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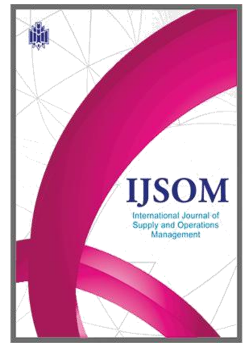

A Multi Echelon Location-Routing-Inventory Model for a Supply Chain Network: NSGA II and Multi-Objective Whale Optimization Algorithm

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Abstract

In this study, we aim to explore the modeling and solution approach for a multi-objective location-routing-inventory problem. The focus is on planned transportation with the goal of minimizing total costs and reducing the maximum working hours of drivers. To achieve these objectives, we need to consider the routing of vehicles between customers and distribution centers, as well as the optimal allocation of product transfer flow between the production center and customers. Therefore, the proposed model incorporates location, routing-inventory, and allocation simultaneously. To solve the two-objective model, we employed the Epsilon-constraint method for small-sized problems. For large-sized problems, we utilized the NSGA-II and MOWOA meta-heuristic algorithms with a new chromosome. The computational results indicate that in order to reduce the maximum working hours of drivers, it is necessary to increase the number of vehicles and minimize travel distances. However, this leads to higher costs due to vehicle utilization and the need for constructing distribution centers closer to customers, which in turn increases construction costs. Finally, based on the analysis, the NSGA-II algorithm outperformed the MOWOA algorithm with a weighted value of 0.983 compared to 0.016, making it the selected algorithm.

Keywords: Facility location; Vehicle Routing; Allocation; Inventory; Meta-heuristic Algorithm.

1. Introduction

Vehicle routing problem has been widely investigated over the past few decades with different developments and solutions because of its importance (Amiri et al. 2023, Seraji et al. 2022). Green vehicle routing is one of the areas recently attracting attention for routing, where the goal is to route the vehicles considering their environmental impacts and fuel consumption (Sar and Ghadimi, 2023). Green vehicle routing problems (GVRPs) are categorized into three general branches as routing with fuel consumption optimization, routing regarding the environmental pollution, and routing in logistics (Ahmadini et al. 2021, Seraji et al. 2019). In routing with fuel consumption optimization, a model termed as energy consumption minimization in vehicle routing problem has been introduced (AlArjani et al. 2021, Ghasemi et al. 2022). Govindan et al. (2023) presented a routing inventory problem for a closed loop supply chain, and considered a problem as nonlinear integer programing. Table 1 shows the summary of most prestigious papers published on vehicle routing problem.

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As depicted in Figure 1, in this research, the final customers require the product demands which should be supplied by the vehicles leaving the potential distribution centers. Moreover, commodity inventory would be managed in the distribution centers, and their required commodities would be supplied by the production centers. This way, in this research after the product being loaded in the production center, the vehicle fulfills the commodity delivery required by the distribution centers, and according to the plans, the products are distributed to the final customers as demanded. Therefore, two strategic decisions, i.e., the location of the production and distribution centers and tactical decision such as the vehicle routing and commodity inventory management are investigated in the present study. Because most literature relevant papers have stated cost objective function as their study objective function in their research cases. In addition to the objective function of minimizing the costs of locating, routing, and inventory, reducing the maximum working hours of drivers has also been addressed as a social aspect in the current study. The model examined in this study is illustrated in Figure 1. It involves different levels, starting with production centers as the first level, followed by distribution centers as the second level, and final customers as the last level. In this framework, the positioning of facilities in production and distribution centers, as well as inventory-routing, occurs at an intermediate level between the distribution centers and the customers.

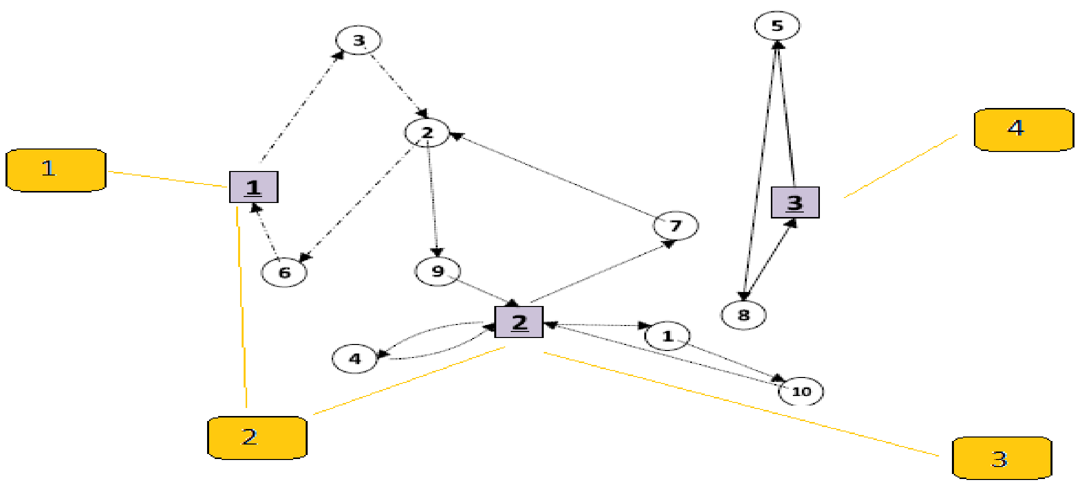

Figure 1. Schematic of the presented model

Thus, to timely deliver the products according to the hard window time makes some drivers take up more working hours compared to other drivers in terms of distributing the products, which brings about imbalances between the working hours of drivers and their fatigue. Consequently, taking this important aspect into account in the problem modeling makes the model approach the real-world location-routing and inventory problems. Ultimately, since the facility location models are NP-hard, it can be concluded that this problem is at least as hard as the facility location problem, and thus, the meta-heuristic algorithms have to be used for solving larger-sized problems. Complying with the literature on the routing-inventory problem, the researcher suggested employing Non-Dominated Sorting Genetic Algorithm (NSGA II) and Multi-Objective Whale Optimization Algorithm (MOWOA). To sum up, the study primary and secondary objectives can be summarized as the following.

The rest of the proposed research is organized into six sections. The second section presents the literature review. In the third section, the problem statement and mathematical model and the assumptions are given. The fourth section presents the solution methods for the proposed model. The fifth section illustrates the numerical results. The sixth section deals with the conclusions.

2. Literature review

Wei et al. (2020) got to survey an integrated location-routing problem using post-disaster relief distribution, where they developed a homogeneous rescue vehicles' allocation system employing some candidate depot locations for relief supplies delivery to the post-disaster regions. Mohammadi et al. (2020) presented their new model on multi objective reliable optimization used for a humanitarian relief chain management for plenty of decision-making cases, such as victim allocation, reliable facility location-allocation, truck routing, and evenly distributing relief items; the objective functions were the total relief operations time, the total logistics costs, and the upper and lower bounds of transportation cost minimization of distribution centers. Biuki et al. (2020) proposed a model as an integrated location, inventory, and routing problem as the key ones for a logistics system optimization by a two-phase method to incorporate the three sustainability dimensions into supply chain processes, where the study concurrently dealt with integrated decision-making on location, sustainability issue, inventory control planning, routing, and real-world assumptions employing two hybrid metaheuristics as parallel and series combinations of GA and PSO for solving the problem. Arani et al. (2020) studied blood banking and distribution in which "lateral resupply" of blood products is permitted through blood supply chain network design made up of four conventional levels: blood centers, donors, collection facilities, and hospitals given two significant features, i.e., ABO-Rh factors and blood products' shelf lives.

Ghasemi et al. (2021) outlined a novel simulation–oriented mathematical model to locate distribution centers, vehicle routing, and inventory problems for seismic circumstances. Their network consists of distribution centers, affected areas, hospitals, and suppliers. The fundamental city infrastructures being highly breakable when struck by a quake were detected plus combining the due demand was in the mathematical model. Pourmohammadi et al. (2021) suggested a novel MO optimization for the hub routing and location problem considering the uncertainty of costs, times, flows, and job opportunities targeting to boost the employment and regional development. In order to calculate the hub nodes' waiting time and increase the responsiveness, an M/M/c/K queue system was utilized. And to solve the problem, a robust evolutionary meta heuristic approach was designed on variable neighborhood search, and fuzzy invasive weed optimization. Rahbari et al. (2021) designed a mathematical model of an LIRP for managing the waste and dangerous materials at two levels of the SC regarding a heterogeneous vehicle fleet, which aimed to reduce the SC risk, its costs and lower greenhouse gas emissions. In addition, in order to solve the MO optimization problems known as MOBWO algorithm, a meta heuristic algorithm was utilized, the performance of which was compared with MOSA and NSGA II.

