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# Designing a Fuzzy Mathematical Model for a Two-Echelon Allocation-Routing Problem by Applying Route Conditions: A New Interactive Fuzzy Approach

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**ABSTRACT**

In vehicle routing problems (VRP), the optimal allocation of transportation by considering factors such as route hardness, driver experience and vehicle worn-out has a significant effect on costs reduction and approaching real-world conditions. In this paper, a novel fuzzy mixed integer non-linear mathematical model to address the two-echelon allocation-routing problem under uncertainty is proposed by applying route and fleet conditions. The cost of allocating drivers to diverse vehicles is computed at the first echelon of the problem, considering factors such as vehicle type, vehicle wear-out, and driver experience. Additionally, different routes are defused with varying levels of hardness. The goal of the second echelon of the model is to improve reliability by defining the reliability of routes within each section. To solve the model, the Torabi and Hessini (TH), the Selimi and Ozkarahan (SO) methods, and a newly proposed approach (PIA) were utilized to transform the multi-objective model into a single-objective one. Numerical tests and performance indicators were used to validate the effectiveness of both the multi-objective mathematical model and the proposed solution method. The validation computation results indicate that the proposed solution approach outperforms both the TH and SO approaches.

## 1. Introduction

One of the issues in supply chain management is the problem of vehicle routing in the supply chain distribution network. Its objective is to choose and allocate feasible routes to available vehicles for distribution and delivery of goods to distribution centers or customers to minimize associated costs. It is critical to find the best solution to this problem to reduce distribution costs, ensure prompt delivery of goods, reduce storage requirements, and enhance customer satisfaction. On the other hand, vehicle routing is among the most formidable challenges in the transportation and supply chain. It entails transporting customer-demand items using a fleet of vehicles. The inventory routing problem arises from the combination of the vehicle routing problem and the vendor-managed

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inventory problem. Farahbakhsh and Kheirkhah [1], presented a mathematical model and a novel genetic algorithm for solving the multi-period inventory routing problem. The objective of this model is to supply products to scattered customers within a given time horizon while managing customer inventories to avoid shortages and minimize total inventory and transportation costs.

There are two types of goods routing and distribution: direct and indirect. Products are transferred directly from the source to the destination in the direct mode, bypassing intermediate facilities. In the indirect mode, products are required to traverse one or more intermediate facilities before arriving at their intended destination, which may include distribution centers or temporary warehouses. Two-echelon routing is a notable example of indirect distribution, in which products initially depart from a designated origin, such as a central warehouse or factory, and then proceed to an intermediate facility like a temporary warehouse or distribution center. The intermediate facility then forms a net (such as one-echelon routing) to distribute products to customers. Essentially, the products depart from the origin and proceed to the intermediate facility in this distribution method. The products are delivered to their final destination after a sequence of activities such as separation, sorting, integration, and classification. Throughout this process, it is crucial to maintain strong and precise coordination between these two echelons. Consequently, this problem cannot solve as two separate one-echelon problems; rather, it necessitates a joint two-echelon approach for modeling and resolution do C. Martins *et al.,* [2]. In many real-world optimization problems, we are facing uncertainties in parameters describing the problem. A mixed linear integer programming for school bus routing with mixed loading by using a heterogeneous fleet is presented by [3]. The uncertainty of travel times has modeled as interval numbers. They proposed a heuristic algorithm to generate extreme scenarios. Each scenario has generated in order to make the last found optimal solution into an infeasible one as much as possible. Experimental results show that deploying this novel algorithm for generating extreme scenarios, efficiently produces diverse scenarios. After the scenario generation algorithm is converged, the intersection of the feasible optimal solutions under diverse scenarios has extracted as robust sub-tours or robust trips. However, it is important to note that organizations' circumstances vary, resulting in a diverse set of goals and constraints in this field. One of these diverse conditions could be the uncertainty that characterizes routing problems, often arising in terms of service time, customer presence, and demand. Employing the fuzzy method is a common approach to deal with such uncertainty. Hence, to better align with real-world scenarios, demand is approached in this article as both uncertain and fuzzy.

What can be observed in the literature review, and tried to be considered as a research gap in this research is Two-Echelon Vehicle Routing Problem (2E-VRP) with new conditions and assumptions, which has not been addressed in the literature, and is explained below. One of the innovative aspects in this research is the consideration of driver's performance records in the proposed mathematical model, which plays an important role in the level of customers' responsiveness. Additionally, another novel aspect of this study is the application of a condition where a driver can have multiple vehicles with heterogeneous capacities, which brings the research closer to real-world conditions. As known, vehicles with heterogeneous capacities have varying lifespans, resulting in changes to problem conditions and the allocation of vehicles to drivers with different levels of experience. Applying this condition in the introduced model is another aspect of this research innovation, which has not been examined in the literature so far. Neglecting to consider the hardness of route is an additional aspect of innovation that has been overlooked in recent research. This article investigates how the presented model adapts to real-world conditions because the routes do not have the same hardness due to natural complications, weather conditions, etc., and some routes are hard to pass. Therefore, it is required to determine appropriate routes for the vehicle with a useful life or wear-out that is proportional to the hardness of route. In other words, it is possible to allocate vehicles with a longer useful life or less wear-out to harder routes, and vice versa. This study proposes a mathematical model for the two-echelon allocation-routing problem to address all identified research gaps. This model's solution involves allocating vehicles to drivers, allocating intermediate facilities to the central warehouse, and ultimately determining the optimal route for each vehicle. To solve the model, an approach for converting the multi-objective model into a single-objective model is proposed. This research presents a novel multi-objective, multi-period mathematical model that considers uncertain demand. Along with demand uncertainty, the model considers driver performance information, route hardness, and vehicle lifespan.

The article is organized into seven sections. The introduction and literature review are provided in the first and second sections. The third and fourth sections focus on the problem statement and mathematical modeling, respectively. The fifth section discusses possible solutions to the model. The sixth section presents calculation results, and the seventh section presents conclusions and suggestions.

## 2. Literature review

Recently, the logistics community has identified two-echelon distribution systems as a major challenge in the field of location-routing problems. This problem has been extensively researched and has been the subject of numerous scientific studies. The 2E-LRP arises when goods from different sources must be transported to their intended destinations via intermediate facilities. Yu *et al.,* [4], for instance, devised a model to address the multi-objective two-echelon location-routing problem (MO-2ELRP) in garbage collection planning. Furthermore, they introduced an NSGA-II algorithm enhanced with directed local search to effectively solve this model. Cheng *et al.*, [5] presented a model in their study that aims to minimize both the cost and the duration of natural disaster debris cleanup. The researchers carefully considered utilizing temporary sites for debris management to achieve this goal. The research focuses on a multi-period 2E-LRP, where critical decisions include identifying suitable locations for temporary waste management sites and optimizing vehicle routes at both levels. To tackle this challenge, the authors presented a mixed integer programming problem as well as a proposed genetic algorithm as an effective solution method.

The conventional reliability of a system is defined as the probability that the system will perform a predefined operation under some specified condition for a fixed time period. Traditionally, system reliability evaluation is dependent on the probabilistic approach. But this approach is not always valid, since in reality a lot of times data related to the system information do not represent the realistic situation correctly due to uncertainties present in it. Therefore, in many cases, reliability assessment of the system becomes a very difficult task. Hence, to evaluate reliability of a system when available information is uncertain, then people apply the fuzzy approach. a procedure to construct the membership and the nonmembership functions of the fuzzy reliability function, by considering the failure rates as time-dependent CBFN is introduced. With the introduced approach, reliability of different systems is evaluated in the form of a triangular CBFN by Chaube *et al.*, [6].

Lagzaie and Hamzehee [7] developed a mathematical model focused on a closed-loop green supply chain operating under uncertain conditions. The model and its assumptions are tailored to a particular industry. The researchers developed a multi-objective, multi-product, and multi-period model to achieve a dual outcome: enhancing profitability while minimizing environmental impact. Fuzzy logic was incorporated into the problem with the aim of network design, and Torabi and Hassini's (TH) method was combined with Jimenez's proposed method to provide a solution.

Wang *et al.*, [8] proposed a Multi-Period Two-echelon Location Routing Problem (MP-2ELRP) that entails optimizing facility location selection and vehicle routing at two distinct echelons. They proposed a two-echelon hybrid algorithm that combines k-means clustering and an improved multi-objective particle swarm optimization (MOPSO) algorithm to handle this model. The k-means clustering algorithm is utilized to allocate customers to distribution centers during various periods, while the PSO algorithm is employed to determine vehicle routes and identify Pareto optimal solutions. Bahmani *et al.,* [9] provided an integrated model for a two-stage assembly flow shop scheduling problem and distribution through vehicle routing in a soft time window. So, a Mixed-Integer Linear Programming (MILP) model has been proposed with the objective of minimizing the total cost of distribution, holding of products, and penalties of violating delivery time windows. To solve this problem, an improved meta-heuristic algorithm based on Whale Optimization Algorithm (WOA) has been developed. The main innovations in the study include considering soft time window, sequence-dependent setup time, delivery time window, heterogeneous vehicles, holding costs of final products, and unrelated assembly machines.

