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A Hub Location-Routing Problem Considering Simultaneous Pickup and Delivery Under Conditions of Uncertainty Considering Environmental Parameters

Ramona Mojarrad langroudi[1], Seyed ahmad Shayannia[2]✉, Ali hajiha[3], Maryam Shoar[4]

1. Ph.D. Candidate, Department of Industrial Management, NT.C., Islamic Azad University, Tehran, Iran, Email: r.mojarrad@iau.ac.ir
2. Corresponding Author, Assistant Professor, Department of Industrial Management, Fi.C., Islamic Azad University, Tehran, Iran, Email: Sa.shayannia@iau.ac.ir
3. Assistant Professor, Department of Industrial Management, NT.C., Islamic Azad University, Tehran, Iran, Email: ahajiha@gmail.com
4. Assistant Professor, Department of Industrial Management, NT.C., Islamic Azad University, Tehran, Iran, Email: m_shoar@iau-tnb.ac.ir

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ABSTRACT

In this paper, a new model for the hub location-routing problem is presented, considering simultaneous delivery and collection operations under uncertainty. The model aims to minimize three main indicators: the total cost of the supply chain network, the maximum travel time of vehicles, and the total greenhouse gas emissions. To control uncertain parameters such as cost, time, and transportation demand, a two-level probabilistic programming approach is used. The proposed model determines the optimal location of hubs and the optimal route of vehicles for simultaneous delivery and collection of goods. The results of the LP-metric method show that there is a trade-off between the model objectives, so that by reducing greenhouse gas emissions and travel time, the total network cost increases. Sensitivity analysis of the savings coefficient also indicates that reducing this coefficient reduces the total system costs and changes its stability. To solve the model in larger dimensions, two meta-heuristic algorithm MOIWO and MOALO, have been used. The results suggest that the MOALO algorithm performs better than MOIWO in terms of efficiency and computing time, and the relative difference in its results with the LP-metric method is less than three percent.

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1) Introduction

Hubs are special facilities used as exchange, transfer, and classification points in many distribution systems. Hub location problems have an effective role in improving the efficiency of transportation systems. Intermediate points, called hubs, have the task of collecting, sorting and distributing to demand locations (Chobar et al., 2025). Hub location problems are a subset of network problems. These problems are raised with the aim of optimal design of all types of transportation networks. Therefore, the goal of solving this problem is to find a suitable place for hubs and routes to send goods from a series of origins to a series of destinations in a way that assist in reducing costs and obtaining the desired economic benefits through multiple transfers between hubs (Szmelter-Jarosz et al., 2021). Among numerous things that companies ought to persistently screen is the collection of items dispersed by their company. Subsequently, in expansion to assembly client request, companies are too dependable for collecting items. This problem has been reported by governments due to the destructive natural impacts (Safizadeh, 2024). In order to overcome these weights, they must frequently update their benefit arrangements and improve logistics processes with better coordination of decisions at strategic and operational levels (Ghahremani-Nahr et al., 2022). Hub-location problem have been broadly utilized in later decades due to their tall applications in present day transportation and communication frameworks. Hubs within the transportation systems of merchandise and travelers, etc., are places that get the stream from distinctive sources and coordinate it to the goal hubs or other hubs; In this manner, the objective of hub location-routing problems is to meet requests by moving individuals, products, and data through extraordinary offices called "hub points" that are known as dissemination middle people between source hubs and goal hubs (Alumur et al., 2021). In a location-routing network, due to the huge volume of merchandise transported from origin to destination, an effective design of the network can ensure high-quality services (Li & Wang, 2023). In this network, by diminishing the number of joins within the source and goal hubs, hub points anticipate any coordinate association of all hubs, which in turn leads to a lessening in costs, a reduction in greenhouse gas emissions, and a diminishment within the time of products exchange compared to systems with total chart associations (Ghaffarinasab et al., 2022). Furthermore, utilizing the rebate factor ($0 < \alpha < 1$) for communication between hubs leads to a significant reuction in the cost of the entire network (Taherkhani & Alumur, 2019).

