA-II are described in the following:

where, N_E: Maximum size of the archive of the non-dominated solutions, *E*, N_F: Population size, *N*: Number of grids along each axis of the objective function.

Step 1. Begin with a randomly generated initial population, P_0, and set the external archive, E_0, to empty and the counter to zero $(t = 0)$.
Step 2. Partition the space into n^k cubic clouds where the n denotes the number of grids along each axis of the objective function and k is the number of objectives.
Step 3. Combine the archive of non-dominated solutions, E_t, with new solutions from the set P_t and proceed as follows:

Case 1: If a new solution was dominated by at least one of the existing solutions in the archive (E_t), then eliminate the new solution.
Case 2: If a new solution happened to dominate multiple solutions in the set E_t, then eliminate the dominated solutions from the archive, add the new solution to the archive E_t, and then update the members of the cubic clouds.
Case 3: If a new solution neither dominated nor was dominated by any solution in the E_t, then add the solution to E_t, then if $|E_t| = N_{E+1}$, then select a cubic cloud randomly (performed using a roulette wheel method, wherein the more crowded cubic clouds have higher chance of being selected) and then chose a solution in that cloud on a random basis and eliminate it, followed by updating the members of the cubic cloud.

Step 4. If the stopping criterion was met, then stop and demonstrate the final E_t.
Step 5. Set $P_t = \emptyset$ and select a number of solutions from the set E_t for crossover and mutation operations based on the information density on the cubic clouds. The selection is performed using a roulette wheel method, wherein the less crowded cubic clouds have higher chance of being selected. Apply the crossover and mutation operators to generate a total of N_P offsprings and copy them into the set P_{t+1}.
Step 6. Set the t to $t + 1$ and go to **Step 3**.

It is worth noting that the procedures used for crossover and mutation operators were the same as those used for the NSGA-II.

3.4 *Final solution selection from the Pareto optimal front*

Given that the choice of final Pareto member for implementing the solution onto the real-world problem has always been a managerial challenge, then the present research used the best-worst method (BWM) to assign scores to different Pareto members by experts, with the member with the highest score selected as the final solution. For this purpose, it is necessary to first explain the structure of the BWM.

3.4a. *Best-worst method (BWM)* Being among the most powerful methods for solving MCDM problems, the best-worst method (BWM) has been used to evaluate weights for different alternatives and criteria [35, 36]. This method can compensate the weaknesses suffered by previous methods based on pair-wise comparisons (e.g., AHP and ANP), including the inconsistency. In addition, this approach reduces the number of pair-wise comparisons significantly by merely performing reference comparisons. In recent years, many researchers have used the BWM for weight evaluation and ranking of alternatives in various fields. In general, the structure of BWM is composed of the following steps:

- **Step 1.** Building decision criterion system: The decision criterion system includes the set of criteria identified upon reviewing the existing literature and experts' opinions; it is written as $\{c_1, c_2, \ldots, c_n\}$. The values of decision criteria may reflect the performance of different alternatives.
- **Step 2.** Determining the best and the worst among the main criteria and also sub-criteria: According to the decision criterion system, the best (c_B) and the worst (w_B) criteria must be identified by the decision-makers.
- **Step 3.** Performing reference comparisons for the best criterion: In this step, priority of the best criterion over other criteria is evaluated based on a verbal scale and expressed numerically in the range of 1–9. Results of this step are expressed in the form of the following vector:

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn}) \tag{44}$$

where a_{Bj} is the priority of the selected best criterion, B, with reference to each criterion j. It is obvious that $a_{BB} = 1$.
- **Step 4.** Performing reference comparisons for the worst criterion: similarly, priority of each criterion over the worst criterion is evaluated based on a verbal scale and expressed numerically in the range of 1 – 9. Results of this step are expressed in the form of the following vector:

$$A_w = (a_{1W}, a_{2W}, \ldots, a_{nW})^T \tag{45}$$

where a_{jW} is the priority of each criterion j over the selected worst criterion, W. It is obvious that $a_{BB} = 1$.
- **Step 5.** Determining optimal weights $\left(W_1^*, W_2^*, \ldots, W_n^*\right)$: In this step, in order to evaluate optimal weights of the criteria, one must minimize the maximum absolute difference $\left\{\left|w_B - a_{Bj}w_j\right|, \left|w_j - a_{jW}w_W\right|\right\}$ for all js, as formulated into the following optimization problem:

$$\begin{aligned} &\min \max_j \left\{\left|w_B - a_{Bj}w_j\right|, \left|w_j - a_{jW}w_W\right|\right\} \\ &\text{s.t.} \\ &\sum_j w_j = 1 \\ &w_j \geq 0, \ \text{for all } j \end{aligned} \tag{46}$$

The Problem (18) can be modeled as follows:

$$\begin{aligned} &\min \xi^L \\ &\text{S.t.} \\ &\left|w_B - a_{Bj}w_j\right| \leq \xi^L, \ \text{for all } j \\ &\left|w_j - a_{jW}w_W\right| \leq \xi^L, \ \text{for all } j \\ &\sum_j w_j = 1 \\ &w_j \geq 0, \ \text{for all } j \end{aligned} \tag{47}$$

Equation (46) represents a linear model with unique solution. As such, one may obtain the optimal weights $\left(W_1^*, W_2^*, \ldots, W_n^*\right)$ and optimum value of ξ^{L*} by solving the above-expressed model. For this model, near-zero values of ξ^{L*} indicate the highest levels of consistency [36].

According to the structure of this method, the objective functions can be seen as criteria and calculate their scores based on experts' opinions. In a next step, by multiplying the matrix containing the scores of the objectives by the one containing the values of objective functions for each of the Pareto members, one can assign a single score to each

Pareto member, so that the best member can be selected by its score-based rank. Figure 2 demonstrates the required calculations appropriately.

According to figure 2, one can calculate a score for each Pareto member and then sort the final solutions according to their scores in a descending order of score. Accordingly, the Pareto member with the highest score will be identified as the best member.

4. Numerical results

In this section, in order to validate the presented model and algorithms, examples of different sizes (small, medium, and large, as per the number of potential points for establishing the designed facilities) are investigated. The CPLEX solver was used to solve the mathematical models. The proposed algorithm was coded in C# and solved on a PC powered by a 3.2 GHz CPU and 16 GB of RAM.