In a separate study, Gandra *et al.*, [10] introduced a generalized 2E-LRP model that incorporates two-dimensional loading constraints for the 2E-LRP. They addressed this model with a heuristic optimization method that accounts for various loading scenarios and assesses its efficiency with real-life examples. Fallahtafti *et al.*, [11] presented a multi-objective two-echelon location-routing model aimed at reducing the risk of theft during cash transportation. The amount of money carried by the vehicle is considered a risk-related function in this model and serves as the first objective, while the duration of the money transfer is regarded as the second. The researchers used a combination of exact and meta-heuristic methods to solve this model, focusing on small to medium dimensions. Cao *et al.,* [12] investigated a two-echelon biomass resource location routing problem (2E-BRLRP) in a separate study. They addressed the challenge by considering a predetermined supply of biomass resources and proposing a mixed integer programming model. The proposed model effectively determines optimal locations for biomass collection facilities as well as corresponding vehicle routes. A hybrid heuristic algorithm combining neighborhood search (NS) and Tabu search (TS) algorithms is introduced to solve the presented model. Hajghani *et al.*, [13] a MILP model including minimization of costs and CO2 emissions and maximization of social responsibility (creating job opportunities and community development) was developed for the problem. The proposed model seeks to minimize the total costs by reducing the use of vehicles through reducing the number of transportation routes in the two-echelon distribution network (due to the incurred fixed cost of transportation per vehicle) and increasing the allowable load of vehicles. Also, in this study, a different type of routing is considered in each echelon. Due to NP-Hardness of the problem, two efficient metaheuristic algorithms of NSGA-II and Multi-Objective Fractal Random Search (MOSFS) have been used to solve the problems.

A two-stage model is introduced for arranging and locating vehicle routes with simultaneous pickup and delivery by Khodashenas *et al.,* [14]. The model developed in the first stage optimizes the arrangement of products in packages and thus optimizes packages' length, width, and height for delivery to customers. In the second stage, the goal is to provide customers with vehicle in simultaneous pickup and delivery. In this part of the model, the location of distribution centers has potentially considered, and the demand and cost parameters are considered uncertain. To solve the problem, precise methods and meta-heuristic algorithms of PSO for the first stage and multi-objective meta-heuristic algorithms NSGA II and MOALO for the set have been used. The results of examining the efficiency of the algorithms in the second stage show the high efficiency of the MOALO algorithm. Mohamed *et al.*, [15] investigated the problem of designing a distribution network under uncertainty, with a focus on strategic levels. The problem, two-echelon stochastic multi-period capacitated location-routing (2E-SM-CLRP), entails dividing the network into two distribution echelons with distinct location-allocation-transport schemes designed to accommodate future demand. The proposed model employs a two-echelon stochastic integer programming approach. The first stage determines location and capacity decisions for each period of the planning horizon, while the second stage determines routing decisions. the Benders decomposition-based approach is proposed as a solution to the proposed problem. In their publication, Xue *et al*., [16] introduced a two-echelon dynamic vehicle routing problem with proactive satellite stations (2E-DVRP-PSSs) to optimize both operational and construction costs. Similarly, Du *et al*., [17] developed a novel joint delivery model to reduce operating costs and carbon emissions through enhanced collaboration and resource sharing. To this end, they proposed a mathematical model for joint delivery (JD) that considers multiple objectives and incorporates a multi-depot two-echelon joint delivery location routing problem (MD-2E-JDLRP). Furthermore, they put forward a hybrid heuristic algorithm as a solution for the proposed model.

In their bi-objective mathematical programming model, Heidari *et al.,* [18] addressed the green two-echelon close and open location-routing problem (G-2E-COLRP), which included factories, warehouses, and customers. The main goals were cost minimization and CO2 emissions reduction. The proposed model can determine the optimal routes, the required number of vehicles, and the location of facilities. To ensure accurate problem-solving, the modified epsilon method was employed to solve the proposed model in small-scale scenarios.

The Vehicle Routing Problem (VRP) is another type of problem that has received considerable attention from researchers. The VRP is a significant supply chain management challenge that involves the task of efficiently serving a set of customers with specific demands using a fleet of vehicles concentrated at one or more locations (warehouses or nodes). This problem aims to minimize metrics such as total travel distance, total travel time, the number of vehicles used, late penalties, and, ultimately, the transportation cost function by utilizing mathematical models and route optimization techniques. The desired outcome is to achieve maximum customer satisfaction. For example, Neira *et al*., [19] introduced multi-trip vehicle routing problems with time windows, service-dependent loading times, and limited trip duration (MTVRPTW-SDLT). The initial model in this paper introduces a representation of the vehicle's return to the warehouse. A deterministic approach is used to solve the problem. Meta-heuristic optimization techniques have presented over the last two decades by [20,21]. The widespread applicability of various optimization methods makes them a hot spot for researchers. also Uniyal *et al*., [22] have explained the basic components and working of some of the most prominent nature inspired optimization algorithms such as Ant colony optimization (ACO), PSO, Cuckoo search algorithm (CSA), and Ant-lion optimization (ALO). in another study, Kumar *et al*., [23], introduced an optimum choice of the mean time between failure (MTBF), mean time to repair (MTTR), and associated costs in a suitable design unit to bring as much efficiency as possible. they used to minimize the cost satisfying the availability constraints of the system by using a few recent nature-inspired optimization techniques named Grey Wolf Optimization (GWO) technique and Cuckoo Search Algorithm (CSA) and proposed a modified wild horse optimizer (MWHO) for system reliability optimization problems (SROPs) and investigates the reliability allocation of two complex SROPs, namely, complex bridge system (CBS) and life support system in space capsule (LSSSC) by Kumar *et al*., [24].

Huang *et al*., [25] introduced multi-trip vehicle routing problems with time windows (MTVRPTW). Vehicles in the presented model unload cargo collected from customers at a warehouse with limited unloading capacity. In addition, a branch-and-price-and-cut algorithm (PBC) is proposed for the

MTVRPTW model. Rezaei Kallaj *et al*., [26] proposed a Multi-Objective - Multiple-vehicle routing problem (MO-MVRP) involving multiple vehicles in critical conditions supplying blood to the injured. The objective functions in this model consider vehicle arrival time and the amount of collected blood. A CPLEX deterministic solution approach is employed to solve the proposed model. Shiri *et al.,* [27] developed a two-stage multi-objective mixed integer linear model for a home healthcare (HHC) network. The first stage is focused on establishing efficient health centers, while the second deals with routing and scheduling, taking both social responsibility and company efficiency into consideration. This model's objectives include minimizing overall costs, addressing inefficiencies, and maximizing social aspects. An innovative aspect of this research is the inclusion of social responsibility, such as job opportunities and regional economic development, as well as efficiency factors like time, energy, and budget management. The proposed optimization model incorporates an upgraded form of the data envelopment analysis approach for measuring efficiency. Additionally, an interactive fuzzy method known as the TH approach is introduced to effectively handle the multi-objective model. In the case of the HHC problem, costs, social factors, and service times are naturally subject to uncertainty. As a result, a robust fuzzy approach is proposed as a solution to this issue.

Wang *et al*., [28] proposed collaborative multi-depot vehicle routing problems with dynamic customer demands and time windows (CMVRPDCDTW), considering resource sharing and dynamic customer requirements. Researchers have developed a bi-objective optimization model aimed at optimizing vehicle routes to fulfill this objective. The model aims to minimize both total operating costs and the number of vehicles used. A hybrid algorithm combining an improved k-medoids clustering algorithm and multi-objective particle swarm optimization (PSO) is presented to solve the proposed model and obtain near-optimum solutions. Hasanpour Jesri *et al*., [29] have addressed the Multi-Trip Open Vehicle Routing Problem (MTOVRP). They formulated an appropriate integer programming model to minimize the total costs of buyers. To solve this model, they presented a decomposition-based algorithm that breaks the problem down into two parts. The first stage involves tactical decisions about supplier selection and the type of cooperation. The visit sequence for each vehicle is determined in the second step. Nozari *et al*., [30] proposed a model for the Multi-Depot Vehicle Routing Problem (MDVRP). The main objective of this model is to determine the optimal locations for warehouses and production centers, as well as the most efficient routes for distributing medical supplies to hospitals. To address the uncertainties associated with parameters such as demand, transmission, and distribution costs, this model was solved using a robust fuzzy method. The impact of uncertainty has been examined using the Neutrosophic fuzzy programming method.

Jiao *et al*., [31] proposed an algorithm for VRP-Energy constraint in disaster scenarios. Their innovative approach utilizes a multi-stage vehicle routing algorithm based on task grouping (MSVR-TG). The algorithm combines k-means clustering and a genetic algorithm to effectively solve the routing model. Pirabán-Ramírez *et al*., [32] presented a problem involving blood unit transportation from collection sites to a blood center, referred to as the Vehicle Multi-trip routing problem (VMRP). To address this problem, they have developed a mixed integer linear programming model that incorporates increasing profit. Moreover, as an alternative approach to finding efficient solutions, they have proposed a local search meta-heuristic solution method. Navazi *et al*., [33] proposed a three-stage supply chain model that encompasses various interconnected problems. The first stage involves determining optimal facility locations, which is linked to a transportation problem with limited truck capacity. Specifically, the problem addresses the routing of cars through distribution center locations. It is crucial in this model to ensure that the duration of product distribution between stages does not exceed the product's useful life. Furthermore, given the growing awareness of carbon footprints among conscious societies, consumers are encouraged to purchase products with lower carbon footprints, as indicated by the carbon footprint (CFP) label. Thus, in addition to minimizing network costs, an objective function is included to minimize fuel consumption and $CO_2$ emissions. Another objective of the model is to improve customer satisfaction. This is achieved by prioritizing on-time delivery, based on customer preferences and deadlines. In addition, the model aims to minimize driver accidents, which are recognized as social side effects of a sustainable design. The TH method was implemented in this study to effectively address this multi-objective problem.