In recent years, different sorts of hub-location problem have been examined, one of the foremost vital of which is the hub covering the location-routing problem. In these systems, each hub can only exchange goods and services with other hubs within a predefined range and collect the returned products. Secured hub location-routing systems have pulled the consideration of numerous analysts due to different application areas in long-distance communication systems, discuss transportation, merchandise transportation, postal administrations, open and urban transportation, rail transportation, and crisis administrations (Mokhtarzadeh et al., 2021). As the request for cargo increments with populace growth, the significance of the correct plan of transportation systems in dubious conditions becomes clear (Davari et al., 2013). The utilization

of hub points in transportation systems not only significantly reduces operating costs, network infrastructure setup costs, and delivery time, but also leads to better services for customers and reduces the harmful effects of environmental pollution (Hasanzadeh et al., 2018; Yalali et al., 2026). Therefore, the most important concept of overlay hub location-routing systems within the design of a transportation network is that several decisions must be made, including the location of hub offices and non-hub nodes, the assignment of all origin and destination nodes (non-hub) directly to the hub, and flow routing. These choices are aimed at lessening the costs of the whole arrangement, diminishing the sum of greenhouse gas emissions, and reducing the optimal travel time of vehicles. Furthermore, considering whether there is a constraint to exchange the sum of items through the transportation network or there is no restraint, hub-location problems are classified into two sub-problems with restricted capacity and boundless capacity. Capacity confinements may be related to arranged joins or center hubs (Rahmati et al., 2022). There is another sort of capacity confinement, related to the number of non-hub nodes, that can be doled out to a particular hub. In this manner, decision makers can incorporate these contemplations into their network (Zahedi & Nahar, 2020).

In many modern transportation networks, simultaneous delivery and pickup operations are recognized as one of the most effective solutions for increasing the efficiency of the logistics system. This approach reduces empty routes, saves fuel consumption, and reduces the total cost of operations. Additionally, performing these two processes simultaneously improves customer response time and reduces the environmental impact of unnecessary trips. Given the dynamic and multi-purpose nature of distribution networks, considering simultaneous delivery and pickup can make decisions about the route and location of hubs more realistic.

On the other hand, in real environments, parameters such as transportation cost, travel time, and demand are often uncertain and variable. To control these uncertainties, this research uses the Multi-level Probabilistic Planning approach. This method, by considering several scenarios for random parameters, enables analysis and optimal decision-making in different conditions. Therefore, the proposed model is able to make location and routing decisions realistically and reliably, considering possible data changes. The combination of these two perspectives (simultaneous delivery and collection and multi-level probabilistic planning) forms the main innovation of this research and provides a comprehensive framework for designing green and resilient networks.

According to what mentioned above, this research aims to plan the positioning-routing demonstration of the covering hub by considering the time window beneath vulnerability. To bargain with the non-deterministic parameters of the demonstration, the two-level probabilistic programming strategy was utilized and distinctive scenarios were proposed for each of the non-deterministic parameters. Moreover, The combination of situating and steering problems within the cover hub system has driven the utilization of LP metric, Multi-Objective Invasive Weed Optimization (MOIWO), and Multi-Objective Ant Lion Optimization (MOALO) algorithm strategies to solve the problem. The results of the multi-objective model will be analyzed to

minimize the total costs, minimize the maximum vehicle travel time, and minimize the amount of greenhouse gas emissions.

In this study, the term two-level probabilistic programming refers to a specific case of multi-level probabilistic planning with two hierarchical decision layers, designed to capture the uncertainty in transportation costs, times, and demands.

The main contributions of this research can be summarized as follows:

(1) The paper develops an integrated hub location–routing model that simultaneously considers delivery and pickup operations, which have rarely been modeled together under uncertainty.

(2) It introduces a two-level probabilistic programming framework capable of addressing stochastic transportation costs, times, and demands within a unified decision structure.