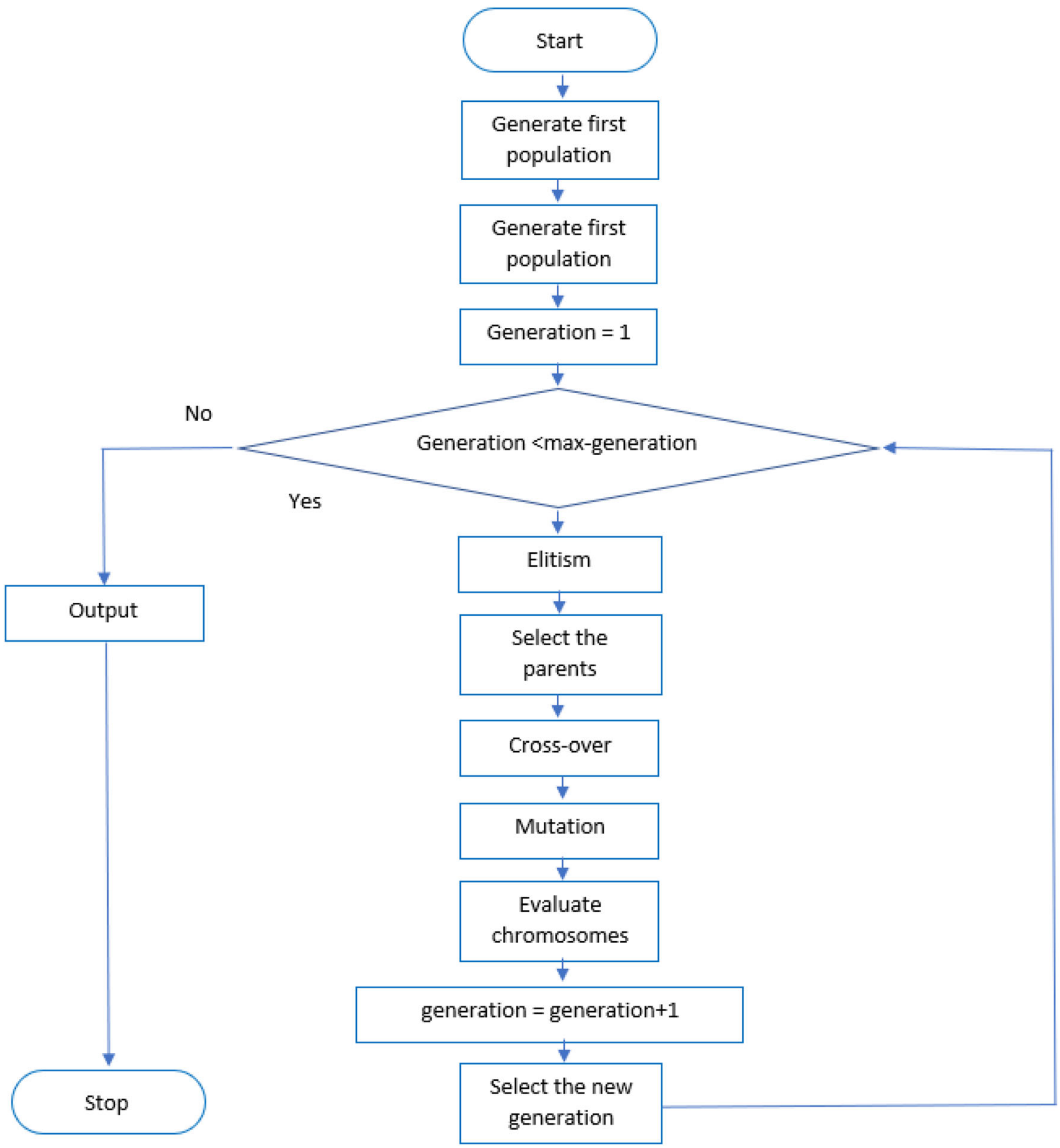

Figure 2. multi-objective genetic algorithm schematic.

Table 2. Substitutability of the considered groups of construction material.

	A	B	C	D	E	F	G	H
A	✔							
B	✔	✔						
C	✔		✔					
D	✔	✔	✔	✔				
E	✔				✔			
F	✔	✔			✔	✔		
G	✔		✔		✔		✔	
H	✔	✔	✔	✔	✔	✔	✔	✔

Table 3. Capacity of each project site.

Center 1	Center 2	Center 3	Center 4	Center 5
552	753	665	590	588

4.1 *Performance evaluation of the mathematical model*

In this subsection, a small-scale numerical example is designed using randomly generated data and then solved by the CPLEX solver, with the results presented in the following tables. For this purpose, we begin with explaining the input parameters of the considered example. In this example, a total of 8 groups of construction material were considered, namely the groups A, B, C, D, E, F, G, and H. Table 2 describes the substitutability of the construction materials.

These groups of construction material shall be transferred to five pre-determined projects at 8 transfer priorities. According to technical specifications of each group of the construction material, maximum storage time was set to 4 days, and the programming should be performed for 4 periods of time.

As shown in table 3, capacities of the distribution centers ranged between 500 and 800 units of the construction material. The demand raised at each project site is presented in tables 4 and 5.

Table 4. Demand of each project site for different groups of construction material during different periods of time.

Project site	Construction material group	Period 1	2	3	Project site	Construction material group	Period 1	2	3	Project site	Construction material group	Period 1	2	3
1	1	33	41	71	2	1	38	27	50	3	1	37	25	26
1	2	24	50	80	2	2	30	72	36	3	2	58	53	22
1	3	55	79	66	2	3	37	56	63	3	3	68	24	31
1	4	28	58	30	2	4	58	48	45	3	4	52	65	31
1	5	35	60	46	2	5	27	39	23	3	5	22	55	57
1	6	42	41	28	2	6	40	31	59	3	6	43	42	35
1	7	29	55	70	2	7	54	66	38	3	7	35	28	76
1	8	34	60	67	2	8	60	65	58	3	8	43	67	38

Table 5. Demand of each project site for different groups of construction material during different periods of time.

Project site	Construction material group	Period 1	2	3	Project site	Construction material group	Period 1	2	3
4	1	28	65	24	5	1	20	44	51
4	2	32	20	36	5	2	58	34	44
4	3	50	29	30	5	3	37	29	76
4	4	40	39	39	5	4	45	28	43
4	5	78	80	42	5	5	42	36	77
4	6	42	66	44	5	6	31	38	24
4	7	75	27	64	5	7	44	26	43
4	8	23	55	23	5	8	39	32	27

Table 6. The cost of procuring different groups of construction material at each project site in different periods of time.

		Period					Period		
Construction material group	Project site	1	2	3	Construction material group	Project site	1	2	3
1	1	25	20	30	5	1	23	25	29
1	2	24	29	24	5	2	23	23	25
1	3	25	26	21	5	3	22	25	23
1	4	23	27	27	5	4	26	23	26
1	5	30	26	23	5	5	20	29	27
2	1	20	29	21	6	1	28	27	27
2	2	22	21	29	6	2	23	23	26
2	3	26	22	21	6	3	22	21	24
2	4	23	27	30	6	4	26	21	27
2	5	24	24	26	6	5	25	24	20
3	1	20	25	23	7	1	28	25	25
3	2	27	24	24	7	2	24	24	23
3	3	22	29	28	7	3	24	23	25
3	4	24	29	25	7	4	24	25	23
3	5	21	28	28	7	5	24	24	20
4	1	23	22	22	8	1	28	23	20
4	2	29	29	27	8	2	30	29	28
4	3	23	24	25	8	3	28	23	24
4	4	30	22	25	8	4	27	27	24
4	5	23	28	21	8	5	24	20	26

Table 7. Input parameters of the problem.