Khan et al. (2022) analyzed system reliability improvement, which brought up a couple of optimization techniques and analyses, targeted to transfer reliability problem into a BLPP in which the Kuhn Tucker approach was employed to solve the formulated BLPP. Safaei et al. (2022) applied a novel, multi-echelon multi-period closed-loop supply chain network, including customers, manufacturers, recycling and recovery units, suppliers, and distribution centers for minimizing the overall network cost. Moreover, a linear programming model was designed regarding factory vehicles and rental cars. Lin et al. (2022) developed a model of grid multi objective stochastic allocation for scooter BSS (MSASBSS) which produced several diverse BSD scenarios in order to solve the uncertain BSD problem based on MCS, SAA, and traffic flow. Moreover, the paper examined the BSS allocation optimization and the various BSD scenarios and the minimal construction cost of BSSs were met. Fahmy et al. (2022) formulated the problem regarding aggregation hubs through a SCNet as a facility location-allocation (FLA) decision, which is an NP-hard optimization problem in the form of an MILP to minimize the transportation, processing, spoilage, and capacity-based hub establishment costs. By the way, two hybrid algorithms on BPSO and SA combining a meta-heuristic with a perishability-modified transportation algorithm were presented. Li et al. (2022) presented an optimization model under uncertainty so that to reduce the cost, which integrated the important properties of the inventory control decisions and the location-allocation scheme under a periodic review order-up-to-S (T, S). Ma et al. (2022) developed an optimization model on multi-scenario supplemental location–allocation investigating the related concerns according to CLA and SLA scenarios through integrating MC evaluation and optimization comparison into location–allocation problems.

Momenitabar et al. (2023) presented an ML and quantitative optimization model so that to develop a SBSCN, where in order to predict the bioethanol demand, ML methods like Extreme Gradient Boosting Method (XGBoost), Random Forest (RF), and Ensemble learning algorithm (Bagging) were used. After that, a MILP was proposed to satisfy the study objective functions' sustainability criteria. Nasiri et al. (2023) designed SCNs through operational and strategic and decisions, raising the efficiency and cutting down the due costs. As known, when operational decisions like vehicle routing and strategic decisions like facility location get optimized, the network greenness is highly affected and concurrent disturbance management and P&D results in the network's sustainability.

Table 1. Reviewing the most prestigious papers published on vehicle routing

Author	Objective function	Certain/Uncertain	Multi-depot/Single - depot	Solution Method
Sethanan and Pitakaso, (2016)	- Minimizing transportation cost	Certain	Single-depot	DEA
Alinaghian, and Shokouhi, (2018)	- Reducing the number of vehicles and distance	Certain	Multi-depot	VNS
Polyakovskiy and M'Hallah, (2018)	- Minimizing total lateness	Certain	-	Heuristic
Li et al. (2019)	- Minimizing transportation and locating cost	Certain	Multi-depot	Firefly algorithm
Hadian et al. (2019)	- Minimizing cost - Minimizing distance	Certain	Multi-depot	MOICA
Spencer et al. (2019)	- Minimizing the number of boxes - Minimizing the average initial heat of each box - Minimizing the max transfer time of commodity to customer	Certain	-	Greedy algorithm
Guimarães et al. (2019)	- Minimizing cost	Certain	Multi-depot	Branch and cut algorithm
Zhang et al. (2019)	- Minimizing transfer time	Certain	Multi-depot	Ant Colony algorithm and annealing simulation
Arani et al. (2020)	- Minimizing transportation cost -	Uncertain	Single-depot	Scenario-based optimization
Sadati et al. (2020)	- Minimizing transportation and locating costs	Certain	Multi-depot	Firefly algorithm
Dell'Amico et al. (2020)	- Minimizing the number of boxes	Certain	-	Branch and price algorithm
Fu and Banerjee (2020)	- Minimizing the number of boxes	Certain	-	Genetic algorithm and annealing simulation
Ghasemi et al. (2021)	- Minimizing transportation cost	Uncertain	Multi-depot	Game theory
Rahbari et al. (2021)	- Minimizing risk and emissions	Uncertain	Single-depot	MOSA and NSGA II
Pourmohammadi et al. (2021)	- Minimizing transportation cost	Certain	Multi-depot	fuzzy invasive weed optimization
Lin et al. (2022)	- Minimizing transportation and locating costs	Uncertain	Multi-depot	Heuristic algorithm
Khan et al. (2022)	- Maximizing reliability	Uncertain	Multi-depot	Kuhn Tucker approach
Safaei et al. (2022)	- Minimizing travel cost	Uncertain	Single-depot	Genetic
Li et al. (2022)	- Minimizing transportation cost	Uncertain	Single-depot	Heuristic algorithm
Ma et al. (2022)	- Minimizing cost	Uncertain	-	GIS
Momenitabar et al. (2023)	- Predict the bioethanol demand	Certain	Single-depot	Random Forest (RF)
Nasiri et al. (2023)	- Minimizing transportation cost	Certain	Single-depot	Exact algorithm
The present study	- location-routing-inventory considering planned transportation	Certain	Multiple distribution and production centers	NSGA II & MOWOA

Having surveyed the most significant papers published on routing-inventory of vehicles, the research innovations have been summarized as it follows:

- Considering the location problem besides routing-inventory problem
- Considering hard time windows in products distribution;
- Adding the objective function of reducing the maximum working hours of drivers, and
- Utilizing a new meta-heuristic algorithm (NSGA II and Multi-Objective Whale Optimization Algorithm) by defining a suitable chromosome.

3. Problem Statement and Mathematical Model

This section introduces an integrated multi-objective model for location-routing-inventory. The study focuses on two key decisions: the strategic decision of determining the locations of production and distribution centers, and the tactical decision of optimizing vehicle routing and commodity inventory management. While previous literature predominantly considers cost as the primary objective function, our model also addresses the social aspect of reducing the maximum working hours of drivers in addition to minimizing costs associated with location, routing, and inventory. In summary, the presented model investigates the multi-objective aspects of location-routing-inventory by considering both cost optimization and the reduction of maximum working hours of drivers as important objectives. Therefore, the requirement of timely product delivery within specified time windows can result in certain drivers having to work longer hours compared to others in order to complete the distribution. This imbalance in working hours can lead to driver fatigue. Hence, incorporating this crucial aspect into the problem modeling allows the model to closely resemble real-world location-routing and inventory problems. Figure 2 displays the flowchart of the research stages. Conforming to the mentioned above, the research structure is depicted in Figure 2. In this study, after identifying the research gap, the multi-objective location-routing-inventory problem considering planned transportation is presented. After that solution approaches including MOWOA and NSGA-II are presented. Then we Adjust the algorithms' parameters by Taguchi method. Finally, the proposed model is solved using the suggested MOIWO and ε-constraint methods, and the output of the decision variables are found and analyzed.

3.1. Assumptions

- The research objective functions pursue to minimize the total network costs and reduce the maximum working hours of drivers.
- The model is multi objective, multi echelon, multi-product and multi-period.
- The number and location of customers are constant and predetermined.
- The total capacity of the production and distribution centers is known and specific.
- Hard time window is considered for the distribution of products.

