Cite as: *Amin-Tahmasbi, H., Sadafi, S., Ekren, B.Y., Kumar, V. (2022), A multi-objective integrated optimisation model for facility location and order allocation problem in a two-level supply chain network, Annals of Operations Research (In Print)*

A multi-objective integrated optimisation model for facility location and order allocation problem in a two-level supply chain network

Abstract

This study proposes a mixed-integer multi-objective integrated mathematical model solving facility location and order allocation optimisation problems simultaneously in a two-echelon supply chain network. The proposed problem is motivated by a factoryless concept and by providing a dynamic decision-making solution under a multi-period time horizon. Within the model, we also determine the optimal replenishment number of production facilities by the multi-objective functions. The multi-objective functions include minimisation of the total cost, rejected and late delivery units and, maximisation of the assessment score of the selected suppliers. The studied dynamic decision model is significant for the cost-efficient management of companies' supply chain networks. The mixed-integer mathematical model is developed by the LP-metric method and it is solved by the GAMS optimisation software. Due to the NP-hard structure of the problem, for large-scale instances, we utilise the Multi-Objective Particle Swarm Optimisation (MOPSO) and Multi-Objective Vibration Damping Optimisation (MOVDO) heuristic solution approaches. Numerical results show that, for large-scale problems, the MOPSO method performs better in Pareto solutions and decreases run times. However, the MOVDO method performs better regarding the Mean Ideal Distance and the Number of Solutions Cover surface criterion. The developed solution approach by this paper is a generic model which can be applied for any two-level network for simultaneous optimisation of supplier selection, location determination of facilities and their replenishment amounts.

Keywords: Supply chain management, Facility location, MOPSO, MOVDO, Supplier selection

1. Introduction

A supply chain involves all activities related to the production and information flow, from raw materials to the final products. Supply chain management involves efficient management of all those processes starting from the design of a product or service until its final delivery to customers (Weng, 1999). Some of the significant goals in supply chain management are empowerment, evaluation and selection of suppliers (Seifbarghy & Esfandiari, 2013).

Factoryless manufacturing is a strategic decision by businesses to contract out part or all of their production. It is a way of operation with the least amount of equipment, facilities and infrastructure (Nazemi, 2013). Factoryless manufacturing strategy is, in fact, the development and application of a system that can be used to produce a variety of products to complete the product portfolio by using the potential capacity of other production units without dealing with factory manufacturing. In other words, it can be declared that factoryless operation considers producing the products by using the empty capacities of other producers with fixed costs and low lateral overhead.

A business that incorporates a factoryless manufacturing strategy into its business process registers a brand in its own name, creates a unique marketing and branding system for itself, and focuses its efforts on that. In this strategy, because the business uses other resources and it just plays a complementary role, the concerns are minimised (Cortinhal et al., 2019). This is a two-pronged game where there is no initial investment in the factoryless manufacturing strategy and the business without the factory can complete the production process and offer the product to the market at the lowest cost. The main issue in this concept is a well-optimised supply chain management issue of those outsourced manufacturers within the supply chain network. As factoryless manufacturing concept is gaining popularity, we also focus on an integrated optimisation procedure for a well-planned supply chain network management.

Since supplier selection covers all activities from the procurement of raw materials to the final product delivery, it plays a significant role in supply chain performance. Supplier selection can be considered as the first stage of decision-making in supply chain management that might also affect the other decisions in the network (Kilic, 2013). For instance, because the cost and quality of the purchased products, as well as their delivery and response time in the network, are strongly related to the selected suppliers, supplier selection becomes a significant decision in a network. Namely, correct supplier selection can reduce the cost of purchasing and increase the competitiveness of the organisation significantly.

Besides supplier selection, capacity allocation decisions for those suppliers is also very important. An optimised quota allocated to suppliers as well as time period-based location determination of production facilities would help to increase the efficiency of the business supply network significantly. In this work, we consider all those issues in our optimisation procedure. In addition, in the selected problem, we also consider a location optimisation decision in the integrated model.

The location problem is generally engaged with finding a set of appropriate local options for a particular application. The purpose of the location problem is to locate facilities in the supply chain by identifying the best locations from different alternatives (i.e., nodes) (Arabzad et al., 2015). Facility location decision plays a significant role in the strategic design of the supply chain network. For instance, generally, a supply network design project starts with identifying potential sites and required capacities for the facilities to be located (Melo et al., 2009). In this paper, the location of facilities along with their availability during each period is also studied.

For effective supply chain management, suppliers and manufacturing centres must work together in a coordinated manner, through partnerships, communication and dialogue. The purpose of this study is to achieve the best supply chain planning decisions also including the location of production facilities and the number of orders of factories from each supplier such that the total cost of the whole chain is minimised. The proposed approach combines two types of planning: production planning for each production facility and planning for allocation of quotas to suppliers for each production facility. The proposed model can be utilised by businesses following a factoryless strategy as well as involving any supply chain network management. For instance, factoryless manufacturers would seek ways to optimise their production resources with minimal investment cost and personnel. Hence, the purpose of this research can also be considered to provide a decision support model to determine the optimal location of given production facilities and allocation of suppliers to those facilities with the optimal quotas, while minimising the total supply chain network cost. The proposed model is a generic solution approach that can be applied to any supply chain network where facilities purchase their materials from a set of suppliers and replenish them within a multi-period planning horizon. The proposed model includes (1) dynamic locating, (2) transaction cost changes for suppliers under multi-period conditions, (3) facility capacity constraint in the network, and (4) safety stocks for production facilities to reduce the shortage risk.

To the best of our knowledge, there is no such integrated model in the literature optimising several objective functions simultaneously for a supply network. The difference between our work and the existing literature is detailed in the following section. To evaluate the proposed mathematical model, first, it is coded in the GAMS software with a small size instance based on the LP-metric method with the norms L_1, L_2, and L_∞. Later, it is solved for large-scale cases by using multi-objective particle swarm optimisation and multi-objective vibration-damping optimisation techniques.

The rest of this paper is organised as follows. Section 2 presents a literature review for appropriate supplier selection works as well as facility location problems in the supply chain. Section 3 explains the developed mathematical model, its assumptions, and all the related details. Section 4 describes the solution approach. Section 5 shows the results to evaluate the validity of the model and its computational complexity as well as a sensitivity analysis. The last section provides the conclusion and some recommendations for future works.

2. Literature Review

In the last decade, supplier selection problem has become strategic decision-making in supply chain management. That decision might be affected by some other critical decisions such as facility location, capacity allocation, inventory decisions, etc., causing an increase in the complexity of the problem. Further, many quantitative and qualitative criteria, such as quality, price, flexibility, and delivery decisions, could also be involved in those decisions. In the following, researches on this category of the subject are briefly mentioned.

The supplier selection problem has been studied extensively in several ways. Seifbarghy and Esfandiari (2013) study the quota allocation for suppliers by considering a multi-objective optimisation model. In their model, five objective functions are optimised. They use a simple weighting method to convert the multi-objective model into a single-objective one and then apply two meta-heuristic algorithms (genetic algorithm and simulated annealing algorithm) to solve the model.

Hamdan and Cheaitou (2017) introduce a multi-objective method to solve a multi-period supplier selection and order allocation problem based on green factors. This approach consists of three tools. First, fuzzy TOPSIS is applied to allocate a weighted priority to each supplier based on two separate traditional and green sets. Then, an analytical hierarchy process is applied to assign a weight to each of the two sets of criteria based on the company's strategies and suppliers. Finally, the fuzzy TOPSIS weighting priority is derived from the traditional criteria for each supplier. Keshavarz-Ghorabaee et al. (2017) proposed an integrated model for multi-objective supplier selection problems by taking into account economic and environmental considerations. To solve the problem, they develop a fuzzy logic solution approach. The results show that the proposed approach is effective in solving such problems. Feng et al. (2011) investigate a decision method for supplier selection in multi-service outsourcing and solve a multi-objective model based on the Tabu search algorithm. Li et al. (2018) introduce a multi-objective model for outsourcing supplier selection problems considering the price, quality, delivery time, reliability and availability and solved by using a particle swarm algorithm. Amin-Tahmasbi and Alfi (2018) study a multi-criteria decision-making model based on a fuzzy optimisation approach for supplier selection and order allocation in the green supply chain. They present a bi-objective mixed-integer linear programming model to minimise total cost and maximise the purchasing value.

Mirzaee et al. (2018) propose a mixed-integer linear model for a bi-objective supplier selection problem using a preemptive fuzzy goal programming approach to solve the model. Three different methods, max-min, weighted fuzzy goal programming, and classical goal programming, are applied to solve the problem and their results are compared. Cheraghalipour and Farsad (2018) present a sustainable supplier selection and order allocation problem with the objectives of minimising total costs and maximising the total score of suppliers. The problem is formulated as a mixed-integer linear programming model and solved by using a revised multi-choice goal programming method. A hybrid multi-criteria decision-making by fuzzy multi-objective optimisation (FMOO) method is proposed by Mohammed et al. (2019) aimed to solve the issues of sustainable supplier selection as well as order allocation problems. They consider environmental, economic and social criteria and propose an integrated Fuzzy AHP-Fuzzy TOPSIS in which suppliers are assessed and ranked according to conventional, green and social criteria. To address the data input uncertainties, they formulate a multi-objective optimisation model by integrating a fuzzy logic approach. In addition, according to the FMOO model, two sets of Pareto solutions are proposed by using the ε-constraint and LP-metrics approaches. They use TOPSIS to find a Pareto solution having the best compliance with the ideal solution. In the case of uncertain environments, Seyed Haeri and Rezaei (2019) propose a grey-based model for green supplier selection. The proposed model includes economic as well as environmental criteria. They combine the best-worst method and fuzzy grey cognitive maps to show the criteria interdependencies. An improved version of the grey relational analysis is proposed to use the grey weights of criteria in evaluating the green suppliers. Later, they are ranked by an interval analysis method. Mohammed (2020) investigates a possible multi-objective method of fuzzy TOPSIS to evaluate green suppliers and presents an environmental assessment method, by which poor supplier setting and suppliers' weak areas are then defined by using a novel interval-valued intuitionistic fuzzy numbers-based reference-neighbourhood rough set approach.