$Stock_{jt}^{rmgl}$	Cost of retaining the safety stock of the construction material with r^{th} technical specifications belonging to the g^{th} group of construction material by f^{th} group with l^{th} order of preference at j^{th} project site during the t^{th} period of time	$Uniform[50, 80]$
$TCost_{jj't}^{rmgl}$	Cost of transporting the construction material with r^{th} technical specifications belonging to the g^{th} group of construction material by f^{th} group with l^{th} order of preference at j^{th} project site from the j'^{th} project site during the t^{th} period of time	$Uniform[50, 80]$
$PO_{jj't}$	1, if the construction material can be transferred between the j^{th} and j'^{th} distribution centers during the t^{th} period of time	$Uniform[0-1]$
$BCost$	Cost of deficiency per unit construction material	10
$HCost$	Cost of storage per unit construction material	5
$WCost^{b}$	Cost of loss per unit construction material	8
$WCost^{h}$	Cost of loss per unit construction material	4
DV_{jt}^{rm}	Demand of the project site for the construction material with r^{th} technical specification belonging to f^{th} group at j^{th} project site in t^{th} period of time	$Uniform[20, 80]$
$TCost_{j}$	Per-unit construction material transportation cost from …. to the j^{th} project site	$Uniform[50, 100]$
PR^{gml}	An auxiliary binary matrix that defines the ABO-Rh for the l^{th} order of preference	
TrT_{j}	Required time for transporting unit construction material to the j^{th} project site	$Uniform[100, 350]$
$TrsT_{jj'}$	Required time for transporting unit construction material between the j^{th} and j'^{th} project sites	$Uniform[60, 200]$
EnT_{j}	Greenhous gas emission per transportation of unit construction material to the j^{th} project site	$Uniform[50, 80]$
$ENsT_{jj'}$	Greenhous gas emission per transportation of unit construction material between the j^{th} and j'^{th} project sites	$Uniform[30, 90]$

$$\begin{bmatrix} obj1_{pareto\ member\ 1} & obj2_{pareto\ member\ 1} & obj3_{pareto\ member\ 1} \\ \vdots & \vdots & \vdots \\ obj1_{pareto\ member\ N} & obj2_{pareto\ member\ N} & obj3_{pareto\ member\ N} \end{bmatrix}_{N\times 3} \times \begin{bmatrix} Cost\_Score \\ Time\_Score \\ Green\_Score \end{bmatrix}_{3\times 1} = \begin{bmatrix} 1_{st}\ pareto\ score \\ \vdots \\ N_{th}\ pareto\ score \end{bmatrix}_{N\times 1}$$

Figure 3. Structure of the required calculations for selecting the best Pareto member.

Table 8. Best criterion – other criteria vectors

		Others		
Experts	Best criteria	Cost	Env	Soc
1	Cost	1	3	7
2	Env	4	1	8
3	Cost	1	8	4
4	Env	3	1	8
5	Env	2	1	9
6	Cost	1	3	7
7	Soc	9	5	1
8	Env	8	1	3

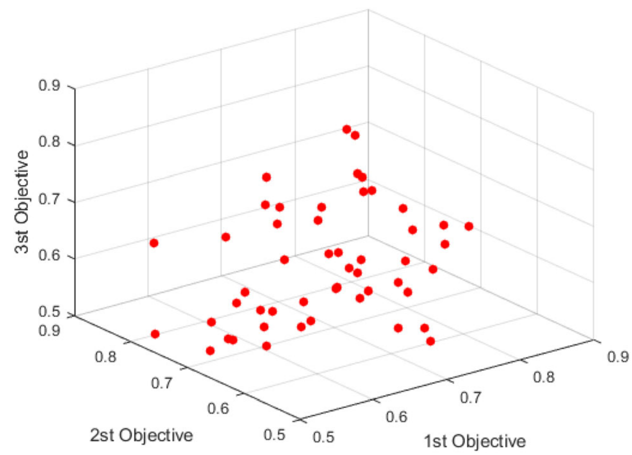

Figure 4. The Pareto front resulted from solving the mathematical model.

Table 9. Other criteria – worst criterion vectors.

	Experts							
	1	2	3	4	5	6	7	8
	Worst criteria							
Others	Soc	Soc	Env	Soc	Soc	Env	Cost	Cost
Cost	7	3	8	4	4	7	1	1
Env	3	8	1	8	9	3	3	8
Soc	1	1	3	1	1	1	9	3

The cost of procuring different groups of construction material at each project site in different periods of time is detailed in table 6.

The other parameters used to solve the problem were randomly generated within the ranges specified in table 7.

Once finished with generating the parameters, the presented model was solved using CPLX solver in GAMS software utilizing the epsilon-constraint method. Given that we are dealing with a set of solutions rather a single final solution, then all of the produced solutions may comprise a Pareto front, as shown in figure 3.

4.1a *Application of the BWM for selecting the final Pareto member* In this section, in order to select the final Pareto member, we followed the BWM approach based on the opinions of 8 experts in construction management. Accordingly, the best and the worst criteria identified by each respondent were taken as the most and least significant criteria for evaluating the Pareto front, respectively. Following with this example, priorities of the best criterion over other criteria and also other criteria over the worst criterion were determined. Finally, each criterion was scored based on the BWM, as reported in tables 8 and 9.

Weights of the main criteria were evaluated by solving the linear BWM model for the 8 respondents (experts) using the BARON solver in GAMS software. These are

Table 10. Final weights of the criteria affecting the choice of the Pareto member.

	Experts								
Criterion	1	2	3	4	5	6	7	8	Final weight
Cost	0.673	0.194	0.722	0.246	0.304	0.673	0.077	0.083	0.372
Env	0.236	0.722	0.083	0.677	0.625	0.236	0.165	0.683	0.428
Soc	0.091	0.083	0.194	0.077	0.071	0.091	0.758	0.233	0.200
ξ^{L*}	0.036	0.056	0.056	0.062	0.018	0.036	0.066	0.017	0.043

Table 11. Amounts of construction materials of different groups dispatched to each project site in each period of time.