(3) The study employs and compares two advanced multi-objective metaheuristic algorithms (the Multi-Objective Ant Lion Optimization [MOALO] and the Multi-Objective Invasive Weed Optimization [MOIWO]) to solve large-scale instances efficiently.

(4) A comprehensive computational analysis, including Pareto front comparison and sensitivity analysis on the economy-of-scale coefficient, is conducted to provide managerial insights for designing sustainable and cost-efficient distribution networks.

Collectively, these contributions establish a novel and realistic decision-making framework that connects uncertainty modeling, environmental sustainability, and logistics optimization in an integrated hub-based system.

2) Literature Review

In recent years, hub-location problems have pulled in the consideration of numerous analysts, and different models have been created, such as covering hub problems, middle of the road centers, P-hubs, etc. According to the focus of this article on the location-routing problems of the cover hub, the research conducted has been reviewed in the following.

Aliahmadi et al. (2018) created a transportation planning and hub location problem where the hub network is not completely interconnected. The objective of the proposed model was to maximize the overall amount of flow delivered by the final predetermined time and also to minimize the entire cost. Wang and Qin (2020) displayed a model of the scope hub location problem under instability. The primary objective of this model was to minimize the costs of establishing hub points. To solve this, a hybrid algorithm named GA-VNS was utilized, and by analyzing several numerical examples, the high efficiency of this strategy was demonstrated. Lopes et al. (2016) solved the hub location-routing problem using a genetic algorithm with a random search. They also used the branch-and-cut algorithm to verify the effectiveness of their solution method. Computational tests on several benchmark instances of routing problems showed that the proposed algorithm is effective on medium-to-large-sized cases, whereas the branch-and-cut algorithm solves small to medium-sized problems optimally. Karimi (2018) presented a model of a hub location-routing problem with simultaneous pickup and delivery. In this article, the objective was to minimize the costs of hub location and vehicle routing

considering the limited capacity of hubs. A tabu search (TS) method was used to solve the model. The results showed that the proposed method is more effective than other methods in finding good-quality solutions. Rajabi and Darestani (2020) displayed a bi-objective optimization to diminish the time and costs of the scope hub-location problem. In this model, the fetch time and capacity of the central hub were considered as fluffy parameters. NSGA II and NRGA were utilized to solve the two-objective model. The result suggested that there is no critical contrast between the normal arrangement times between the two arrangement strategies. Moreover, by ranking the solution methods with TOPSIS, the NSGA-II algorithm has proven its efficiency in solving large numerical instances. Ratli et al. (2022) developed an innovative method to solve the hub location-routing problem. Their algorithm used a sequential variable neighborhood descent with different neighborhoods required to address the complex nature of the problem. The algorithm's results on 912 instances showed that the presented innovative method can solve 691 problems. Fallah-Tafti et al. (2022) developed a mathematical model for rapid transit systems based on the hub location model, which includes stops (stations) at the hub and non-hub levels. In this model, which aimed to minimize the costs of locating the hub and routing the means of transportation, a local search algorithm was used. Hajipour et al. (2022) presented a mathematical model for locating fire stations and facilities assigned to the stations across multiple periods and emergency circumstances (wars and natural disasters). This model was designed dynamically according to demand and the coverage range of the facilities, based on activity, the type of area, and the stage in different periods. Due to the NP-hardness of the problem, PSO and ABC algorithms were used to solve the problem, and the results showed that the proposed PSO is better than ABC in terms of solution quality and computing time. Pourmohammadi et al. (2021) presented a multi-objective mathematical model for hub location and routing problems under uncertainty in flow, cost, time, and number of work opportunities. The objective of this model is to minimize the total transportation cost, including routing and fixed costs, and to maximize business and regional development as a social responsibility. FIWO calculation, variable neighborhood look, and diversion hypothesis were utilized to solve the problem. Ghiasi and Vahdani (2021) displayed a model for the hub location-routing problem, considering adjustment and capacity choices. To diminish the entire cost of situating and directing, GA and ICA calculations were utilized. The comparision of the problem illustrations shows that the hereditary calculation incorporates a superior execution compared to the colonial competition calculation, and considering the capacity and adjust contemplations can be effective in reducing the costs of the examined arrangement. More studies are (Marjani et.al 2026; Jahromi 2026; Kiani 2026, Molani et. al 2026; Joshan 2026; Jamshidi et. al 2026; Shahabi et. al 2025, Riki et. al 2025; Mansori 2025; Jafari et. al 2025; Hassani et. al 2025).

