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Designing a Mathematical Model for Two-Echelon Allocation-Routing Problem by Applying the Route and Transportation Fleet Conditions

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Abstract – A novel mixed integer non-linear mathematical model is presented in this paper for the two-echelon allocation-routing problem by applying the conditions of the route and transportation fleet under uncertainty. The cost of allocating drivers to non-homogeneous vehicles is calculated in this model based on the type of the vehicle, the lifecycle of the car, the experience of the driver, and different degrees of hardness that are defined for various routes. The cost of passing the route is defined based on an initial fixed cost and the degree of hardness of the route. Also, the reliability of the routes in each section is defined as an objective in the second echelon of the model aimed at enhancing the reliability rate. Two metaheuristic algorithms, NSGAII and MOPSO, are utilized to solve the model. Then, their performance rates in problems with different sizes are statistically evaluated and compared by different indices, following the adjustment of their parameters by Taguchi's method, through which results indicated the high efficiency of the model. A sensitivity analysis is ultimately performed on the results obtained from the solution, and some suggestions are made for the development of the model.

Keywords– Two-echelon allocation-routing model, Reliability, Multi-objective optimization, Metaheuristic algorithms.

I. INTRODUCTION

The VRP in the supply chain distribution network is known as one of the main problems of supply chain management, which seeks to choose and allocate possible routes to available vehicles for the distribution and delivery of goods to distribution centers or customers aimed at minimizing the relevant costs (Hosseini-Motlagh et al., 2020). Besides reducing the distribution costs, the optimal solution to this problem leads to the timely delivery of goods, reduces the need for storage and warehousing of goods, and enhances customer satisfaction (Hosseini and Hassani, 2017).

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On the other hand, one may claim that vehicle routing is one of the most challenging issues in the area of transportation and supply chain which focuses on the delivery of items requested by customers using a fleet of vehicles (Sabbagh et al., 2014). The routing and distribution of goods can be classified into two direct and indirect categories. In direct mode, the products are transferred directly from the origin to the destination without passing through intermediate and intermediary facilities. In the indirect mode, the products should be passed through one or more intermediate facilities to come from the origin to the destination and those facilities can be distribution centers or temporary warehouses.

The two-echelon routing is recognized as one of the important examples of indirect distribution. The products are transported from a specific source (a central warehouse or factory) and then sent to an intermediate facility (a temporary warehouse or distribution center) in the two-echelon routing. This intermediate facility then distributes the products among customers by forming a net (such as a single-echelon routing). Simply put, the products are taken out of their origin locations in this type of distribution and transported to the intermediate facility and then sent to the destination after going through a series of activities such as separation, sorting, integration, classification, and etc. Meanwhile, there has to be strong and accurate coordination between these two echelons. Thus, this problem cannot be considered two single-echelon problems and solved separately and needs to be modeled and solved conjointly as a two-echelon problem (Martins et al., 2021).

In contrast, the goals and constraints of this problem vary dramatically since organizations have different conditions (Kahfi and Tavakkoli-Moghaddam, 2014). One of these different conditions may depend on the uncertainty status existing in the nature of routing problems. Uncertainty often manifests itself in the time of providing the service, the customer’s presence, as well as the demand. The probability of distribution is usually utilized to deal with the problem of uncertainty. This type of vehicle routing is named VRPSD (Salavati-Khoshghalb et al., 2019). Thus, the demand is considered uncertain and random in this paper to get closer to the real world. What is clearly visible in the literature review and is considered a research gap in this research is the optimization of two-echelon routing problem with new conditions and assumptions. So the “Driver experience” is recognized as one of the important aspects of this research.

To put flesh on the issue, while it has not been included in the reviewed studies that one driver can have “multiple vehicles with heterogeneous capacity”, an issue that is quite evident in the real world. In addition to the fact that drivers have multiple vehicles with heterogeneous capacities, the useful life of each vehicle cannot be the same, and this will lead to changes in the problem conditions as well as allocation. It seems to be true that failure to pay attention to the “Hardness of Route” is another gap in the reviewed studies. On the other hand, due to the existence of natural effects, the routes definitely do not have the same hardness, and some routes are impassable. Thus, determining proper routes for vehicles with a useful life or worn-out proportional to the difficulty of the route can also be studied. In other words, this issue has been neglected in many studies that vehicles with longer useful life or less worn-out can be allocated to routes with higher hardness and vice versa. This research does its best to compensate for all the aforementioned research deficiencies in a mathematical model for a two-echelon allocation and routing problem. The result of solving this model would be the allocation of vehicles to drivers and intermediate facilities to central warehouses, and ultimately determining the optimal route for each vehicle. A new multi-objective, multi-period mathematical model is presented in this research based on an uncertain demand rate which, besides the uncertainty of the demand, encompasses the driver's experience, the hardness of the route, and the life span of the vehicles.

This article includes seven sections: the introduction and literature review are presented in the first and the second sections; the problem statement and mathematical modeling are the focus of the third and the fourth sections; the model solution approaches are described in the fifth section; the calculation results are presented in the sixth section; and the conclusion and suggestions are provided in the seventh section.

II. LITERATURE REVIEW

Two-echelon distribution systems are a major logistics challenge in the LRP and have been the subject of several recent academic research studies (Dumez et al., 2023). The 2E-LRP issue, a load distribution problem, occurs when goods that are accessible at different origins must be delivered via intermediate facilities to their respective destinations. Rezaeipanah et al. (2019) investigated the VRPTW and presented a solution. The limited CVRP is extended by the VRPTW, which mandates completion of the service within a certain time range. The goal of this challenge is to increase customer satisfaction by minimizing the number of vehicles employed and the overall cost of the route by optimizing the route for each vehicle. To tackle the VRPTW problem, they suggested a hybrid approach based on the greedy algorithm and cuckoo search. Yu et al. (2020) developed a model for 2E-LRP with multiple objectives for waste collection planning. Moreover, they introduced an NSGA-II algorithm with a directed local search to solve the model. Cheng et al. (2022) took into account the utilization of temporary sites for natural disaster waste management when developing a model to reduce the cost and time required to clear up the debris left behind after natural disasters. A MP-2ELRP was identified as the issue in their study, wherein the primary choices are where to locate temporary waste management sites and how to route vehicles at both echelons. They did this by putting forth a MIP problem and offering a Genetic Algorithm (GA) as a solution.

A comparison of a single-echelon and two-echelon distribution scheme was conducted by Esmaeili & Sahraeian (2019). The SE-CVRP was given a mathematical model. When delivering perishable goods, the suggested mathematical approach, known as MINLP, concurrently minimized total trip expenses, total customer waiting times, and total carbon dioxide emissions. The MINLP model was transformed into the MILP by applying several linearization techniques. Whereas direct shipments were employed in SE-CVRP, shipments in 2E-CVRP were supplied to clients through intermediate depots known as satellites. The VRP and its expansions were NP-hard, so the NSGA-II meta-heuristic method was used to solve the model.

Anderluh et al. (2020) used simulated journey time scenarios to assess the deterministic solution of this kind of problem. Iteratively, the optimization process has integrated the data from the simulation. According to computational findings, there is a clear correlation between an instance's level of synchronization and possible gains through re-optimization. They revealed their research on how many journey time scenarios are needed to get a good representation of the stochastic solutions. Furthermore, they showed that, without sacrificing dependability, time-dependent journey times may be combined on a city-wide scale and linearized as a function of free flow times. A garbage collecting issue with economic, environmental, and social objective functions was examined by Rabbani & Farrokhi-Asl (2019). The primary goal function was to reduce the system's total expenses, which included building depots and treatment facilities. The second objective function addressed environmental concerns by minimizing greenhouse gas emissions, while the third function maximized the distances between each customer and treatment facilities. To find the best answers in a reasonable amount of time, three metaheuristic algorithms were developed in conjunction with a clustering technique. Performance indicators from NSGA-II, improved SPEA-II, and MOEA/D were compared. The outcomes showed that NSGA-II was superior to the other algorithms in the model that were given.

An MO-MVRP was presented by Rezaei Kallaj et al. (2021) to provide blood to injured individuals under severe conditions. In the proposed model, the goal functions of the issue were defined as the vehicle arrival time and the volume of blood collected. Also, the suggested model was solved using the CPLEX deterministic solution. An MP-2ELRP was presented by Wang et al. (2021) which included facility location selection and two-tiered vehicle routing optimization. To solve the given model, they also proposed a two-stage hybrid approach that consisted of an enhanced MOPSO algorithm and K-means clustering. Customers were assigned to distribution centers to receive services over a period using the K-means clustering method, and Pareto optimal solutions were found for vehicle routes using the

MOPSO algorithm. A 2E-LRP2LR for a two-echelon LRP was presented by Gandra et al. (2021) in a different research. To solve the suggested model, they also presented a novel scenario-based optimization technique for various loadings, and they evaluated the model's effectiveness using actual samples.

To lower the danger of theft in transportation, Fallahtafti et al. (2021) proposed the MO-2ELRP model for transferring cash. To achieve this, the first and second objectives were the amount of money carried by the vehicle as a risk function and the length of the money transfer, respectively. To solve the problem, several exact and meta-heuristic approaches at small to medium scales were used. Another kind of LRP that has caught academics' interest is the VRP. One of the main issues in supply chain management is the VRP, which involves some vehicles centralized in one or more places (warehouses or nodes) and their task of visiting several customers, each with a specific request and offering a service to them. To minimize the distance traveled, total journey time, number of vehicles, late fines, and finally the function of transportation cost, this problem aims to use mathematical models and route optimization approaches. By doing so, it will ultimately maximize customer satisfaction.

A multi-period mathematical model including environmental and economic variables was created by Rabbani et al. (2020). Because of the decrease in routing costs, a VRP is now seen as a critical issue, particularly in the associated bioenergy supply chain. Several of the optimization models identified the vehicle routing for the supply chain design of bioenergy. The economic objective function of the bi-objective MILP model they proposed minimized costs associated with transportation, capacity expansion, fixed and variable costs, and location routing. A non-dominant genetic algorithm is used to solve the suggested bi-objective model (NSGA-II). Furthermore, the enhanced ε- constraint approach and the CPLEX solver are used to tackle the small-size problem. For MTVRPTW-SDLT, Neira et al. (2020) offered an integer programming approach. The first model in their paper represented the car being returned to the warehouse. To overcome the challenge, deterministic methods have been applied. A model for the MTVRPTW was presented by Huang et al. (2021). In the proposed model, the vehicles unloaded the cargo that was collected from clients at a warehouse with a limited unloading capacity. For the suggested MTVRPTW model, a Branch-Price-Cut (PBC)-based solution algorithm was developed. In the proposed model, the objective functions were defined as the vehicle arrival time and the volume of blood collected. To solve the suggested model, the CPLEX deterministic solution was applied.