One of the other important issues in supply chain decisions is to determine the optimal number of facilities and the allocation of suppliers for those facilities (Kim et al., 2005). A facility location problem can be defined as selecting the location of one or more centres, regarding other facilities and constraints, to optimise a special goal. Production facility locations have a significant impact on supplier selection decisions also because that they also affect transportation and distribution planning decisions. Not only decisions on facility location problems but also the physical structure of supply chain network designs are important factors to consider. We examine the related researches in the literature on these topics and provide some of the recent ones here.

Mousavi et al. (2015) study the optimisation of distributor-retailer network design for location allocation-inventory problems to minimise the total supply chain cost. In that paper, several seasonal products in the planning multiple horizons are modelled. The problem is formulated as a mixed binary-integer programming model and it is solved by using a modified fruit fly optimisation (MFOA) algorithm. Two different methods, including particle swarm optimisation and simulated annealing algorithms, are used to solve and validate the results. Computational experiments show that the MFOA performs better than the other two algorithms. Yu et al. (2015) introduce a single objective for a location, production and distribution planning problem in a multi-period and multi-echelon environment. The purpose of the model is to determine the appropriate locations to build a new plant and a distribution centre. In that work, a multi-echelon supply chain network including suppliers, factories and distribution centres is investigated. A mathematical model minimising the total cost of the studied supply chain network is proposed. They describe a pure integer linear programming (PILP) model for that network. To solve the problem, a branch and bound algorithm is applied. The results show that the proposed model is applicable for solving such problems. Atabaki et al. (2017) study a hybrid method based on Genetic Algorithm and Invasive Weed Optimisation (i.e., GAIWO) to determine the plants and distribution centres to be opened in the supply chain. They present a single-objective mixed-integer linear programming model intending to minimise total costs under capacity constraints. Four different methods including genetic, invasive weed optimisation, Teaching–Learning-Based optimisation, and GAIWO algorithms are used to compare their performances with the GAIWO. The proposed algorithms are evaluated and ranked with the Wilcoxon test and a chess rating system. Rohaninejad et al. (2017) provide a mathematical model for facility location problems to maximise investor utility. They convert the multi-objective model into a single-objective one and then apply a new approximation meta-heuristic algorithm called APHAL, to solve it. The problem is formulated as a mixed-integer nonlinear programming model. They use the relative percentage deviation criterion to evaluate the effectiveness of APHAL. Correia and Melo (2017) study an integrated single-objective multi-period optimisation model to redesign a facility network problem and to optimise facility location and allocation decisions for retailers; the objective function considers the minimisation of the total cost.

Dai et al. (2018) introduce a simultaneous location and inventory optimisation model in a three-echelon supply chain network for perishable products and present a mixed-integer nonlinear programming model intending to minimise total cost under fuzzy constraints. Two meta-heuristic algorithms, hybrid genetic algorithms, and hybrid harmony search methods are used to solve the model. Numerical experiments show that the hybrid harmony search algorithm produces better results regarding the quality of the solution. Rohaninejad et al. (2018) propose a Benders Decomposition algorithm for a multi-echelon supply chain network to design a reliable network minimising total fixed and service costs. They use a scenario-based approach for the formulation of the problem. Another meta-heuristic approach (a sample average approximation algorithm) is also used to solve the single-objective programming model. Biajoli et al. (2019) study a two-stage capacitated facility location problem and formulate the problem by using a single objective optimisation model minimising the total network cost. To solve the proposed models, a biased random-key genetic algorithm is utilised. Brahami et al. (2020) examine an integrated problem of sustainable supply chain network design, facility location decisions and transportation network design under limited capacity, and environmental protection constraints by applying a multi-objective model. They implement a non-dominated Sorting Genetic Algorithm to solve the problem.

A limited number of articles has been examined in the subjects of supplier selection and facility location jointly. Ranjbar Tezenji et al. (2016) propose a bi-objective model for the location and order allocation of suppliers in an uncertain environment. The objective function of the proposed model is considered to be the optimisation of the mean and variance of the total cost. The problem is formulated by a mixed-integer nonlinear programming model and solved by two heuristic algorithms: genetic and simulated annealing. Arabzad et al. (2017) discuss a case study for location-allocation in a steel supply chain to determine the level of capacity of factories, selection of suppliers and order allocation for suppliers. A multi-objective model with the objectives of minimising total supply chain costs and deterioration rate are proposed. They also use fuzzy goal programming to convert the multi-objective model into a single-objective model. Saidi-Mehrabad et al. (2017) examine a four-level location-allocation problem with the aim of minimisation of total cost and maximisation of customer satisfaction, simultaneously. They introduce a multi-objective hybrid particle swarm algorithm (MOHPSO) to solve the model. The results are compared with the results of the NSGA-II algorithm. The comparison results show that the proposed algorithm performs better regarding time and solution quality. By considering multiple quantitative and qualitative objectives, Lai et al. (2019) propose a novel non-dominated sorting simplified swarm optimisation for multi-stage capacitated facility location (CFL) problem. Feasible solutions are obtained by random repair, cost-based and utility-based repair mechanisms. Those mechanisms enhance the efficiency of search and diversity of populations. Weight for the qualitative objectives is calculated by using a fuzzy analytic hierarchy process. To evaluate the efficiency and effectiveness of the proposed algorithms, several experiments are conducted based on benchmark and experimentally generated instances from four stages of CFL problems. The obtained results are compared with the results of the non-dominated sorting genetic algorithm-II, multi-objective simplified swarm optimisation, and multi-objective particle swarm optimisation from the literature. According to the computational results, the solution quality and time competitiveness of the proposed algorithm are very high. A mixed-integer mathematical model is proposed by Emirhüseyinoğlu and Ekici (2019) for the dynamic facility location problem where supplier selection is completed under a quantity discount. They analyse the decision of a multi-period facility location problem for a retailer and estimate those facilities' demands. They assume that the retailer obtains the products from multiple suppliers under an incremental quantity discount scheme. The decisions of the retailer include: when and where to deploy the facilities, how big the number of orders should be from each supplier in each time period, and which facility locations will be assigned to which retailers to fulfil the demands. They develop a decomposition-based solution method to solve large instances. Table 1 summarises the research studies in these fields.

Differently, in this paper, we study an integrated model for facility location, supplier selection and order allocation problem, under a multi-period time horizon in the supply chain network having multi-products. We optimise those decisions simultaneously by considering minimisation of total cost and number of rejected and late delivered products, and maximisation of evaluated scores of the selected suppliers.

Overall, no research is found considering all those features simultaneously under a multi-objective optimisation perspective. By reviewing the literature on the subject, and according to Table 1, we summarise our work's contributions as follows.

1) Major researches in this subject mostly focus on solely economic objectives (e.g., profit maximisation or cost minimisation). However, in this research, in addition to minimising total network cost, we also aim to maximise the reliability of the network by maximising the total score of the suppliers in the network.
2) To involve more real-life practices in the model, the transaction costs are considered to be changing based on the suppliers under multi-period time assumptions.
3) We consider capacity constraints for suppliers and production facilities.
4) We also allow dynamic location decisions based on different time periods.
5) We consider a safety stock policy for production facilities to reduce shortage risk.
6) We also consider the problem of factoryless manufacturing and using the empty capacity of existing factories in the conditions of sanctions and its effects.

To the best of our knowledge, these considered objectives have been disregarded entirely in the previous studies. However, in this work, we optimise them simultaneously by a comprehensive multi-objective model. We provide several exact solution methods based on various norms of LP-metric and multi-objective particle swarm optimisation and multi-objective vibration-damping optimisation methods by also introducing some criteria to compare the results.

Table 1. A summary of key research studies

	Supplier selection	Outsourcing	Facility location	Factory less manufacturing	Capacity of supplier	Capacity of facility	Probabilistic Demand	Purchasing cost	Transferring cost	Transaction cost	Rejected units	Late delivered units	Score of suppliers	Activating (opening) the facilities at candidate sites	Periodic
Seifbarghy, Esfandiari	✓				✓			✓		✓	✓	✓	✓		✓
Hamdan, Cheaitou	✓				✓			✓							✓
Keshavarz et al.	✓				✓			✓					✓		
Feng et al.	✓	✓													
Li et al.	✓	✓			✓				✓			✓			✓
Amin-Tahmasbi, Alfi	✓				✓			✓	✓		✓	✓			✓
Mirzaee et al.	✓				✓	✓		✓							✓
Cheraghalipour, Farsad	✓				✓			✓	✓				✓		✓
Mohammed et al.	✓				✓			✓	✓						
Seyed Haeri, Rezaei	✓							✓	✓		✓	✓			
Mohammed	✓				✓			✓	✓						
Mousavi et al.			✓			✓		✓	✓						✓
Yu et al.			✓		✓	✓	✓	✓	✓					✓	✓
Atabaki et al.			✓		✓	✓			✓					✓	
Rohaninejad et al.			✓			✓	✓							✓	
Correia, Melo			✓			✓	✓		✓			✓		✓	✓
Dai et al.			✓			✓			✓					✓	
Rohaninejad et al.			✓			✓			✓					✓	
Biajoli et al.			✓			✓			✓					✓	
Brahami et al.			✓			✓	✓		✓					✓	
Ranjbar Tezenji et al.	✓		✓		✓		✓	✓	✓						
Arabzad et al.	✓		✓			✓		✓	✓					✓	
Saidi-Mehrabad et al.	✓		✓		✓	✓			✓					✓	
Lai et al.	✓		✓			✓			✓					✓	
Emirhüseyinoğlu, Ekici	✓		✓			✓		✓	✓					✓	✓
This study	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

3. Problem Definition

As mentioned, factoryless manufacturing is a strategy aiming to make better use of existing production facilities. In industries such as textiles, sheds, elevators, etc., for instance, due to the current situation in Iran, like sanctions, the barriers of trade with the world countries and decline in purchasing power of people, many manufacturers encounter with a large amount of unutilised capacities. Those unutilised capacities might range between 10% and 20%. However, with the recent conditions, it has been reaching around 50%, hence, factories are willing to sell those capacities. For example, the Guilan province has about ten towel and carpet weaving factories working with a capacity of 40% to 50%, resulting in high unutilised capacities. So, in an effort to use those unutilised capacities, we develop the integrated model under consideration of the factoryless manufacturing concept. The capacity limitation of the production candidate site is one of the significant constraints in that problem,. Note that factoryless manufacturing businesses already know their suppliers and the available unutilised capacities of the producers; these are the constraints and opportunities of factoryless manufacturing. The main problem in such a manufacturing environment is managing and optimising the connected supply chain network effectively by integrating several issues and objectives in the solution approach.