The literature review indicated a gap in objective capacities, limitations, and arrangement strategies. Since the minimization of arrangement costs is investigated in most of the articles, this study aims to minimize total vehicle travel time by developing a mathematical model designed to simultaneously reduce operational costs and minimize the cumulative greenhouse gas emissions resulting from transportation activities. On the other hand, there is no hub location model that is

integrated with the vehicle routing problem. Using the two-level probabilistic programming strategy can effectively control the non-deterministic parameters of the problem. In addition to delivering goods, the presented model also collects returned items simultaneously. On the other hand, the literature review shows that the use of meta-heuristic methods is common, but modern algorithms have not been utilized on the hub location-routing model. This problem led to MOALO and MOIWO algorithms being used in this article in addition to the LP metric method.

3) Definition of the Problem

In this section, the hub location-routing problem is discussed considering the simultaneous delivery and pickup under conditions of uncertainty. Figure 1 can be considered as an example of the investigated problem.

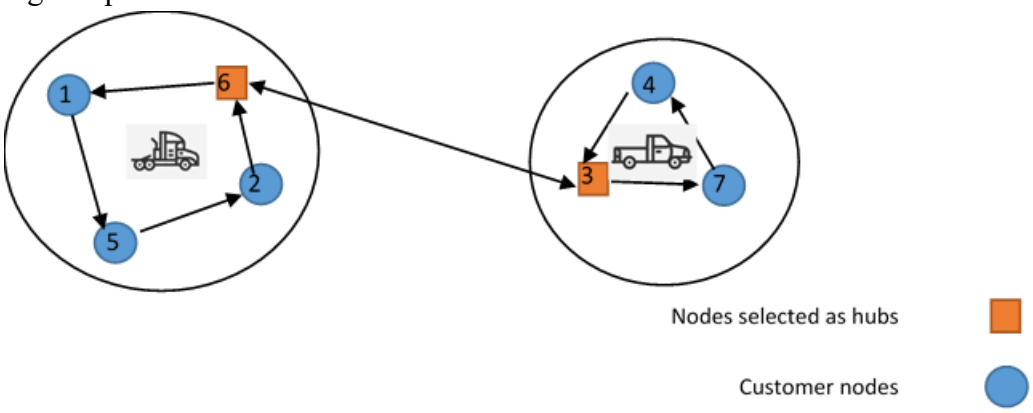

Figure 1. Hub Location-Routing Problem

The most important objective in the studied problem is to determine the optimal number and location of nodes from the network as hubs, assign non-hub nodes to hub points, determine the optimal transportation route to meet non-deterministic simultaneous pickup and delivery, and determine the optimal number of vehicles to distribute goods.

In this article, parameters such as delivery and pickup demand, transportation time, and transportation cost are considered in a non-deterministic manner, which takes on different values in various scenarios, the result of which can be altered in the optimal location of the facility as well as the optimal routing of vehicles. Accordingly, the modeling of a hub location and routing problem by considering non-deterministic delivery and pickup can be done according to the following assumptions and scope of the study:

- Delivery and collection request parameters, transportation time and fetch time are dubiously taken into consideration.
- Modeling the non-deterministic problem with the probabilistic strategy will be based on the situation.
- The coverage radius of each hub is variable and features a coordinated relationship with the quality of its benefit.
- All capacities of the center and vehicles are known and indicated.
- Transportation between hubs features a rebate (economies of scale are included).