A CMVRPDCDTW was assertively developed by Wang et al. (2022) by taking resource sharing and customer dynamic requirements into consideration. To do this, a bi-objective optimization model was developed to optimize vehicle routes while reducing the overall cost of operation and the quantity of vehicles. The enhanced K-Medoids clustering method and the MOPSO algorithm were coupled to offer a combined algorithm that finds near-optimal solutions for the suggested model. Hasanpour Jesri et al. (2022) developed the MTOVRP in their study. To do this, they presented an appropriate integer programming model to minimize the total cost to customers. The model is solved with a decomposition-based approach that splits the issue into two sections. Tactical decisions about the supplier and the type of cooperation were taken in the first stage. The order in which each vehicle makes its visits is determined in the second stage. An MDVRP with uncertainty was presented by Nozari et al. in 2022. The proposed model's main objective was to locate industrial facilities and warehouses as well as vehicle routes for the delivery of medical supplies to hospitals. This model was solved using a robust fuzzy technique with uncertain inputs including demand, transmission, and distribution costs. The Neutrosophic fuzzy programming approach was used to assess the impact of uncertainty.

An MSVR-TG was presented by Jiao et al. (2023) to address the Rescue VRP with Energy Constraints in disaster situations. They suggested a heuristic method based on k-means clustering and the genetic algorithm to solve the problem. A VMRP was proposed by Pirabán-Ramírez et al. (2022) to deliver blood units from collecting sites to a blood center. An MILP technique was offered for this problem, which has been characterized as a multi-trip VRP with profit maximization. They also proposed a local search meta-heuristic solution approach. Xue et al. (2022) introduced a 2E-DVRP-Psss, which was capable of optimizing the operating cost and construction costs.

To save operating expenses and carbon emissions, Du et al. (2023) developed an innovative JD model that encourages horizontal cooperation and resource sharing among express enterprises. Moreover, they created a mathematical model for JD called MD-2E-JDLRP that considered several objectives. To solve the suggested model, a hybrid heuristic method was presented. This algorithm's performance was evaluated using case studies and benchmarks. Ultimately, a case study was carried out to confirm the MD-2E-JDLRP model's efficacy. The outcomes show that the JD model could successfully lower expenses and carbon emissions while maintaining greater levels of customer satisfaction.

For this issue, Hajghani et al. (2023) developed an MILP model that included optimizing social responsibility, and reducing expenses in addition to CO2 emissions. Because each vehicle had a fixed cost, the suggested model reduced the number of transport routes in the two-echelon distribution network while raising the maximum load that could be carried by a vehicle in an effort to reduce the total cost. Also, in the presented study, a different type of routing was considered at each echelon. Due to the NP-hardness of the problem, two efficient meta-heuristic algorithms of NSGA-II and MOSFS were used to solve the model (Jafarzadeh et al., 2022).

Presently, research on VRP primarily concentrates on examining solution techniques, with minimal emphasis on their pragmatic consequences. Because they tackle real-world issues and offer workable answers that can enhance performance and streamline operations, practically motivated VRP models are crucial. To close this gap, Fernando et al. (2024) integrated several real-world factors associated with the distribution of fresh agricultural items in retail chains. To maintain freshness, retail chains often distribute fresh produce—daily, in most cases.

As a result, manually organizing this daily distribution takes effort and time. The suggested VRP model for route optimization and integrated planning (i.e., load slot allocation, and order allocation) was effectively applied in the actual world. Furthermore, because it takes less time to arrive at the ideal distribution schedule, the suggested VRP model is effective as a tool for operational planning. Three meta-heuristic approaches (GLS, SA, and TS) have been evaluated to get close to optimal solutions for the suggested optimization model. It may also take into account the perishability of fresh agricultural goods. Escobar-Vargas and Crainic (2024) introduced the 2E-MALRPS and presented an MIP formulation on a hybrid time–space network which combined continuous and discrete time representations. They also presented an exact solution method that iteratively refined a reduced time–space network, and solved the 2E-MALRPS formula defined on the reduced network to extract bounds and temporal granularity refinements, so that the method led to the optimal solution of the main problem. They have extended the dynamic discretization discovery method to complex problem settings involving multiple levels of location, routing, and synchronization decisions.

Based on the mentioned cases and literature review, the following research gaps were identified:

1. Lack of attention to driver's experience and performance and its application in VRP models: In the presented model, there is a set of drivers who the vehicles are divided between to carry out product distribution operations. In this regard, an allocation cost has been defined based on the type of vehicle, the worn-out type of the vehicle and the driver's experience. This cost is measured based on the parameters of the vehicle type, worn out type of the vehicle, and the driver's experience. The more experience a driver has, the higher the cost of assigning a vehicle to him, and vice versa. It should be noted that each driver can drive different vehicles that differ from each other in terms of load volume and capacity.
2. Lack of attention to the hardness of route as an important parameter in the VRP models: In the proposed model, different hardness degrees are defined for different routes. The cost of the route is determined based on an initial fixed cost and the hardness degree of the route, in which higher hardness degrees, result in higher cost of the routes.
3. Lack of attention to the life cycle stage of the transport fleet in VRP models: In the presented model, in addition to the experience of the driver, the worn-out type of the vehicle is an effective factor in the allocation cost. In other words, more used a vehicle is, the more likely it is for it to break down. Therefore, the cost of allocating this vehicle to drivers will be lower.

III. PROBLEM STATEMENT

The number of orders and their routing are initially determined at the second echelon in the proposed model, followed by determining the amounts of orders sent to them and the routes of vehicles at this echelon by specifying the demand of other intermediate warehouses. Moreover, the route costs of the first and second echelons' vehicles and maintenance costs in other places are included. Also, environmental pollution as well as the reliability of the routes at every echelon are considered as the second and third objectives of the mathematical model in addition to the costs.

In this problem, consumers have demands that can not be met from central warehouses or manufacturing factories for some reason. Thus, these customers sent their requests to intermediate warehouses located on the outskirts of cities, through which, their demands will be fulfilled. However, these intermediate warehouses meet the requested demands through central warehouses or manufacturing factories. As a result, the warehouse or factory in the system sends the products to the intermediate warehouses by vehicles assigned to the first echelon according to the requests sent by intermediate warehouses. Then, in the intermediate warehouses, the products are separated, sorted, and repackaged according to the requests sent from the customers and sent and delivered to the customers by the vehicles assigned to the second echelon through the routes of the second echelon. The customer service has to be done by a single vehicle in this problem and the demand cannot be segmented. It should be noted that in this research, the demand is considered uncertain and probable based on a normal distribution. There is a set of drivers in the presented model, among which, the vehicles will be divided to perform the product distribution operations. An allocation cost will be defined accordingly based on the type of vehicle, the worn out type of the vehicle, and the experience of the driver. This cost will be measured based on the parameters of the type of vehicle, worn out type of the vehicle, and the experience of the driver. The more experienced a driver, the higher the cost of vehicle allocation to him would be, and vice versa.

Worn-out type of the vehicle is another influential parameter in the allocation cost. A vehicle with a longer age naturally has a higher worn-out and a higher probability of breakdown. Thus, the cost of allocating such vehicles to drivers will be lower. Also, different degrees of hardness will be defined for different routes in this study. The cost of passing the route will be determined based on an initial fixed cost and the degree of hardness of the route. Naturally, the higher the degree of hardness, the higher the cost of traveling the route would be.

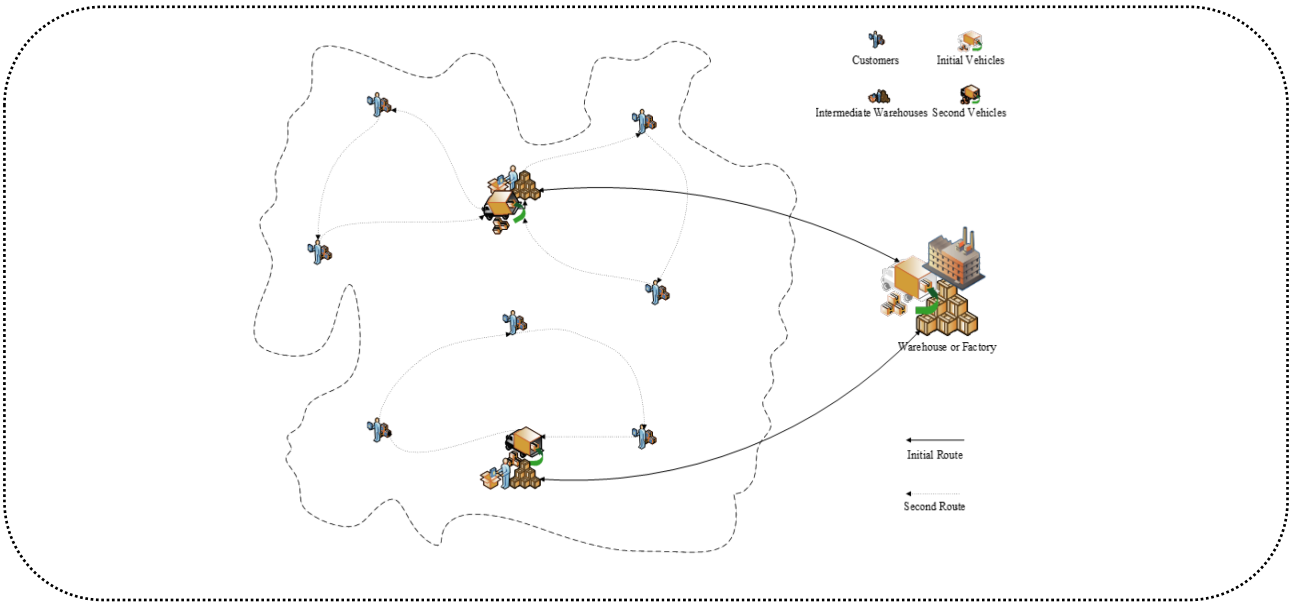

Fig 1. An example of a two-echelon inventory routing

There are 10 points or facilities in Figure 1. There is a warehouse or factory, two intermediate warehouses, and 7 customers. The factory, located outside the urban area, transports the goods and delivers them to intermediate warehouses through the first-echelon routes by first-echelon vehicles, which are generally heavy vehicles with traffic restrictions in the urban environment. Following a series of non-manufacturing activities, the products will be delivered to customers on the second echelon routes by second echelon vehicles, which are generally proper vehicles for urban traffic. It should be noted that it is not allowed to send goods directly to customers, and every vehicle in the second-echelon can serve several customers without forming a sub-network. Two different vehicles are used in the first-echelon for service-providing in this example. Also, three vehicles are used in the second echelon, each of which has provided service to more than one customer and returned to the origin without forming a sub-network.