For modeling the sets, the decision-making parameters and variables of location- routing-inventory problem are defined below considering the planned transportation:

Sets:

$\boldsymbol{k}$	the set of production centers	$k = \{1, \dots, K\}$
$\boldsymbol{l}$	the set of distribution centers	$l, l' = \{1, \dots, L\}$
$\boldsymbol{c}$	the set of fixed customers	m,c={1,…,C}
$\boldsymbol{p}$	the set of products	p={1,…,P}
$\boldsymbol{t}$	the set of time periods	t={1,…,T}
$\boldsymbol{v}$	the set of vehicles	v={1,…,V}

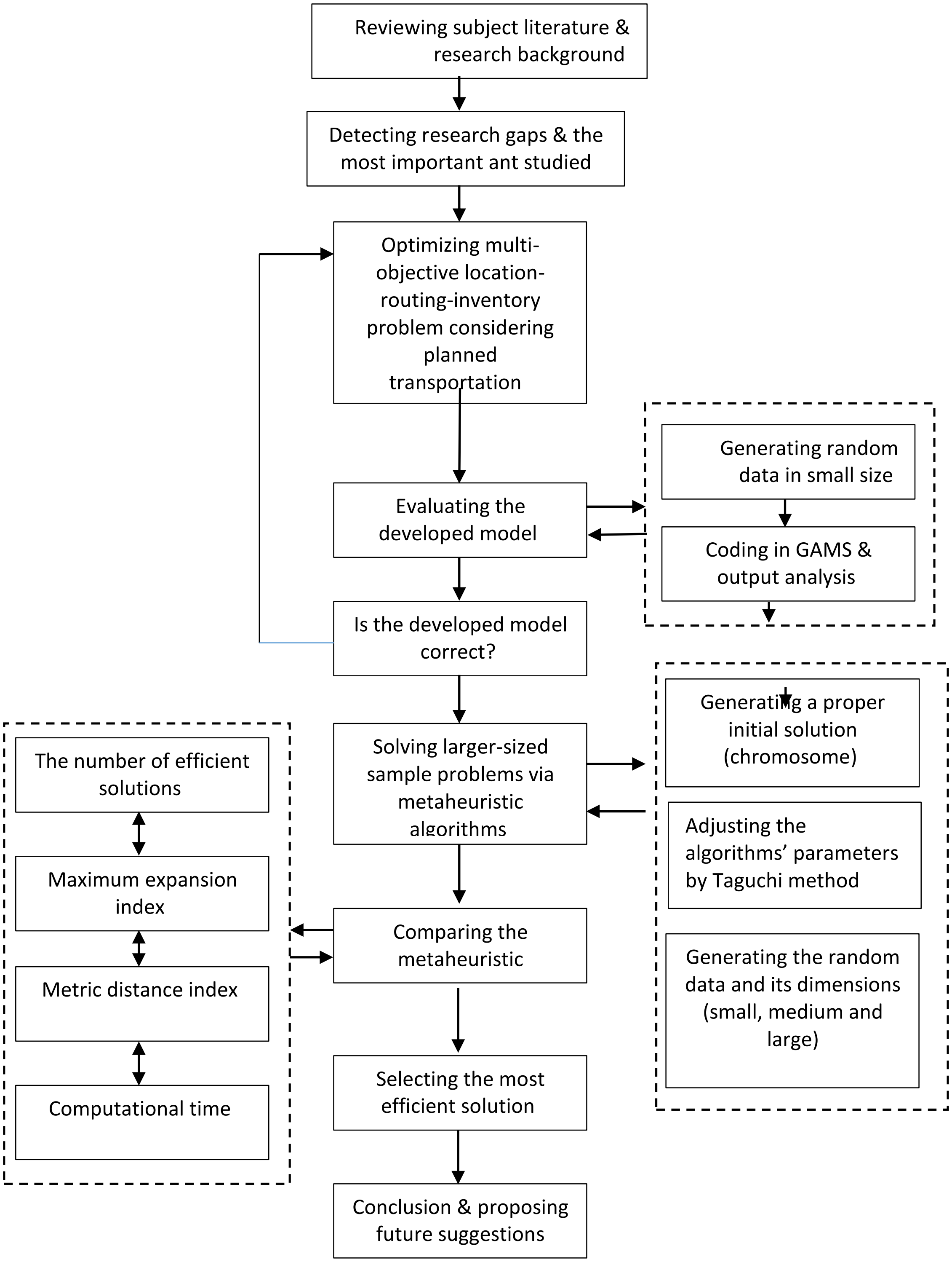

Figure 2. Research framework

Parameters:

H_k	Cost of constructing production center k
U_l	Cost of constructing distribution center l
F_v	Fixed cost of using vehicle v
$T_{k,l,v}$	Cost of transportation between production center k and distribution center l by vehicle v
$T_{l,c,v}$	Cost of transportation between distribution center l and customer c by vehicle v $l,c \in L \cup C$
$Ti_{l,c,v}$	Time of transportation between distribution center l and customer c by vehicle v $l,c \in L \cup C$
$H_{l,p}$	Cost of maintenance per each unit of product p in warehouse of distribution center l
$C_{l,p}$	Cost of distribution per each unit of product p in warehouse of distribution center l
$Dem_{c,p,t}$	Customer c's demand for product p during time period t
$CapK_{k,p}$	Max capacity of production center k of product p
$CapL_{l,p}$	Max capacity of distribution center l of product p
Cap_v	Max capacity of vehicle v
$[AH_c, BH_c]$	Hard time window for delivering products to customer c

Decision Variables:

$X_{k,l,p,t}$	The amount of product p transferred between production center k and distribution center l during time period t
$V'_{l,p,t}$	Total amount of product p transferred from distribution centers l during time period t
$Q_{l,p,t}$	Inventory level of product p in distribution center l during time period t
Z_k	If production center k is constructed, the value is 1, otherwise 0.
Z_l	If distribution center l is constructed, the value is 1, otherwise 0.
Z_v	If vehicle v is employed, the value is 1, otherwise 0
$Y_{l,c,t}$	If customer c is allocated to distribution center l during time period t, the value is 1, otherwise 0.
$Z_{l,c,v,t}$	If customer c is visited after distribution center l by vehicle v during time period t, the value is 1, otherwise 0. $l,c \in L \cup C$
$U_{c,v,t}$	Auxiliary variable for sub-tour elimination constraint
$R_{k,l,v,t}$	If the route between production center and distribution center l is visited by vehicle v during time period t, the value is 1, otherwise 0.
$Tc_{l,c,v,t}$	The time of vehicle v reaching the customer c and leaving the distribution center l during time period t
$Tw_{l,v,t}$	Max time for visiting by vehicle v leaving the distribution center l during time period t

Based on the definition of the above-mentioned sets, parameters, and decision variables, the multi-objective location-routing-inventory problem considering the planned transportation is viewed as a mixed integer linear mathematical programming model as it follows:

$$Min\omega 1 = \sum_{k=1}^{K} H_k Z_k + \sum_{l=1}^{L} U_l Z_L + \sum_{v=1}^{V} F_v Z_v + \sum_{l=1}^{L\cup C}\sum_{c=1}^{L\cup C}\sum_{v=1}^{V}\sum_{t=1}^{T} T_{l,c,v} Z_{l,c,v,t} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{v=1}^{V}\sum_{t=1}^{T} T_{k,l,v} R_{k,l,v,t} + \sum_{l=1}^{L}\sum_{p=1}^{P}\sum_{t=1}^{T} H_{l,p} Q_{l,p,t} + \sum_{l=1}^{L}\sum_{p=1}^{P}\sum_{t=1}^{T} C_{l,p} V'_{l,p,t} \quad (1)$$

$$Min\omega 2 = max\{TW_{l,v,t}, \quad \forall l \in L, v \in V, t \in T\} \quad (2)$$