Project site	Construction material group	Period 1	Period 2	Period 3	Project site	Construction material group	Period 1	Period 2	Period 3	Project site	Construction material group	Period 1	Period 2	Period 3
1	1	50	43	77	2	1	38	27	50	3	1	37	23	23
1	2	40	69	91	2	2	30	72	36	3	2	58	47	12
1	3	60	92	74	2	3	37	56	63	3	3	64	13	29
1	4	44	75	30	2	4	58	48	45	3	4	42	58	31
1	5	53	73	61	2	5	27	39	23	3	5	11	52	53
1	6	43	53	35	2	6	40	31	59	3	6	43	31	31
1	7	43	65	80	2	7	54	66	38	3	7	34	28	68
1	8	38	67	69	2	8	60	65	58	3	8	41	66	37

Table 12. Demand of each project site for different groups of construction material during different periods of time.

Project site	Construction material group	Period 1	Period 2	Period 3	Project site	Construction material group	Period 1	Period 2	Period 3
4	1	28	63	21	5	1	20	44	51
4	2	32	14	26	5	2	58	34	44
4	3	46	18	28	5	3	37	29	76
4	4	30	32	39	5	4	45	28	43
4	5	67	77	38	5	5	42	36	77
4	6	42	55	40	5	6	31	38	24
4	7	74	27	56	5	7	44	26	43
4	8	21	54	22	5	8	39	32	27

Table 13. Amounts of cross-referenced construction material from the project site 1.

Project site	Construction material group	Period 1	Period 2	Period 3	Project site	Construction material group	Period 1	Period 2	Period 3
3	1	0	2	3	4	1	17	0	3
3	2	0	6	10	4	2	16	13	1
3	3	4	11	2	4	3	1	2	6
3	4	10	7	0	4	4	6	10	0
3	5	11	3	4	4	5	7	10	11
3	6	0	11	4	4	6	1	1	3
3	7	1	0	8	4	7	13	10	2
3	8	2	1	1	4	8	2	6	1

average weights obtained for each criterion, as shown in table 10 in the form of a single weighting vector.

The close-to-zero values obtained for ξ^{L*}indicate consistency of the comparisons. Accordingly, it can be stipulated that the obtained scores can be reliably used to undertake final ranking of the Pareto members. Therefore, in order to carefully investigate the structure of the presented results, one can consider the Pareto point with the highest score as the final solution and graphically present the proposed optimal network as follows (figure 4).

Considering the figure, transported amounts of construction material from the main center to project sites are reported in table 11. This report contains group of material, Project Site and period for each item.

Table 14. Comparison between the results of proposed algorithm and mathematical model.

Instances size	Instances number	$\Gamma 1 = \frac{\lvert J1 \rvert}{2}$ *and* $\Gamma 2 = \frac{\lvert J2 \rvert}{2}$ Run time (second) CPLEX	NSGAII	SPEA	PESA	MID	$\Gamma 1 = \frac{\lvert J1 \rvert}{3}$ *and* $\Gamma 2 = \frac{\lvert J1 \rvert}{3}$ Run time (second) CPLEX	NSGAII	SPEA	PESA	MID	$\Gamma 1 = \frac{\lvert J1 \rvert}{5}$ *and* $\Gamma 2 = \frac{\lvert J1 \rvert}{5}$ Run time (second) CPLEX	NSGAII	SPEA	PESA	MID
Small	SM1	153	50	31	50	3.41	162	25	48	41	3.76	167	27	26	72	1.55
	SM2	201	53	37	77	3.76	192	46	79	54	4.90	323	32	43	73	1.71
	SM3	302	72	62	84	5.74	309	121	113	63	6.52	357	69	83	97	2.61
	SM4	330	78	170	88	8.07	326	125	175	70	6.64	341	99	98	100	3.67
	SM5	335	89	186	94	9.75	348	133	182	81	7.46	343	108	128	151	4.43
	SM6	337	91	200	167	9.81	363	181	197	251	9.04	358	148	165	168	4.46
	SM7	361	117	208	192	12.83	368	187	218	280	12.08	362	155	168	199	5.83
	SM8	383	162	230	192	13.2	357	200	221	305	13.12	311	163	247	202	6.00
	SM9	394	257	233	217	13.29	481	243	228	320	15.18	322	165	277	208	6.04
	SM10	447	297	237	238	18.85	484	246	236	329	15.40	422	178	296	216	8.57
Medium	ME1	549	304	248	265	20.5	501	331	304	341	17.32	427	224	306	241	9.32
	ME2	582	315	255	331	21.93	519	347	350	346	17.46	432	358	343	251	9.97

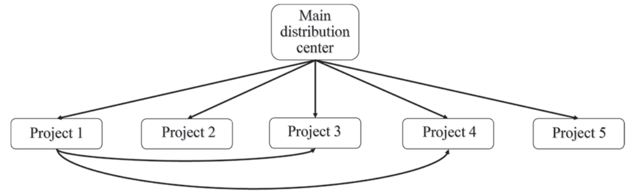

Figure 5. Graphical structure of construction material transportation from the main center to project sites and inter-site transfers.

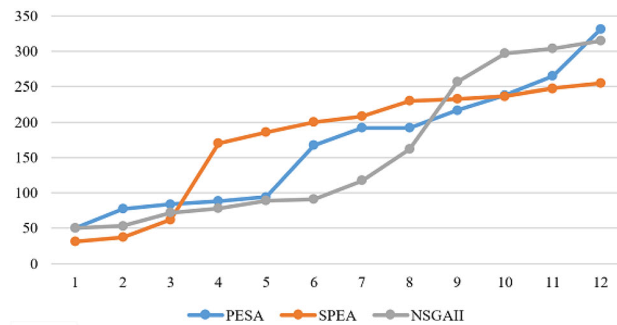

Figure 6. Variations of processing time at $\Gamma 1 = \frac{|J1|}{2}$ and $\Gamma 2 = \frac{|J2|}{2}$.

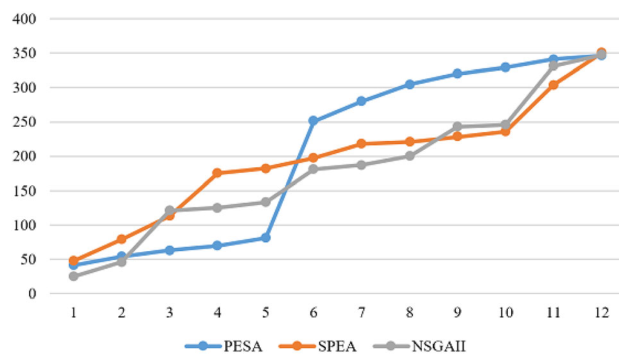

Figure 7. Variations of processing time at $\Gamma 1 = \frac{|J1|}{3}$ and $\Gamma 2 = \frac{|J2|}{3}$.