IV. FORMULATION THE MODEL

This section defines an arc-based formula for 2e on the graph $G(V, E)$, in which, V includes all the network nodes, V_0 is a single-member central depot set, V_s is the intermediate warehouse set, and V_c is the customers set. Also, $V_0 \cup V_s$ is the set of nodes of the first echelon, and $V_s \cup V_c$ is the set of nodes of the second echelon. E is the set of all edges in the distribution graph, including undirected edges connecting the central depot to the centers of intermediate warehouses, the centers of intermediate warehouses to customers, and customers to each other as well. The trip between any two nodes is determined by a network edge with a non-negative cost that applies to the inequality $C_{ik} \geq C_{ij} + C_{jk}$.

A. Model assumptions

1. The round trip time of each vehicle is less than one period.
2. Since the being studied problem is an operational one, the planning horizon encompasses several months, and this time horizon is divided into equal and specific periods (for example, months or weeks).
3. There is a feature for multi-part delivery to intermediate warehouses.
4. There is no feature for multi-part delivery to customers.
5. Three types of vehicles are considered in the first echelon: small vehicles (M_1), medium vehicles (M_2), and large vehicles (M_3). $K_1 = \{M_1 \approx 1,\ M_2 \approx 2,\ M_3 \approx 3\}$, in which, the allocation cost increases by enhancing the capacity of the vehicle (from small to large). $C^3_{i'j'} > C^2_{i'j'} > C^1_{i'j'}, i'j' = Constant$.
6. The driver's experience is considered in three levels in the first echelon: low level (P_1), medium level (P_2), and high level (P_3). $j' = \{P_1 \approx 1, P_2 \approx 2, P_3 \approx 3\}$, in which, the allocation cost increases with increasing the driver's experience (from low to high) $C^k_{i'3} > C^k_{i'2} > C^k_{i'1}, i', k = Constant$.
7. In the first echelon, the cost of passing the route is determined based on the degree of hardness of the route, and the cost of vehicle allocation is determined based on the type of vehicle, the worn-out type of the vehicle, and the driver's experience.
8. There is no feature to send the customers' requests directly from the central warehouse.
9. There is a feature to store goods in any of the intermediate and customer warehouses, and thereby, the cost of warehousing the goods in each of these points is considered.
10. There is no return flow of goods from customers to the intermediate warehouse and from the intermediate warehouse to the central warehouse, and there is no lateral connection between the intermediate warehouses.
11. Each customer can only receive goods from a few intermediate warehouses in each period. Whilst each vehicle is allowed to visit each customer at most once (In fact, each customer is served once in each period).
12. Each route in the first echelon has a different hardness rate; a higher degree of hardness imposes a higher cost for the distribution.
13. All the demands of the intermediate warehouse are met by the central warehouse.

B. Indices

i, j: Index of the network points

e: Index related to the product distribution echelons (echelon 1 and echelon2)

k: Index of the vehicles

t: Index of the time periods

i': Index related to the type of worn-out (type 1, type 2, and type 3)

j': Index related to the type of the driver's experience (level 1, level 2, and level 3)

C. Parameters

$C^k_{i'j'}$	The cost of allocating a type k vehicle at the first echelon with worn-out of type i' to an experienced driver j'
$C^k_{iji'j'}$	The cost of allocating a type k vehicle with worn-out of type i' on the route from i to j to an experienced driver j'
t_{ijk}	The duration of the trip along the arc (i, j) with the vehicle k
$C0_{ij}$	The initial fixed cost related to traveling the route (i, j)
C'_{ij}	The cost of travel related to the arc (i, j) with the vehicle k at the second echelon
H_{ij}	The degree of route hardness (i, j)
E_{ijk}	The amount of environmental pollution caused by the travel related to the arc (i, j) with the vehicle k
r_{ijk}	The degree of reliability of the vehicle in the travel related to the arc (i, j) with the vehicle k
α	The conversion factor of the degree of hardness of the route (i, j) with vehicle type k and worn-out type i' based on the type of driver's experience j' to the cost
β	The conversion factor of the vehicle type k and the worn-out type i' based on the driver's experience type j' to the cost
Q_{ke}	The weight capacity of the k^{th} vehicles at the e^{th} echelon
$d_{it} \sim N(\mu_{it}, \sigma_{it})$	The amount of random demand of the customer i in the period t, which has a normal distribution with a mean of μ_{it} and a standard deviation of σ_{it}

EW_{it}	The lower limit of the time window of the customer i in the period t
LW_{it}	The upper limit of the time window of the customer i in the period t
PE_{it}	The penalty for early delivery of the order to the customer i in the period t
PL_{it}	The penalty for late delivery of the order to the customer i in the period t
$invi_0$	The initial inventory at the point i
h_i	The cost of maintenance at the point i
BM	The large positive number
$\mathrm{ord}_{i'}$	The degree of worn-out of i'

D. Variables

x_{ijkt}	It is one if in the first echelon from i to j using the vehicle $k \in K_1$ on day t , otherwise 0
$Z_{iji'j'}^{k}$	It is one if the type k vehicle with worn-out type i'on the route i to j is allocated to an experienced driver j', otherwise 0
y_{ijkt}	It is one if in the second echelon from i to j using the vehicle $k \in K_2$ on the day t, otherwise 0
Z_{jt}	It is one if the point j has been chosen for giving services on day t, otherwise 0
Ct_{kt}	It is one if the vehicle k has been chosen for use on day t, otherwise 0
ds_{it}	The total demand requested from temporary warehouse i on day t
pd_{it}	The amount of product sent to the i^{th} customers on day t
pd_{jkt}	The amount of product sent to the j^{th} temporary warehouse using the vehicle $k \in K_1$on day t

l_{ki}	It is one if the vehicle $k \in K_1 \cup K_2$ is dependent on the temporary warehouse i, otherwise 0
a_{kt}	The amount of the product transported by the vehicle $k \in K_1$ on day t
inv_{it}	The inventory of point i (the temporary warehouse and customers) on day t
Tr_{ikt}	The arrival time to point i on day t by the vehicle k
ER_{it}	The amount of earliness to reach to point i on day t
LA_{it}	The amount of lateness to reach to point i on day t
uu_{ikt}	The auxiliary variable to remove the sub-network

E. Objective functions

$$Min\ Z_1 = \sum_{i\in V_o}\sum_{j\in V_s}\sum_{k\in K_1}\sum_{t\in T}\sum_{i'\in I'}\sum_{j'\in J'} C^k_{iji'j'} z^k_{iji'j'} x_{ijkt} + \sum_{i\in V\backslash V_o}\sum_{j\in V\backslash V_0}\sum_{k\in K_2}\sum_{t\in T} y_{ijkt} c'_{ij} + \sum_{i\in V\backslash V_o}\sum_{t\in T} h_i inv_{it} + \sum_{t\in T}\sum_{i\in V_c} PE_{it} ER_{it} + \sum_{t\in T}\sum_{i\in V_c} PL_{it} LA_{it} \quad (1)$$

Where,

$$C^k_{i'j'} = \beta \frac{kj'}{ordi'} \quad (2)$$

$$C^k_{iji'j'} = C0_{ij} + \alpha H_{ij} C^k_{i'j'} \quad (3)$$

Phrase (2) is the cost of allocating the vehicle based on the worn-out and experience of the driver, which has a direct relationship with the type of vehicle and the experience of the driver and is inversely related to the worn-out of the vehicle. Also, the vehicle allocation cost will be calculated in Phrase (3) based on the degree of hardness of the route, the type of vehicle, the worn-out of the vehicle, and the driver's experience.

Equation (1), the first objective function minimizes the sum of maintenance costs of other points, variable and fixed costs of transportation related to the vehicles of the first and second echelons, and ultimately, the cost of early and late fines in the delivery of the customers' orders.

$$Min\ Z_2 = \sum_{i\in V_o}\sum_{j\in V_s}\sum_{k\in K_1}\sum_{t\in T} x_{ijkt} E_{ijkt} + \sum_{i\in V\backslash V_o}\sum_{j\in V\backslash V_o}\sum_{k\in K_2}\sum_{t\in T} y_{ijkt} E_{ijkt} \quad (4)$$

Equation (4) is the second objective function associated with the environmental pollution of routing. These pollutions will be formed through traveling the routes in the first echelon plus the pollutions of the second echelon (Xue et al., 2022).