Based on the foregoing, the research gap is examined by addressing three aspects: the neglect of drivers and their performance, the inclusion of multiple heterogeneous vehicles allocated to each driver, and the consideration of varying levels of hardness for different routes. Given these considerations, the current study aims to bridge the research gap across three distinct domains.

1. Including multiple vehicles adds heterogeneity to the driver pool by allowing each driver to operate different vehicles with varying load volume and capacity. Moreover, the wear-out characteristics of these vehicles vary, which can impact the problem-solving process.

2. Drivers' experience, as reflected in their performance records, is considered. Consequently, drivers with more experience are allocated greater load responsibilities. Drivers' performance records are assessed on three levels: low, medium, and high.

3. The process involves assessing the level of hardness for various routes. For instance, routes considered easier or commonly referred to as "not hard" are more manageable than routes allocated a hardness level of one. As a route's hardness level increases, so do the desired criteria for allocation. The hardness level assessment is a suitable basis for allocating vehicles with less wear-out. In other words, vehicles with fewer wear signs are allocated to more challenging routes, while vehicles with more wear are considered for smoother routes.

## 3. Problem statement

The initial step in the proposed model is to quantity the orders and their corresponding routes at the second echelon. Subsequently, the number of orders dispatched to other intermediate warehouses and the corresponding vehicle routes are determined considering the demand of those warehouses. Furthermore, the model considers the costs of both the first and second echelons, as well as maintenance costs in other locations. In addition to costs, the model considers environmental pollution and route reliability as secondary and tertiary objectives, respectively. Customers who cannot have their demands met by central warehouses or production plants send their requests to intermediate warehouses on the outskirts of cities, which then fulfill these demands. Currently, intermediate warehouses play a crucial role in meeting the requested demands by relying on central warehouses or production factories. Consequently, the warehouse or factory responds to requests from intermediate warehouses within the system by dispatching products through vehicles assigned to the first echelon. Once the products reach the intermediate warehouses, they are categorized, sorted, repackaged, and finally distributed to customers via vehicles designated for the second echelon, based on customer demands received. It is important to note that customer service must be provided by a single vehicle, and demand cannot be divided.

A notable aspect of this research is the consideration of fuzzy demand. Furthermore, the proposed model includes a group of drivers who are assigned to different vehicles to carry out product distribution operations. Consequently, an allocation cost has been established, taking into account factors such as vehicle type, vehicle wear-out (life), and driver experience. The cost of allocating a vehicle to a driver increases with experience and decreases with inexperience. In addition, the wear-out (life) of the vehicle influences the allocation cost. As the vehicle's wear-out (life) increases, maintenance issues and breakdowns are expected to become more likely, resulting in a lower allocation cost for that specific vehicle. Moreover, this study introduces varying levels of hardness for various routes. The cost of each route is determined by an initial fixed cost combined with the route's hardness level. Routes with higher hardness levels, by definition, incur higher costs.

Figure 1 helps to enhance problem comprehension and depicts a scenario involving 10 points or facilitation. It includes one warehouse or factory, two intermediate warehouses, and seven customers. The factory is outside the urban area and is serviced by first-echelon vehicles, which are typically heavy vehicles subject to traffic restrictions in urban environments. Goods are transported to the intermediate warehouses in the first echelon routes. Following a series of non-production activities, the products are transported to customers in second-echelon vehicles designed specifically for urban traffic. It is worth mentioning that direct delivery of goods to customers is prohibited, and second-echelon vehicles can serve multiple customers without forming sub-nets. In this example, two different vehicles are utilized for service at the first echelon, while three vehicles are employed at the second echelon. Each vehicle serves multiple customers without forming sub-tours and ultimately returns to the origin.

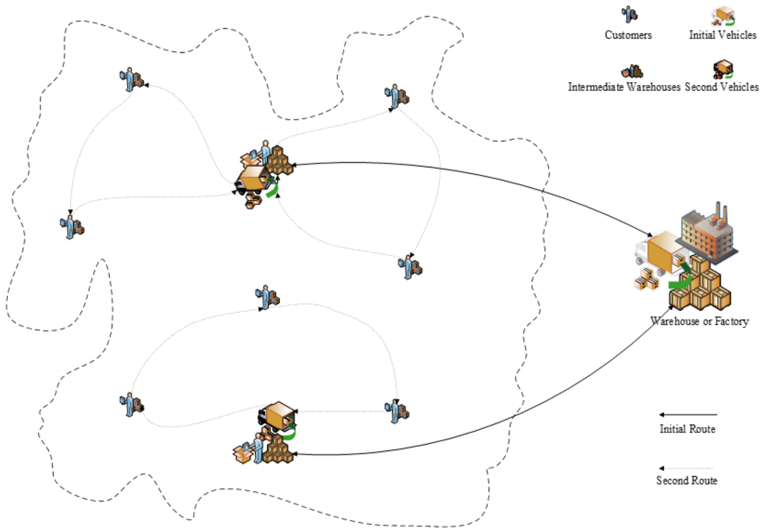


**Fig. 1.** A sample of two-echelon inventory routing

## 4. Model formulation

An arc-based formula is defined for two-echelon (2e) on the graph $G(V, E)$ in this section, which $V$ includes all network nodes, $V_0$ represents a single member set of the central depot, $V_s$ is the set of intermediate depots, and $V_c$ represents the set of customers. Additionally, $V_0 \cup V_s$ denotes the first echelon's set of nodes, and $V_s \cup V_c$ represents the second echelon's set of nodes. Furthermore, $E$ shows all existing edges in the distribution graph, comprising directionless edges, connecting the central depot to intermediate warehouse centers, intermediate warehouse centers to customers, and customers to each other. Travel between any two nodes is defined by a network edge with a non-negative cost that applies to the inequality $C_{ik} \geq C_{ij} + C_{jk}$.

### *4.1 Model hypothesis*

1. The model under discussion is a multi-period model.
2. Each vehicle completes a round trip in less than one period.

3. Because the problem under investigation is an operational problem, therefore, the time horizon is considered monthly, during which decisions are made according to each of the customer's orders and other parameters.
4. There are customers with uncertain demands in each period, where the demand is considered fuzzy.
5. There is a central warehouse and a specific number of intermediate warehouses.
6. There is a feature that allows for multi-trip delivery to an intermediate warehouse.
7. There is no feature for multi-trip delivery for customers.
8. Each level has a limited number of vehicles.
9. Vehicle capacity is considered heterogeneous (varying capacity)
10. The first echelon considers three types of vehicles: small ($M_1$), medium ($M_2$), and large ($M_3$) $K_1 = \{M_1 \approx 1,\ M_2 \approx 2,\ M_3 \approx 3\}$, in which the allocation cost increases as the vehicle capacity increases from small to large $C^3_{i'j'} > C^2_{i'j'} > C^1_{i'j'}, i'j' = Constant$.
11. The first echelon also considers the driver's experience in three levels: low ($P_1$), medium ($P_2$), and high ($P_3$) with $j' = \{P_1 \approx 1, P_2 \approx 2, P_3 \approx 3\}$, in which the allocation cost increases as the driver's experience increases from low to high ($C^k_{i'3} > C^k_{i'2} > C^k_{i'1}, i', k = Constant$).
12. In the first echelon, the passing route cost is calculated considering route hardness level, and the vehicle allocation cost is determined by factors such as the vehicle type, vehicle wear-out, and driver experience.
13. Directly sending customer requests from the central warehouse is not feasible.
14. There is no capacity limit for the supplier.
15. When utilizing any vehicle, a fixed fee must be paid along with a variable fee for each route.
16. Goods can be stored in any of the intermediate and customer warehouses, and thus the cost of storing the goods at each of these points is considered.
17. There is no lateral communication between the intermediate warehouses, and goods cannot be returned from customers to the intermediate warehouse or from the intermediate warehouse to the central warehouse and each customer is served once in each period.
18. Each route in the first echelon has a distinct hardness rate, and a higher degree of hardness imposes higher distribution costs.

Indices, parameters, and variables of the model are presented in Table 1.