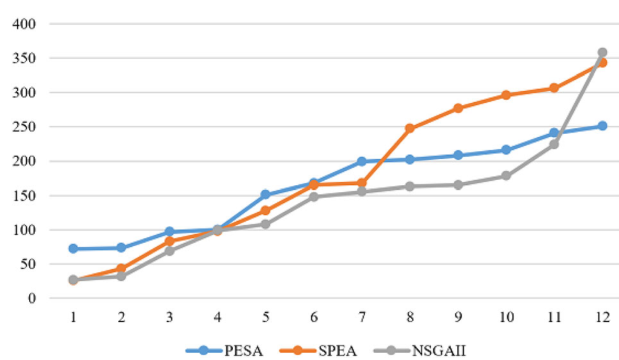

Figure 8. Variations of processing time at $\Gamma 1 = \frac{|J1|}{5}$ and $\Gamma 2 = \frac{|J2|}{5}$.

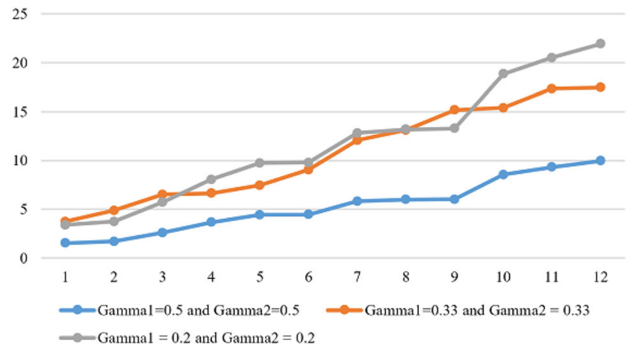

Figure 9. Variations of MID with different values of $\Gamma 1$ and $\Gamma 1$.

Considering the figure, Demand of each project considering different groups of construction material are reported in table 11. This report contains group of material, Project Site and period for each item (tables 12, 13).

As observed, the demands of centers 2 and 5 in each period of time have been completely transferred, with neither excess nor deficiency of construction material. Indeed, these centers have received their required deals of construction material primarily with neither excess nor deficiency of construction material. However, the project site 1 ended up demanding for material. This project site has received excessive construction material, which has been then cross-transferred, either during the same period or the proceeding ones, to the distribution centers 3 and 4. Moreover, the distribution centers 3 and 4 received less construction material from the main supply center depending on the amount of the material delivered to them from the project site 1. This indicates the efficiency of the proposed model in terms of allocating construction material to different project sites via not only direct dispatches, but also cross-transfers. Moreover, the level of inventory at project site has been high enough for the site to address its own needs while dispatching some construction material to the associated distribution centers (distribution centers 1 and 3).

As observed, the model exhibited an appropriate level of efficiency, making it appropriate for solving various problems in the present field of study. However, since the presented model is an NP-Hard problem, meta-heuristic algorithms are required for solving the model when the problem size goes large. Given the ransom structure of meta-heuristic algorithms in the generation of initial population of solutions, various example problems shall be solved by such algorithms to ensure their efficiency. Accordingly, continuing with the research, results of the CPLEX solver are compared to those of the proposed algorithms.

4.1b *Comparison between the proposed algorithm and mathematical model*: In this subsection, in order to compare the results of the proposed algorithm to those of the mathematical model, a number of numerical examples were generated according to the procedure described in previous sections, and performance evaluation of the proposed algorithm and mathematical model was done based on the MID index. The MID is a measure of the Euclidian distance between the final non-dominated solutions generated by the algorithm and the optimal Pareto set obtained from the CPLEX solver according to Equation (22):

$$MID = \frac{\sum_{i=1}^{|Q|}\left(\sqrt{\sum_{j=1}^{n_{obj}}\left(\frac{f_i^j - f_{best}^j}{f_{\max}^j - f_{\min}^j}\right)^2}\right)}{|Q|} \tag{48}$$

where f_i^j denotes the $^{\text{th}}$ objective function, f_{best}^j is the ideal point on the j^{th} objective function, and f_{max}^j and f_{min}^j are the maximum and minimum values over all Pareto solutions for the j^{th} objective function. In addition, $|Q|$ refers to the number of points within the Pareto optimal region and n_{obj} is the number of objective functions.

According to table 14, one may observe that an increase in the denomination of the fractions describing the $\Gamma 1$ and $\Gamma 1$ induces significant changes into the processing time of the problem. This can be attributed to decreased number of the constraints due to reduced level of associated uncertainty with the parameters. Figures 5, 6, 7 demonstrate these variations.

As can be seen on figures 5, 6, 7, the corresponding processing times to different algorithms approach one another as the level of uncertainty decreases. This can be explained by the reduction in the solution space and hence the lower count of required computation in various iterations. Therefore, the algorithms cannot be ranked by the required processing time. However, it is evident that a decrease in the level of uncertainty of the parameters lowers the value of MID index and brings the solutions obtained from different solutions closer to those evaluated via the CPLEX solver. Figure 8 shows the trend of such variations.

According to this figure, it is well-evident that the solutions produced at $\Gamma 1 = \frac{|J1|}{5}$ and $\Gamma 2 = \frac{|J2|}{5}$ are always closer to those obtained using the CPLEX solver, which is attributed to the lower number of uncertain parameters and hence reduced space of the problem and the required number of computations per iteration. An important conclusion drawn out of this section is that, no single algorithm can be acknowledged as the best algorithm for all real-world problems. That is, as far as small-sized examples were concerned, all of the algorithms exhibited similar performance to that of the CPLEX, with no significant difference observed between them. However, in order to investigate the behaviors of the proposed algorithms on problems of larger sizes, the next subsection generates a number of numerical demonstrations at different levels of uncertainty and examines the results (figure 9).

4.1c *Performance evaluation of the proposed algorithms*: In order to examine the efficiency of the proposed algorithm in producing appropriate solutions, a total of 10 small-sized, 10 medium-sized, and 10 large-sized examples were generated according to the proposed structure, and then investigated using two indices, namely the spread of non-dominance solution (SNS) [37] and maximal spread (MS) [38], for different values of *bal* and $L_{\max}$. The SNS and MS indices were calculated via Equations (49) and (50), respectively.

$$SNS = \sqrt{\frac{\sum_{i=1}^{|Q|}\left(MID - \sum_{j=1}^{n_{obj}} f_i^j\right)^2}{|Q| - 1}} \tag{49}$$

$$MS = \sqrt{\sum_{j=1}^{n_{obj}} \left(f_{\max}^j - f_{\min}^j\right)^2} \tag{50}$$

Here we generated 30 numerical examples of different sizes and the results were compared to those of different algorithms based on the SNS and MS indices.

According to table 15, it is well evident that the SPEA algorithm exhibited higher values of SNS and MS, indicating higher performance of this algorithm, as compared to other proposed algorithms. Therefore, this algorithm can be used to solve large-scale problems.

Table 15. Results of sensitivity analysis on the robustness parameter.