In this section, we present a two-level model for facility location and supplier selection in the form of a multi-objective optimisation model. It is assumed that the company in question consists of several production facilities and these facilities purchase their required materials from several suppliers. We seek to provide an analytical plan to determine the location of production facilities and their order quantities from an optimal manner. The proposed model simultaneously seeks to reduce economic objectives and increase the reliability of the product supply network and maximise the amount of purchases from top suppliers with higher evaluation scores. This model is used in almost all companies that procure some materials (parts) from a number of selected suppliers in different time periods to supply the materials they need. First, we introduce the model assumptions, the notations, parameters, related variables and finally the multi-objective mathematical model.

3.1. Problem assumptions

The assumptions of the problem are as follows:

- The supply chain is considered to be a connected network for all production facilities and suppliers where information flow is visible.
- The production facilities supply their required materials from a set of pre-defined suppliers.
- A facility is assumed to produce a specific product type that might be different from the other factories' product types.

• Because of that, some product types might not be demanded by a production facility at a period of *h*. Then, facilities may become inactive in those time periods.

• Demand for each factory is known in each period. In different time periods, based on the existing demand, we may use the unutilised capacities of the existing factories (i.e., capacities of those are already pre-defined).

• The safety stock of each facility at each period is considered to be 5% of the demand in period *h*.

• There is an upper bound for not delivered and late delivered units for each supplier.

• Based on multi-attribute decision-making methods, the assessment scores of suppliers are considered (details are explained in Section 3.3).

3.2. Notations

The indices, parameters and variables used in the proposed model are shown in Tables 2, 3, and 4, respectively.

Table 2. The indices

Set	Definition
s	Set of the suppliers $\{1, 2, \ldots, S\}$
i	Candidate site set for production facility location $\{1, 2, \ldots, I\}$
p	Set of product types $\{1, 2, \ldots, P\}$
h	Set of periods $\{1, 2, \ldots, H\}$

Table 3. The parameters

Parameter	Definition
Pi_{sph}	Price of product p at period h offered by supplier s
g_{spi}	The unit cost of transferring product p from the supplier s to production site i
W_{sh}	Assessment score of supplier s at period h
q_{sp}	Percentage of the rejected units of product p delivered by supplier s
t_{sp}	Percentage of the late delivered units of product p by supplier s
Q'_p	Maximum acceptable percentage of the rejected units of product p during the planning horizon
T'_p	Maximum acceptable percentage of the late delivered units of product p during the planning horizon
D_{ph}	The demand of product p at period h
C_{sph}	The maximum production capacity of supplier s for product p at period h
α_{sph}	The transaction cost of purchasing product p from supplier s at period h
H_{ih}	Cost of activating a production facility at candidate site i at period h
b_{sph}	A binary parameter, which is set to one if supplier s can provide product p at the period h, otherwise set to zero
$Max\ C_{ih}$	Maximum capacity of production facility i at period h

M	A very large number
n	Maximum number of production facilities that can be activated at any period
MH_{ih}	Maximum budget to activate the production facilities at the period h
Ze_{ph}	Safety stock of the product p at period h

Table 4. The variables

Variable	Definition
X_{spih}	order quantity of product p sent by the supplier s to the production site i at period h
Y_{spih}	Binary variable, set to one if product p is sent by the supplier s to the production site i at period h, otherwise set to zero
Z_{ih}	Binary variable, set to one if production facility is activated in the candidate production site i at period h, otherwise set to zero

3.3. Mathematical model

In this subsection, we propose a multi-objective mathematical model for the problem. According to that, the objective function (1) minimises the total transaction costs of purchasing from suppliers. The objective function (2) minimises the total purchasing costs of materials and the cost of transporting them to facilities. The objective function (3) represents the minimisation of total rejected units to diminish the cost of unqualified returned products. The objective function (4) minimises the total amount of late delivered units and the objective function (5) minimises the cost of activating the facilities at candidate sites. Here, note that the activating cost is defined to be a period-based cost which can be assumed to be a termly contract or renting cost for the facility which might change period to period. Finally, the objective function (6) maximises the total score of suppliers (e.g., suppliers having environmental considerations in the production process have higher scores). It is assumed that the assessment score of each supplier in different time periods is obtained by evaluating pre-specified numbers of suppliers by utilising multi-objective decision-making methods such as AHP and TOPSIS as in Kang et al. (2012) and Kubat and Yuce (2012). For example, in sample problem No. 4 in Table 8, there are five suppliers with different evaluation scores where we set them as $w_1 = 90$, $w_2 = 85$, $w_3 = 80$, $w_4 = 75$, $w_5 = 70$, from out of 100.

$$Min\ \ Z_1' = \sum_{s=1}^{S}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{h=1}^{H} a_{sph} y_{spih} \tag{1}$$

$$Min\ \ Z_2' = \sum_{s=1}^{S}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{h=1}^{H} \left(Pi_{sph} + g_{spi}\right) x_{spih} \tag{2}$$

$$Min\ \ Z_3' = \sum_{s=1}^{S}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{h=1}^{H} q_{sp}x_{spih} \tag{3}$$

$$Min\ \ Z_4' = \sum_{s=1}^{S}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{h=1}^{H} t_{sp}x_{spih} \tag{4}$$

$$Min\ \ Z_5' = \sum_{i=1}^{I}\sum_{h=1}^{H} H_{ih}z_{ih} \tag{5}$$

$$Max\ \ Z_6' = \sum_{s=1}^{S}\sum_{p=1}^{P}\sum_{i=1}^{I}\sum_{h=1}^{H} w_{sh}x_{spih} \tag{6}$$

subject to

$$D_{ph} + Ze_{ph} = \sum_{s=1}^{S}\sum_{i=1}^{I} x_{spih} \qquad \forall\, p,h \tag{7}$$

$$\sum_{s=1}^{S}\sum_{i=1}^{I} q_{sp}\, x_{spih} \leq\ Q_p'\, D_{ph} \qquad \forall\, p,h \tag{8}$$

$$\sum_{s=1}^{S}\sum_{i=1}^{I} t_{sp}\, x_{spih} \leq\ T_p' D_{ph} \qquad \forall\, p,h \tag{9}$$

$$\sum_{i=1}^{I} x_{spih} \leq C_{sph} \quad \forall\, p,s,h \tag{10}$$

$$x_{spih} \leq\ M\, y_{spih} \quad \forall\, p,h,s,i \tag{11}$$

$$\sum_{s=1}^{S}\sum_{p=1}^{P} y_{spih} \leq M\, z_{ih} \qquad \forall\, i,h \tag{12}$$

$$\sum_{i=1}^{I} z_{ih} \leq n \qquad \forall\, h \tag{13}$$

$$\sum_{p=1}^{P}\sum_{s=1}^{S} x_{spih} + M(z_{ih} - 1) \leq MaxC_{ih} \ \ \forall\, i,h \tag{14}$$

$$\sum_{i=1}^{I} y_{spih} \leq\ \ M\, b_{sph} \qquad \forall\, p,h,s \tag{15}$$

$$\sum_{i=1}^{I} H_{ih}z_{ih} \leq MH_{ih} \qquad \forall\, h \tag{16}$$

$$x_{spih}, Ze_{ph} \in \{0,1,2,3,\ldots.\}\ \ and \quad y_{spih}\,, z_{ih} \in \{0,1\} \qquad \forall\, p,h,s,i \tag{17}$$

Constraint (7) ensures that the supply network meets the demand for each product type. Constraint (8) satisfies that total rejected units of each product type are less than the allowed maximum level whereas constraint (9) ensures that total late delivered units of each product are less than the permitted maximum level. Constraints (8) and (9) impose upper bounds for the amount of returned products and total late delivered units for each supplier. Constraint (10) indicates that the order quantity of each product type ordered from a supplier cannot exceed the supplier's capacity. Constraint (11) shows the logical relationship between the decision variables. Constraint (12) satisfies that the products can only be sent to active facilities. Constraint (13) imposes the upper bound for the maximum number of production facilities. By constraint (14), the total capacity of the production facilities is considered. According to the definition of the problem, for instance in factoryless manufacturing, by identifying the candidate production sites, these facilities are practically active for a certain amount of capacities, where their capacities may change over time and their empty capacities can be utilised by any facilities. Constraint (15) is defined to ensure that the order of product *p* is assigned to supplier *s* within the period *h*, only if the corresponding supplier produces that product in the corresponding period. Because the company has a budget constraint, (16) considers the budget ceiling to activate a production facility at each period. Finally, (17) shows the decision variables of the model.

4. Solution Method

As mentioned previously, the objective functions, Z_1', Z_2' and Z_5' are related to each other. Therefore, these three objectives are merged (Z_1' + Z_2' + Z_5') and they are considered as the economic objective function of the problem to be minimised. The objectives Z_3' and Z_4' are the number of returned products and the number of late deliveries, respectively. Hence, RT is defined to be the sum of $Z_3' + Z_4'$ to be minimised. Finally, Z_6' is the total supplier score and it is considered as the third objective function to be maximised. As a result, three-objective functions are proposed and solved by using the Lp-metric method based on the distances mentioned above ($p = 1, 2, \infty$). Because of the complexity and large-scale size of the problem, we use Multi-Objective Particle Swarm Optimisation (MOPSO) and Multi-Objective Vibration Damping Optimisation (MOVDO) methods to solve the proposed model.