**Table 1**
Indices, parameters, and variables of the model

| **Indices** | |
|---|---|
| $i, j$ | Network points index |
| $e$ | Product distribution echelons-related index (echelon 1 and echelon 2) |
| $k$ | Vehicle Index |
| $t$ | Periods index |
| $i'$ | Index related to wear-out type (type 1, type 2 and type 3) |
| $j'$ | Index related to the type of driver's experience (level 1, level 2 and level 3) |

| **Parameters** | |
|---|---|
| $C^k_{i'j'}$ | The cost of allocating a type $k$ vehicle at the first echelon with wear-out type $i'$ to an experienced driver $j'$ |
| $C^k_{iji'j'}$ | The cost of allocating a type $k$ vehicle with wear-out of type $i'$ on the route from $i$ to $j$ to an experienced driver $j'$ |
| $t_{ijk}$ | Travel time along the arc $(i, j)$ with vehicle $k$ |
| $C0_{ij}$ | The initial fixed cost related to 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 wear-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 wear-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 |
| $\widetilde{d_{it}}$ | The amount of fuzzy demand of customer $i$ in period $t$ |
| $EW_{it}$ | The lower bound of the time window of customer $i$ in period $t$ |
| $LW_{it}$ | The upper bound of the time window of customer $i$ in period $t$ |
| $PE_{it}$ | Early penalty in order delivery to customer $i$ in period $t$ |
| $PL_{it}$ | The late penalty in product delivery to customer $i$ in period $t$ |
| $invi_0$ | The initial inventory at the point $i$ |
| $h_i$ | The maintenance cost at the point $i$ |
| $BM$ | The positive large numbers |
| $ord_{i'}$ | Level of wear-out from the degree $i'$ |
| **Variables** | |
| $x_{ijkt}$ | It is one if in the first echelon from $i$ to $j$ using the vehicle $k \in K_1$ on day $t$ |
| $Z^k_{iji'j'}$ | It is one if the type $k$ vehicle with wear-out type $i'$on the route $i$ to $j$ is allocated to an experienced driver $j'$ |
| $y_{ijkt}$ | It is one if in the second echelon from $i$ to $j$ using the vehicle $k \in K_2$ on the day $t$ |
| $Z_{jt}$ | It is one if the point $j$ has been chosen for giving services on day $t$ |
| $Ct_{kt}$ | It is one if the vehicle $k$ has been chosen for use on day $t$ |
| $ds_{it}$ | 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 $i$ |
| $a_{kt}$ | 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 time to reach to point $i$ on day t using 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 $t$ |
| $uu_{ikt}$ | Sub-tour removal covariate |

## *4.2 Objective functions*

$$Min\ Z1 = \sum_{i\in V_o}\sum_{j\in V_s}\sum_{k\in K_1}\sum_{t\in T}\sum_{i'\in I'}\sum_{j'\in J'} C^k_{iji'j'} z^k_{iji'j'} x_{ijkt} + \sum_{i\in V\setminus V_o}\sum_{j\in V\setminus V_o}\sum_{k\in K_2}\sum_{t\in T} y_{ijkt} c'_{ij} + \sum_{i\in V\setminus V_o}\sum_{t\in T} h_i inv_{it} + \sum_{t\in T}\sum_{i\in V_c} PE_{it} ER_{it} + \sum_{t\in T}\sum_{i\in V_c} PL_{it} LA_{it} \tag{1}$$

where

$$C^{k}_{i'j'} = \beta \frac{kj'}{ord_{i'}} \tag{2}$$

$$C^{k}_{iji'j'} = C0_{ij} + \alpha H_{ij} C^{k}_{i'j'} \tag{3}$$

Expression (2) calculates the cost of vehicle allocation based on vehicle wear-out and the driver's experience. It has a direct relationship with vehicle type and driver experience and an inverse relationship with vehicle wear-out. Expression (3) calculates the cost of vehicle allocation based on route hardness degree, vehicle type, vehicle wear-out, and driver's experience.

The first objective function, Eq. (1), minimizes the total maintenance costs of other points, variable and fixed transportation costs related to first and second-echelon vehicles, and the cost of early and late fines in customer order delivery.

$$Min\ Z2 = \sum_{i \in V_0} \sum_{j \in V_s} \sum_{k \in K_1} \sum_{t \in T} x_{ijkt} E_{ijk} + \sum_{i \in V \setminus V_o} \sum_{j \in V \setminus V_o} \sum_{k \in K_2} \sum_{t \in T} y_{ijkt} E_{ijk} \tag{4}$$

Eq. (4) is the second objective function related to environmental pollution of routing. It consists of the routes in the first echelon plus the pollution of the second echelon. Since a complete tour is considered a consecutive route, its reliability should be calculated using the logic governing sequential systems. Eq. (5) is used to solve this problem because the product of the unselected paths in the remaining links will be zero [34].

$$f(y_{ijkt}) = 1 - (1 - r_{ijk}) y_{ijkt} \tag{5}$$

$\forall i, j \in V_s \cup V_c, \forall k \in K_2, \forall t \in T$

Eq. (6) is the third objective function, which maximizes the reliability of the routes traveled in the grid:

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

*4.3 Constraints*

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

$$\sum_{i \in V_0} \sum_{j \in V_s} x_{ijkt} \leq BM.ct_{kt} \qquad \forall\, k \in K_1, t \in T \tag{8}$$

$$inv_{i\,1} = invi_0 + pd_{i\,1} - \tilde{d}_{i\,1} \qquad \forall\, i \in V_c \tag{9}$$

$$inv_{it} = inv_{i(t-1)} + pd_{it} - \tilde{d}_{it} \qquad \forall\, i \in V_c, t \geq 2 \tag{10}$$

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

$$inv_{i1}=invi_0+\tilde{d_{i1}}-\sum_{k\in K_2} pd_{ik1} \qquad \forall\, i\ \in\ V_s \tag{28}$$

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

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

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

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

Constraint (7) states that if a route exists from point $i$ to point $j$ with a type $k$ vehicle, the type of wear-out the driver's experience must be determined. Constraint (8) allows goods to be transported between the central warehouse and temporary warehouses on a specific day with a truck, subject to the payment of a fixed truck fee and the use of that truck on that day. Expressions (9) and (10) are the inventory equations for customers. Constraint (11) states that if customer $j$ is selected for service on that day, a load will be sent to him. Constraint (12) ensures that each customer is served only once if they are selected to be served. In the case of entering customer's points, Constraint (13) is also the condition for exiting them. Constraint (14) ensures that the total load carried by a truck from all points on a given day is less than the truck's capacity. Expressions (15) and (16) prevent impossible commuting between two echelons. Constraint (17) returns the sum of loads sent by each truck on a given day, and constraint (18) returns the sum of demands requested from each temporary warehouse on each day. According to constraint (19), a special truck can only travel from a temporary warehouse to a customer if it is affiliated with that temporary warehouse. Constraints (20) and (21) are related to permission to travel at the first echelon. Constraint (22) is the condition for exiting a second-echelon temporary warehouse after entering it. Constraint (23) ensures that the load sent to each temporary warehouse is exactly equal to the total demand requested from it. Constraint (24) is concerned with meeting the capacity of second-echelon trucks. Constraint (25) states that if transportation can be accomplished with a truck in the second echelon, whose fixed cost has been paid for use on a specific day, that truck must be used. Constraints (26) and (27) prevent sub-tour formation in the second echelon. Constraints (28) and (29) are related to the inventory balance in the second echelon. Eq. (30) defines lateness as the positive difference between the delivery time and the upper bound of the time window. Eq. (31) defines earliness in order delivery as the positive difference between the delivery time and the lower bound of the time window. Constraint (32) specifies the model's decision variables.

### *4.4 Linearization of the first objective function*

Since the initial objective function of the proposed mathematical model is the product of two binary variables, it is non-linear. To linearize this expression, suppose that $z = x_1 + x_2$ is the product of two binary variables. The expression $z$ is equal to one only when both of its binary variables equal one; otherwise its zero. We can linearize $z$ using auxiliary constraints (33) to (35) by Norouzi *et al.*,[35].

$$z \leq x_1 \quad (33)$$

$$z \leq x_2 \quad (34)$$

$$z \geq x_1 + x_2 - 1 \quad (35)$$

We will use the above noted to linearize the expressions in the first objective function as below:

$$Z1 = \sum_{i \in V_o} \sum_{j \in V_s} \sum_{k \in K_1} \sum_{t \in T} \sum_{i' \in I'} \sum_{j' \in J'} C^{k}_{iji'j'} \rho^{ijkt}_{iji'j'} + \sum_{i \in V \setminus V_o} \sum_{j \in V \setminus V_o} \sum_{k \in K_2} \sum_{t \in T} y_{ijkt} c'_{ij} + \sum_{i \in V \setminus V_o} \sum_{t \in T} h_i inv_{it} + \sum_{t \in T} \sum_{i \in V_c} PE_{it} ER_{it} + \sum_{t \in T} \sum_{i \in V_c} PL_{it} LA_{it} \quad (36)$$

$$\rho^{ijkt}_{iji'j'} = z^{k}_{iji'j'} x_{ijkt} \quad (37)$$

$$\rho^{ijkt}_{iji'j'} \leq z^{k}_{iji'j'} \quad (38)$$

$$\rho^{ijkt}_{iji'j'} \leq x_{ijkt} \quad (39)$$

$$\rho^{ijkt}_{iji'j'} \geq z^{k}_{iji'j'} + x_{ijkt} - 1 \quad (40)$$

*4.5 Defuzzification of the demand parameter*

Triangular fuzzy numbers (TFNs) are the most popular type of fuzzy numbers and are widely used in representing uncertainty in applied sciences because of their ability to express the perception of experts. This paper used the TFN to represent the fuzzy demand parameter. TFN can accurately represent the uncertainty of the parameter and is close to the actual situation because it represents uncertainty as a main-pointed value surrounded by margins [36]. In this article, we use triangular fuzzy numbers to express fuzzy parameters. The demand fuzzy parameter is defined as $(d_{it}^{p}, d_{it}^{m}, d_{it}^{o})$, with indices $p, m$ and $o$ repressing the most pessimistic, possible, and optimistic values for the fuzzy parameter, respectively. We use the weighted mean method to defuzzify the fuzzy demand parameter into a deterministic parameter. Therefore, the fuzzy constraints (9), (10), (28), and (29) are defuzzified using Eqs. (41)-(44).