	Robust Parameters				Results					
					NSGAII		PESA		SPEA	
Problem Size	$\|J1\|$	$\Gamma1$	$\|J2\|$	$\Gamma2$	SNS	MS	SNS	MS	SNS	MS
1	54	13	60	22	900646	5447	1350969	7625.8	2026454	9150.96
2	66	19	105	31	684040	5823	889252	7569.9	889252	9840.87
3	72	18	111	14	601712	5476	782225.6	8214	938670.7	12321
4	92	11	112	31	235710	6213	235710	6213	329994	9319.5
5	130	19	115	18	642520	7444	899528	11166	1349292	16749
6	144	21	133	27	84891	9459	110358.3	14188.5	110358.3	14188.5
7	146	17	190	43	993107	7292	1191728	10208.8	1787593	11229.68
8	156	45	269	67	129627	9796	168515.1	13714.4	168515.1	20571.6
9	186	24	304	42	308880	7871	401544	9445.2	401544	10389.72
10	199	59	339	71	367890	6124	515046	8573.6	618055.2	9430.96
11	233	30	347	79	312993	5956	312993	5956	375591.6	6551.6
12	284	28	355	78	290586	6970	348703.2	9061	488184.5	12685.4
13	292	49	360	93	668889	6095	802666.8	6095	1043467	9142.5
14	339	101	369	70	342566	5714	479592.4	6856.8	479592.4	8228.16
15	339	40	392	101	916787	9059	1100144	9059	1650217	9059
16	385	127	394	114	789653	6526	868618.3	9136.4	955480.1	10050.04
17	391	148	400	108	641945	9729	641945	13620.6	834528.5	16344.72
18	420	163	413	74	643529	8533	900940.6	11946.2	1171223	14335.44
19	435	143	436	87	480899	9413	673258.6	10354.3	875236.2	14496.02
20	466	121	485	155	881236	9629	1145607	14443.5	1489289	15887.85
21	482	106	489	185	293192	7465	439788	7465	527745.6	9704.5
22	487	165	493	69	556841	7130	612525.1	7843	673777.6	11764.5
23	493	108	494	128	385585	6658	385585	9987	578377.5	12983.1
24	502	190	518	67	205631	5815	267320.3	7559.5	320784.4	10583.3
25	521	67	532	133	189897	6563	208886.7	8531.9	229775.4	11944.66
26	532	164	540	210	401992	5115	562788.8	6138	562788.8	6751.8
27	556	150	546	98	672824	9182	1009236	11018.4	1009236	13222.08
28	562	89	558	200	581954	9197	640149.4	11956.1	704164.3	17934.15
29	569	85	574	103	13254	9717	14579.4	11660.4	21869.1	16324.56
30	590	171	594	130	869273	5944	1216982	7132.8	1582077	8559.36

5. Conclusion and recommendations for future research

The present research proposed a three-objective mathematical model for optimization of construction supply chain under uncertainty. Many researches show that multi objectives genetic algorithm is one of the proper and efficient algorithms for solving optimization problems [39]. The purpose solution have been used in energy saving, expert system and decision making fields [40]. There are two major limitations in this study that could be addressed in future research. First, the study focused on Supply chain for petrochemical industry which was hard to obtain several PLANTs Data and the second was hardware limitation for computation of model [41, 42]. This model can provide the managers with a tool for making final decisions. However, since the proposed model was NP-Hard, meta-heuristic algorithms shall be used to solve one real-size problems. Accordingly, we proposed three algorithms, namely NSGA-II, PESA, and SPEA-II. Appropriate comparison criteria were introduced to investigate the proposed algorithms in terms of performance. A review on the results highlights that the SPEA-II algorithm outperformed the other two algorithms. It was further evident that the resultant Pareto front exhibits a non-dominated structure. Moreover, complete description of one of the produced points shows that the optimal structure exhibits well reasonable conditions. Therefore, results of this model can be used to implement the algorithm on real cases. The comparison among different algorithms also showed that, compared to other algorithms, results of NSGA-II were farther from the optimal front produced by the CPLEX solver. This points out that the use of the operators in the SPEA-II and PESA may end up with superior outcomes. However, a comparison between the results of several numerical examples of various dimensions shows that the SPEA-II exhibits the highest performance level and hence can be used as the final algorithm. When the uncertainty came into play, the results showed that, an increase in the robustness parameter affected the results by improving the sum of objective functions. This shows that, the higher the level of uncertainty, the higher will be the levels of objective functions, thereby making the final results worse. In order to extend the spread of research in future, the following recommendations are presented:

- Examination of different case studies and implementation of the obtained results in larger-sized real environments are the very first recommended activities for future research. These are important since the results of the proposed structure on real cases can delineate the scope of applicability of the proposed model and algorithms clearly.
- As another recommendation for future research, one may refer to the use of other new meta-heuristic algorithms and comparison between their results. This can provide an appropriate basis for producing even better solutions by other algorithms and also for comparing the performances of different algorithms on similar problems.
- The use of new robust programing approaches may also provide for suitable applications. Given that there are always some parameters that are either inherently uncertain or difficult to evaluate certainly, application of the uncertainty-considered approaches may extend the scope of applicability of such problems. One of the most credited uncertainty-considered approaches is the robust programing, which ends up producing robust solutions against variations.
- Presentation of exact algorithms such as branch-and-bound and branch-and-cut may ensure achievement of exact solutions for problems of medium and sometimes large sizes.

Nomenclatures

Symbols and sets

m, g	Construction material groups, m, g = 1…8
j	Construction workshops, j = 1…J
l	Order of preference, l = 1…8
r	Technical specification of the construction material, r = 1…U
t	Time periods, t = 1…T

Parameters

$Capacity_j$	Stock capacity at j^{th} construction workshop
Dem_{jt}^{m}	Total demand of the j^{th} construction workshop for different units of a construction material in f^{th} group in t^{th} period of time
$Stock_{jt}^{rmgl}$	Cost of retaining the safety stock of the construction material with r^{th} specification belonging to the g^{th} construction material group by the f^{th} group with the l^{th} order of preference at j^{th} construction workshop in t^{th} period of time
$TCost_{jj't}^{rmgl}$	Cost of transferring the construction material with r^{th} specification belonging to g^{th} group by the f^{th} group using the l^{th} order of preference at j^{th} construction workshop from the j'^{th} construction workshop in t^{th} period of time
$PCost_{jt}^{m}$	Cost of purchasing the construction materials at j^{th} construction workshop for units belonging to f^{th} group in the t^{th} period of time
$PO_{jj't}$	1, if construction material can be transferred between the j^{th} and j'^{th} construction workshops in the t^{th} period of time
M	A large value
$BCost$	Cost of deficiency per unit construction material