Since a complete network is considered a consecutive route, thus the logic governing sequential systems needs to be used to calculate the reliability of the complete network. As the product of the unchosen routes will be zero in the rest of the links; therefore, Equation (5) would be utilized to solve this problem (Asefi et al., 2020):

$$f(y_{ijkt}) = 1 - (1 - r_{ijk})y_{ijkt} \qquad \forall i, j \in V_s \cup V_c, \forall k \in K_2, \forall t \in T \tag{5}$$

The third objective function, seeking to maximize the reliability of the routes traveled in the network, is represented in the form of Equation (6):

$$Max\ Z_3 = \sum_{k\in K_2}\sum_{t\in T}\prod\prod_{i,j\in V_s\cup V_c} f(y_{ijkt}) + \sum_{i\in V_o}\sum_{j\in V_s}\sum_{k\in K_1}\sum_{t\in T} x_{ijkt}r_{ijkt} \tag{6}$$

F. Constraints

$$z^k_{iji'j'} \geq x_{ijkt} \qquad \forall\, i \in I, j \in J, i' \in I', j' \in J', k \in K_1, t \in T \tag{7}$$

$$\sum_{i\in V_o}\sum_{j\in V_s} x_{ijkt} \leq BM.ct_{kt} \qquad \forall\, k \in K_1, \forall\, t \in T \tag{8}$$

$$inv_{i1} = inv_{i_0} + pd_{i1} - \mu_{i1} - Z_\alpha\sigma_{i1} \qquad \forall\, i \in V_c \tag{9}$$

$$inv_{it} = inv_{i(t-1)} + pd_{it} - \mu_{it} - Z_\alpha\sigma_{it} \qquad \forall\, i \in V_c, t \geq 2 \tag{10}$$

$$pd_{jt} \leq BMz_{jt} \qquad \forall\, j \in V_c, \forall\, t \in T \tag{11}$$

$$\sum_{i\in V\setminus V_o}\sum_{k\in K_2} y_{ijkt} = z_{jt} \qquad \forall\, j \in V_c, \forall\, t \in T \tag{12}$$

$$\sum_{i\in V_s\cup V_c} y_{ijkt} = \sum_{i\in V_s\cup V_c} y_{jikt} \qquad \forall\, j \in V_s \cup V_c, \forall\, k \in K_2, \forall\, t \in T \tag{13}$$

$$\sum_{i\in V_0}\sum_{j\in V_s} pd_{jkt}\, x_{ijkt} \leq Q_{k_1} \qquad \forall\, k \in K_1, \forall\, t \in T \tag{14}$$

$$\sum_{i\in V_0}\sum_{j\in V_c}\sum_{k\in K_1}\sum_{t\in T} X_{ijkt} = 0 \tag{15}$$

$$\sum_{i\in V_c}\sum_{j\in V_0}\sum_{k\in K_2}\sum_{t\in T} y_{ijkt} = 0 \tag{16}$$

$$a_{kt} = \sum_{i\in V_0}\sum_{j\in V_s} pd_{jkt}x_{ijkt} \qquad \forall\, k \in K_1, \forall\, t \in T \tag{17}$$

$$ds_{it} = \sum_{k \in K_1} l_{ki} . a_{kt} \qquad \forall\, i \in V_s, \forall\, t \in T \tag{18}$$

$$\sum_{j \in V_c} \sum_{t \in T} y_{ijkt} \le BM . l_{ki} \qquad \forall\, i \in V_s, \forall\, k \in K_2 \tag{19}$$

$$\sum_{i \in V_0} x_{ijkt} \le ds_{jt} \qquad \forall\, j \in V_s, \forall\, k \in K_1, \forall\, t \in T \tag{20}$$

$$BM(\sum_{i \in V_0} \sum_{k \in K_1} x_{ijkt}) \ge ds_{jt} \qquad \forall\, j \in V_s, \forall\, t \in T \tag{21}$$

$$\sum_{i \in V_0 \cup V_s} x_{ijkt} = \sum_{i \in V_0 \cup V_s} x_{jikt} \qquad \forall\, j \in V_0 \cup V_s, \forall\, k \in K_1, \forall\, t \in T \tag{22}$$

$$\sum_{k \in K_2} pd_{jkt} = ds_{jt} \qquad \forall\, j \in V_s, \forall\, t \in T \tag{23}$$

$$\sum_{i \in V_c \cup V_s} \sum_{j \in V_c \cup V_s} pd_{it} . y_{ijkt} \le Q_{k_2} \qquad \forall\, k \in K_2, \forall\, t \in T \tag{24}$$

$$\sum_{i \in V \setminus V_O} \sum_{j \in V \setminus V_O} y_{ijkt} \le BM . ct_{kt} \qquad \forall\, k \in K_2, \forall\, t \in T \tag{25}$$

$$\sum_{k \in K_2} \sum_{t \in T} uu_{1kt} = 0 \qquad \forall\, k \in K_2, \forall\, t \in T \tag{26}$$

$$uu_{ikt} + 1 \le uu_{jkt} + BM(1 - y_{ijkt}) \qquad \forall\, i \in V_c \cup V_s, \forall\, j \in V_c, \forall\, k \in K_2, \forall\, t \in T \tag{27}$$

$$inv_{i1} = invi_0 + \mu_{i1} + Z_\alpha \sigma_{i1} - \sum_{k \in K_2} pd_{ik1} \qquad \forall\, i \in V_s \tag{28}$$

$$inv_{it} = invi_{i(t-1)} + \mu_{it} + Z_\alpha \sigma_{it} - \sum_{k \in K_2} pd_{ikt} \qquad \forall\, t \ge 2, \forall\, i \in V_s \tag{29}$$

$$\sum_{k \in K_2} Tr_{ikt} - LW_{it} \le LA_{it} \qquad \forall\, i \in V_c, \forall\, t \in T \tag{30}$$

$$EW_{it} - \sum_{k \in K_2} Tr_{ikt} \le ER_{it} \qquad \forall\, i \in V_c, \forall\, t \in T \tag{31}$$

$$\begin{aligned} & ds_{it}, pd_{it}, pd_{jkt}, a_{kt}, inv_{it}, Tr_{ikt}, ER_{it}, LA_{it}, uu_{ikt} \ge 0 \\ & x_{ijkt}, z^{k}_{iji'j'}, y_{ijkt}, z_{jt}, ct_{kt}, l_{ki} \in \{0, 1\} \end{aligned} \tag{32}$$

Constraint (7) states that, if there is a route from point i to point j with a type k vehicle, then the types of worn-out and the experience of the driver of that type of vehicle should be determined. Constraint (8) conditions the possibility of sending goods between the central warehouse and temporary warehouses using a truck on a specific day to the payment of the fixed cost of the truck and using that truck on that day. Phrases (9) and (10) are the inventory equations of the customers. Constraint (11) suggests that the cargo will be sent to customer j if he has been chosen for delivery on that day. Constraint (12) guarantees that each customer, if chosen to be provided with service, will be served only once. Constraint (13) also sets the condition for exiting customers' points in the case of entering them. Constraint (14) guarantees that the total load sent from all points by the truck on a certain day would be lower than the capacity of that truck. Phrases (15) and (16) are set to avoid impossible travel between the two echelons. Constraint (17) obtains the total loads sent by each truck on a specific day, and Constraint (18) achieves the total of demands requested from each temporary warehouse on each day. Constraint (19) states that a trip can be made from the temporary warehouse to the customer with a specific truck only if that truck is affiliated with that temporary warehouse. Constraints (20) and (21) are related to the travel permit at the first echelon. Constraint (22) is the condition for exiting a second-echelon temporary warehouse in the case of entering that warehouse. Constraint (23) guarantees that the amount of load sent to every temporary warehouse would be exactly equal to the total demands requested from that temporary warehouse. Constraint (24) is concerned about respecting the capacity of the second-echelon trucks. Constraint (25) states that transportation can be made with a second-echelon truck only if its fixed cost has been paid for use on that certain day. Constraints (26) and (27) are for the non-formation of sub-network in the second echelon. Constraints (28) and (29) are also associated with the inventory balance in the second echelon. Equation (30) considers the delay rate equal to the positive difference between the delivery time and the upper limit of the time window. Equation (31) considers the amount of early delivery of the order equal to the positive difference in the delivery time from the lower limit of the time window. Finally, Constraint (32) involves the decision variables of the model.

V. PROBLEM SOLVING APPROACHES

A. The ε-constrained Approach

This approach assumes that the decision made to minimize the objective functions (33) is associated with the Constraint (34).

$$Min\ \ F(x) = \{f_1(x), \dots, f_n(x)\} \tag{33}$$

$$st: \quad \begin{aligned} & g(x) \leq 0 \\ & h(x) = 0 \end{aligned} \tag{34}$$

One of the objective functions is chosen as the main objective function according to Equation (35) based on this method. Other objective functions are considered as Constraint (36). Each time, the problem is solved according to one of the objective functions and the optimal and corresponding values are calculated for each objective function. The range between two optimal and corresponding values of the sub-objective functions is divided by a predetermined number, a table of values is determined for the *"ε"*, and ultimately, the Pareto Solutions are obtained (Fakhrzad and Sadri Esfahani, 2014).

$$Min\ \ F(x) \tag{35}$$

$$st: \quad \begin{aligned} & f_j(x) \leq \varepsilon_j \\ & f_j^{min}(x) \leq \varepsilon_j \leq f_j^{max} \\ & g(x) \leq 0 \\ & h(x) = 0 \end{aligned} \qquad j = 1, \dots, n, j \neq 1 \tag{36}$$

The simple VRP problem as an NP-hard problem has many generalizations (Lenstra and kan, 1981). Since the presented model can be adjusted to a simple VRP problem, it is placed in the category of NP-Hard problems. Therefore, to solve the model in high dimensions and reasonable time, one should use metaheuristic methods. In this article, two metaheuristic algorithms of MOPSO and NSGA II are used.

B. MOPSO Algorithm

In this algorithm, presented for the first time by Coello and Lechuga (2002) the search process begins with randomly generating a number of particles and distributing them in the solution space. Similar to the single-objective PSO algorithm, the velocity and position of each particle need to be calculated. The only difference is that the position of one of the members of the archive is randomly selected and determined as the leader rather than the best collective position. The speed and location of the particle in stage $t+1$ can be computed using Equations (37) and (38):

$$v_{t+1}^{i} = w_t v_t^i + c_1 r_1 \left(x_t^{i,best} - x_t^i\right) + c_2 r_2 \left(rep_{rand} - x_t^i\right) \tag{37}$$

$$x_{t+1}^{i} = x_t^i + v_{t+1}^i, -v_{max} \leq v_{t+1}^i \leq v_{max}, w_t = w_{min} + \frac{w_{max} - w_{min}}{t} \tag{38}$$

Where,

$x_t^i \& v_t^i$	Location and velocity vectors, respectively of the particle *i* at time *t*
rep_{rand}	A random member from the archive
$x_t^{j,best}$	The best personal experience of the particle *i*
w_t	The variable inertia coefficient from 0.9 to 0.4
r_1, r_2	Random numbers with a uniform distribution between zero and one
c_1, c_2	The coefficient of personal learning and the coefficient of collective learning, respectively

C. The NSGA II Algorithm

NSGA was developed and presented by Deb et al. (2000). By adding two required operators to the usual single-objective genetic algorithm, this algorithm has been transformed into a multi-objective algorithm. Rather of finding the best solution, the Pareto Front provides groups of best answers. Thus, Deb et al.(2000) proposed the NSGA II algorithm, the second version of the NSGA algorithm. This algorithm's steps are generally as follows:

generating the initial population based on the scale and constraints of the problem,

1. evaluating the generated population according to the objective functions,
2. applying the non-dominated sorting method,
3. calculating the control parameter called crowding distance,
4. choosing the parent population for reproduction, and
5. performing the intersect-mutation operator.