$$inv_{i1} = invi_0 + pd_{i1} - (w_1 d_{i1,\beta}^{p} + w_2 d_{i1,\beta}^{m} + w_3 d_{i1,\beta}^{o}) \quad \forall\, i \in V_c \quad (41)$$

$$inv_{it} = inv_{i(t-1)} + pd_{it} - (w_1 d_{it,\beta}^{p} + w_2 d_{it,\beta}^{m} + w_3 d_{it,\beta}^{o}) \quad \forall\, i \in V_c, t \geq 2 \quad (42)$$

$$inv_{i1} = invi_0 + \left(w_1 d_{i1,\beta}^{p} + w_2 d_{i1,\beta}^{m} + w_3 d_{i1,\beta}^{o}\right) - \sum_{k \in K_2} pd_{ik1} \quad \forall\, i \in V_s \quad (43)$$

$$inv_{it} = inv_{i(t-1)} + \left(w_1 d_{it,\beta}^{p} + w_2 d_{it,\beta}^{m} + w_3 d_{it,\beta}^{o}\right) - \sum_{k \in K_2} pd_{ikt} \quad \forall\, t \geq 2, \forall\, i \in V_s \quad (44)$$

where $w_1 + w_2 + w_3 = 1$ and $\beta$ denote the minimum acceptable possibility for converting the fuzzy parameter into an equivalent real number. $w_1, w_2, w_3$ indicate weights of the most pessimistic, possible, and optimistic fuzzy demand values, respectively. The appropriate values for these weights are often determined by decision-makers (DM) based on their experience and expertise, which is considered $\beta = 0.5, w_1 = w_3 = \frac{1}{6}, w_2 = \frac{4}{6}$ using the suggested values of Liang and Wang, as well as other studies by [37,38].

## 5. Solution Methodologies

The following is a definition of a multi-objective planning problem:

$$\begin{aligned} &Max\ Z_1, Z_2, \dots, Z_k \\ &Min\ Z_1, Z_2, \dots, Z_l \\ &s.t\ \ x \in F_x = \{x | g_s(x) \leq 0, \forall_s\} \end{aligned} \quad (45)$$

where $Z_k$ maximization and $Z_l$ minimization are considered concurrently in the solution space $F_x$. In multi-objective problems, since no solution vector can simultaneously optimize all $Z_k$ and $Z_l$, the optimal solution is no longer significant, and only efficient solutions (Pareto optimal) are considered. This way, in addition to the set of justified solutions known as the decision space ($F_x$), other solutions can be considered as the goal space, which are images of the points in the decision space in terms of the values of the goal functions. There are generally three main approaches to solving multi-objective problems: pre-solution weighting, post-solution weighting, and the interactive approach.

Before solving the problem, the DM's preferences are collected using the pre-solution weighting approach. This information includes the degree of importance (weights) or the acceptable minimum/maximum values for the objective functions. This category includes several approaches such as the weighted sum method, the limit method, and reference points-based methods like the goal programming method. In the post-solution weighting methods, also referred to as Pareto frontier approximation methods, a set of efficient solutions (known as Pareto optimal) is initially generated. The DM's preferences are then used to select the final preferred solution. In the interactive approach, an effective solution is created and offered to the DM throughout the problem-solving process. If the DM does not approve it, an alternative solution is attempted by collecting modified preferences from the DM. This interaction with the DM continues until a final, satisfactory solution is reached.

One approach to solving deterministic multi-objective problems is to use concepts from the well-known technique of fuzzy multi-objective programming (FMODM). These FMODM approaches offer a distinct advantage over other methods by utilizing fuzzy membership functions to represent the level of satisfaction for each objective function with respect to each decision vector. The foundation of all FMODM methods is defining membership functions for the functions and transforming the multi-objective model into a single-objective model using an integration function by [39,40].

This article employs the methodologies proposed by [41,42], as well as an interactive approach based on the TH method to transform the multi-objective model into a single-objective model. The fuzzy membership functions of the objective functions are specified in these approaches as follows:

$$\mu_{zl}(x) = \begin{cases} 1 & Z_l \le Z_l^- \\ \frac{Z_l^+ - Z(x)}{Z_l^+ - Z_l^-} & Z_l^- \le Z_l \le Z_l^+ \\ 0 & Z_l \ge Z_l^+ \end{cases} \quad (46)$$

$$\mu_{zk}(x) = \begin{cases} 1 & Z_k \ge Z_k^+ \\ \frac{Z_k(x) - Z_k^-}{Z_k^+ - Z_k^-} & Z_k^- \le Z_k \le Z_k^+ \\ 0 & Z_k \le Z_k^- \end{cases} \quad (47)$$

where $\mu_{zl}(x)$, $\mu_{zk}(x)$represent the fuzzy membership function for minimization of objectives ($Z_l$), and linear membership function for objective maximization ($Z_k$), respectively, and $Z_l^-$and$Z_k^+$ obtain a single-objective problem from a multi-objective problem in each solution. Furthermore, $Z_k^-$ indicates the minimum value (worst solution) of the maximization objective function $Z_k$, and $Z_l^+$expresses the maximum value (worst solution) of the minimization objective function $Z_l$.

## *5.1 The Selim and Ozkarahan Approach*

Selim and Ozkarahan introduced the SO approach, which utilizes the Werners, [43] integration function to solve FMODM problems in a fuzzy manner. Using this approach, the original general model (45) is transformed into the following model:

$$\begin{aligned} & Max\ \lambda(x) = \gamma\lambda_0 + (1-\gamma)\sum_k \theta_k \lambda_k(x) \\ & \lambda_0 + \lambda_k \le \mu_k(x) \quad \forall_k \\ & \qquad x \in F(x) \\ & s.t \quad \lambda_0, \lambda_k, \gamma \in [0,1] \end{aligned} \quad (48)$$

$\mu_k(x), \lambda_0 = \min_k\{\mu_k(x)\}$ show the degree of satisfaction of the $k^{th}$ objective function and the minimum degree of satisfaction of the objective functions. $\theta_k$ parameters are determined by DM and based on its priorities so that $\sum_k \theta_k = 1, \theta_k > 0$. In this model, $\lambda_k = \mu_k - \lambda_0$ and $\gamma$ denote the compromise coefficient between min and weighted sum operators.

*5.2 The Torabi and Hassini approach*

Torabi and Hassini's approach (TH) combines elements from Lia and Huang's and the SO methods Diaz-Madronero *et al*., [44]. It is known as the TH approach. Applying this approach leads to the transformation of the general model (45) into the subsequent model:

$$Max\ \gamma\lambda_0 + (1-\gamma)\sum_k \theta_k \mu_k(x)$$

$$\begin{aligned} & \lambda_0 \le \mu_k(x) \quad \forall_k \\ s.t \quad & \lambda_0, \gamma \in [0,1] \end{aligned} \tag{49}$$

$\mu_k(x), \lambda_0 = \min_k\{\mu_k(x)\}$ indicates the satisfaction degree of the $k^{th}$objective function and the minimum satisfaction degree of the objective functions, respectively. The parameters $\theta_k$are set by the DM and are based on its preferences, so that $\sum_k \theta_k = 1,\ \theta_k > 0$. In this model, $\gamma$ is a compromise coefficient among the objectives. $\lambda_0$ is given more importance as $\gamma$ increases and indeed, a more balanced response will be generated. In addition, more importance is given to increasing the satisfaction level of the objective function with more $\theta_k$ as $\gamma$ level decreases, and more unbalanced efficient solutions are produced. Accordingly, given the DM preferences and as the $\gamma$ value changes (from zero to one), differentiated balanced and unbalanced efficient solutions can be obtained.

*5.3 Proposed interactive approach (PIA)*

The TH method uses $\gamma$ parameter to determine and control the minimum satisfaction level for the objective functions. Increasing this parameter raises the minimum satisfaction level ($\lambda_0$), and the amount of raise is not controlled by the DM. On the other hand, as the satisfaction level increases, the objective functions with $\theta_k$ are given less priority. To control the minimum satisfaction level, the following single objective function, which is an extended TH model, is proposed.

$$Max\ \gamma\lambda_0 + (1-\gamma)\sum_k \theta_k \mu_k(x)$$

$$\begin{aligned} s.t \quad & \mu_k(x) \ge \lambda_0 \\ & \mu_k(x) \ge \alpha_k \quad \forall_k \\ & x \in F_X \\ & \gamma, \lambda_0 \in [0,1] \\ & \textstyle\sum_k \theta_k = 1, \theta_k > 0 \end{aligned} \tag{50}$$

In TH and SO models, the DM lacks control over the minimum satisfaction level for each objective function. This minimum satisfaction is determined by both the variable $\lambda_0$ and the model itself. In other words, the DM has no control over the degree of compromise between the goals of the multi-objective mathematical model and the minimum level of satisfaction of those goals. However, in the proposed approach, by implementing constraint $\mu_k(x) \ge \alpha_k \ \ \forall k$, the DM controls the minimum satisfaction level for each objective function through the parameter $\alpha_k$. In other words, the DM can regulate the compromise between the objectives and the minimum level of satisfaction for the objective functions using the $\gamma, \alpha_k$ parameters, thereby enhancing the controllability of the single-objective model.