$s.t.$:

$$Q_{l,p,t} = \sum_{k=1}^{K} X_{k,l,p,t} + Q_{l,p,t-1} - V'_{l,p,t}, \quad \forall l,p,t \quad (3)$$

$$V'_{l,p,t} = \sum_{c=1}^{C}\sum_{v=1}^{V} Dem_{c,p,t} Z_{l,c,v,t}, \quad \forall l,p,t \quad (4)$$

$$\sum_{v=1}^{V}\sum_{l=1}^{C\cup L} Z_{l,c,v,t} = 1, \quad \forall c,t \quad (5)$$

$$\sum_{c=1}^{C}\sum_{l=1}^{C\cup L}\sum_{p=1}^{P} Dem_{c,p,t} Z_{l,c,v,t} \le Cap_v Z_v, \quad \forall v,t \quad (6)$$

$$U_{m,v,t} - U_{c,v,t} + |C| Z_{m,c,v,t} \le |C| - 1, \quad \forall m,c \in C, v, t \quad (7)$$

$$\sum_{c=1}^{C\cup L} Z_{l,c,v,t} = \sum_{c=1}^{C\cup L} Z_{c,l,v,t}, \quad \forall v,t,l \in C \cup L \quad (8)$$

$$\sum_{l=1}^{L}\sum_{c=1}^{C} Z_{l,c,v,t} \le 1, \quad \forall v,t \quad (9)$$

$$-Y_{l,c,t} + \sum_{u=1}^{C\cup L} \left(Z_{l,u,v,t} + Z_{u,c,v,t}\right) \le 1, \quad \forall l,c,v,t \quad (10)$$

$$\sum_{l=1}^{L} X_{k,l,p,t} \le CapK_{k,p} Z_k, \quad \forall k,p,t \quad (11)$$

$$V'_{l,p,t} + Q_{l,p,t} \le CapL_{l,p} Z_l, \quad \forall l,p,t \quad (12)$$

$$\sum_{p=1}^{P} X_{k,l,p,t} \le \sum_{p=1}^{P} Cap_v R_{k,l,v,t}, \quad \forall k,l,t \quad (13)$$

$$Tc_{l,c,v,t} \ge Ti_{l,c,v} - M.\left(1 - Z_{l,c,v,t}\right), \quad \forall l,c,v,t \quad (14)$$

$$Tc_{l,m,v,t} \geq Tc_{l,c,v,t} + Ti_{c,m,v} - M.\left(2 - Z_{c,m,v,t} - Y_{l,c,t}\right), \quad \forall l, c, m, v, t \tag{15}$$

$$Tc_{l,c,v,t} \leq BH_c.Z_{l,c,v,t}, \quad \forall l, c, v, t \tag{16}$$

$$Tc_{l,c,v,t} \geq AH_c.Z_{l,c,v,t}, \quad \forall l, c, v, t \tag{17}$$

$$Tw_{l,v,t} \geq Tc_{l,c,v,t} + Ti_{c,l,v}Z_{c,l,v,t}, \quad \forall l, c, v, t \tag{18}$$

$$\sum_{k=1}^{K} R_{k,l,v,t} \leq \sum_{c=1}^{C} Z_{l,c,v,t}, \quad \forall l, v, t \tag{19}$$

$$X_{k,l,p,t}, V'_{l,p,t}, Q_{l,p,t}, U_{c,v,t}, Tc_{l,c,v,t}, Tw_{l,v,t} \geq 0 \tag{20}$$

$$Z_k, Z_l, Z_v, Y_{l,c,t}, Z_{l,c,v,t}, R_{k,l,v,t} \in \{0,1\} \tag{21}$$

Constraint (1) states the problem's first objective function value including the location, routing, and inventory related cost minimization. Constraint (2) indicates minimizing the maximum working hours of drivers during each time period. This equation serves as an equilibrium relation in the distribution of working hours among the drivers of each vehicle. Constraint (3) calculates the inventory at the end of each period in the selected distribution center. Constraint (4) shows the total flow of products (demand) in the distribution centers due to be transferred to the customers. Constraint (5) guarantees allocating each distribution center to only one customer. Constraint (6) represents the maximum product transportation capacity by the vehicle at hand. Constraint (7) is related to the sub-tour elimination constraint. Constraint (8) guarantees the vehicle entering and leaving each customer cluster only once. Constraints (9-10) guarantee the start and end points of the vehicle routing in the distribution of products to customers or distribution centers. Constraints (11-12) indicate the location of the production and distribution centers, respectively, and guarantee not being able to benefit from their capacity for the products' production and distribution until such centers are selected. Constraint (13), we can get to see the vehicle used for transferring the products between the production and distribution centers. Constraint (14) displays the time required for the vehicle to reach the first customer node leaving the distribution center. Eq. (3-15) indicates the time required for the vehicle to reach each customer node in terms of the loading and unloading times and the commutes between the nodes. Constraints (16-17) guarantee that the time for each vehicle reaching each customer node should be within a hard time window. In Constraint (18), the total value of the visiting vehicle from the time staring the operation from the distribution center until completing the operation at the distribution center is given. Constraint (19) indicates the planned transportation ensuring that once the vehicle leaves the production center, it takes up distributing the products to the customers. Constraints (20-21) state the type and nature of the decision-making variables.

4. Solution Approaches

In this section, solution approaches including MOWOA and NSGA-II are presented. NSGA II and MOWOA are specifically designed to address multi-objective optimization problems, where multiple conflicting objectives need to be optimized simultaneously. NSGA II and MOWOA encourage diversity within the population by promoting solutions from different regions of the Pareto front (Goli et al. 2019). This helps to capture a wide range of possible trade-off solutions and provides decision-makers with more options to choose from (Goli et al. 2020). Overall, these algorithms offer robust performance, good convergence properties, and a diverse set of non-dominated solutions (Deb et al. 2002, Mirjalili and Lewis, 2016).

4.1. MOWOA

Another point worth being noticed is the whale's social behavior. They live alone or in groups. However, they are mostly seen in groups. Some of their species can keep living in a large family throughout their lives. Figure 3 represent the flowchart of MOWOA algorithm.

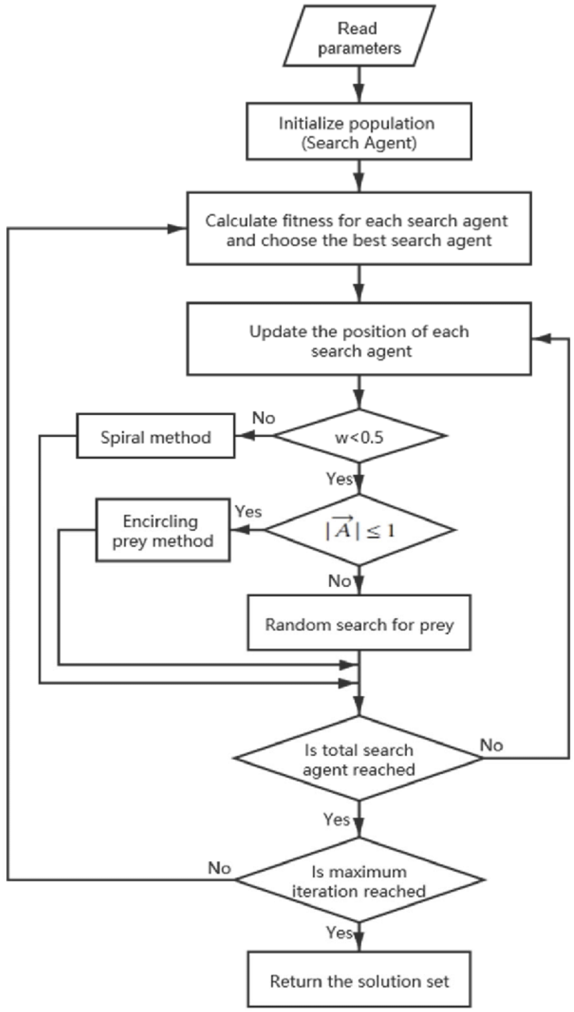

Figure 3. Flowchart of MOWOA algorithm

- Encircling the prey

Humpback whales are equipped with the potential to sense the location of the prey and encircle them. Because in the search space the optimal design position is not known in advance, Whale Optimization Algorithm assumes that at the time being the best candidate solution is the target prey or it's close to optimal (Ghahremani-Nahr et al. 2019). After the best search agent is defined, other search agents make efforts to update their position in relation to the best search agent, the behavior which is displayed by the equations (22-23):

$$\vec{D} = |\vec{C}.\vec{X}(t) - \vec{X}(t)| \quad (22)$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A}.\vec{D} \tag{23}$$

Where, t stands for the current iteration, $\vec{A}$ and $\vec{C}$ represent the vector of coefficients, X^* indicates the position of the best solution gained so far, and $\vec{X}$ denotes the object's position vector. It should be stressed that here in case a better solution exists, X^* should be updated in each iteration.

$\vec{A}$ and $\vec{C}$ vectors are calculated as it follows:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{24}$$
$$\vec{C} = 2\vec{r} \tag{25}$$

Where, $\vec{a}$ is linearly reduced from 0 to 2 during iteration, and $\vec{r}$ is a random vector [0,1].