$HCost$	Cost of storage per unit construction material
$WCost^b$	Cost of loss per unit construction material
$WCost^h$	Cost of loss per unit construction material
DV_{jt}^{rm}	Demand of the construction workshop for the construction material with r^{th} technical specification belonging to f^{th} group at j^{th} construction workshop in t^{th} period of time
$TCost_j$	Per-unit construction material transportation cost from …. to the j^{th} construction workshop
PR^{gml}	An auxiliary binary matrix that defines the ABO-Rh for the l^{th} order of preference
TrT_j	Required time for transporting unit construction material to the j^{th} construction workshop
$TrsT_{jj'}$	Required time for transporting unit construction material between the j^{th} and j'^{th} construction workshops
EnT_j	Greenhous gas emission per transportation of unit construction material to the j^{th} construction workshop
$ENsT_{jj'}$	Greenhous gas emission per transportation of unit construction material between the j^{th} and j'^{th} construction workshops

Decision variables

$TDem_{jt}^{rmgl}$	The demand of the j^{th} construction workshop for a construction material with r^{th} technical specifications belonging to the g^{th} group has been fulfilled by f^{th} group with l^{th} order of preference in t^{th} period of time
SeV_{jt}^{rmgl}	The level of safety stock for the construction material with r^{th} specification belonging to the g^{th} group by the f^{th} group using the l^{th} order of preference at j^{th} construction workshop in t^{th} period of time
$TrV_{jj't}^{rmgl}$	The transported amount of construction material with r^{th} specification belonging to g^{th} group by the f^{th} group using the l^{th} order of preference at j^{th} construction workshop from the j'^{th} construction workshop in t^{th} period of time via a cross transfer
$ILvL_{jt}^{rm}$	Stock level of priority construction material at j^{th} construction workshop with r^{th} technical specification belonging to f^{th} group by the end of t^{th} period of time
$BLvL_t^{rm}$	Stock level of non-priority construction material at j^{th} construction workshop with r^{th} technical specification belonging to f^{th} group by the end of t^{th} period of time
UCD_{jt}^{Frm}	Non-fulfilled demand for priority construction material belonging to f^{th} group at j^{th} construction material during the t^{th} period of time
UCD_{jt}^{Om}	Non-fulfilled demand for non-priority construction material belonging to f^{th} group at j^{th} construction material during the t^{th} period of time
EM_{tr}	Number of expired construction material with r^{th} technical specification at construction workshops during the t^{th} period of time
EMH_{jrt}	Number of expired construction material with r^{th} technical specification at j^{th} construction workshop during the t^{th} period of time
Por_{jt}^{rm}	Ratio of maximum demand for the construction material with r^{th} technical specification belonging to the f^{th} group to the delivered amount of that construction material to the j^{th} construction workshop in the t^{th} period of time
RM_{jt}^{m}	Prepared amount of the construction materials belonging to the f^{th} group at j^{th} construction workshop in the t^{th} period of time
X_t^r	1, if the stock of the construction material with r^{th} technical specification is used to fulfill the demands of construction workshops during the t^{th} period of time

References

[1.] Irizarry J, Karan E P and Jalaei F 2013 Integrating BIM and GIS to improve the visual monitoring of construction supply chain management. *Autom. Constr.* 31: 241–254

[2.] Eccles R G 1981 Bureaucratic versus craft administration: the relationship of market structure to the construction firm. *Adm. Sci. Q.* 26(3): 449–469

[3.] Segerstedt A and Olofsson T 2010 Supply chains in the construction industry. *Supply Chain Manag: Int. J.* 15(5): 347–353

[4.] Vrijhoef R and Koskela L 2000 The four roles of supply chain management in construction. *Eur. J. Purch. Supply Manag.* 6(3–4):169–178

[5.] O'Brien W J, Formoso C T, Ruben V and London K 2008 Construction supply chain management handbook. CRC Press

[6.] Frodel M and Josephson P E 2009 Perceived Constraints when Establishing and Maintaining Contractor-Supplier Relations in Construction. Construction Management, Chalmers University of Technology

[7.] Tuzkaya G, Gülsün B and Önsel Ş 2011. A methodology for the strategic design of reverse logistics networks and its application in the Turkish white goods industry. *Int. J. Prod. Res.* 49(15): 4543–4571

[8.] Pishvaee M S and Razmi J 2012 Environmental supply chain network design using multi-objective fuzzy mathematical programming. *Appl. Math. Model.* 36(8): 3433–3446

[9.] Pishvaee M S, Razmi J and Torabi S A 2012 Robust possibilistic programming for socially responsible supply chain network design: a new approach. *Fuzzy Sets Syst.* 206: 1–20

[10.] Badri H, Bashiri M and Hejazi T H 2013 Integrated strategic and tactical planning in a supply chain network design with a heuristic solution method. *Comput. Oper. Res.* 40(4): 1143–1154

[11.] Shankar B L, Basavarajappab S, Chen J C H, Rajeshwar S and Kadadevaramatha S 2013 Location and allocation decisions for multi-echelon supply chain network–A multi-objective evolutionary approach. *Expert Syst. Appl.* 40(2): 551–562

[12.] Kanzian C, Kühmaier M, Zazgornik J and Stampfer K 2013. Design of forest energy supply networks using multi-objective optimization. *Biomass Bioenergy* 58: 294–302

[13.] Wu T and Zhang K 2014 A computational study for common network design in multi-commodity supply chains. *Comput. Oper. Res.* 44: 206–213

[14.] Sarrafha K, Rahmati S H A, Niaki S T A and Zaretalab A 2015 Bi-objective integrated procurement, production, and distribution problem of a multi-echelon supply chain network design: a new tuned MOEA. *Comput. Oper. Res.* 54: 35–51

[15.] Soleimani H and Kannan G 2015 A hybrid particle swarm optimization and genetic algorithm for closed-loop supply chain network design in large-scale networks. *Appl. Math. Model.* 39(14): 3990–4012

[16.] Fattahi M, Mahootchi M, Govindan C and Moattar-Husseini M 2015 Dynamic supply chain network design with capacity planning and multi-period pricing. *Transp. Res. Part E: Logist. Transp. Rev.* 81: 169–202

[17.] Hasani A and Khosrojerdi A 2016 Robust global supply chain network design under disruption and uncertainty considering resilience strategies: a parallel memetic algorithm for a real-life case study. *Transp. Res. Part E: Logist. Transp. Rev.* 87: 20–52

[18.] Chibeles-Martins N, Pinto-Varela T, Dias Barbosa-Póvoa APF and Novais AQ 2016 A multi-objective meta-heuristic approach for the design and planning of green supply chains-MBSA. *Expert Syst. Appl.* 47: 71–84

[19.] Zohal M and Soleimani H 2016 Developing an ant colony approach for green closed-loop supply chain network design: a case study in gold industry. *J. Clean. Prod.* 133: 314–337

[20.] Kumar R S, Choudhary A, Irfan Babu S A K, Kumar S K, Goswami A and Tiwari M K 2017 Designing multi-period supply chain network considering risk and emission: a multi-objective approach. *Ann. Oper. Res.* 250(2): 427–461

[21.] Fahimnia B, Davarzani H and Eshragh A 2018 Planning of complex supply chains: a performance comparison of three meta-heuristic algorithms. *Comput. Oper. Res.* 89: 241–252