The proposed model is developed under several key assumptions, which are summarized and justified as follows:

(1) *Homogeneous vehicle capacity:* All vehicles are assumed to have equal capacity to simplify the routing structure and maintain balance among delivery and pickup operations. This assumption is common in hub-based logistics models and enables consistent flow assignment between hubs.

(2) *Limited hub coverage radius:* Each hub operates within a maximum coverage distance, ensuring service quality and preventing unrealistic long-haul connections.

(3) *Uncertain transportation parameters:* Transportation cost, time, and demand are treated as probabilistic variables to capture real-world variability and reflect uncertainty in logistics operations.

(4) *Deterministic hub capacities:* The hub processing capacities are considered known and fixed, which allows focusing the analysis on uncertainty in routing rather than hub expansion decisions.

(5) *Economies of scale:* A discount factor ($0 < \alpha < 1$) is applied to inter-hub transportation costs, consistent with prior works (Taherkhani & Alumur, 2019), reflecting reduced cost per unit distance in consolidated shipments.

These assumptions strike a balance between realism and computational tractability, allowing for large-scale scenario-based optimization while maintaining interpretability for practical applications.

Based on the above assumptions, the mathematical model seeks to minimize the total costs, minimize the maximum travel time between the hubs, and minimize the amount of CO_2 gas emissions caused by the traffic of vehicles at the same time. Considering the assumptions of the above model, the number of $i, j, k, m \in N$ nodes and $v \in V$ vehicles are considered. Parameters can be presented as follows.

Parameters

$\tilde{C}_{i,j}$	The cost of non-deterministic transportation between node i and node j
$\tilde{T}_{i,j}$	The time of non-deterministic transport between node i and node j
$DI_{i,j}$	The distance between node i and node j
$Co_{i,j,v}$	The emission rate of Co_2gas from the traffic of vehicle v between node i and node j
Fk_k	The fixed cost of determining node k as a hub based on the quality of service
FV_v	The initial fixed cost of using the vehicle v
$\widetilde{W}_{i,j}$	The amount of non-deterministic delivery and withdrawal demand between node i and node j
P	The number of nodes that should be selected as hubs.
R_v	The maximum coverage radius of the vehicle v in the distribution of products based on the quality of service
VN	Number of vehicles in each hub

$Capk_K$	Maximum capacity of hub k
$Capv_v$	Capacity of vehicle v in product distribution
O_i	The total amount of output flow from node i $O_i = \sum_j \widetilde{W}_{i,j} \quad \forall i$
α	Coefficient of economies of scale

Decision-Making Variables

$Tmax$	Maximum of travel time by vehicles from hub centers
$F_{i,j,k}$	The amount of flow that starts from node i and passes through hubs j and k
$X_{i,j,v}$	It takes value 1 if vehicle v passes through nodes i and j, and 0 otherwise.
$G_{i,j,k}$	The amount of flow that starts from node i and passes through node j and hub k
$Z_{i,v}$	Takes the value 1 if node i is assigned to vehicle v, and 0 otherwise.
H_k	It takes the value 1 if hub k is selected, and 0 otherwise

Modeling the problem

$$MinOBF_1 = \sum_{i,j,k} \tilde{C}_{j,k} G_{i,j,k} + \sum_{i,j,k} \alpha \tilde{C}_{j,k} F_{i,j,k} + \sum_{k} Fk_k H_k + \sum_{i,v} FV_v Z_{iv} \tag{1}$$

$$MinOBF_2 = Tmax \tag{2}$$

$$MinOBF_3 = \sum_{i,j,v} CO_{i,j,v} X_{i,j,v} \tag{3}$$

$s.t.$:

$$\sum_{\substack{k \\ k \neq i}} \left(G_{i,i,k} + F_{i,i,k}\right) = O_i, \quad \forall i \tag{4}$$

$$\sum_{k} \left(G_{i,k,j} + F_{i,k,j}\right) = \sum_{k} \left(G_{i,j,k} + F_{i,j,k}\right) + \widetilde{W}_{i,j}, \quad \forall i,j \quad i \neq j \tag{5}$$