D. The Chromosome Structure in the NSGA II

The coding of the problem solution significantly affects the quality of the solution and the computational time. The chromosome structure in the NSGAII algorithm consists of two permutation strings. The first string represents the routes between intermediate warehouses, customers, and vehicles on the second echelon (Rahmanifar et al., 2024). In this string, if n_{k_2}, n_c, and n_s are the number of vehicles on the second echelon, the number of customers at this echelon, and the number of intermediate warehouses, respectively, then, the first string would have $n_{k_2} + n_c - 1$ numbers, which includes the permutation of numbers between 1 and $n_{k_2} + n_c - 1$. The numbers between 1 and n_c indicate the number of customers, the numbers between n_c and $n_s + n_c$ represent the separators of the intermediate warehouses, and the numbers bigger than n_c indicate the separators of vehicles. For example, for four customers, three vehicles, and two intermediate warehouses, a feasible string will be as depicted in Figure 2.

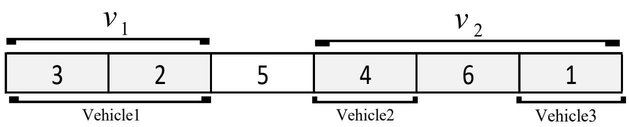

Fig 2. The chromosome structure for four customers, three vehicles, and two intermediate warehouses of a feasible string at the second echelon

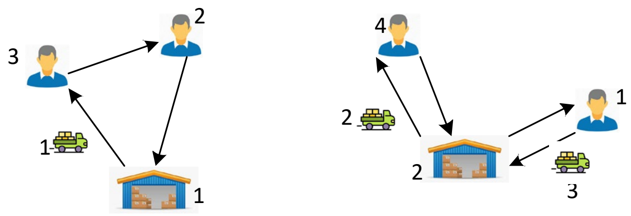

Fig 3. Displaying the phenotype of the chromosome structure of Fig. 2

In this solution, at the second echelon, vehicle 1 is allocated to intermediate warehouse 1, and vehicles 2 and 3 are assigned to intermediate warehouse 2. The obtained routes include 2-1-2, 2-4-2, and 3-1-2-1. The second string indicates the routes between the central warehouse and intermediate warehouses, which includes $n_s + n_{k_1} - 1$ numbers, in which, n_s represents the number of intermediate warehouses and n_{k_1} indicates the number of vehicles at the first echelon. A total of $n_{k_1} - 1$ zeros need to be added to the numbers 1 to n_s as separators of vehicles in the first echelon, and then a random permutation should be created. For example, for two intermediate warehouses and two vehicles at the first echelon, a feasible string will be as shown in Figure 4.

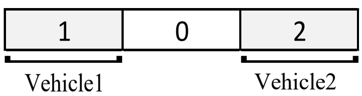

Fig 4. The chromosome structure of two intermediate warehouses, two vehicles at the first echelon, and a feasible string at the first echelon

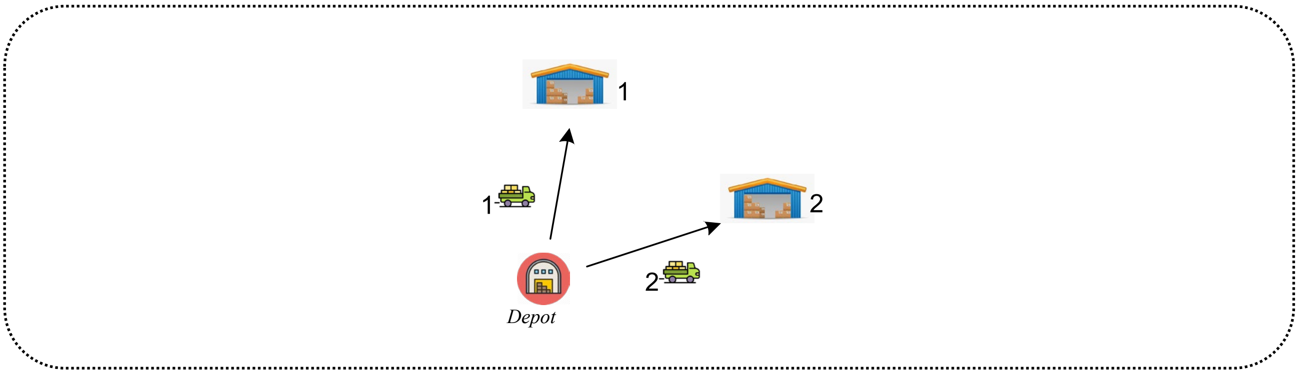

Fig 5. Displaying the phenotype of the chromosome structure of Fig. 4

The obtained routes are 1-0-3-0 and 2-0-0. The general structure of the solution is depicted in Fig. 6.

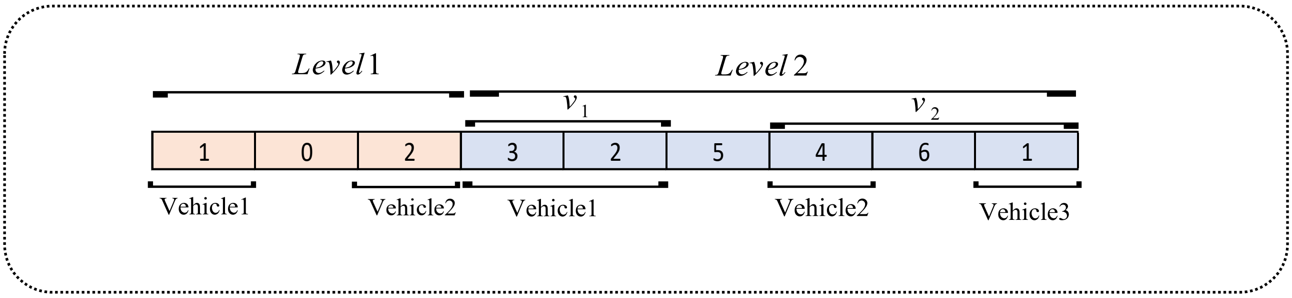

Fig 6. The general structure of the chromosome in the first and second echelons

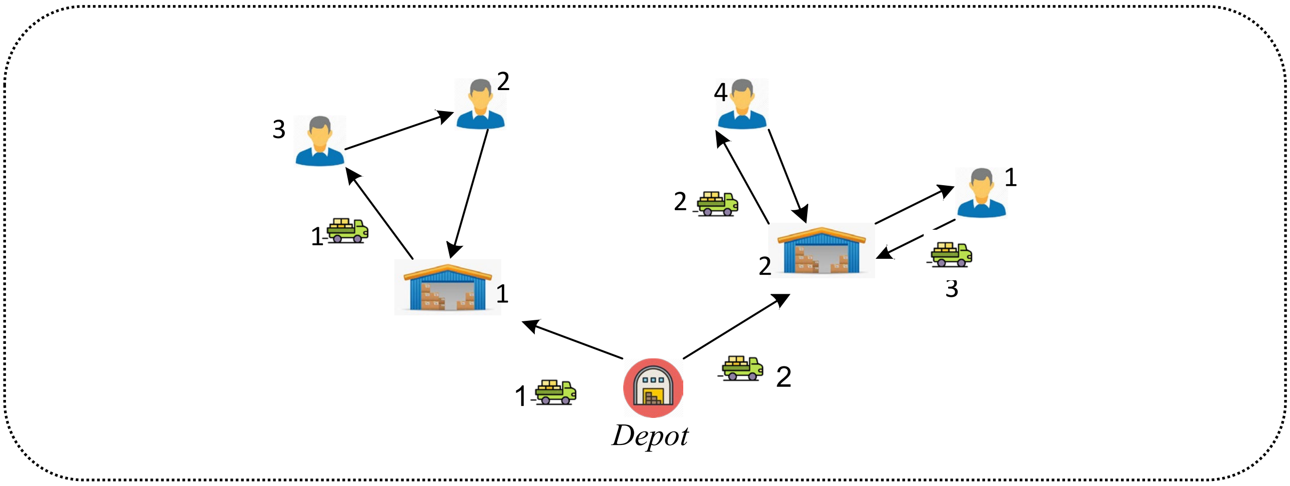

Fig 7. Displaying the phenotype of the chromosome structure of Fig. 6

E. The Intersect-mutation Operator

The intersect operator functions to discover the new space. This operator performs the displacement of parts of strings between the chosen parents. There are various types of intersecting operators according to the type of problem in the genetic algorithm literature.

Here, the parents were first randomly selected using the "roulette wheel operator" to perform the intersect operation by the "Binary Tournament Selection" operator. Then, the random number $c_1 \in (0, n_{k_1} + n_s - 1), c_1$ at the first echelon of the chromosome and the random number $c_2 \in (n_{k_1} + n_s - 1, n_{k_1} + n_{k_2} + n_s + n_c - 2), c_2$ at the second echelon of the chromosome were selected. The first offspring is generated by the first part of the first parent and the second part of the second parent (both at the first and second echelons) (Figures 8 & 9). There may be some duplicate genes in the children. In such a case, the duplicate genes of the first offspring need to be replaced with the duplicate genes of the second offspring and vice versa.

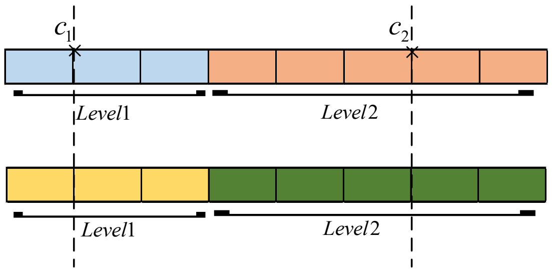

Fig 8. Parents

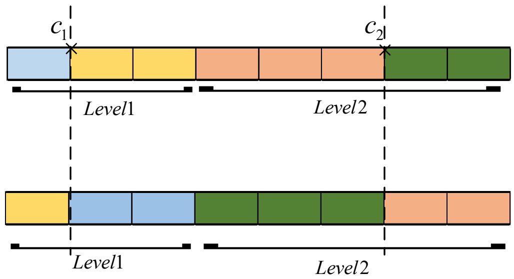

Fig 9. Children

The reverse mutation operator is also utilized to explore new solutions. Thus, two genes will be randomly selected at the first and second echelons of the chromosome, and their positions will be replaced with each other.