- Bubble-Net Attacking Technique (Exploitation Phase)

Two methods have been designed for mathematical modeling of the humpback whale bubble-net behavior, which are illustrated below:

1- Reducing the encirclement mechanism: This behavior is achieved via $\vec{a}$ value reduction in Eq. (26). Note that the $\vec{A}$ fluctuation range also gets reduced to α; In other words, $\vec{A}$ is a random number within $[-a, a]$, where α drops from 2 to 0 during iteration.

2- This approach first calculates the distance between the whale's position at (X, Y) and the prey's position at (X*, Y*). Next, a spiral equation is created between the whale's position and the prey's position in order to mimic the spiral-shaped movement of the humpback whale, as it follows:

$$\vec{X}(t+1) = \overrightarrow{D'}.e^{BL}.Cos(2\pi L) + \overrightarrow{X^*}(t) \tag{26}$$

Where, $\overrightarrow{D'} = |\overrightarrow{X^*}(t) - \vec{X}(t)|$, exhibiting the distance between the ith whale to the prey (the best solution achieved so far), b is a constant for defining the logarithmic spiral shape, and l is a random number within [-1,1] range.

- Search for the prey (Exploration Phase)

The mathematical model is as the following:

$$\vec{D} = |\vec{C}.\overrightarrow{X_{rand}} - \vec{X}| \tag{27}$$
$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \tag{28}$$

Where, $\overrightarrow{X_{rand}}$ stands for a random position vector (a random whale) selected out of the current population.

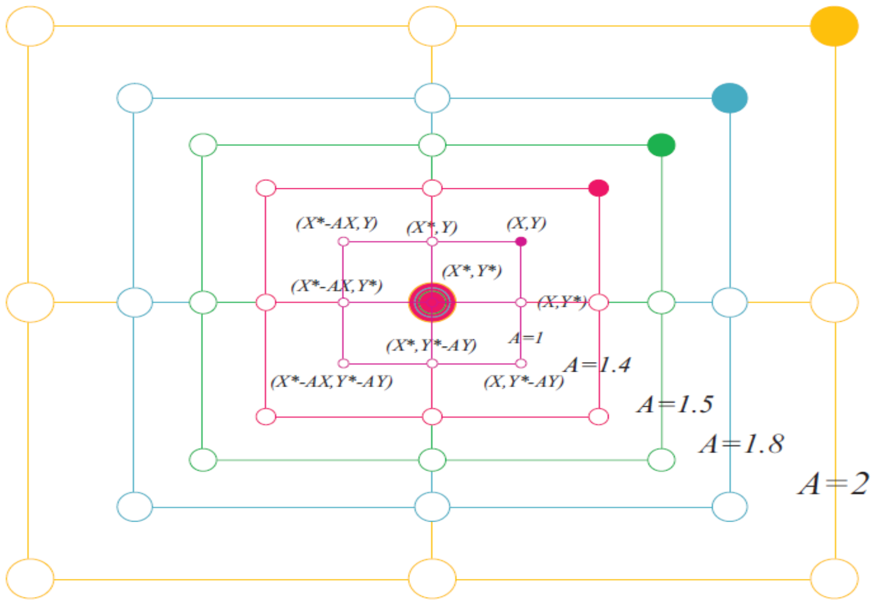

Figure 4. Exploration Mechanism Performed in WOA

Some of the possible positions around a special solution are displayed with A>1 in Figure 4.

4.2. NSGA II

As a rule, the algorithm implementation steps are as it follows:

Step 1: Create the initial population P0 as large as N with random solutions, and set t=0,

Step 2: Return back to Pt if the stop condition does not hold,

Step 3: Select N parents out of population Pt through binary tournament selection operator,

Step 4: Generate the offspring population Qt as large as N by applying cross and mutation operators to population Pt,

Step 5: Set Rt = $P_t \cup Q_t$,

Step 6: Employ non-dominated sorting method for determining the Pareto sets F_i in population Rt,

Step 7: Set $P_{t+1} = \emptyset$ and i=1,

Step 8: As long as $|P_{t+1}| + |F_i| < N$:

A) Add the solutions of set Fi to population Pt+1, and

B) Set i=1+1,

Step 9: Put the Fi set solutions based on crowding distance in a descending order,

Step 10: Transfer $N - |P_{t+1}|$ of the initial solutions of Fi to population Pt+1, and

Step 11: Set t=t+1 and return back to step 2.

Figure 5 represent the flowchart of NSGA-II algorithm.

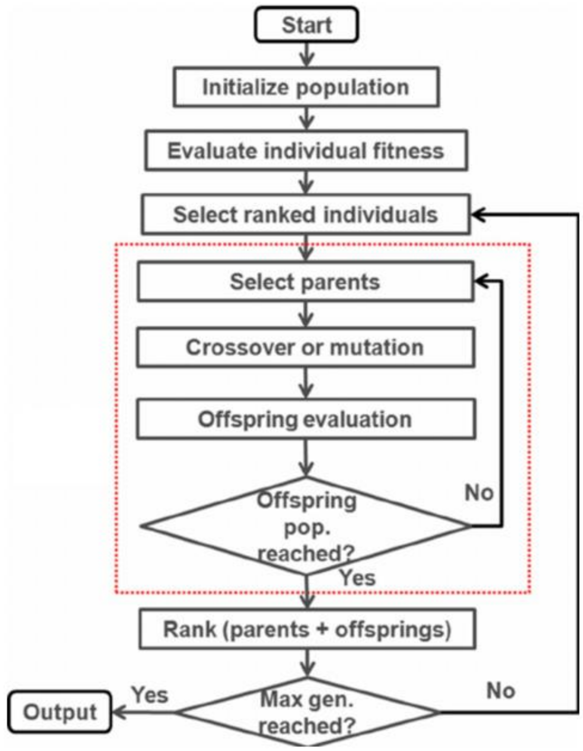

Figure 5. Flowchart of NSGA-II algorithm

5. Numerical results

5.1. Solving the Small-Sized Sample Problem

In this section, we get to check the model's efficiency and ensure the modeling's accuracy by designing a small-sized sample problem by considering 3 production centers, 3 distribution centers, 4 customers, 2 types of products, 5 types of vehicles, and 2 designing time periods, as shown in Table 2. Due to lack of access to real-world data, the random data based on the uniform distribution function have been exploited.

Table 2. The value of problem parameters based on uniform distribution function

Parameter	Numerical value based on uniform distribution function
H_k, U_l	$\sim U[10000{,}12000]$
F_v	$\sim U[1000{,}2000]$
$T_{k,l,v}, T_{l,c,v}$	$\sim U[10{,}20]$
$Ti_{l,c,v}$	$\sim U[10{,}30]$
$H_{l,p}$	$\sim U[3{,}5]$
$C_{l,p}$	$\sim U[1{,}3]$
$Dem_{c,p,t}$	$\sim U[20{,}30$
$CapK_{k,p}$	$\sim U[25{,}60]$
$CapL_{l,p}$	$\sim U[25{,}60]$
Cap_v	$\sim U[150{,}160]$
AH_c	$\sim U[5{,}10]$
BH_c	$\sim U[150{,}300]$

In order to explore the accuracy of the model, Epsilon-constraint method and coding in GAMS software have been applied in the research because of presenting a two-objective model. Table 3 reports the objective functions' optimal values using the individual optimization methods, and the efficient solutions of the problem have been displayed by the Epsilon-constraint method.

Table 3. The objective functions' optimal values and the small-sized sample problem's efficient solutions

	Total cost	**Max working hours**
Optimal solution of objective functions individually	34703	36
Efficient solution 1	34887	48
Efficient solution 2	45305	46
Efficient solution 3	46377	43
Efficient solution 4	46851	42
Efficient solution 5	47316	41
Efficient solution 6	71029	38

As perceived from the results given in Table 3, the optimal value of the cost function amounts for 34703 units and that of the second objective function equals 36. Moreover, through Epsilon Constraint method 6, the efficient solution has been achieved as reported in Table 3. Figure 6 demonstrates the Pareto front resulting from solving the small-sized sample problem pursuant to Epsilon constraint method.