$$G_{i,k,j} \leq O_i \sum_{v} X_{k,j,v}, \quad \forall i,j,k \quad k \neq j \tag{6}$$

$$\sum_{\substack{j \\ j \neq i}} X_{i,j,v} - \sum_{\substack{j \\ j \neq i}} X_{j,i,v} = 0, \quad \forall i,v \tag{7}$$

$$\sum_{k} H_k = P \tag{8}$$

$$\sum_{j} \left(F_{i,k,j} + F_{i,j,k}\right) = O_i H_k, \quad \forall i,k \tag{9}$$

$$Z_{i,v} \leq \sum_{\substack{j \\ j \neq i}} X_{j,i,v}, \quad \forall i,v \tag{10}$$

$$\sum_{v} Z_{i,v} = VNH_i, \quad \forall i \tag{11}$$

$$\sum_{i} Z_{i,v} = 1, \quad \forall v \tag{12}$$

$$\sum_{\substack{j,v \\ j \neq i}} X_{i,j,v} = 1 + (VN - 1)H_i, \quad \forall i \tag{13}$$

$$Tmax \geq \sum_{i,j} \tilde{T}_{i,j} X_{i,j,v}, \quad \forall v \tag{14}$$

$$\sum_{i,j} DI_{i,j} X_{i,j,v} \leq R_v, \quad \forall v \tag{15}$$

$$\sum_{i,j} \widetilde{W}_{i,j} X_{i,j,v} \leq Capv_v, \quad \forall v \tag{16}$$

$$\sum_{i,j} F_{i,j,k} \leq Capk_k H_k, \quad \forall k \tag{17}$$

$$X_{i,j,v}, H_k, Z_{i,v} \in \{0,1\}, \quad \forall i, j, k, v \tag{18}$$

$$Tmax, F_{i,j,k}, G_{i,j,k} \geq 0, \quad \forall i, j, k \tag{19}$$

Equation (1) decreases the overall cost of the network. These costs include the cost of transporting items between nodes, the cost of locating nodes as hubs, and the fixed costs of using vehicles. Equation (2) shows the second objective function of the problem and includes minimizing the maximum travel time between hubs. Equation (3) deals with the minimization of CO_2 emissions caused by transportation activity. Equation (4) calculates the total output current from each node. Equation (5) gives stream balance between nodes and guarantees that the amount of pickup and delivery happens at the same time at each hub. Equation (6) ensures that the overall output stream from each hub can be carried by only one of the available vehicles. Equation (7) ensures that each vehicle visits each hub (client) as it were once. Equation (11) ensures that the vehicles must pass through the chosen centers. Equations (12) and (13) ensure that each course ought to be doled out as it were one vehicle. Equation (14) appears the greatest travel time between hubs. Equation (15) calculates the scope span coming about from the activity of each vehicle. The relation (16) ensures that each vehicle cannot move more than its capacity. Equation (17) guarantees that only the centers that can exchange items between their hubs as much as their capacity allows are selected. Equations (18) and (19) indicate the nature and type of decision variables of the hub location and routing problem.

Due to the uncertainty of the parameters of demand, time, and transportation cost, a two-level probabilistic programming strategy has been utilized to control the model. Therefore, by defining s ∈ S as the number of scenarios, parameters and decision variables need to be redefined and modified as follows.