4.1. Multi-objective optimisation and Lp-metric method

In some cases, the optimal value of those multi-objectives $i = 1, 2, \ldots, n$ may exist. For instance, let us assume that it is equal to f_i^*. In reality, in most multi-objective decision-making (MODM) problems, due to the conflict between the objectives, there is usually no exact answer $x^* \in X$ that is optimal for all objectives ($\nexists\, x^* \in X$: $f_i^* = f_i^*(x^*)$). For instance, if *A* is a solution method and the answer x^A is an output, then *A* is more efficient when $f_i\,(x^A)$ has less distance from f_i^*. In other words, based on the Mean Ideal

Distance (MID), if the solution $F^* = (f_1^*, f_2^*, ..., f_n^*)$ is considered as the ideal solution, the closer the solution $F^A = (f_1(x^A), f_2(x^A), ..., f_n(x^A)))$ is to $F*$, the better the performance of method *A* is, and its solution is more appropriate. The distance between F^A and F^* is defined as the basis of the Lp-metric method in the definition. If the objectives have different degrees of importance, the distance is defined by (18) as norm *p*. The less the value of $|F^* - F^A|_p$ is, the more valuable method *A* is.

$$Norm_p(F^*, F^A) = |F^* - F^A|_p = \left(\sum_{i=1}^{n} w_i\big(f_i^* - f_i(x^A)\big)^p\right)^{\frac{1}{p}} \tag{18}$$

w_i indicates the weight or relative importance of each objective, usually determined by the decision-maker. In the Lp-metric method, for some of the *p*'s, the known models are obtained:

- In the Lp-metric method, if $p = 1$, a linear model known as the Weighted Sum Method (WSM) is obtained by (19).

$$|F^* - F^A|_{p=1} = \sum_{i=1}^{n} w_i(f_i(x^A) - f_i^*) \tag{19}$$

- In the Lp-metric method, if $p = 2$ the Euclidean distance is obtained by considering (20). Finally, a convex quadratic model is obtained which has a globally optimal solution. Note that the distance for $p = 2$ emphasises more on the deviation of each objective from its optimal value compared to $p = 1$.

$$|F^* - F^A|_{p=2}^2 = \sum_{i=1}^{n} w_i\big(f_i^* - f_i(x^A)\big)^2 \tag{20}$$

- Another important distance measure is obtained with $p \to \infty$. This case results in (21), which shows the maximum deviation from the optimal value across the objectives. In other words, this model is called the Minimax model showing that the greatest deviation from the optimal value for all objectives is minimised. Although this case provides the least deviation from the optimal value across the objectives, the sum of deviations is usually more than that of the two previous cases.

$$|F^* - F^A|_{p=\infty} = max\{\, i\ |w_i(f_i(x^A) - f_i^*)\} \tag{21}$$

In this study, we utilise the Lp-metric method with all three values $p = 1$, $p = 2$, and $p \to \infty$ to solve the defined MODM problem.

4.2. Multi-Objective Particle Swarm Optimisation Algorithm

The MOPSO algorithm is proposed by Coello and Lechuga (2002) and generalises the particle swarm optimisation (PSO) algorithm to solve multi-objective problems. This algorithm is a population-based stochastic optimisation algorithm based on the group movement rules of birds and fishes. In that group movement, each particle tries to create a distance from other particles and improve it gradually. The main difference between the MOPSO and the PSO is based on the choice of the best particle in the population and the best personal memory of each particle as well as the concept of the archive or repository. There is no reservoir in PSO. Namely, there are only one objective and one particle, which are the best ones. However, in MOPSO, a few particles are non-dominated, and they belong to the solution set. In the MOPSO algorithm, first, the initial population is created, and the initial value of the speed vectors and particle locations are determined (i.e., the particle speed vector is set to the zero vector, and the location vector is randomly generated). Then, cost functions for particles are calculated, and non-dominated members of the population are found that are saved in the archive. In the next stage, some super-cubes in the objective space are produced, and the particles are placed in these super-cubes. Finally, each particle selects a leader from the archive randomly and moves towards it. Like a single-objective PSO, the motion of each particle requires updating the speed and the particle position. However, the concept is exceptional in that the best particle in the total population and the best personal memories of each particle are different from those of single-objective mode.

4.3. Multi-Objective Vibration Damping Optimisation (MOVDO) Algorithm

MOVDO is one of the meta-heuristic algorithms developed by the use of the vibration damping concept in vibration theory. The vibration damping optimisation algorithm was first proposed by Mehdizadeh and Tavakkoli-Moghaddam (2008) and is derived from the damping mechanical vibration process. There is a proper and useful relationship between vibration that is the behaviour of the oscillator system in the damping mode and hybrid optimisation (finding the minimum of a given function with a large number of parameters). When the energy source of an oscillator is cut off, the oscillation range is decreased and interrupted, gradually (e.g., it is damped). MOVDO algorithm produces a solution and uses the rules of probability based on neighbourhood search in each iteration based on the nature of objects having elastic properties.

After developing a vibration-damping optimisation algorithm, to solve multi-objective optimisation problems, a new version of this algorithm, MOVDO, was introduced by Hajipour et al. (2014). The

MOVDO algorithm includes two important concepts, Fast Non-Dominated Sorting (FNDS) and Crowding Distance (CD). *R* individuals belong to initial populations and they are compared and categorised in FNDS. For this purpose, primarily all chromosomes from the first non-dominated front are found. It is assumed that all objective functions are minimisation type, and chromosomes are chosen by using the concept of domination. Then, by finding chromosomes in the next non-dominated front, the previous front solutions are disregarded temporarily. This process is repeated until all solutions are set into fronts. After individual classification, a CD measure is defined to evaluate population solutions in terms of the relative density of individual solutions (Deb et al., 2002). The tournament is applied to select the results of progeny. For this purpose, *n* individuals are selected from the population, randomly. The non-dominated rank of each individual is obtained. Then, CD solutions are calculated for the same non-dominated grade. The lowest-ranked solutions are selected. Moreover, if more than one case shares the least rank, the highest CD should be selected.

By using the aforementioned concepts and operations, the population of parents and progenies should be combined to ensure elitism. Where the combined population is naturally greater than the original *N*, another non-domination sorting is performed again. Higher rank chromosomes are selected and added to the populations until reaching the size *N*. The last front is also included in the population-based on crowding distance. The algorithm stops when a predetermined number of iterations, computational time (or any stopping criterion) is reached and feasible solutions obtained in Pareto front.

By initialising the preliminary population of the solution vectors, P_j, the process starts. Later, new operators are implemented on P_j to make a novel population, Q_j. The combination of P_j and Q_j result in R_j to maintain elitism in the algorithm. In this stage, R_j vectors are sorted in several fronts based on FNDS and CD. Applying the proposed selection method, the next iteration P_{j+1} population is selected to have a predetermined size. The evolution process of the MOVDO algorithm is summarised in Figure 1.

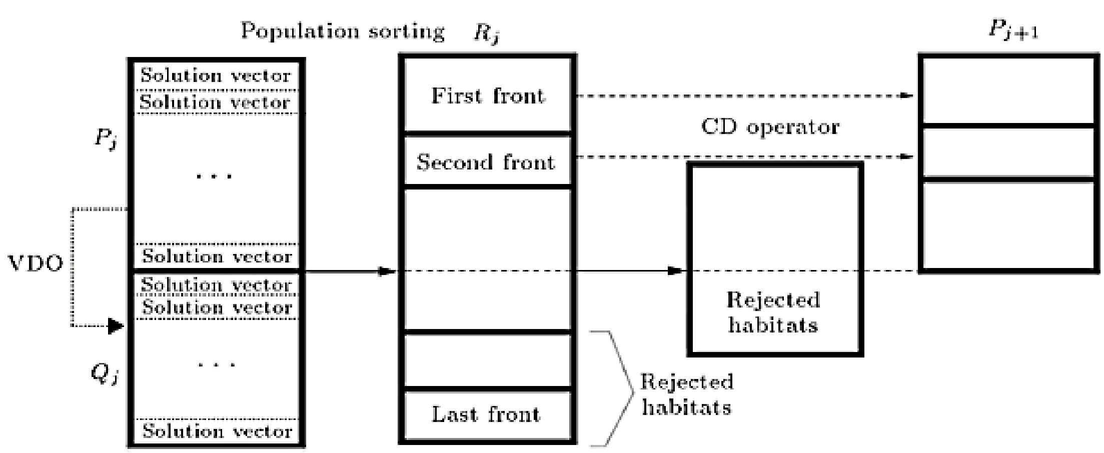

Figure 1. The evolution process of the MOVDO algorithm (Hajipour et al. 2016)

4.4. The Proposed MOPSO and MOVDO algorithms

In the two previous sections, we present a general description of the MOPSO and MOVDO algorithms to solve an MODM problem. In this section, to solve the MODM problem defined in Section 4, we explain the usage of these two algorithms simultaneously. For this purpose, first, we aim to present the representation of the solution. Second, we explain the update process of the solutions based on neighbourhood functions as well as the general process of the algorithm. Third, we explain the conducted experimental design. Fourth, we discuss the evaluation functions and finally we describe the stopping condition.

A) Representation of the solution: The representation of the solution (i.e., location of production facilities at each period) has I*H dimensions and its row entries are defined by random numbers 0 or 1. An example of this matrix is shown in Table 5 when $I = 2$ and $H = 3$. This matrix is used to determine which sites are to be candidates for activating production facilities in each period. The second part of the representation of the solution (i.e., product flow from supplier to an activated facility) has P*I rows and H*S columns. This matrix is shown in Table 6 when $I = 2$ and $S = 2$ and $H = 3$ and $P = 2$. It is used to show the flow of product p from the supplier s to the activated site I at period h for product P. Hence, each entry of this matrix is either the value of 0 or $D_{ph} + Ze_{ph}$. Note that, in this matrix, the flow rate from all suppliers to all activated facilities at each period will be equal to $D_{ph} + Ze_{ph}$. This point is considered for producing the initial solution.