F. Setting the Parameters

The performance of the meta-heuristic algorithm largely depends on the values of their input parameters so that if the parameters of an efficient algorithm are not set accurately, it will make that algorithm inefficient. Various techniques such as the multi-factor design of experiments (DOE) technique, response surface method, and designing experiments by Taguchi method will be used to adjust the parameters of the algorithms. This paper will utilize Taguchi's method to set the parameters of the proposed meta-heuristic algorithms.

G. Designing Experiments for the Algorithms' Parameters

Table I. The parameters and levels of their values for NSGA-II and MOPSO algorithms

Algorithm	Parameter	Values of each level		
		Level 1	Level 2	Level 3
MOPSO	The weight of the previous position in the movement of particles (NM)	2	3	5
	The number of primary particles (T)	50	100	150
	Velocity change factor (alpha)	0.85	0.9	0.95
	Maximum iteration (Max-iteration)	100	200	300
NSGA-II	Percent of crossover (Pc)	0.7	0.8	0.9
	Percent of mutation (Pm)	0.05	0.1	0.15
	Population size (N-pop)	50	100	150
	Maximum iteration (Max-iteration)	100	200	300

Three values are suggested for each of the parameters of NSGA-II and MOPSO algorithms based on the structure of the Taguchi method. The recommended values are described in Table I.

Then, the proposed algorithms are for the following states according to Taguchi's L9 scheme. Following the data entry in the MINITAB software and performing the Taguchi method, the S/N diagram are presented in Figures 10 and 11, by using which, the optimal values of the parameters will be obtained.

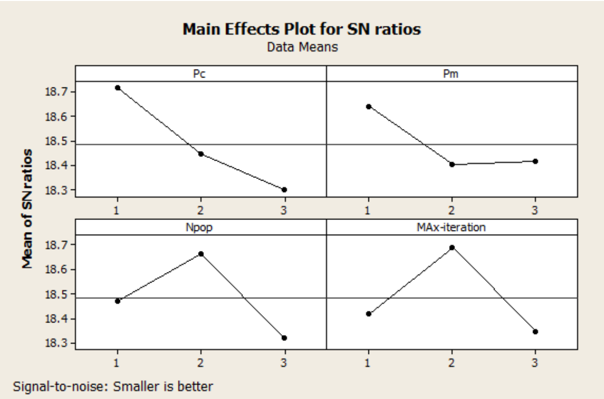

Fig 10. The MINITAB output for the Taguchi method in the NSGA-II algorithm

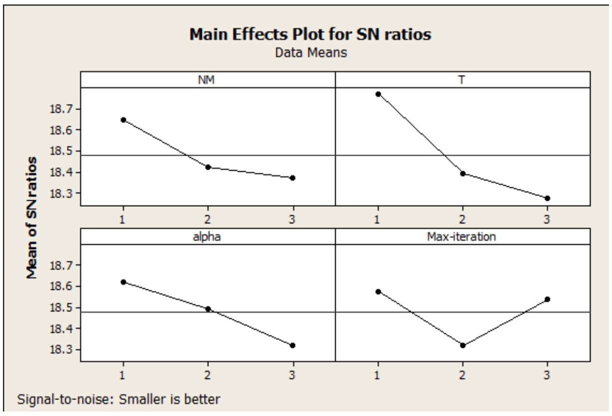

Fig 11. The MINITAB output for the Taguchi method in the MOPSO algorithm

VI. NUMERICAL EXPERIMENTS

This section focuses on evaluating the efficiency of the epsilon-constraint (EPC) method and the NSGA-II and MOPSO algorithms by using the numerical results. To this end, three categories of problems are utilized in the size of small, medium, and large samples. Examples of the mentioned problems are coded using GAMS and MATLAB software and then implemented on a computer with the specifications of CPU Core i5 2.3 GHz and 4G RAM. The input information of these problems is given in Table II.

Table II. The dimensions of the generated problems

Size	Problem No.	Number of intermediate warehouses	Number of level I vehicles	Number of level II vehicles	Number of customers	Number of periods	Types of worn-out	Types of experience
Small	1	1	2	2	3	1	1	1
	2	1	2	3	4	1	1	1
	3	2	3	3	5	1	1	1
	4	2	3	4	6	2	2	2
	5	3	4	4	7	2	2	2
	6	3	4	5	8	2	2	2
	7	4	5	5	9	3	3	3
	8	4	5	6	10	3	3	3
	9	5	5	6	11	3	3	3
	10	5	5	7	12	3	3	3

Continue Table II. The dimensions of the generated problems

Size	Problem No.	Number of intermediate warehouses	Number of level I vehicles	Number of level II vehicles	Number of customers	Number of periods	Types of worn-out	Types of experience
Medium	11	5	5	8	15	4	1	1
	12	5	5	8	20	4	1	1
	13	5	5	8	25	4	1	1
	14	5	5	8	30	4	2	2
	15	6	5	8	35	4	2	2
	16	6	6	8	40	4	2	2
	17	6	6	9	45	4	3	3
	18	6	6	9	50	4	3	3
	19	6	6	9	55	4	3	3
	20	6	6	9	60	4	3	3
Large	21	7	7	9	65	5	1	1
	22	7	7	9	70	5	1	1
	23	7	7	9	75	5	1	1
	24	7	7	9	80	5	2	2
	25	7	7	9	85	5	2	2
	26	8	8	10	90	5	2	2
	27	8	8	10	95	5	3	3
	28	8	8	10	100	5	3	3
	29	8	8	10	105	5	3	3
	30	8	8	10	110	5	3	3

A. Algorithms Evaluation Indices

Different performance evaluation criteria are considered aimed at quantitatively comparing the quality of the non-dominant solutions obtained from the proposed algorithms. The metric characteristics of the performance evaluation criteria used in this article are explained in Table III.

Table III. The indices used to evaluate NSGA II and MOPSO algorithms

Metrics	Definition
Diversification Metric (DM)	Measures the spread of non-dominated solution set (more is better).
Spread of Non-dominated Solution (SNS)	Measures the diversity of solutions(more is better).
Number of Pareto solutions (NPS)	counts the total non-dominated solutions acquired by an algorithm (more is better).
Mean ideal distance (MID)	presents the distance between non-dominated solutions and ideal point. (less is better)

The results related to different evaluation indices in the NSGA II and MOPSO algorithms and the EPC method are given in Tables IV to VI. This was done as follows:

Table IV. The values of the evaluation indices for the MOPSO algorithm

Size	Problem No.	DM	MID	SNS	NPS	CPU time(s)
Small	1	16.73	0.117	43.94	3	2.732
	2	17.994	0.129	47.889	3	3.090
	3	19.134	0.142	49.153	3	3.147
	4	20.035	0.145	49.304	4	3.804
	5	20.839	0.163	51.345	4	4.129
	6	23.403	0.169	51.867	4	4.247
	7	26.088	0.170	52.195	5	4.444
	8	26.481	0.172	57.289	5	4.704
	9	27.770	0.190	62.007	5	4.712
	10	28.869	0.203	73.246	5	5.706
Medium	11	33.126	0.225	80.902	6	6.575
	12	36.459	0.245	90.697	6	8.483
	13	41.012	0.245	94.088	7	9.904
	14	41.654	0.264	108.267	7	10.041
	15	41.672	0.281	122.168	7	11.110
	16	44.750	0.306	134.082	7	14.029
	17	50.083	0.320	153.210	7	17.244
	18	55.769	0.322	162.911	8	21.903
	19	62.389	0.358	178.975	8	26.688
	20	74.793	0.395	181.068	8	27.285
Large	21	83.347	0.417	185.044	9	30.269
	22	83.503	0.434	206.190	10	37.456
	23	90.224	0.472	232.638	11	41.777
	24	96.234	0.535	236.354	12	50.505
	25	114.624	0.564	268.013	13	62.165
	26	134.131	0.570	316.836	13	77.870
	27	146.125	0.624	368.427	13	99.764
	28	172.885	0.694	378.240	13	125.569
	29	198.570	0.717	428.872	15	151.911
	30	216.893	0.767	505.019	15	184.688
Ave		68.18621	0.345223	165.6745	7.8360326	35.19834

Table V. The values of the evaluation indices for the NSGA II algorithm

Size	Problem No.	DM	MID	SNS	NPS	CPU time(s)
Small	1	16.73	0.117	43.94	3	1.93
	2	17.885	0.123	49.838	3	2.214
	3	20.056	0.127	56.308	3	2.537
	4	22.599	0.138	61.722	3	2.980
	5	25.963	0.152	64.160	4	3.545
	6	27.794	0.170	69.268	4	3.970
	7	30.574	0.173	69.443	4	4.392
	8	34.871	0.186	79.135	4	4.917
	9	40.008	0.190	81.395	4	6.244
	10	42.834	0.207	85.578	4	7.148
Medium	11	46.623	0.217	95.241	5	7.920
	12	51.296	0.243	103.768	5	9.002
	13	57.767	0.256	118.048	5	11.064
	14	60.770	0.286	125.629	5	12.737
	15	69.551	0.291	131.079	5	15.974
	16	76.739	0.298	146.446	6	17.912
	17	80.218	0.332	151.991	6	19.674
	18	89.626	0.344	154.409	7	25.231
	19	93.978	0.376	171.160	7	31.140
	20	105.896	0.407	173.404	8	33.269
Large	21	110.214	0.413	197.463	8	34.563
	22	126.723	0.441	214.142	8	42.218
	23	129.877	0.480	235.629	9	46.697
	24	147.630	0.513	243.167	10	50.366
	25	162.429	0.530	245.888	10	55.616
	26	174.828	0.601	254.426	11	64.271
	27	179.003	0.683	289.862	12	73.451
	28	185.558	0.740	322.750	13	91.594
	29	190.451	0.812	351.171	14	111.321
	30	205.962	0.827	373.868	14	128.325
Ave		87.48175	0.355892	158.6777	6.877554	30.74074

Table VI. The values of the time index for the EPC method

Size	Problem No.	CPU time(s)
Small	1	1623
	2	3600
	3	*
	4	*

The results provided in Tables IV to VI suggest that the epsilon constraint method succeeded in solving only 2 out of 30 problems, while meta-heuristic algorithms have solved all 30 problems in a short time. Thus, the epsilon constraint method does not seem to be a proper method for solving the studied mathematical model. As can be observed in Tables IV and V, both algorithms were successful in resolving the 30 problems under examination, and the offered values' production process is entirely rational. The graphical analysis of the results related to each index is given below.