In the proposed approach, if model (50) is possible, the following restrictions will be applied (assuming that $F_X$ is possible):

$$\begin{aligned} & \mu_k(x) \ge \lambda_0 \\ & \mu_k(x) \ge \alpha_k \quad \forall_k \end{aligned} \tag{51}$$

That is, the model could find the variable $\lambda_0$ in such a way that $\forall_k;\ \lambda_0 \geq \alpha_k$, otherwise, (if the model is impossible), then:

$$\exists k;\ \lambda_0 < \alpha_k \tag{52}$$

Otherwise, DM should either increase $\gamma$ i.e. the compromise level, or decrease $\alpha_k$ as much as the model becomes possible. The objective function of model (50) is converted to the weighted sum method of satisfaction levels of the objective functions per $\gamma = 1$, i.e., max-min model and per $\gamma = 0$, which in this state, it is possible to obtain an effective solution that satisfies the objective functions to a higher degree by allocating greater importance to the minimum level of satisfaction. The flowchart of the proposed algorithm is shown in the Figure 2.

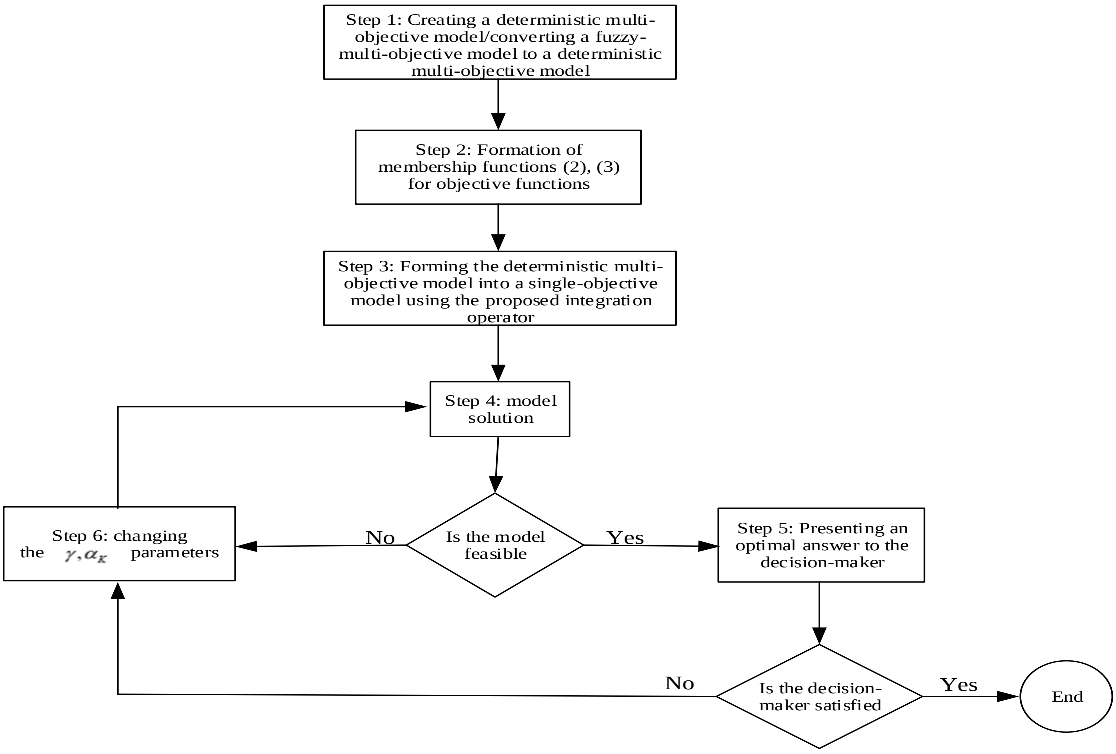


**Fig. 2.** Flowchart of the proposed algorithm

### *5.4 Limitation and application of PIA approach*

Since introducing an additional limitation to an assumed mathematical model can lead to either the infeasibility of the model, or if it remains feasible, the resulting solution will not be superior, the constraints $\mu_k(x) \geq \alpha_k\ \ \forall k$ can render the model infeasible in the presented approach, or negatively impact the value of the optimal solution, which can be considered as the controllability cost of the minimum satisfaction level of the objective functions. While the proposed approach may not generate all Pareto solutions as decision alternatives for DM or stakeholders, in such situations, the mathematical model should be solved using metaheuristic methods. However, when the minimum satisfaction level of the objective functions is important for the DM or stakeholders, the presented approach proves highly beneficial and practical because if the model is feasible, the output will fulfill the minimum expectations of the stakeholders. On the other hand, if the model becomes infeasible, DM and stakeholders will recognize the need to lower their minimum satisfaction level for the objective functions or adjust it in a way that the mathematical model becomes feasible. In either case, they will gain a better understanding of the decision-making environment.

## 6. Computational Experiments

### *6.1 Experimental Design*

The effectiveness of the SO, TH, and proposed interactive approaches has been investigated in this section through numerical results analysis. For this purpose, 30 randomly generated problems were used and coded using GAMS software and executed on a computer with a CPU Core i5 2.3 GHz and 4GB RAM. Table 2 contains the specific input details for these problems.

**Table 2**
Dimensions of generated problems

| Problem No. | Number of intermediate warehouses | Number of echelon 1 vehicles | Number of echelon 2 vehicles | Number of customers | Number of periods | Type of wear-out | Types of experience |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 3 | 2 | 5 | 3 | 1 | 1 |
| 2 | 2 | 3 | 2 | 5 | 2 | 1 | 1 |
| 3 | 2 | 4 | 4 | 8 | 4 | 1 | 1 |
| 4 | 3 | 2 | 2 | 4 | 4 | 2 | 2 |
| 5 | 4 | 3 | 5 | 9 | 2 | 2 | 2 |
| 6 | 2 | 4 | 2 | 5 | 3 | 2 | 2 |
| 7 | 2 | 3 | 3 | 5 | 4 | 3 | 3 |
| 8 | 2 | 4 | 2 | 6 | 3 | 3 | 3 |
| 9 | 2 | 2 | 5 | 4 | 4 | 3 | 3 |
| 10 | 3 | 3 | 3 | 7 | 4 | 3 | 3 |
| 11 | 3 | 4 | 5 | 4 | 2 | 1 | 1 |
| 12 | 2 | 2 | 4 | 5 | 3 | 1 | 1 |
| 13 | 4 | 4 | 5 | 4 | 2 | 1 | 1 |
| 14 | 1 | 3 | 5 | 5 | 4 | 2 | 2 |
| 15 | 4 | 3 | 2 | 3 | 3 | 2 | 2 |
| 16 | 4 | 2 | 2 | 6 | 4 | 2 | 2 |
| 17 | 4 | 3 | 2 | 9 | 3 | 3 | 3 |
| 18 | 4 | 3 | 5 | 5 | 2 | 3 | 3 |
| 19 | 1 | 3 | 5 | 6 | 2 | 3 | 3 |
| 20 | 4 | 3 | 3 | 8 | 4 | 3 | 3 |
| 21 | 2 | 4 | 5 | 3 | 4 | 1 | 1 |
| 22 | 3 | 2 | 5 | 9 | 2 | 1 | 1 |
| 23 | 3 | 3 | 2 | 3 | 4 | 1 | 1 |
| 24 | 4 | 2 | 2 | 5 | 4 | 2 | 2 |
| 25 | 1 | 2 | 4 | 3 | 3 | 2 | 2 |
| 26 | 1 | 3 | 5 | 7 | 2 | 2 | 2 |
| 27 | 1 | 4 | 3 | 5 | 4 | 3 | 3 |
| 28 | 1 | 3 | 5 | 7 | 3 | 3 | 3 |
| 29 | 3 | 4 | 4 | 8 | 4 | 3 | 3 |
| 30 | 3 | 4 | 4 | 5 | 3 | 3 | 3 |

The weights vector of the objective function has been considered $\theta = (0.5, 0.3, 0.2)$ based on the relative importance of model objectives by the DM ($\theta_1 > \theta_3 > \theta_{2)}$. Therefore, an unbalanced compromise solution with the highest degree of satisfaction for $Z_1$ is of particular interest.