Table 5. A sample of the solution matrix (Location of production facilities in each period)

	H_1	H_2	H_3
I_1	1	1	0
I_2	0	0	1

Table 6. The sample of the solution matrix (Products flow from suppliers to activated facilities)

		H_1		H_2		H_3	
		S_1	S_2	S_1	S_2	S_1	S_2
P_1	I_1	10	12	12	9/5	0	0
	I_2	0	0	0	0	1/5	33/5
P_2	I_1	22	20	11/5	28/5	0	0
	I_2	0	0	0	0	12	18

According to Table 6, during period 1, the flow rates from suppliers 1 and 2 to facility 1 for Product 1 are 10 and 12, respectively. Note that no production facility is activated in candidate site 2 during period 1 since the entry is zero. Thus, no product is sent by any supplier to site 2, in period 1.

B) Neighbourhood structure (update the solution):

Neighbourhood structure of the MOPSO algorithm: In this structure, a certain percentage of two parts of the representation solution is selected randomly. Then, the previous ones are replaced by the newly and randomly generated values. This structure is based on the following relationships (i.e., movement of each particle towards the leader selected from the archive). First, the speed of each particle is updated by (22).

$$v_i^{t+1} = wv_i^t + c_1r_1\left(Pbest_i^t - x_i^t\right) + c_2r_2\left(gbest_i^t - x_i^t\right) \tag{22}$$

Then, the location of each particle is updated by (23), which is a new solution.

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{23}$$

C) Design of experiment (DOE):

Experimental design or design of experiment (DOE) is a design tool analysing the relation between independent (i.e., parameters) and dependent (i.e., outputs) variables in order to identify the significant factors affecting the dependent variables. By utilising the DOE method, the level of parameters/factors influencing the result of a process can be adjusted optimally (or at least close to optimal).

D) Evaluation function in solution algorithms:

In the proposed MOPSO and MOVDO algorithms, the evaluation function is the same as the objective function. However, a penalty method is used for capacity constraints of non-renewable resources. Penalty methods are special classes of algorithms used to solve constrained optimisation problems. In the penalty method, a constrained optimisation problem is changed to a set of unconstrained problems. An unconstrained problem is created by adding a condition to an objective function consisting of a penalty parameter and a degree of violation of conditions and constraints. If a constraint is violated, the violation rate turns out to be non-zero; otherwise, it is zero.

E) Stopping criterion in MOPSO and MOVDO algorithms:

Various criteria can be considered to stop the algorithm. One of them could be that the algorithm is stopped when the result cannot be improved anymore after a certain number of iterations. Another one could be that the fitness average of the solutions in the current population is the same as the fitness of the best solution (or very close to it), then the algorithm is stopped. Another example for stopping conditions is assigning a limit on the number of iterations (e.g., the most widely used stopping criterion). In the proposed MOPSO and MOVDO method, a limit on the number of iterations is considered as the stopping criterion. Since, the computational time of the algorithm is also an important issue in reaching the optimal solution, in the proposed MOPSO and MOVDO algorithms, the computational time limit is considered as the stopping criterion.

5. Computational Results

In this study, to test the performance of the proposed models, we utilise previous studies' cases. We generate ten cases for small, medium and large-scale numerical problems. The small and medium-size problems are solved by the GAMS software by considering the Lp-metric method, MOPSO, and MOVDO meta-heuristic algorithms. Due to the size and complexity of the problem, we apply the proposed meta-heuristic algorithms to solve the large-scale instances.

To generate random data and parameters for numerical problems, appropriate domains from uniform and Bernoulli distributions are considered by using the DOE method. Remember that DOE deals with the determination of a relationship between factors affecting an output of a process. The primary purpose is to find the cause-and-effect relationships between the process inputs and outputs. Table 7 shows the framework for data and parameters with their descriptions. Later, the data are randomly picked from the corresponding interval. Tables 8 and 9 show the studied parameter values generated randomly. For instance, a schematic representation of the network for sample problem No 4 from Table 8 is shown in Figure 2. In the next section, sensitivity analysis is performed to examine the impact of model parameters on the optimal solution.

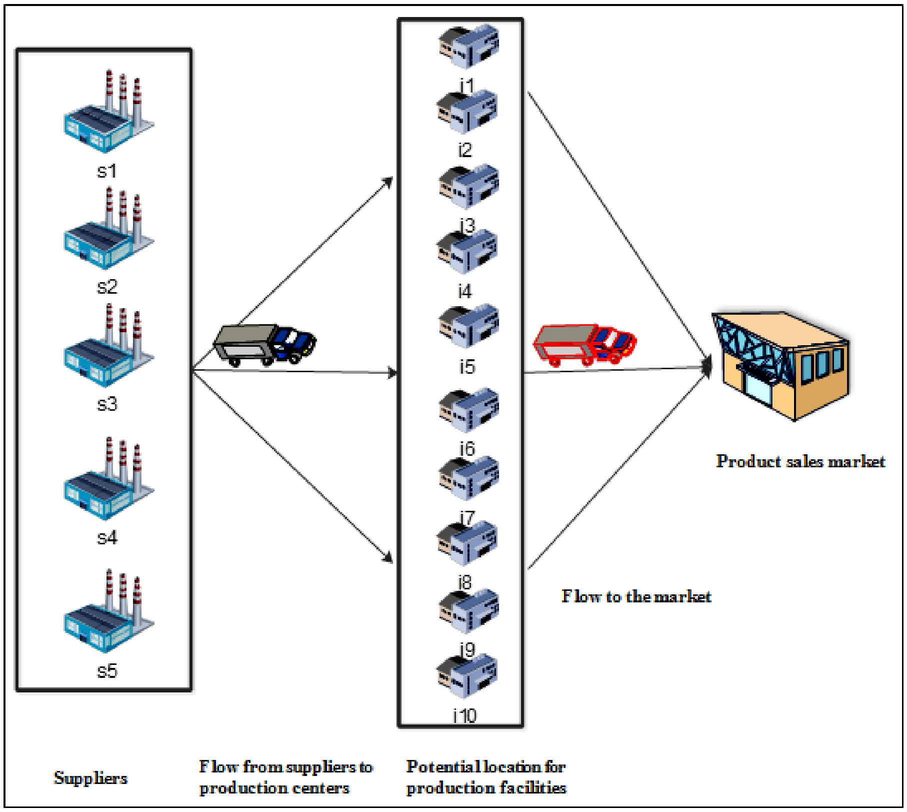

Figure 2. Product supply network in sample problem number 4

Table 7. The random generation framework and parameters		
Parameter	Generation method	Description
Pi_{sph}	$uniform(10,30)$	---
g_{spi}	$uniform(1,5)$	---
w_{sh}	$uniform(0,100)$	---
q_{sp}	$uniform(0,0.1)$	A maximum of 10% of the products may be defective.
t_{sp}	$uniform(0,0.2)$	A maximum of 20% of products may be delivered with a delay.
D_{ph}	$uniform(500,1000)$	The capacity of facilities depends on the defined demand.
C_{sph}	$\frac{uniform(1,2)D_{ph}}{\lvert S\rvert}$	Based on products demand and the total number of suppliers
a_{sph}	$uniform(1000,1500)$	---
H_{ih}	$uniform(1000,2000)$	The network development budget depends on the fixed cost of activating each facility.
b_{sph}	$ber(0.8)$	In each period, a flow can be created from any supplier to the facilities with a probability of 0.8. For simplicity, this parameter is set to 1.
$MaxC_{ih}$	$\frac{uniform(1,2)\sum_p D_{ph}}{\lvert I\rvert}$	Based on product demand and the total number of potential facilities

MH_{ih}	$\lvert I \rvert uniform(1000{,}2000)$	In problems with an increase in the number of potential sites, we increase the budget so that we can develop the network.

Table 8. The dimensions of the small and medium numerical problems

Sample problem No.	Number of suppliers	Number of potential sites	Planning periods	Number of products
1	2	4	2	2
2	3	5	2	3
3	4	7	3	3
4	5	10	4	4
5	6	12	4	4
6	10	15	4	4
7	12	18	5	5
8	13	20	5	5
9	14	22	5	5
10	15	25	5	5

Table 9. The dimensions of the large numerical problems

Sample problem No.	Number of suppliers	Number of potential sites	Planning periods	Number of products
1	20	30	6	6
2	22	35	6	7
3	24	35	7	8
4	24	40	7	9
5	26	40	8	9
6	26	45	8	9
7	29	45	8	10
8	29	50	10	10
9	30	50	12	10
10	35	50	12	10

To solve the problem, we utilise the CPLEX Solver of GAMS software version 25.1.2. The Lp-metric method guarantees the global optimal solution of the problem in small-scale cases. MOPSO and MOVDO meta-heuristic algorithms are coded in MATLAB software version R 2017b for solving large-scale problems. To run those codes of GAMS and MATLAB, a personal computer with a 5-core CPU and 6 GB RAM has been used. To evaluate the MODM solutions, Pareto optimal solutions had less diversion of objectives from their optimal state and the solutions that are non-dominated are produced. For that, the following four indicators are presented to evaluate the performance of the multi-objective meta-heuristic algorithms. These indicators are:

5.1 Cover Surface Criterion (CS)

In this criterion, the number of non-dominated solutions of each method is compared to that of the other method. For instance, when there are two solution methods, *A* and *B*, for a MODM problem in which *F*(*A*) denotes the Pareto front of the method *A*, and *F*(*B*) represents the Pareto front of *B*, for each $pa \in F(A)$ and $pb \in F(B)$, the domination of *pb* by *pa* is represented as pa*Dom*pb (Coello et al., 2007). By using those definitions, the *CS* criterion to compare the two solution methods, *A* and *B,* is expressed by (24).

$$CS(A,B) = \frac{||\{pb \in F(B)|\exists\ pb \in F(A): pa\ Dom\ pb\}||}{||F(B)||} \tag{24}$$

CS(*A*, *B*) shows the proportion of total Pareto solutions of method *B* in which at least one of the Pareto solutions of method *A* dominates. It is clear that $0 \leq CS\ (A,\ B) \leq 1$. If *CS (A, B)* is close to 0, method *B* would have a better performance, and most of its solutions would be efficient. However, if *CS (A, B)* is close to 1, method *A* would have a better performance, and most of its solutions would be inefficient. The smaller the *CS(A, B)* is, the better the performance of method *B* is.