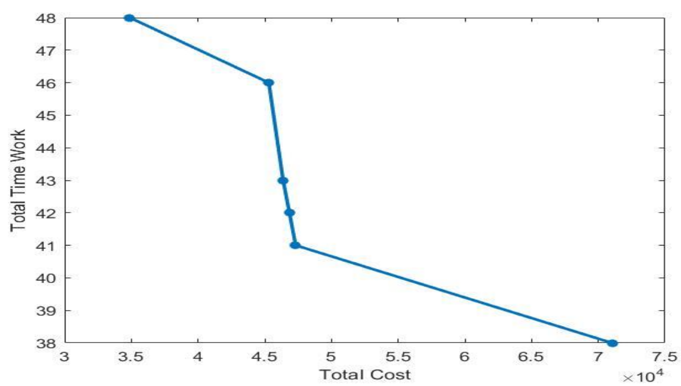

Figure 6. Pareto front resulting from solving the small-sized sample problem

Regarding figure 6 and Pareto front analysis, it can be stated that to reduce the maximum working hours of drivers, more vehicles with shorter distances should be hired. For this reason, employing more vehicles leads to increased costs of the vehicles being utilized, while it reduces the transfer distance resulting in the distribution centers being constructed closer to the customers, through which the construction costs go up.

5.2. Parameter Adjustment of Meta-Heuristic Algorithms

When implementing meta-heuristic algorithms, an important decision required to be made is to adjust the parameters and to find an optimal combination. The input parameters' values of such algorithms strongly influence their performance and efficiency so that slightly changing them may considerably affect their solution quality. Traditionally, parameter adjustment relies upon trial-and-error method. In Taguchi method, it's a must to first identify the appropriate factors, and then to select the levels of each of the factors, and after that, to define the proper design of experiments for these control factors. Once the design of experiment is determined, the experiments are run and analyzed targeting to discover the best combination of the parameters. In the current research, three levels have been considered for each factor. With respect to the number of the factors and the number of the levels, the design of experiment has been determined and then implemented for each algorithm. It's worth pointing out that each of the experiments has been replicated five times on average, and the resulted mean values have been used in the final investigation. Because of the proposed model being a bi-objective one, first off, the value of each experiment should be calculated by Eq. (1), in the numerator of which the indices including the number of Pareto front solutions (NPF), the maximum spread index (MSI), the spacing metric (SM), and the computational time (CPU-time) have been used for comparing the meta-heuristic algorithms. After determining the value of each experiment, Eq. (2) is applied to compute the descaled (RPD) value of each experiment for analyzing the Taguchi design of experiment

$$S_i = \left|\frac{NPF + MSI + SM + CPU\_time}{4}\right| \tag{1}$$

$$RPD = \frac{S_i - S_i^*}{S_i^*} \tag{2}$$

In Eq. (2), Si is the index value resulting from performing each Taguchi experiment, and S_i^* denotes the best index value out of all Taguchi experiments. In Table 4, the levels of the proposed parameters of NSGA II and MOWOA are given.

Table 4. The proposed parameter levels for parameter adjustment of meta-heuristic algorithms via Taguchi method

Algorithm	Parameter	Symbol	Level 1	Level 2	Level 3
MOWOA	Number of populations	Npop	100	200	500
	Max number of iterations	Max it	100	150	300
	Combination type	A	1	2	4
	Mutation type	C	1	2	4
NSGA II	Max number of iterations	Max it	100	200	500
	Number of populations	Npop	100	150	500
	Combination type	Pc	0.1	0.4	0.8
	Mutation type	Pm	0.1	0.4	0.8

Having performed the experiments for the parameter adjustment of the two proposed algorithms, the plots of the average S/N ratio and the means have been reported as it follows. Fig. 7 shows the plot of the average S/N ratio and the mean for the NSGA II.

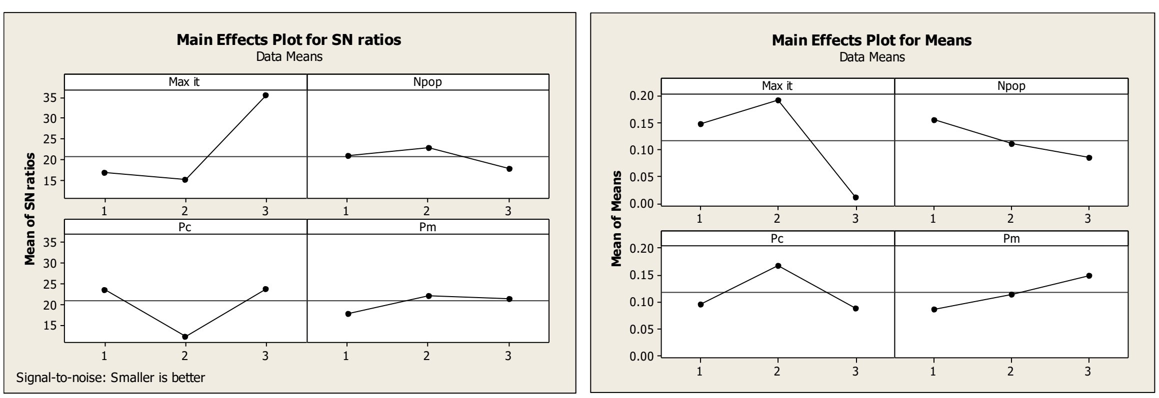

Figure 7. Plot depicting the average S/N ratio and means in NSGA II

As the results of Fig. 7 indicate, if the maximum value of the number of iterations stands at level 3, the number of populations at level 2, the combination rate at level 3, and mutation rate at level 2, NSGA II would have the greatest efficiency in problem solving. Moreover, Fig. 8 depicts the plot of the average S/N ratio and the mean for the MOWOA.

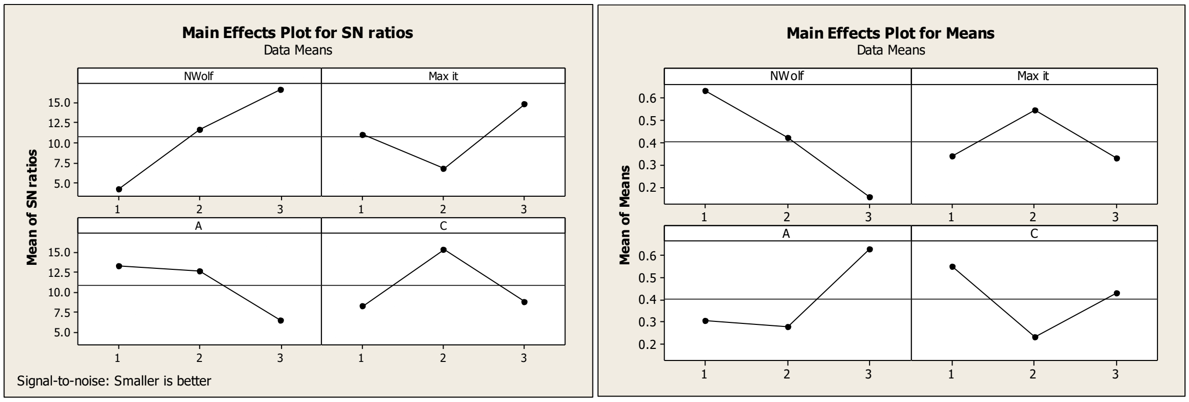

Figure 8. Plot depicting the average S/N ratio and means in MOWOA

Therefore, after adjusting the parameters of the NSGA II and MOWOA as the meta-heuristic algorithms, the small-sized sample problem, and the findings have been compared through the Epsilon constraint method.

5.3. Solving Small-Sized Sample Problem via Meta-Heuristic Algorithms

This section aims to investigate the output variables resulting from solving the problem by the meta-heuristic algorithms based on the design chromosome and to compare them with the outputs from the Epsilon constraint method. Accordingly, due to the difference in the number of the efficient solutions of the problem achieved from various solution methods, Table 5 exhibits the comparison of the solution methods based on four indices (the NPF, the MSI, the SM, and the CPU Time).