Sets

S The number of scenarios $s \in S$

parameters

$C_{i,j,s}$	Cost of transportation between nodes i and j in scenario s
$T_{i,j,s}$	Transportation time between nodes i and j in scenario s
P_s	The probability of occurrence of scenario s
$W_{i,j,s}$	The amount of delivery and withdrawal demand between nodes i and j in scenario s

Additionally, the amount of the total output flow from node i can be defined as follows.

$$O_{is} = \sum_{j} W_{i,j,s}, \quad \forall i, s \tag{20}$$

Decision-making Variables

$F_{i,j,k,s}$	The amount of flow that starts from node i in scenario s and passes through hubs j and k
$G_{i,j,k,s}$	The amount of flow that starts from node i and passes through node j and hub k in scenario s
$Z_{i,v,s}$	It takes the value 1 if node i is assigned to vehicle v in scenario s, and 0 otherwise.
$X_{i,j,v,s}$	It takes the value of 1 if, in scenario s, vehicle v passes through nodes i and j, and 0 otherwise.

$$MinOBF_1 = \sum_{s} P_s \left(\sum_{i,j,k} C_{j,k,s} G_{i,j,k,s} + \sum_{i,j,k} \alpha C_{j,k,s} F_{i,j,k,s} + \sum_{k} Fk_k H_k + \sum_{i,v} FV_v Z_{ivs} \right) \tag{21}$$

$$MinOBF_2 = Tmax \tag{22}$$

$$MinOBF_3 = \sum_{s} P_s \left(\sum_{i,j,v} CO_{i,j,v} X_{i,j,v,s} \right) \tag{23}$$

$s.t.$:

$$\sum_{\substack{k \\ k \neq i}} \left(G_{i,i,k,s} + F_{i,i,k,s} \right) = O_{i,s}, \quad \forall i, s \tag{24}$$

$$\sum_{k} \left(G_{i,k,j,s} + F_{i,k,j,s} \right) = \sum_{k} \left(YG_{i,j,k,s} + F_{i,j,k,s} \right) + W_{i,j,s}, \quad \forall i, j, s \quad i \neq j \tag{25}$$

$$G_{i,k,j,s} \leq O_{i,s} \sum_{v} X_{k,j,v,s}, \quad \forall i, j, k, s \quad k \neq j \tag{26}$$

$$\sum_{\substack{j \\ j \neq i}} X_{i,j,v,s} - \sum_{\substack{j \\ j \neq i}} X_{j,i,v,s} = 0, \quad \forall i, v, s \tag{27}$$

$$\sum_{k} H_k = P \tag{28}$$

$$\sum_{j} \left(F_{i,k,j,s} + F_{i,j,k,s}\right) = O_{i,s} H_k, \quad \forall i,k,s \tag{29}$$

$$Z_{i,v,s} \leq \sum_{\substack{j \\ j \neq i}} X_{j,i,v,s}, \quad \forall i,v,s \tag{30}$$

$$\sum_{v} Z_{i,v,s} = VNH_i, \quad \forall i,s \tag{31}$$

$$\sum_{i} Z_{i,v,s} = 1, \quad \forall v,s \tag{32}$$

$$\sum_{\substack{j,v \\ j \neq i}} X_{i,j,v,s} = 1 + (VN - 1)H_i, \quad \forall i,s \tag{33}$$

$$Tmax \geq \sum_{i,j} T_{i,j,s} X_{i,j,v,s}, \quad \forall v,s \tag{34}$$

$$\sum_{i,j} D_{i,j} X_{i,j,v,s} \leq R_v, \quad \forall v,s \tag{35}$$

$$\sum_{i,j} W_{i,j,s} X_{i,j,v,s} \leq Capv_v, \quad \forall v,s \tag{36}$$

$$\sum_{i,j} F_{i,j,k,s} \leq Capk_k H_k, \quad \forall k,s \tag{37}$$

$$X_{i,j,v,s}, H_k, Z_{i,v,s} \in \{0,1\}, \quad \forall i,j,k,v,s \tag{38}$$

$$Tmax, F_{i,j,k,s}, G_{i,j,k,s} \geq 0, \quad \forall i,j,k,s \tag{39}$$

4) Solution Methods

Three different strategies have been utilized to solve the problem. These strategies incorporate LP metric, MOALO and MOIWO calculations. For this reason, a brief portrayal of the arrangement strategies is provided in the following.