### *6.2 Results analysis*

Two efficiency indices $d_p(v)$ and $RSD$ by Torabi & Hassini approach have been used to compare the efficiency of both introduced approaches to solve the proposed mathematical model:

$$d_p(v) = \left[\sum_h \theta_h^p \left(1 - \mu_h(v)\right)^p\right]^{\frac{1}{p}} \quad p \geq 1 \,\&\, Integer \tag{53}$$

$$RSD(v) = \max_h\{\mu_h(v)\} - \min_h\{\mu_h(v)\} \tag{54}$$

Eq. (53) measures the closeness degree of each solution to the corresponding ideal solution, where p is a distance parameter. The $p = 1, 2, \infty$ states is of particular importance in the literature so that $d_1$ (the Manhattan distance) and $d_2$ (the Euclidean distance) are the longest and shortest distances in the geometrical sense, respectively, and $d_\infty$ (the TChebyshev distance) is the shortest distance in the numerical sense. Generally, $d_p$ distance decreases as $p$ increases Lai *et al.,* [45]. It is worth noting that based on the $d_p$ definition, the approach with the least $d_p$value (particularly for p = 1) is preferred over others Torabi and Hassini [42] approach. The *RSD* (range of satisfaction degrees) index is a dispersion index that calculates the maximum difference between the satisfaction degrees of objectives to measure the balancing amount of a compromise solution by Torabi & Hassini approach. Considering Eq. (54), higher RSD values are preferred.

The problems in Table 2 were solved with different $\gamma$ values to analyze the $\gamma$ interaction on the final solutions of the SO and TH methods and the PIA proposed approach; the mean results of each are given in Tables 3 and 4.

**Table 3**
The effect of changes in $\gamma$ values on the satisfaction level of objective functions in SO, TH, and PIA methods

| $\gamma - Value$ | PIA Method(mean) | | | TH Method(mean) | | | SO Method(mean) | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\mu_{Z_1}(v)$ | $\mu_{Z_2}(v)$ | $\mu_{Z_3}(v)$ | $\mu_{Z_1}(v)$ | $\mu_{Z_2}(v)$ | $\mu_{Z_3}(v)$ | $\mu_{Z_1}(v)$ | $\mu_{Z_2}(v)$ | $\mu_{Z_3}(v)$ |
| 0 | 0.820 | 0.748 | 0.168 | 0.800 | 0.724 | 0.181 | 0.801 | 0.814 | 0.167 |
| 0.1 | 0.839 | 0.693 | 0.095 | 0.819 | 0.669 | 0.108 | 0.784 | 0.801 | 0.183 |
| 0.2 | 0.609 | 0.342 | 0.422 | 0.589 | 0.318 | 0.435 | 0.804 | 0.819 | 0.164 |
| 0.3 | 0.580 | 0.309 | 0.449 | 0.560 | 0.285 | 0.462 | 0.792 | 0.813 | 0.187 |
| 0.4 | 0.580 | 0.309 | 0.449 | 0.560 | 0.285 | 0.462 | 0.800 | 0.814 | 0.167 |
| 0.5 | 0.580 | 0.309 | 0.449 | 0.560 | 0.285 | 0.462 | 0.818 | 0.833 | 0.146 |
| 0.6– 0.9 | 0.580 | 0.309 | 0.449 | 0.560 | 0.285 | 0.462 | 0.560 | 0.375 | 0.448 |
| 1 | 0.573 | 0.309 | 0.433 | 0.553 | 0.285 | 0.446 | 0.553 | 0.375 | 0.432 |

**Table 4**
Comparing the performance indicators for different $\gamma$ values

| $\gamma - Value$ | Fuzzy Approach | Mean distances measures | | | Mean of RSD |
|---|---|---|---|---|---|
| | | $d_1$ | $d_2$ | $d_\infty$ | |
| 0.0 | SO | 0.342 | 0.271 | 0.198 | 0.285 |
| | TH | 0.386 | 0.274 | 0.230 | 0.312 |
| | PIA | 0.366 | 0.307 | 0.202 | 0.425 |
| 0.1 | SO | 0.407 | 0.288 | 0.173 | 0.493 |
| | TH | 0.382 | 0.303 | 0.165 | 0.578 |
| | PIA | 0.330 | 0.313 | 0.202 | 0.548 |
| 0.2 | SO | 0.410 | 0.314 | 0.221 | 0.263 |
| | TH | 0.398 | 0.312 | 0.199 | 0.312 |
| | PIA | 0.399 | 0.314 | 0.219 | 0.493 |
| 0.3 | SO | 0.369 | 0.315 | 0.209 | 0.274 |
| | TH | 0.399 | 0.303 | 0.179 | 0.315 |
| | PIA | 0.380 | 0.298 | 0.199 | 0.415 |
| 0.4 | SO | 0.394 | 0.296 | 0.202 | 0.775 |
| | TH | 0.403 | 0.296 | 0.221 | 0.712 |

| $\gamma - Value$ | Fuzzy Approach | Mean distances measures | | | Mean of RSD |
|---|---|---|---|---|---|
| | | $d_1$ | $d_2$ | $d_\infty$ | |
| | PIA | 0.405 | 0.313 | 0.171 | 0.624 |
| 0.5 | SO | 0.361 | 0.266 | 0.193 | 0.432 |
| | TH | 0.326 | 0.293 | 0.225 | 0.512 |
| | PIA | 0.397 | 0.311 | 0.216 | 0.641 |
| 0.6-0.9 | SO | 0.372 | 0.278 | 0.218 | 0.432 |
| | TH | 0.385 | 0.300 | 0.181 | 0.529 |
| | PIA | 0.347 | 0.266 | 0.173 | 0.628 |
| 1 | SO | 0.419 | 0.273 | 0.176 | 0.319 |
| | TH | 0.404 | 0.301 | 0.206 | 0.615 |
| | PIA | 0.382 | 0.307 | 0.176 | 0.712 |

As shown in Table 3, the PIA and TH membership functions are less sensitive to $\gamma$ parameter changes and give unique balanced solutions for $0.3 \leq \gamma \leq 0.9$. In addition, the membership functions' values are better in the PIA proposed approach since their values are controllable by DM in this part.