[22.] Tsao Y C, Thanh V V, Lu J C and Yu V F 2018 Designing sustainable supply chain networks under uncertain environments: fuzzy multi-objective programming. *J. Clean. Prod.* 174: 1550–1565

[23.] Ghahremani-Nahr J, Kian R and Sabet E 2019 A robust fuzzy mathematical programming model for the closed-loop supply chain network design and a whale optimization solution algorithm. *Expert Syst. Appl.* 116: 454–471

[24.] Hamdan B and Diabat A 2019 A two-stage multi-echelon stochastic blood supply chain problem. *Comput. Oper. Res.* 101: 130–143

[25.] Eriksson P E 2010. Improving construction supply chain collaboration and performance: a lean construction pilot project. *Supply Chain Manag.: Int. J.* 15(5): 394–403

[26.] Cheng J C P, Law K H, Bjornsson H, Jones A and Sriram R D 2010 A service oriented framework for construction supply chain integration. *Autom. Constr.* 19(2): 245–260

[27.] Meng X, Sun M and Jones M 2011. Maturity model for supply chain relationships in construction. *J. Manag. Eng.* 27(2): 97–105

[28.] Wibowo M A and Sholeh M N 2015 The analysis of supply chain performance measurement at construction project. *Procedia Eng.* 125: 25–31

[29.] Meng X 2013 Change in UK construction: moving toward supply chain collaboration. *J. Civ. Eng. Manag.* 19(3): 422–432

[30.] Tennant S and Fernie S 2013 Organizational learning in construction supply chains. *Eng. Constr. Archit. Manag.* 20(1): 83–98

[31.] Bertsimas D and Sim M 2004 The price of robustness. *Oper. Res.* 52(1): 35–53

[32.] Deb K, Agrawal S, Pratap A and Meyarivan T 2000 A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. *Int. Conf. Parallel Probl. Solving Nat.* 1917: 849–858

[33.] Zitzler E, Laumanns M and Thiele L 2001 SPEA2: Improving the strength Pareto evolutionary algorithm. TIK-report 103

[34.] Corne D W, Knowles J D, Oates M J and Jerram N R 2001. PESA-II: Region-based selection in evolutionary multiobjective optimization. In: *Proceedings of the 3rd Annual Conference on Genetic and Evolutionary Computation.* 283–290

[35.] Rezaei J 2015. Best-worst multi-criteria decision-making method. *Omega.* 53: 49–57

[36.] Rezaei J 2016. Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega.* 64: 126–130

[37.] Maghsoudlou H, Kahag M R, Niaki S T A and Pourvaziri H 2016 Bi-objective optimization of a three-echelon multi-server supply-chain problem in congested systems: Modeling and solution. *Comput. Ind. Eng.* 99: 41–62

[38.] Samadi A, Fathollahi-Fard A M, Hajiaghaei-Keshteli M and Mehranfar N 2018 Heuristic-based metaheuristics to address a sustainable supply chain network design problem. *J. Ind. Prod. Eng.* 35(2): 102–117

[39.] Gong D, Sun J and Miao Z 2016 A set-based genetic algorithm for interval many-objective optimization problems. *IEEE Trans. Evol. Comput.* 22(1): 47–60

[40.] Zhang R and Chiong R 2016 Solving the energy-efficient job shop scheduling problem: A multi-objective genetic algorithm with enhanced local search for minimizing the total weighted tardiness and total energy consumption. *J. Clean. Prod.* 112: 3361–3375

[41.] Metawa N, Hassan M K and Elhoseny M 2017 Genetic algorithm based model for optimizing bank lending decisions. *Expert Syst. Appl.* 80: 75–82

[42.] Guerrero C, Lera I and Juiz C 2018 Genetic algorithm for multi-objective optimization of container allocation in cloud architecture. *J. Grid Comput.* 16(1): 113–135

[43.] Dehghanian F and Mansour S 2009 Designing sustainable recovery network of end-of-life products using genetic algorithm. *Resour. Conserv. Recycl.* 53(10): 559–570

[44.] Galante G, Giallanza A, Enea M and Panascia E 2010 A multi-objective approach to solid waste management. *Waste Manag.* 30(8–9): 1720–1728

[45.] Ramudhin A, Chaabane A and Paquet M 2010 Carbon market sensitive sustainable supply chain network design. *Int. J. Manag. Sci. Eng. Manag.* 5(1): 30–38

[46.] Chaabane A, Ramudhin A and Paquet M 2011 Designing supply chains with sustainability considerations. *Prod. Plan. Control.* 22(8): 727–741

[47.] Pinto-Varela T, Dias Barbosa-Póvoa A P F and Novais A Q 2011 Bi-objective optimization approach to the design and planning of supply chains: economic versus environmental performances. *Comput. Chem. Eng.* 35(8): 1454–1468

[48.] Jamshidi R, Ghomi S F and Karimi B 2012 Multi-objective green supply chain optimization with a new hybrid memetic algorithm using the Taguchi method. *Sci. Iran.* 19(6): 1876–1886

[49.] Xifeng T, Ji Z and Peng X 2013 A multi-objective optimization model for sustainable logistics facility location. Transportation Research Part D. *Transp. Environ.* 22: 45–48

[50.] Hiremath N C, Sahu S and Tiwari M K 2013. Multi objective outbound logistics network design for a manufacturing supply chain. *J. Intell. Manuf..* 24(6): 1071–1084

[51.] Yue D, Kim M A and You F 2013 Design of sustainable product systems and supply chains with life cycle optimization based on functional unit: general modeling framework, mixed-integer nonlinear programming algorithms and case study on hydrocarbon biofuels. *ACS Sustain. Chem. Eng.* 1(8): 1003–1014

[52.] Ruiz-Femenia R, Guillen-Gosalbez G, Jiménez L and Caballero J A 2013 Multi-objective optimization of environmentally conscious chemical supply chains under demand uncertainty. *Chem. Eng. Sci.* 95: 1–11

[53.] Özceylan E and Paksoy T 2014 Interactive fuzzy programming approaches to the strategic and tactical planning of a closed-loop supply chain under uncertainty. *Int. J. Prod. Res.* 52(8): 2363–2387

[54.] Govindan K, Jafarian A, Khodaverdi R and Devika K 2014 Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food. *Int. J. Prod. Econ.* 152: 9–28

[55.] Bandyopadhyay S and Bhattacharya R 2014 Solving a tri-objective supply chain problem with modified NSGA-II algorithm. *J. Manuf. Syst.* 33(1): 41–50

[56.] Subulan K, Taşan A S and Baykasoğlu A 2015 Designing an environmentally conscious tire closed-loop supply chain network with multiple recovery options using interactive fuzzy goal programming. *Appl. Math. Model.* 39(9): 2661–2702