5.2 Mean Ideal Distance (*MID*) criterion

This criterion is one of the most important criteria to evaluate MODM solution methods. It represents the average deviation of the Pareto solutions from the ideal solution. The ideal solution shown by the I_{sol} is a point whose components are the optimal values of the objectives (I_{sol}=(min(z_1), min (z_2))). In the minimisation problems, we can consider the origin as the ideal solution (I_{sol}=(0,0)). If *F*(*A*) represents the Pareto front of the solution method *A*, then the *MID* criterion is calculated by (25) (Behnamian et al., 2009).

$$MID\ (A) = \frac{\sum_{pa \epsilon F(A)} ||pa - I_{sol}||_2}{||F(A)||} \tag{25}$$

where $||I_{sol} - pa||_2$ represents the Euclidean distance of $pa \in F(A)$ from the ideal solution. Clearly, the smaller *MID* is more desirable.

5.3 Number of Solutions (*NOS*) or quantity of solutions

This criterion shows the number of Pareto solutions. A higher *NOS* value is desirable. For each solution method *A*, *NOS(A)*= |*F(A)*| (Zitzler, 1999). Although this criterion may be useful to measure the diversity of the solutions, it does not show the quality of the solutions. This weakness is resolved in the next proposed criterion.

5.4 Number of Solutions Cover Surface (*NS_CS)* or quality of solutions

One of the weaknesses of the *NOS* criterion is when *NOS(B)* > *NOS(A)*, while *CS(A, B)* has a large value. In this case, although most of the solutions of method *B* are dominated by the solutions of method *A*, a better situation is reported for method *B* by the NOS criterion. To overcome this weakness, we propose the following criterion by (26).

$$NS\_CS\ (A, B) = [NOS\ (B)(1- CS\ (A, B))] \tag{26}$$

NS_ CS (*A*, *B*) shows the number of Pareto solutions of method *B* that are not dominated by the solutions of method *A*. Clearly, the higher value of this criterion means that method *B* performs better than *A*.

The proper performance of each metaheuristic algorithm is significantly affected by the values of the parameters set up. The main parameters of the MOPSO algorithm include coefficients w, c_1, c_2 and number of population. The parameter w is called the inertia coefficient and expresses the tendency of the particle to maintain its original motion. Parameters c_1 and c_2 are individual and collective learning coefficients. These parameters determine the extent to which the available answer moves towards the best answers found in the population. Also, MOVDO includes parameters like number of populations, damping coefficient (γ), initial amplitude (A_0), maximum iteration at each amplitude (L), and standard deviation (σ).

We follow those steps in DOE application: design of experiments, perform experiments, analysis of results and validation of experiments. After defining the parameters, first, the order of experiments and the number of their replications are determined. In the second step, according to the selected order, the experiments are performed and the system response is measured. It should be noted that, in order to reduce possible errors, random selection for the test numbers as well as repetition is important. In the third step, the factors' main effects as well their interactions are determined separately. In the last step, additional tests are performed to validate the findings and repeat the tests to confirm the results.

In the proposed meta-heuristic algorithms, parameter setting up plays an important role. The Taguchi method is one of the fractional factorial experiments used in DOE for setting up the parameters (controlling the optimal level of the factors). In the Taguchi method, the factors affecting the results are divided into two: uncontrollable (called noisy factors, *N*) and controllable (the signal *S*). Then, the *S*/*N* ratio is defined to maximise it. Namely, while performing the proposed set of experiments in the Taguchi method, in order to determine the optimal level of each factor, the *S*/*N* ratio is first evaluated. Factor levels providing larger *S*/*N* values than others are considered to be the optimal levels. However, if there is no significant difference between the ratios, then the second evaluation criterion, which is the runtime of the algorithm, is considered. Table 10 shows the parameter values set in the Taguchi method to solve the problems by MOPSO and MOVDO algorithms.

Table 10. Parameter values for MOPSO and MOVDO algorithms

Problem size	*MOPSO*				*MOVDO*				
	pop	***w***	c_1	c_2	***pop***	A_0	γ	σ	***L***
Small and medium	150	0.5	1	2	180	6	0.5	1.5	10
Large	200	0.5	0.85	2.5	250	9	0.4	1.6	12

After setting the parameters of the proposed algorithms, in the Lp-metric method (of all three norm *p = 1,2, inf*), *N = 100* different weights that are produced randomly and implemented. By observing the average output results, Pareto solutions are obtained. Remember that we define, small, medium and large size numerical problems and solve them by the proposed solution methods. Results are analysed based on the defined criteria. The comparison between the performance and response level of MOPSO and MOVDO algorithms and the Lp-metric method in the small and medium-scale problems is shown in Tables 11 and 12.

Table 11. Evaluation of MOPSO in comparison with Lp-metric method in small and medium numerical problems

Sample problem No.	*CS* (Lp, MOPSO)	*MID* (Lp)	*MID* (MOPSO)	*NOS* (Lp)	*NOS* (MOPSO)	*NS_CS* (Lp, MOPSO)
1	0	150/83	151/14	4	4	4
2	0	134/60	135/07	4	4	4
3	0.33	221/89	204/11	5	6	4
4	0	304/05	288/04	7	8	8
5	0.20	278/51	276/12	11	10	8
6	0	351/43	391/19	13	13	13
7	0.14	400/85	431/22	16	14	12
8	0.07	531/15	495/27	17	15	14
9	0	560/13	560/02	17	15	15
10	0	587/42	605/09	19	17	17

Table 12. Evaluation of MOVDO in comparison with Lp-metric method in small and medium numerical problems

Sample problem No.	*CS* (Lp, MOVDO)	*MID* (Lp)	*MID* (MOVDO)	*NOS* (Lp)	*NOS* (MOVDO)	*NS_CS* (Lp, MOVDO)
1	0	150.83	133/15	4	4	4
2	0	134.60	135/07	4	4	4
3	0	221.89	202/07	5	5	5
4	0.10	304.05	281/31	7	8	7
5	0.20	278.51	272/43	11	10	8
6	0	351.43	391/18	13	13	13
7	0.20	400.85	404/61	16	14	12
8	0.07	531.15	481/49	17	15	14
9	0	560.13	560/02	17	17	17
10	0	587.42	659/74	19	17	17

In order to validate the proposed models, one of the sample problems (i.e., Design No. 4 in Table 8) is examined. Figure 3 shows the Pareto front diagram of the proposed meta-heuristic algorithm results by comparing the method results with each other and with the three selected Lp metric solutions. The results show that the proposed meta-heuristic algorithms to solve the numerical models are providing acceptable performance (Figure 3). Both algorithms resulted in a diverse number of Pareto solutions and the quality of the results are generally good because both methods provide small errors. However, for the three selected solutions of the exact Lp metric method, the performance of the MOVDO is better than the MOPSO because that MOVDO's deviations are less than MOPSO's method. Because it is hard to solve large-scale problems, the proposed algorithms can be used for such problems. Note that, according to the obtained values, the Pareto fronts in both meta-heuristic algorithms are close to the global front (front of the Lp-metric method) in small and medium-scale problems. Although in these problems, the diversity and quality of the proposed meta-heuristic algorithms are acceptable, the MOVDO algorithm has better results than MOPSO regarding the *MID* criteria. Table 13 presents the results of large-scale problems solved by the proposed algorithms. The results show that each meta-heuristic method can solve large-scale problems in a reasonable time and obtain a set of Pareto solutions, in contrast to the exact LP-metric method. The results indicate that the MOPSO algorithm solves the problem faster than the others. This algorithm usually has a good state in terms of the qualitative criteria, such as the number of Pareto solutions. Although the MOVDO algorithm solves the problem in a longer time than MOPSO, the quality of its solutions (especially in terms of *MID* and the Number of Solutions Cover Surface) are better than that of the MOPSO algorithm. These are shown in Figures 4 and 5, respectively. For example, as shown in the results of the sample problem (4) in Table 13, the values of *MID* and *NOS*, for the MOVDO algorithm are 2855 and 25, respectively. Also, the corresponding values for the MOPSO algorithm are 3107 and 24, respectively. These results show the superiority of the MOVDO algorithm over the MOPSO algorithm in these two criteria in large-scale problems.

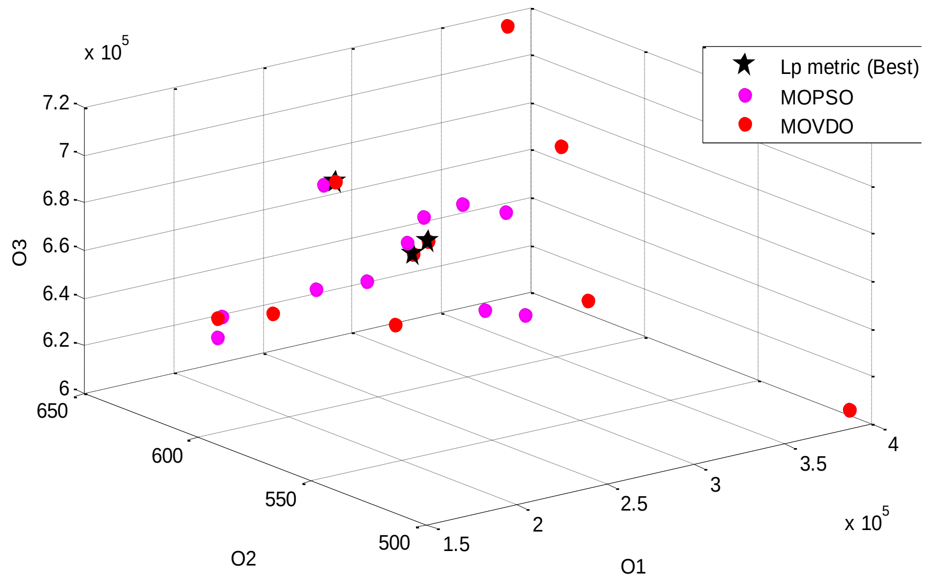

Figure 3. Pareto front diagram of MOVDO and MOPSO methods versus three selected answers in Lp metric method