Table 5. Comparing the comparison indices for the efficient solutions among different solution methods in the small-sized sample problem

Index	Epsilon constraint method	NSGA II	MOWOA
Number of Pareto Front	6	10	12
Maximum spread	36142.00	3426.00	37561.00
Spacing metric	0.806	0.647	0.805
Computational time	612.37	62.28	73.18

Comparing the computational indices, it can be asserted that when solving the problem, the meta-heuristic algorithms have gained more efficient solutions within shorter computational time using the maximum spread index than by the Epsilon-constraint method. As perceived from the results in Table 4-6, NSGA II has successfully achieved the spacing metric and the computational time and the MOWOA has managed to come up with the NPF and the MSI. Table 6 presents the efficient solutions from solving the small-sized problem.

Table 6. The efficient solutions from solving the small-sized sample problem by meta-heuristic algorithms

Efficient solution	**NSGA II**		**MOWOA**	
	Total cost	**Max working hours**	**Total cost**	**Max working hours**
1	38428	50	35984	49
2	42524	50	41128	46
3	43160	50	42168	45
4	44144	49	42391	45
5	46324	46	43184	43
6	48108	46	43194	43
7	49496	45	44049	43
8	50778	42	45065	45
9	51420	41	46445	41
10	72694	39	47988	40
11	-	-	47988	39
12	-	-	73545	38

Analyzing the Pareto front resulting from all of the solution methods for solving the small-sized sample problem revealed that by the costs increase, the maximum working hours of all driver get down, which is due to increased number of vehicles and distribution and production centers for shortening the transfer distance and consequently, reducing the maximum working hours of drivers. In Fig. 9, the first efficient solution from solving the problem via NSGA II and MOWOA is analyzed.

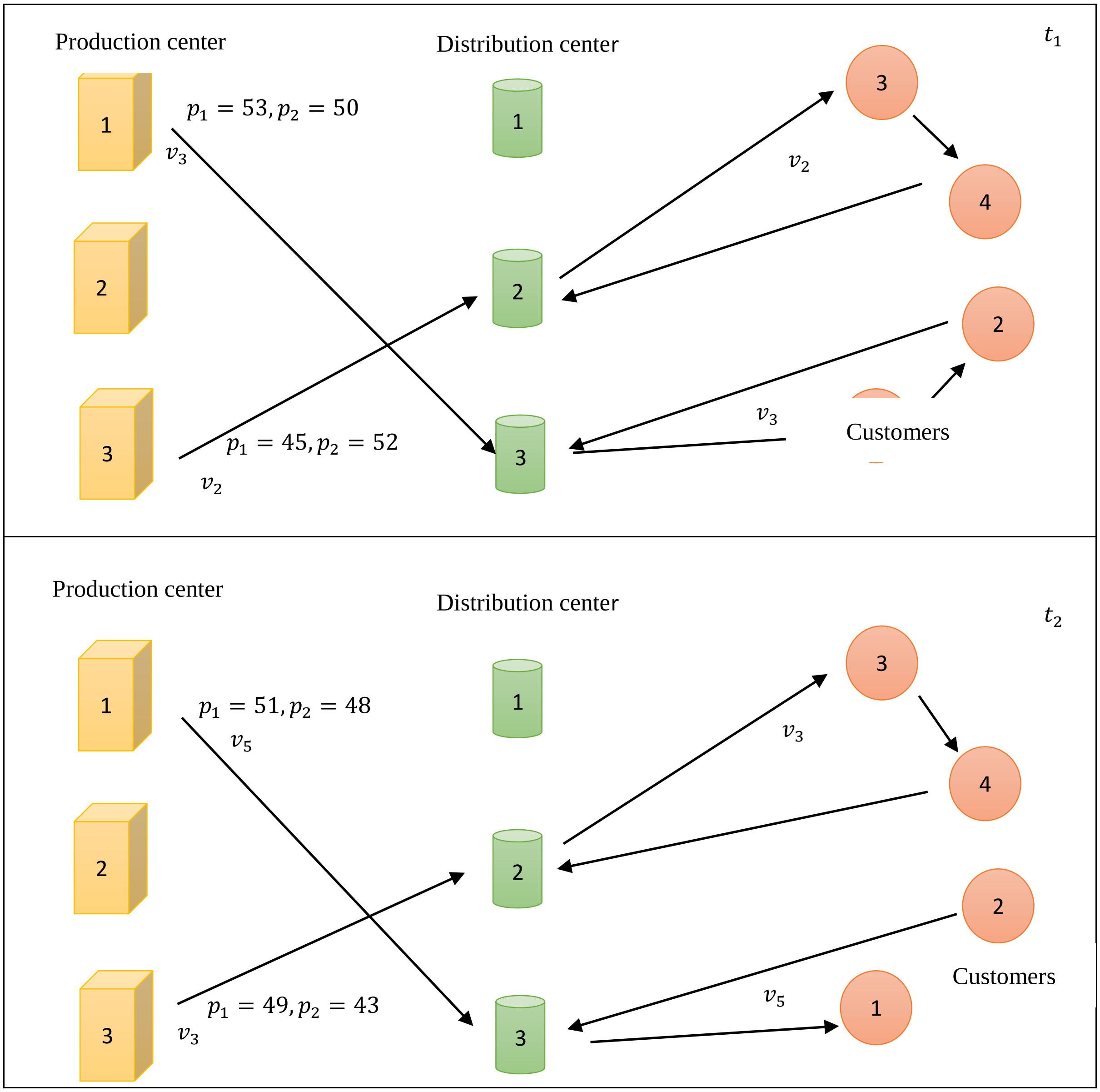

Figure 9. Optimal location-routing and allocation of the flow in small-sized problem for NSGAII

The results exposed that NSGA II and MOWOA as the study algorithms have had greater efficiency in solving the multi-objective location-routing-inventory problem while considering planned transportation. Thus, the two mentioned algorithms have been employed to solve larger problems and next, they have been compared based on four indices (the NPF, the MSI, the SM, and the CPU Time).

5.4. Analyzing Large-Sized Sample Problems

After investigating the designed model's outputs via Epsilon-constraint method and meta-heuristic algorithms, this section deals with larger-sized sample problems. Accordingly, 12 sample problems have been designed at small, medium, and large sizes as given in Table 7.

Table 7. Sample problems in small, medium and large sizes

Size	Sample problem	K	L	C	P	T	V
Small	1	4	6	10	3	4	10
	2	5	8	15	3	4	15
	3	6	10	20	3	4	20
	4	7	12	25	4	6	25
Medium	5	12	20	35	4	6	30
	6	18	25	42	5	6	35
	7	24	28	50	5	6	35
	8	30	30	60	5	6	45
Large	9	50	40	80	6	8	50
	10	60	50	100	6	8	55
	11	70	60	120	6	8	60
	12	80	70	150	70	80	12

Each sample problem has been run three times by each algorithm and the mean values of the objective functions and the comparison indices have been presented in Tables 8 and 9 for NSGA II and MOWOA.

Table 8. The mean results from solving the sample problem via NSGA II

Size	Sample problem	Z1	Z2	NPF	MSI	SM	CPU Time
Small	1	54329	67	104	31282.09	0.967	110.26
	2	68425	80	86	30931.57	0.749	126.38
	3	76913	94	120	32677.76	0.823	148.67
	4	86625	115	117	21871.13	0.722	174.90
Medium	5	120564	136	108	31368.12	0.709	296.33
	6	136425	149	98	23981.06	0.899	334.69
	7	149213	152	105	22777.36	0.893	396.18
	8	153165	166	93	22507.67	0.832	486.22
Large	9	256976	215	92	24770.25	0.882	683.24
	10	326459	234	110	29025.42	0.704	752.12
	11	424465	256	81	29139.81	0.896	863.38
	12	535452	291	96	24235.28	0.779	992.28
Mean		199084.3	162.91	100.83	27047.29	0821	447.05

Table 9. The mean results from solving the sample problem via MOMOA

Size	Sample problem	Z1	Z2	NPF	MSI	SM	CPU Time
Small	1	54852	68	83	23030.12	0.714	118.62
	2	69416	81	106	34192.70	0.755	134.68
	3	78228	93	92	20761.07	0883	159.23
	4	87835	113	100	33071.47	0.978	190.34
Medium	5	120943	138	117	33333.08	0.890	332.36
	6	137161	140	91	20547.84	0.900	386.48
	7	151634	149	94	32470.94	0.951	483.25
	8	150424	168	114	23476.99	0.756	554.49
Large	9	255187	219	110	28317.61	0.707	794.65
	10	332474	234	88	30741.30	0.792	886.44
	11	426638	257	110	22131.91	0.826	994.28
	12	541942	288	82	23250.88	0.921	1135.22

As perceived from the mean results and Tables 8 and 9, the NSGA II has achieved the minimum total cost in solving the sample problems. The MOWOA has also gained the minimum working hours of drivers. Comparing the comparison indices of efficient solutions, on average the NSGA II has led to the maximum NPF, minimum SM, and shortest CPU Time. Figs 10 and 11 depict comparing the means of the objective functions between the two proposed algorithms.