B. The Statistical Analysis of the Evaluation Indices

According to Table VII, the efficiency rates of the two algorithms have no significant differences at the 5% error level based on the NPS, SNS, DM, MID, and CPU time indices since the P-value > 0.05 is established for all performance indices. The average value of the DM index for the NSGA-II and MOPSO algorithms is equal to 68.18 and 87.41, respectively. Also, one can realize according to Figure 12 that the MOPSO algorithm has obtained a higher value of the DM index in all the solved problems. In total, the MOPSO algorithm has performed about 28% better than the NSGA-II algorithm in terms of the DM index. In other words, compared to the NSGA-II algorithm, this algorithm shows higher potential for exploring and extracting the solution space. Based on Figure 13, the DM index in the MOPSO algorithm is less sensitive and more stable than increasing the dimensions of the problem, and this sensitivity is much lower in problems with small dimensions. Therefore, increasing the dimensions of the problem does not have much effect on exploring and extracting the solution space by this algorithm.

The average value of the MID index for the MOPSO and NSGA-II algorithms is equal to 0.34 and 0.35, respectively. Also, one can realize according to Figure 14 that the two algorithms have obtained very close values in terms of the MID index. In total, the MOPSO algorithm has performed about 3% less than the NSGA-II algorithm in terms of the MID index. This suggests the slight superiority of the MOPSO algorithm over the NSGA-II algorithm in terms of the MID index. In other words, this algorithm shows a higher potential to converge to the ideal solution compared to the NSGA-II algorithm. Based on Figure 15, the MID index has the same sensitivity to increasing the problem dimensions in both algorithms.

The average value of the SNS index for the MOPSO and NSGA-II algorithms is equal to 165.67 and 158.67, respectively. Also, one can realize according to Figure 16 that the MOPSO algorithm has obtained a higher value of the SNS index in most of the solved problems. In total, the MOPSO algorithm has performed about 4% better than the NSGA-II algorithm in terms of the SNS index. In other words, this algorithm has produced better-quality Pareto solutions. Also, based on Figure 17, the quality of the Pareto solutions produced by the MOPSO algorithm is more stable and changes less with the increase in the dimensions of the problem. These changes are less in issues with smaller dimensions.

Based on the NPS index, the average value of the NPS index for the MOPSO and NSGA-II algorithms is equal to 7.83 and 6.87, respectively. Also, one can realize according to Figure 18 that the MOPSO algorithm has obtained a higher value of the NPS index in most of the solved problems. In total, the MOPSO algorithm has performed about 13% better than the NSGA-II algorithm in terms of the NPS index. Therefore, this algorithm produces non-dominated solutions and more alternatives for more decisions. Based on Figure 19, the number of Pareto solutions produced by the MOPSO algorithm is more sensitive to the increase in the dimensions of the problem, and this sensitivity is greater in problems with higher dimensions.

The results of comparing the two MOPSO and NSGA-II algorithms based on the solution time as shown in Figure 20 suggest that the average solution time for the MOPSO and NSGA-II algorithms is equal to 35.19 and 30.74, respectively. In total, the MOPSO algorithm has spent about 14% more time than the NSGA-II algorithm. In general, the last row of tables IV and V indicate that the MOPSO algorithm shows a better performance based on the MID, SNS, and NPS indices, while the NSGA-II algorithm performs better based on the DM and CPU time indices.

Table VII. Summary of t-test results in the study of metrics

Algorithm	Metrics	Means difference	T-Value	P-Value
MOPSO – NSGA II	DM	-19.296	-1.286	0.203
MOPSO – NSGA II	MID	-0.011	-0.203	0.732
MOPSO – NSGA II	SNS	6.997	0.242	0.810
MOPSO – NSGA II	NPS	1.067	1.158	0.252
MOPSO – NSGA II	CPU time(s)	4.458	0.418	0.677