Table 13. The performance of MOPSO and MOVDO in the large-scale problems

Sample problem No.	*CS* (MOPSO, MOVDO)	*MID* (MOPSO)	*MID* (MOVDO)	*NOS* (MOPSO)	*NOS* (MOVDO)	*NS_CS* (MOPSO, MOVDO)	*NS_CS* (MOVDO, MOPSO)	runtime (min)	
								MOPSO	**MOVDO**
1	0	1314	1075	20	17	18	17	36/15	30/21
2	0	1945	1401	17	15	15	14	44/59	41/37
3	0	2519	2077	25	22	23	23	51/72	57/09
4	0	3107	2855	30	25	25	24	74/81	82/52
5	0	5184	4622	22	15	15	14	90/62	92/45
6	0	7936	6814	27	20	20	17	101/27	125/58
7	0	8009	6063	35	28	29	22	142/41	155/19
8	0	9038	8102	27	23	24	20	179/32	193/42
9	0	10078	9819	40	32	33	30	205/77	225/65
10	0	20915	16842	45	40	40	35	301/59	336/24

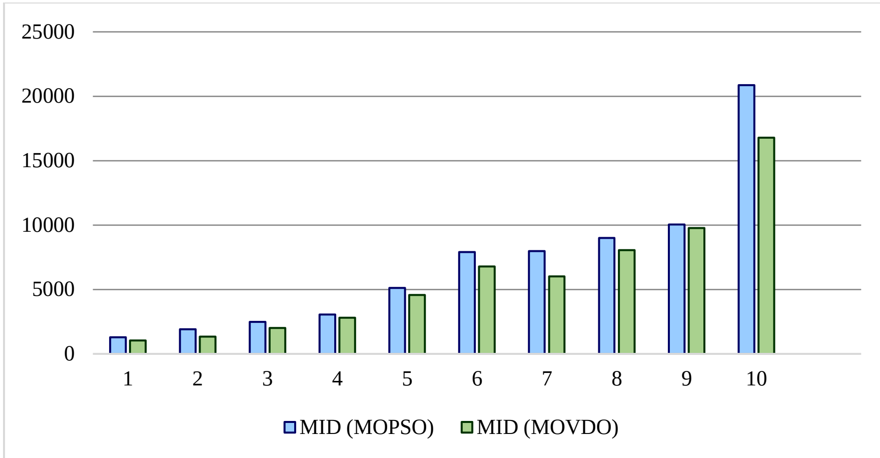

Figure 4. Comparison of the *MIDs* of MOPSO and MOVDO algorithms in large-scale problems

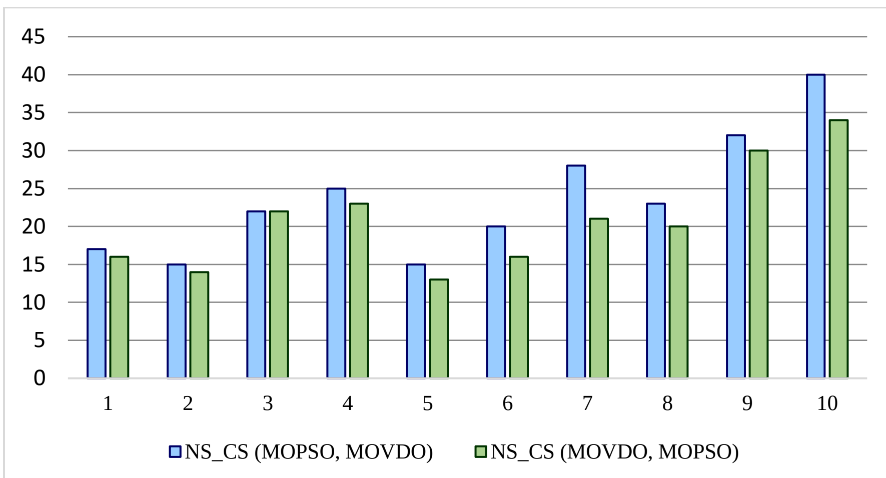

Figure 5. Comparison of non-dominated solutions of MOPSO and MOVDO algorithms in large-scale problems

5.5 Sensitivity Analysis

In this section, a sensitivity analysis is presented for some parameters. The results based on those are reported and explained. For this purpose, one of the sample numerical problems (i.e., design no. 4 of Table 8) is considered. The sensitivity analysis is performed on the fixed cost of facility activation and the capacity of facilities. To do a sensitivity analysis on the fixed cost of facilities activation, the data values of this parameter have been increased and decreased by 10%. It is observed that the length of the step is 2% for the changes.

Figure 6 shows the chart of variations in the objective functions with the changes applied. It is observed that increase in the fixed cost of facility activation causes total cost (i.e., the first objective function) to increase; the customer-orientation rate (i.e., the second objective function) to increase, and the value of product supply (i.e., the third objective value) to decrease. Conversely, if that fixed cost parameter decreases, then all those three objective values are improved. Namely, the first and second objectives would decrease while the third one would increase.

To perform a sensitivity analysis for the facility capacity parameter, the value of this parameter is increased and decreased by 10% in the sample problem. The length of the step is 2% for the changes. The results are shown in Figure 7. According to that, increasing the facility capacity improves the objective functions. However, when we decrease the capacity, it affects the objective function values negatively. From Figure 7, it is observed that facility capacity change does not always cause a change in the objective function values. For example, if capacity is reduced up to 4%, the optimal solution remains unchanged. Also, increasing the facility capacity does not necessarily improve the objective function values. In general, increasing the facility capacity causes the total cost (the first objective function) not to increase. Also, it does not cause any change in the customer orientation rate (the second objective function) and the value of products supplied (the third objective function). Conversely, in the case of the negative change in that parameter, the first and second objectives would be non-decreasing while the third one is non-increasing.

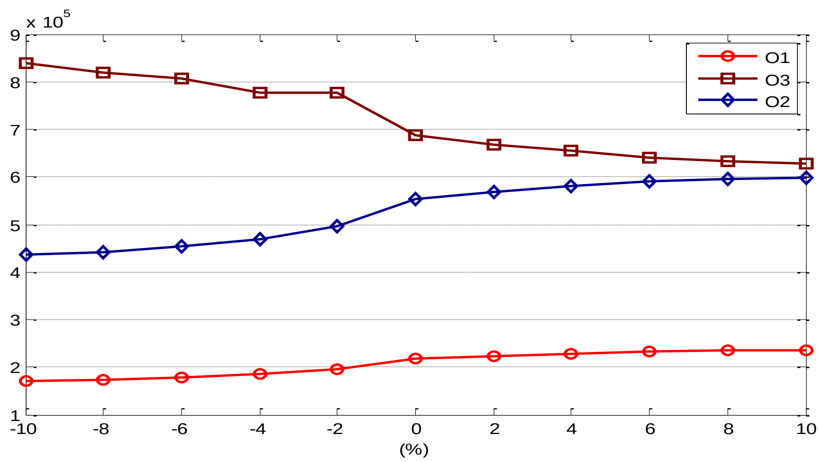

Figure 6. Sensitivity analysis on the fixed cost of facilities activation

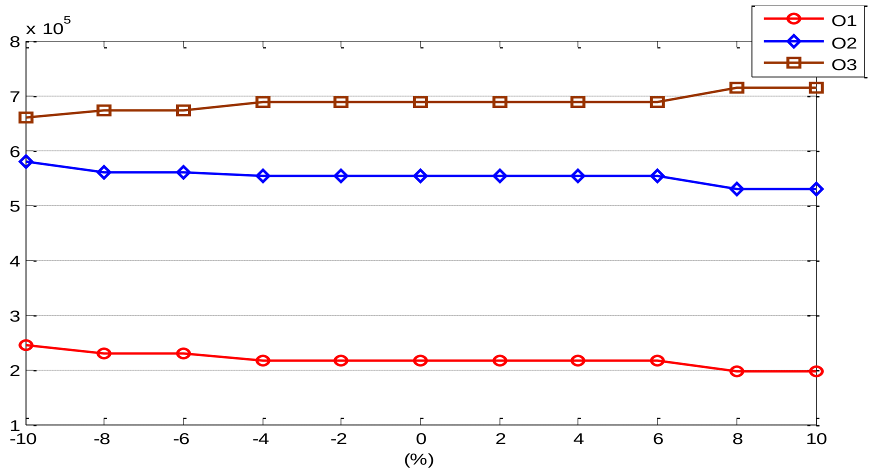

Figure 7. Sensitivity analysis of the facilities capacity

6. Conclusion

In this work, we study an integrated model for supplier selection and production facility location problems by motivating from a factoryless manufacturing problem in a multi-product supply chain network where non-activation of facilities is also allowed in a multi-horizon time period. Factoryless manufacturing is a strategy aiming to make better use of existing production facilities. One of the significant features of this method is decreased investment cost to produce a particular product. Therefore, in general, the product is produced at a lower cost. However, supply chain management issues may become complicated and require integrated models taking into consideration several parameters simultaneously.

In this paper, we study an integrated supply chain model involving production facilities location (i.e., identifying candidate points for production centres), the best supplier selection, order amount determination from each supplier, etc., decisions. We develop a multi-objective optimisation model for the solution of the problem where three objectives are defined. The objectives are defined to be the minimisation of the total cost (e.g., an economic objective), minimisation of the number of products delayed or defectively delivered (e.g., a customer-oriented objective increasing the network reliability), and maximisation of the total score of selected suppliers (e.g., the value of environmental considerations). Due to the NP-hard property of the problem, we utilise heuristic algorithms to solve the model. To evaluate the performance of the proposed meta-heuristic algorithms, several small and large-scale numerical problems are developed. We introduce several criteria for the performance validation of the methods that might be categorised into two categories based on quality and quantity. The results show that in small and medium-scale problems, the Lp-metric method performs better in terms of performance criteria. For large-scale problems, results show that the MOPSO algorithm solves the problem faster, and usually has a good state for parameters such as the number of Pareto solutions. Although the running time of the MOVDO algorithm is longer compared to that of the MOPSO algorithm, the quality of the solution is usually better than that of MOPSO, especially in terms of *MID* criterion and the Number of Solutions Cover Surface. After comparing the results, a sensitivity analysis is performed on parameters of one of the designed problems and the results are reported and explained.