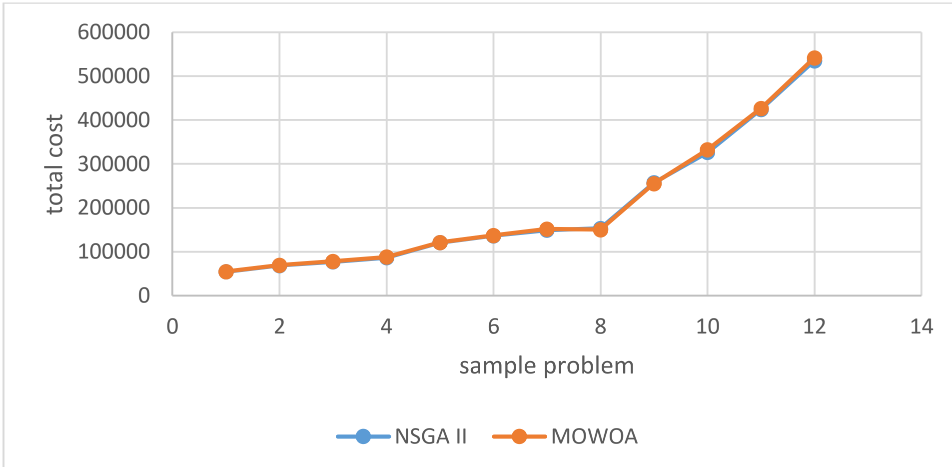

Figure 10. Comparing the means of the 1st objective function between NSGA II and MOWOA

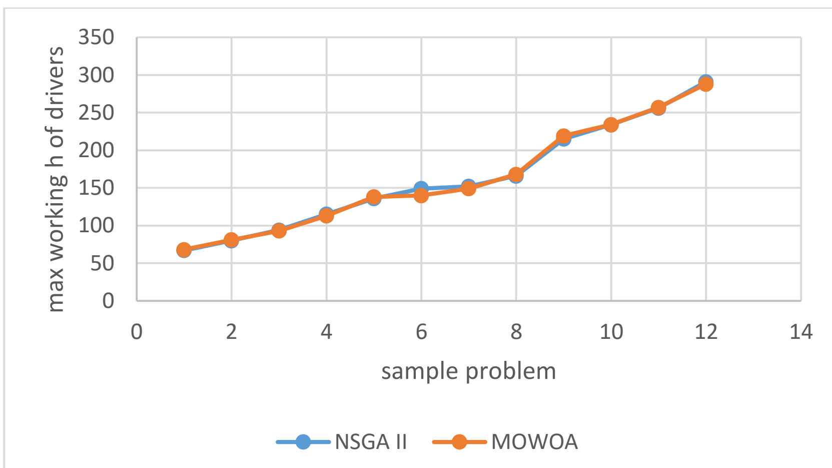

Figure 11. Comparing the means of the 2nd objective function between NSGA II and MOWOA

Since two algorithms have been considered for solving the problem, for comparing the most efficient solution method, TOPSIS has been used as the multiple-criteria decision-making method. Therefore, by setting the means of the comparison indices between the two solution methods as the criterion, the options have been weighted and ranked. Table 10 presents the initial decision-making matrix for selecting the most efficient solution method.

Table 10. The initial decision-making matrix for selecting the most efficient solution method

Solution Method	NPF	MSI	SM	CPU Time
NSGA 11	100.83	27047.29	0.821	447.05
MOWOA	98.91	27110.49	0.839	514.17
Applied Weight	0.25	0.25	0.25	0.25

Using the TOPSIS as the multiple-criteria decision-making method, the NSGA II has been weighted as 0.983 and the MOWOA as 0.016. Thus, NSGA II is selected for the analyses considering its high weight.

5.5. Discussion

To deliver the products on time pursuant to a hard time window makes some drivers take up longer hours of product distribution compared to other drivers, which leads to working imbalance between the working hours of drivers and their fatigue. Thus, taking this critical aspect into account in modeling the problem results in the model getting closer to location-routing and inventory problems in the real world. At last, because of the location models being of NP-hard nature, it's concluded that this problem's degree of hardness is at least similar to that of the facility location, and meta-heuristic algorithms should be used for solving larger-sized problems. According to the results from solving the small-sized model by the Epsilon constraint method, in order to reduce the maximum working hours of drivers, more vehicles with shorted distances should be hired. For this reason, employing more vehicles results in increased costs of vehicles being utilized, and shortening the transfer distance leads to the distribution centers being constructed closer to the customers and as a result, increasing the construction costs. In the sensitivity analysis of the model relative to demand, it has been observed that as the demand quantity increases, due to the increased volume of production and distribution and the limited capacity of the vehicles, more vehicles should be employed for distributing and transferring the products from the production center to the distribution center. Subsequently, the total costs of the network increase. Meanwhile, as the number of vehicles increases and the commodity volume is properly distributed among the vehicles, the maximum working hours of drivers get reduced.

6. Conclusion

Because the vehicle routing and commodity inventory management are so significant, the current study has presented a novel location-routing-inventory model and its solution. The location of warehouses and distribution centers in logistic systems is as important as vehicle routing, and takes up the major portion of the system costs. Our paper contributes to the field by addressing multiple aspects in the location-routing-inventory problem. Firstly, we consider the location problem in conjunction with the routing-inventory problem, providing a comprehensive and integrated approach. Secondly, we take into account the challenging constraint of hard time windows in product distribution, ensuring timely deliveries. Thirdly, we introduce the objective of reducing the maximum working hours of drivers, addressing the social aspect of driver fatigue. Lastly, we propose a new meta-heuristic algorithm with a carefully designed chromosome, enhancing the optimization process. These contributions collectively advance the understanding and solution approach for real-world location-routing-inventory problems.

In the proposed study model, the levels such as the production centers have been considered as the first level, the distribution centers as the second level, and the final customers as the final level. Thus, the location of facilities in the distribution and production centers and the inventory-routing will occur at the level between the distribution centers and the customers. The final customers require the demand for the products which has to be supplied by the vehicles leaving the potential distribution centers. Besides, the commodity inventory is managed by the distribution centers and their required commodities are supplied by the production centers. This way, in this research, after the product loading in the production center, the vehicle supplies the commodity required by the distribution centers, and as the predefined plan prescribes, it delivers the products to the final customers as demanded. Thus, two strategic systems including the location of the production and distribution centers and the tactical decision such as the vehicle routing and the commodity inventory management have been investigated in this research. Regarding that most study papers have pointed out the cost objective function as the study objective function, in this research besides the objective function, i.e., minimizing the costs of location, routing, and commodity inventory, reducing the maximum working hours of drivers has also been examined as a social aspect.

To sum up, two algorithms called NSGA II and MOWOA have been employed for solving large-sized problems. The mean value of the accrued results has revealed the NSGA II with the minimum total cost in solving the sample problems. Meanwhile, the MOWOA has acquired the shortest working hours for drivers. According to the comparison indices of the efficient solutions, on average the NSGA II has acquired the largest NPF, the minimum SM, and the shortest CPU Time. Finally, TOPSIS has been applied for decision-making about the most efficient solution method, whose results indicated that the NSGA II has been selected for the analyses considering its high weight. The results of this research can be useful for organizations that are somehow related to the transportation and distribution of goods. Also, routing and inventory control helps managers to reduce costs as much as possible. As there was no systematic database for some parts of cost elements, driver's estimations were asked to help.

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