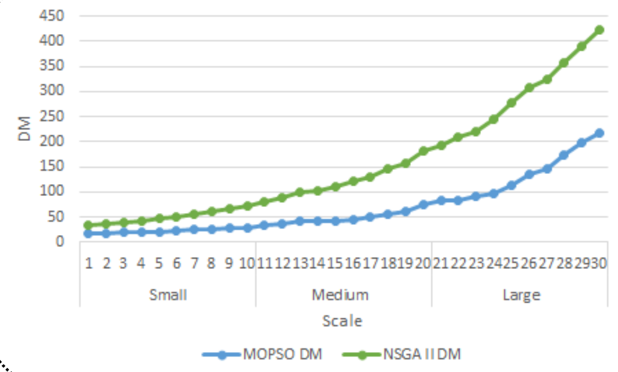

Fig 12. The result of comparing the algorithms in terms of DM

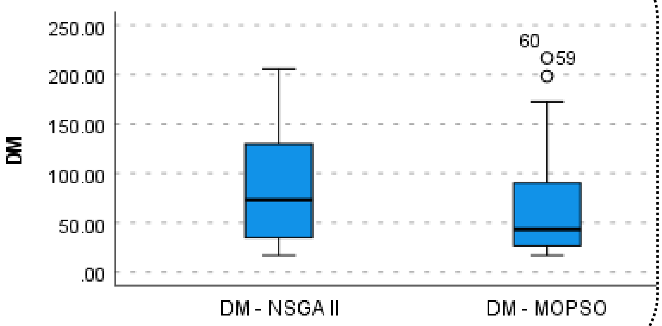

Fig 13. Box plot of DM algorithms performance indicators

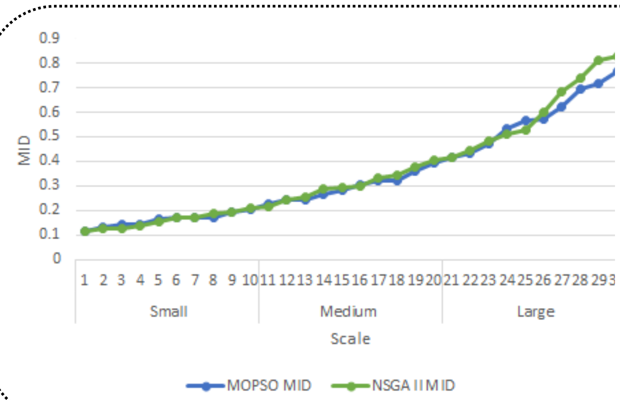

Fig 14. The result of comparing the algorithms in terms of MID

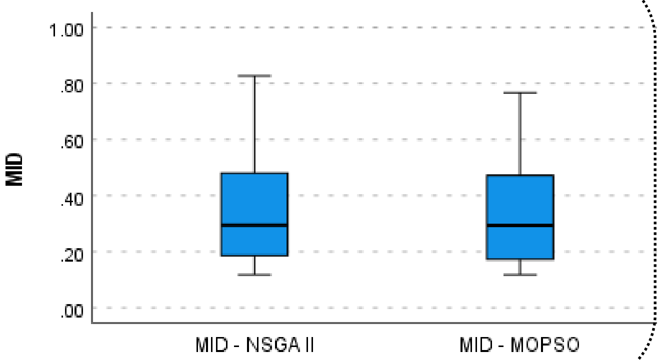

Fig 15. Box plot of MID algorithms performance indicators

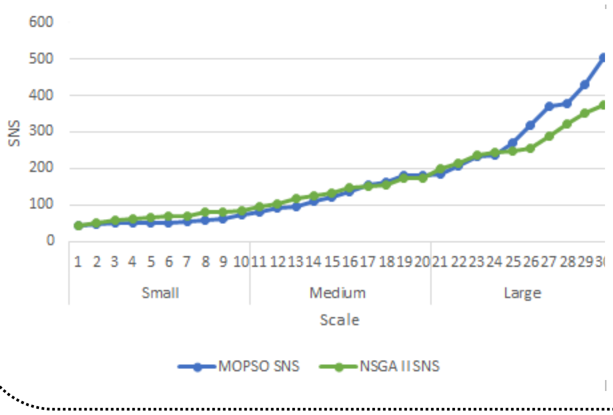

Fig16. The result of comparing the algorithms in terms of SNS

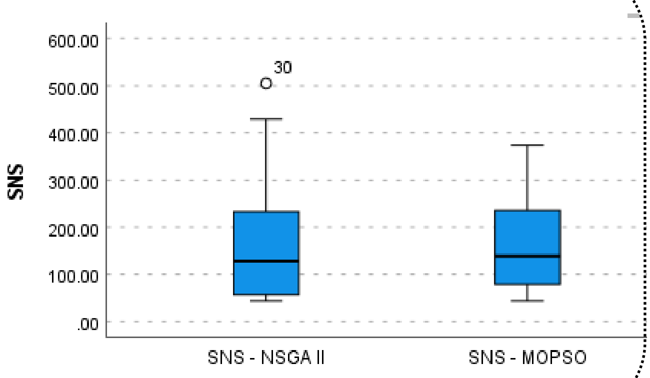

Fig 17. Box plot of SNS algorithms performance indicators

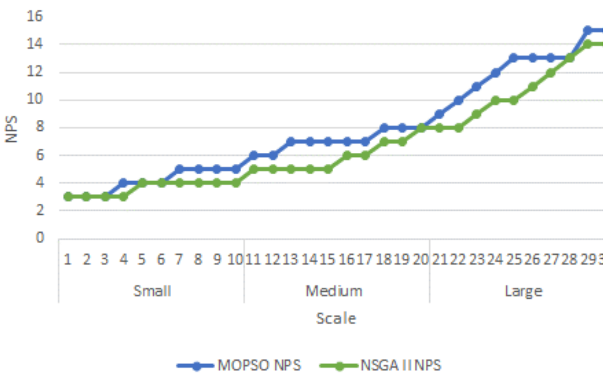

Fig 18. The result of comparing the algorithms in terms of NPS

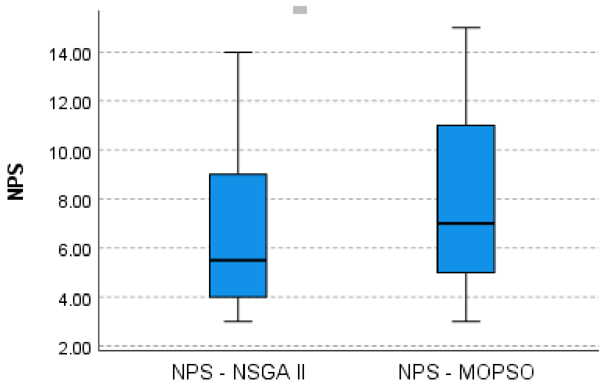

Fig 19. Box plot of NPS algorithms performance indicators

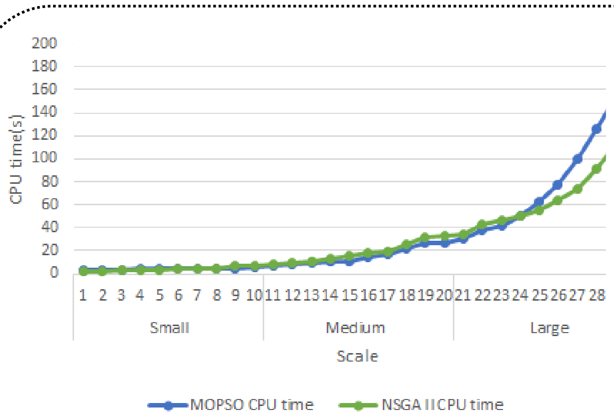

Fig 20. The result of comparing the algorithms in terms of DM

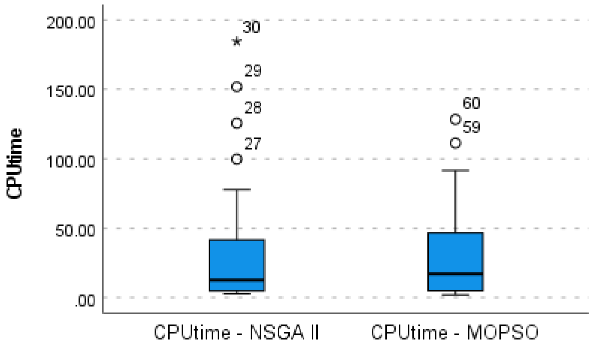

Fig 21. Box plot of CPU time algorithms performance indicators

C. Sensitivity Analysis

One of the advantages of mathematical models is their capability to examine changes and fluctuations in each of the mentioned parameters and observe their impacts on the final output of the model. To do so, the most key parameters are evaluated in the presented mathematical model. Following the review of the subject literature, it was found that demand is a parameter that may undergo different fluctuations due to its high dependence on production conditions and limitations. In such conditions, the effect of changes in demand can significantly affect the entire supply chain.

Thus, it seems necessary to analyze the sensitivity of this parameter. Hence, the demand for each product was increased based on an upward trend aimed at analyzing the sensitivity of this parameter, followed by examining its effect on different objectives. To this end, a coefficient of variation from 0.9 to 1.5 was considered. The reason for choosing this range for the coefficient of variation is to create low fluctuations for the amount of demand according to its initial value. Then, in each case, the base demand amount of each product unit was multiplied by this value, and afterward, the model was implemented per the result to determine its impact on the value of the total function. The result of this implementation is provided in Table VIII.

Table VIII. The results of demand sensitivity analysis

Coefficient of variation	0.9	1	1.1	1.2	1.3	1.4	1.5
Economic objective value	16260	16400	16540	16680	16820	16960	17100
Environmental objective value	395	482	598	776	1358	2772	3951
Reliability objective function	16.1	16.1	16.5	16.5	16.5	16.6	16.7

As seen in the above table, with the increase in the demand for each product unit, the values of the economic and environmental objective functions also follow an increasing trend. It also has a small impact on the reliability objective function. Figures 22 to 24 are presented to better understand this issue.

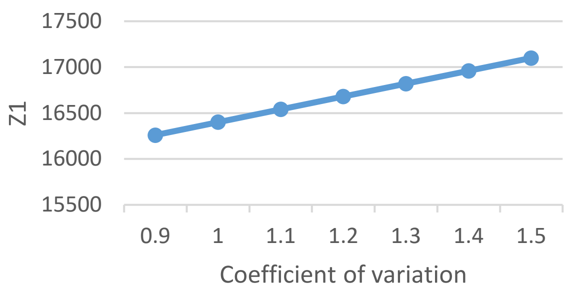

Fig 22. The effect of demand changes on the first objective function

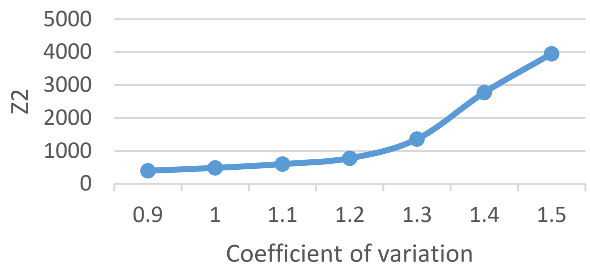

Fig 23. The effect of demand changes on the second objective function

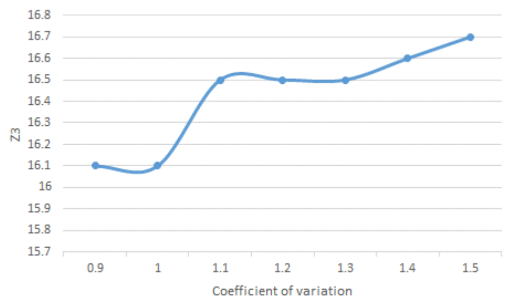

Fig 24. The effect of demand changes on the third objective function

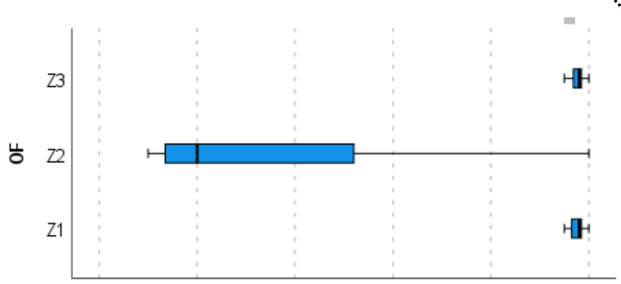

Fig 25. The effect of demand changes on the third objective function

As can be realized from Figure 22, the increase in the value of the first objective function has an almost linear relationship with the increase in the coefficient of variation. Therefore, one may claim that the increase or decrease in the demand value has a clear impact on the total costs of the chain. Figure 23 indicates that the demand change has a non-linear relationship with the second objective function. In other words, the increase in environmental pollution will enhance dramatically from the coefficient of variation of 1.3 onwards. Thus, the increase in demand will lead to a severe increase in environmental pollution. Figure 24 shows that the reliability rate will not enhance significantly from the coefficient of variation of 1.1 onwards; i.e., the increase in demand will not significantly increase the reliability rate. However, this figure generally shows its increasing trend. To compare the behavior of the objective functions with each other, because they have different units, their normalized values have been used. According to Figure 25, the objective function related to environmental pollution (Z_2) is the most sensitive to demand changes. In other words, the increase in demand has many effects on environmental pollution, which can be caused by the worn-out level of vehicles or transportation routes. The objective functions Z_1 and Z_3 respectively show less sensitivity to demand changes; these changes are very small. According to part C of section IV, the demand is considered non-deterministic and random with a normal distribution and all calculations have been done at the 0.05% error level ($\alpha = 0.05$). In general, with the increase of uncertainty and error level of α, $(1-\alpha)\%$, the confidence to estimate the amount of demand decreases. Therefore, the distance between the estimated values for the demand and the actual values increases and the effectiveness and efficiency of the model decreases.

VII. COCLUSION AND SUGGESTIONS

A new multi-objective, multi-period MIP model for location-routing with non-deterministic demand was provided in this research, in which, the records of the driver's performance, the degree of hardness of the route, and the lifespan of the vehicles (heterogeneous) have been applied. In addition to costs, environmental pollution and the reliability of routes were considered as second and third objectives in this model.

In the presented model, consumers have demands that may not be fulfilled by the central warehouses or manufacturing factories for some reason. These customers send their requests to intermediate warehouses located on the outskirts of cities, and their demands are met through these warehouses. Meanwhile, these intermediate warehouses also meet the requested demands through central warehouses or manufacturing factories.

As a result, the warehouse or factory available in the system sends the products to the intermediate warehouses by vehicles assigned to the first echelon according to the requests sent by intermediate warehouses. Then, the products are separated, sorted, and reclassified inside the intermediate warehouses according to the requests sent by the customers, which will be sent and delivered to the customers by the vehicles assigned to the second echelon on the routes of the second echelon. In this model, providing service to the customers should be done by a vehicle, and the demand cannot be partitioned.

There is a set of drivers in the presented model that the vehicles are divided between them to carry out the product supply operations. In this regard, an allocation cost has been defined based on the type of vehicle, the worn-out level of the vehicle, and the experience of the driver. This cost has been measured based on the parameters of the type of vehicle, the worn-out level of the vehicle, and the experience of the driver. The more experienced a driver, the higher the cost of vehicle allocation to him would be, and vice versa. The worn-out level of the vehicle is another influential parameter in the allocation cost. A vehicle with a longer age naturally has a higher worn-out level and a higher probability of breakdown. Thus, the cost of allocating such vehicles to drivers will be lower.

Also, different degrees of hardness are defined for different routes in this model. The cost of passing the route is determined based on an initial fixed cost and the degree of hardness of the route. Naturally, the higher the degree of hardness, the higher the cost of traveling the route would be. The epsilon constraint method was used to solve problems in small dimensions in the presented model. Moreover, two MOPSO and NSGA II algorithms were utilized to solve it in large and medium dimensions, knowing the NP-hard nature of the problem.

The results obtained from solving by efficiency indices revealed that the MOPSO algorithm provides a better performance based on the MID, SNS, and NPS indices, while the NSGA II algorithm performed better based on the DM and CPU time indices. In this regard, the following may be suggested for future studies:

1. the use of a robust planning approach to deal with the uncertainty of the two-echelon model can make the model more powerful and flexible in the condition of uncertainty,
2. the use of data mining and machine learning methods to classify drivers based on performance,
3. considering direct shipping from the factory to the customer, if the customer has a high demand rate,
4. taking into account the disruption in the capacity of vehicles for reasons such as theft or attack, as well as considering the disruption on the route that may be caused by natural disasters or unplanned operations such as floods, earthquakes, or unexpected events, and
5. considering a more appropriate criterion for calculating routing costs such as time since conditions like the breakdown of the vehicle or traffic may occur where defining the shipping cost per distance unit would not be accurate.

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