This work is proposed to be an initial work for a multi-objective optimisation model in a two-echelon supply network whose objective functions include multi-objectives which are: minimisation of total network cost (i.e., maximisation of total profit), and maximisation of the total score of suppliers in the network, simultaneously. Furthermore, this is the first development of a model under a dynamic location problem concept as well as transaction value change policy under a multi-horizon time period in the network.

For further development of this research, one may focus specifically on inventory control models, including dynamic product pricing in different time periods as well as uncertainty for parameters. Safety stock levels can also be considered as separate decision variables. In addition, the use of uncertainty approaches such as robust optimisation and fuzzy or random planning, etc., can also be utilised in the modelling approach. Use of exact solution methods to solve large-scale problems such as parser-based methods (Benders' decomposition or Lagrangian algorithms), incorporating the competition of firms in the supply chain using Game theory approaches or using two-level planning models to apply the current research to real problems can also be some other future work suggestions.

References

Amin-Tahmasbi, H., Alfi, S., 2018. A fuzzy multi-criteria decision model for integrated suppliers selection and optimal order allocation in the green supply chain. Decision Science Letters 7, 549-566.

Arabzad, S. M., Ghorbani, M., Ranjbar, M. J., 2017. Fuzzy goal programming for linear facility location-allocation in a supply chain; The case of steel industry. International Journal of Research in Industrial Engineering 6, 90–105.

Arabzad, S.M., Ghorbani, M., Zolfani, S.H., 2015. A multi-objective robust optimization model for a facility location-allocation problem in a supply chain under uncertainty. Journal of Inzinerine Ekonomika-Engineering Economics 26, 227-238.

Atabaki, M.S., Mohammadi, M., Naderi, B., 2017. Hybrid genetic algorithm and invasive weed optimization via priority based encoding for location-allocation decisions in a three-stage supply chain. Asia-Pacific Journal of Operational Research 34, 44 pages.

Behnamian, J., Fatemi Ghomi, S.M.T., Zandieh, M., 2009. A multi-phase covering Pareto-optimal front method to multi-objective scheduling in a realistic hybrid flowshop using a hybrid metaheuristic. Expert Systems with Applications 36, 11057–11069.

Biajoli, F.L., Chaves, A.A., Lorena, L.A.N., 2019. A biased random-key genetic algorithm for the two-stage capacitated facility location problem. Computers & Industrial Engineering 115, 418-426.

Brahami, M.A., Dahane, M., Souier, M., Sahnoun, M., 2020. Sustainable capacitated facility location/network design problem: a Non-dominated Sorting Genetic Algorithm based multiobjective approach. Annals of Operations Research, 1-32.

Cheraghalipour, A., Farsad, S., 2018. A bi-objective sustainable supplier selection and order allocation considering quantity discounts under disruption risks: A case study in plastic industry. Computers & Industrial Engineering 118, 237-250.

Coello Coello, C.A., Lechuga, M.S., 2002. MOPSO : A proposal for multiple objective particle swarm optimization. In Proceedings of the 2002 Congress on Evolutionary Computation (CEC'2002), 02, 1051-1056.

Coello Coello, C.A., Van Veldhuizen, D.A., Lamont, G.B., 2007. Evolutionary Algorithms for Solving Multi-Objective Problems. Kluwer Academic Publishers, New York.

Correia, I., Melo, T., 2017. A multi-period facility location problem with modular capacity adjustments and flexible demand fulfillment. Computers & Industrial Engineering 110, 307-321.

Cortinhal, M.J., Lopes, M.J., Melo, M.T., 2019. A multi-stage supply chain network design problem with in-house production and partial product outsourcing. Applied Mathematical Modelling 70, 572-594.

Dai, Z., Aqlan, F., Zheng, X., Gao, K., 2018. A location-inventory supply chain network model using two heuristic algorithms for perishable products with fuzzy constraints. Computers & Industrial Engineering 119, 338-352.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm:NSGA-II. IEEE Transactions on Evolutionary Computation 6, 182-197.

Emirhüseyinoğlu, G., Ekici, A., 2019. Dynamic facility location with supplier selection under quantity discount. Computers & Industrial Engineering 134, 64-74.

Feng, B., Fan, Z.P., Li, Y., 2011. A decision method for supplier selection in multi-service outsourcing. International Journal of Production Economics 132, 240-250.

Hajipour, V., Mehdizadeh, E., Tavakkoli-Moghaddam, R., 2014. A novel pareto-based multi-objective vibration damping optimization algorithm to solve multi-objective optimization problems. Scientia Iranica, Transaction E: Industrial Engineering 21, 2368-2378.

Hajipour, V., ZanjiraniFarahani, R., Fattahi, P., 2016. Bi-objective vibration damping optimization for congested location–pricing problem. Computers & Operations Research 70, 87-100.

Hamdan, S., Cheaitou, A., 2017. Supplier selection and order allocation with green criteria: An MCDM and multi-objective optimization approach. Computers & Operations Research 81, 282-304.

Kang, H.Y., Lee, A.H.I., Yang, C.Y., 2012. A fuzzy ANP model for supplier selection as applied to IC packaging. Journal of Intelligent Manufacturing 23, 1477–1488.

Keshavarz Ghorabaee, M., Amiri, M., Zavadskas, E.K., Turskis, Z., Antucheviciene, J., 2017. A new multi-criteria model based on interval type-2 fuzzy sets and EDAS method for supplier evaluation and order allocation with environmental considerations. Computers & Industrial Engineering 112, 156-174.

Kilic, H.S., 2013. An integrated approach for supplier selection in multi-item/ multi-supplier environment. Applied Mathematical Modelling 37, 7752-7763.

Kim, T., Hong, Y., Lee, J., 2005. Joint economic production allocation and ordering policies in a supply chain consisting of multiple plants and a single retailer. International Journal of Production Research 43, 3619-3632.

Kubat, C., Yuce, B., 2012. A hybrid intelligent approach for supply chain management system. Journal of Intelligent Manufacturing 23, 1237–1244.

Lai, CH.M., Chiu, CH.CH., Liu, W.CH., Yeh, W.CH., 2019. A novel nondominated sorting simplified swarm optimization for multi-stage capacitated facility location problems with multiple quantitative and qualitative objectives. Applied Soft Computing 84, 105684.

Li, Y., Ding, K., Wang, L., Zheng, W., Peng, Z., Guo, S., 2018. An optimizing model for solving outsourcing supplier selecting problem based on particle swarm algorithm. Journal of Industrial and Production Engineering 35, 526-534.

Mehdizadeh, E., Tavakkoli-Moghaddam, R., 2008. Vibration Damping Optimization. Proc. of the Int. Conf. Operations Research - OR and Global Business, Germany, 3-5 September.

Melo, M.T., Nickel, S., Saldanha-Da-Gama, F., 2009. Facility location and supply chain management – A review. European Journal of Operational Research 196, 401-412.

Mirzaee, H., Naderi,B., Pasandideh, S.H.R., 2018. A preemptive fuzzy goal programming model for generalized supplier selection and order allocation with incremental discount. Computers & Industrial Engineering 122, 292-302.

Mohammed, A., 2020. Towards a sustainable assessment of suppliers: an integrated fuzzy TOPSIS-possibilistic multi-objective approach. Annals of Operations Research 293, 639-668.

Mohammed, A., Harris, I., Govindan, K., 2019. A hybrid MCDM-FMOO approach for sustainable supplier selection and order allocation. International Journal of Production Economics 217, 171-184.

Mousavi, S.M., Alikar, N., Akhavan Niaki, S.T., Bahreininejad, A., 2015. Optimizing a location allocation-inventory problem in a two-echelon supply chain network: A modified fruit fly optimization algorithm. Computers & Industrial Engineering 87, 543-560.

Nazemi, J., 2013. Strategies for factory less manufacturing. Journal of Industrial Management 7, 1-17.

Ranjbar Tezenji, F., Mohammadi, M., Pasandideh, S.H.R., Nouri Koupaei, M., 2016. An integrated model for supplier location-selection and order allocation under capacity constraints in an uncertain environment. Journal of Sharif University of Technology 23, 3009-3025.

Rohaninejad, M., Navidi, H., Vahedi Nouri, B., Kamranrad, R., 2017. A new approach to cooperative competition in facility location problems: Mathematical formulations and an approximation algorithm. Computers & Operations Research 83, 45–53.

Rohaninejad, M., Sahraeian, R., Tavakkoli-Moghaddam, R., 2018. An accelerated Benders decomposition algorithm for reliable facility location problems in multi-echelon networks. Computers & Industrial Engineering 124, 523-534.

Saidi-Mehrabad, M., Aazami, A., Goli, A., 2017. A location-allocation model in the multi –level supply chain with multi-objective evolutionary approach. Journal of Industrial and System Engineering 10, 140–160.

Seifbarghy, M., Esfandiari, N., 2013. Modeling and solving a multi-objective supplier quota allocation problem considering transaction costs. Journal of Intelligent Manufacturing 24, 201-209.

Seyed Haeri, S.A., Rezaei, J., 2019. A grey-based green supplier selection model for uncertain environments. Journal of Cleaner Production 221, 768-784.

Weng, Z.K., 1999. The power of coordination decisions for short life cycles products in a manufacturing and distribution supply chain. IIE Transactions 31, 1037–1049.

Yu, V.F., Normasari, N.M.E., Luong, H.T., 2015. Integrated location-production-distribution planning in a multiproducts supply chain network design model. Mathematical Problems in Engineering 13, 13 pages.

Zitzler, E., 1999. Evolutionary algorithms for multi-objective optimization: method and applications. Ph.D. Thesis, dissertation ETH NO. 13398, Swaziland Federal Institute of Technology Zorik