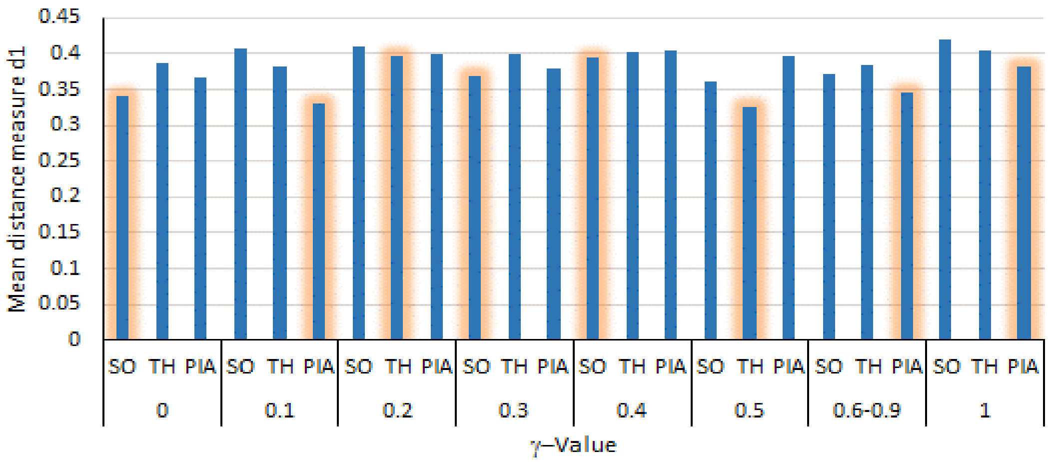


**Fig. 3.** The impact of different $\gamma$ values on the $d_1$ efficiency index

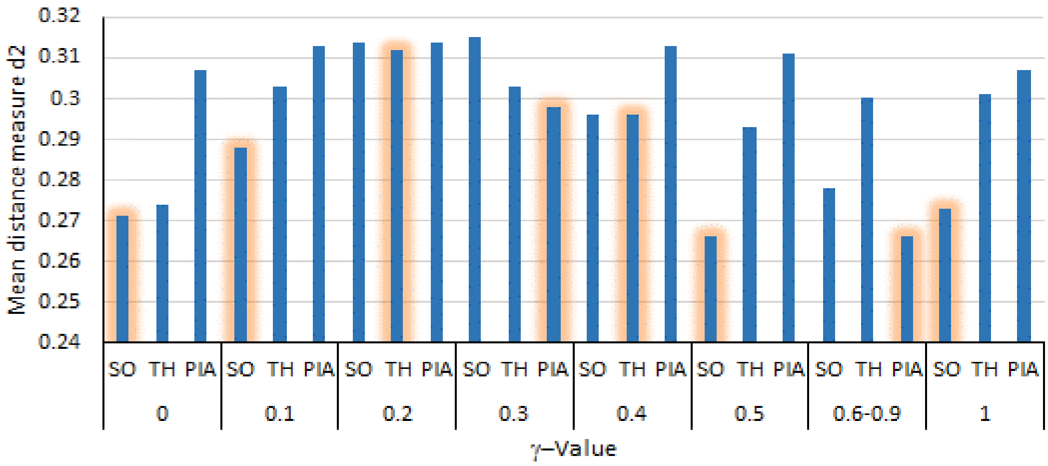


**Fig. 4.** The impact of different $\gamma$ values on the $d_2$ efficiency index

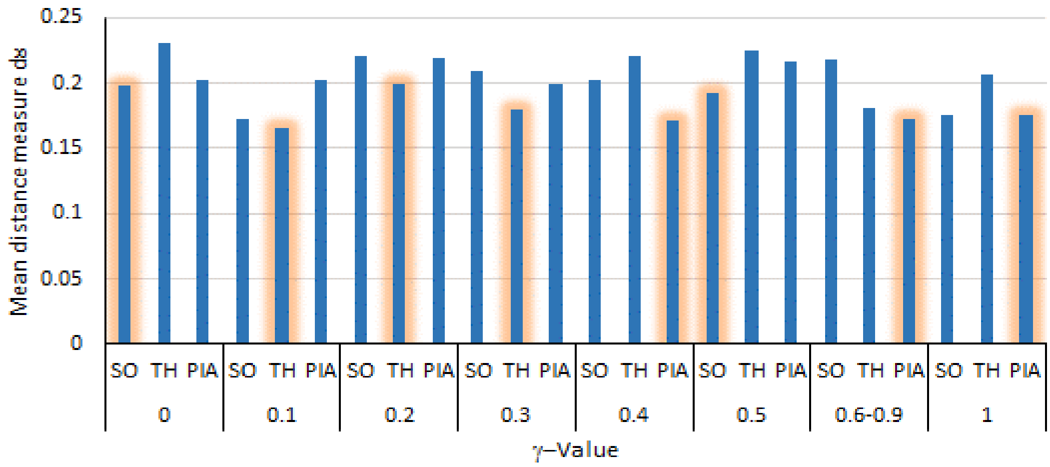


**Fig. 5.** The impact of different $\gamma$ values on the $d_\infty$ efficiency index

As shown in Figure 3, considering $d_1$ index, SO, $\gamma = 0.2, 0.5$, TH, and $\gamma = 0.1, 0.6 - 0.9, 1$ methods, the PIA proposed method is more efficient in $\gamma = 0, 0.3, 0.4$ states. In other words, when $\gamma > 0.5$, the PIA method generates better-balanced solutions. Concerning $d_2$ index, SO, $\gamma = 0.2, 0.4$, TH, $\gamma = 0.1, 0.6 - 0.9$ methods, the proposed PIA method is more efficient as seen in Figure 4. That is, if $\gamma > 0.5 - \{1\}$, the PIA method is more efficient, and based on $d_\infty$ index in Figure 5, in $\gamma = 0.1, 0.2, 0.3$ states, TH, and $\gamma = 0.4, 0.6 - 0.9, 1$ methods, the proposed PIA method generates more balanced solutions. Figures 3-5 demonstrate that the PIA method can produce more balanced solutions.

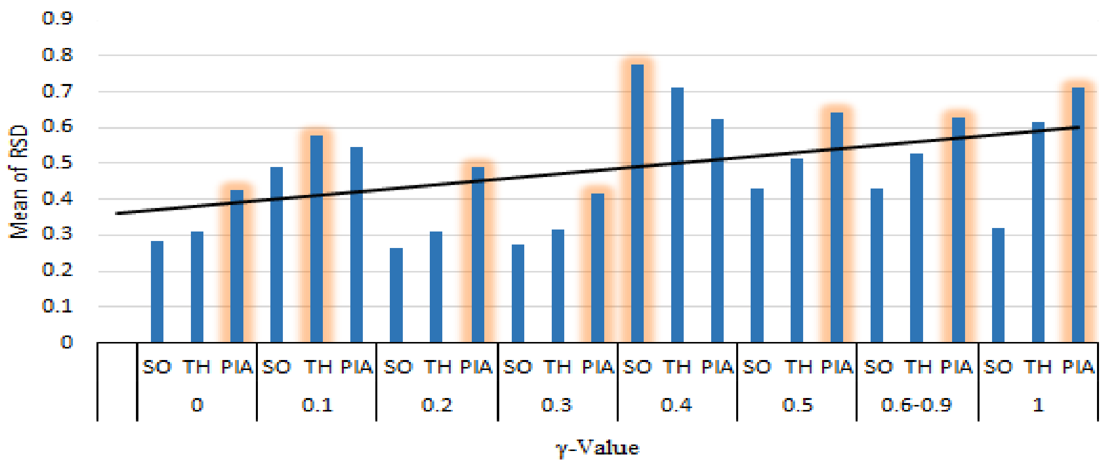


**Fig. 6.** The impact of different $\gamma$ values on RSD efficiency value

Considering Figure 6, the proposed PIA method is more efficient in the RSD index, $\gamma = 0.4$ state, TH method, and others since the minimum satisfaction level of the objective functions is more controllable by the DM and more consistent with the DM's preferences. Furthermore, based on the procedure line in Figure 6, as $\gamma$ increases, a more balanced solution is generated, and the objective's satisfaction increases due to the maximum difference among the satisfaction degrees

.

## 7. Conclusion and suggestions

A novel multi-objective, multi-period mixed integer programming model for routing allocation with non-deterministic demand was introduced in this study. The model incorporates driver performance records, route hardness, and vehicle lifetime (heterogeneous vehicles). In addition to costs, the model also accounts for environmental pollution and route reliability as secondary and tertiary objectives. The proposed model evaluates costs by considering vehicle type parameters, vehicle wear-out, and driver experience. The cost of allocating a vehicle to a driver increases with their level of experience and decreases with less experience. Another factor influencing allocation cost is the vehicle wear-out. A vehicle that has been used for a longer period is expected to have higher wear-out, increasing the probability of breakdown. Consequently, the cost of assigning such a vehicle to drivers is reduced. This model also defines varying degrees of hardness for different routes. The cost of traveling a route is determined by an initial fixed cost and the hardness level of the route. Naturally, higher hardness levels result in higher route costs. In addition to the commonly used SO and TH methods, an interactive approach was proposed to solve the presented model. In the previous approaches, the DM has no control over the minimum satisfaction of each objective function, and this minimum satisfaction of the objective functions is determined by the model; but in the proposed approach, the DM controls the compromise between the goals and the minimum level of satisfaction for the objective functions by $\gamma, \alpha_k$ parameters, thereby increasing the controllability of the single-objective model. To compare the efficiency of the introduced approaches to solve the proposed mathematical model, two efficiency indices $d_p(v)$ and $RSD$ have been used. The results showed that in the proposed approach of PIA and TH, the membership functions are less sensitive to the changes of parameter $\gamma$ and give unique balanced solutions for $0.3 \leq \gamma \leq 0.9$. Based on index $d_1$, in the case where $\gamma > 0.5$, the PIA method created better-balanced solutions. Regarding the index $d_2$, while $\gamma = 0,0.1,0.5,1$, SO method, $\gamma = 0.2, 0.4$, TH method and $\gamma = 0.1, 0.6 - 0.9$, proposed PIA method, showed better efficiency. Based on index $d_\infty$, in cases $\gamma = 0.1, 0.2, 0.3$, the TH method and $\gamma = 0.4, 0.6 - 0.9, 1$ proposed PIA method created better-balanced solutions. Finally, based on the RSD index, in case $\gamma = 0.4$ the TH method and in the remaining cases, the proposed PIA method showed better performance.

For future study, applying the reliability of vehicles causes the amount of cargo carried by each of them is determined and optimized in such a way as to reduce their failure rate, thus the logistics process will be more agile and responsive. Furthermore, it is possible to incorporate a reward system into the model, where the amount of reward allocated to a driver increases in proportion to their performance. In addition, the use of a robust planning approach to deal with the uncertainty of the two-echelon model to face stronger uncertainty and make the model more flexible, utilization of data mining and machine learning methods to categorize drivers based on performance and considering a more appropriate criterion such as time to calculate routing costs are suggestions for further study due to factors like vehicle break down or traffic congestion, which lead to delays and increasing logistics expenses. Because Neutrosophic sets extend the representation of uncertainty beyond what traditional fuzzy sets provide. While traditional fuzzy sets express degrees of membership and non-membership, Neutrosophic sets add a third component: indeterminacy. This three-degree membership concept allows for a more comprehensive and accurate representation of uncertainty, which is particularly useful when dealing with complex and ambiguous data. Therefore, it is suggested to use Neutrosophic numbers to express uncertainty to reach more accurate results in future studies

As it is known, this research also has limitations like other research works. Here, some useful suggestions for future studies are presented based on these main limitations. In this article, to simplify the mathematical model and prevent its excessive complexity, the capacity limit for the supplier is considered unlimited, which is practically not possible in the real world. Therefore, it is suggested to consider limited capacity in future studies and include its inventory equations in the model. Another important and significant limitation of this article is the lack of benchmark functions and the lack of access to real data. For this reason, it is designed from simulated data in different sizes to validate the proposed model. Therefore, it is suggested that the effectiveness of the mentioned model be measured and investigated with completely real data.

**Author Contributions**

Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, Z.Y., S.M.H.M. and A.H.; writing—original draft preparation, writing—review and editing, visualization, Z.Y. and S.E.N. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement**

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data. However, they can be obtained from the corresponding author upon reasonable request.

**Conflicts of Interest**

The authors declare no conflict of interest.

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