4-1 LP Metric

To analyze numerical examples in small sizes, one of the multi-objective decision-making strategies, called the comprehensive criteria method, has been utilized. To use this strategy to convert the multi-objective model into a single-objective model, the three-objective model must first be solved through the individual optimization method, and the optimal value of each objective function must be determined.

Therefore, the optimal value of each objective function is obtained using the individual optimization method without considering other objective functions, denoted as wi∗*wi*∗, i = 1, 2, 3*i* = 1, 2, 3, where i*i* represents the number of objective functions of the problem. Then, by using

Equation (40) and the optimal values of the obtained objective functions wi∗$wi*$, i = 1, 2, 3i = 1, 2, 3, the problem can be solved:

$$minW_{\mathrm{T}} = \theta_1 \frac{(W_1 - w_1^*)}{w_1^*} + \theta_2 \frac{(W_2 - w_2^*)}{w_2^*} + \theta_3 \frac{(W_3 - w_3^*)}{w_3^*} \quad (40)$$

In this Equation, $\theta_i, i = 1,2,3$ is the weight assigned to each objective function, which must be their sum in model 1.

4-2 MOALO

As other population-based calculations, the MOALO calculation approximates ideal solutions to optimization problems by applying an irregular set of solutions. This collection is based on science propelled by the interaction between ants and subterranean insect lion. There are two groups within the ant-lion calculation: the set of ants and the set of ant-lion. The common steps of the insect lion calculation are to alter these sets and, at long last, to gauge the global optimality for the required optimization problem as follows:

1. The ant set is initialized with random values and the main search factors in the ant-lion algorithm.
2. The fitness value of each ant is evaluated using the objective function in each iteration.
3. Ants move around the anthill using random steps in the search space.
4. The ant-lion set is never assessed. In fact, the ant-lion set assumes the location of the ants in the first iteration and moves to the new location of the ants in the remaining iterations, if the ants get better.
5. An ant valve is assigned to each ant, and its position is revealed when the ant becomes fitter.
6. There is a selective ant-lion that affects the movement of ants regardless of its distance.
7. If any ant lion is better than the chosen ant, it takes its place as the chosen ant.
8. Steps 2 to 7 are repeated until the final criterion is met satisfactorily.
9. The position and fitness value of the selected ant-lion is returned as the best estimate for the global optimum.

The main responsibility of ants is to investigate the search space. They should move through the search space employing a random walk. Ant-lions hold the best position obtained by ants and direct the search of ants to promising regions of the search space. In order to solve optimization problems, the ant-lion algorithm mimics the random walk of ants, jumping into the ant-lion hole, building the hole, moving the ant to the ant-lion, catching the prey, rebuilding the hole, and selecting the fittest one.

4-3 MOIWO

This algorithm has taken advantage of the weed propagation pattern and is used today in various users such as designing supply chain networks, vehicle routing, and other optimization problems. In this algorithm, the goal is to find the best point of a certain environment for seeds to live. Parent grasses search by seed dispersal. In the first stage, the parts of the environment that are candidates for the best area to live are determined, and in the next stages, the search is carried out in areas with better living conditions. Therefore, the main idea of the method is to increase focus

and search power with the passage of time in a range with the possibility of a better answer. The implementation steps of this algorithm are expressed as a mixture:

1- Generating the initial population: a certain number of answers are selected with a uniform distribution in the problem search space.
2- Calculating the degree of qualification: The degree of qualification of grasses is measured by the qualification function
3- Determining the number of new grasses: According to the qualification level of each parent grass, the number of new seeds around each grass is determined.
4- Distribution of new seeds: the seeds of new grasses are distributed for each parent (old) grass, with Gaussian distribution around the parent half.
5- Struggle to maintain survival: At each stage, the qualification level of all grasses is determined and both old and new grasses are ranked in order. If the final population exceeds the maximum population limit, additional responses with lower eligibility are eliminated.
6- Repetition of steps: return to the fifth step and repeat the steps until we reach the maximum number of repetition steps.

The selection of these three solution methods was based on their suitability for addressing different aspects of the proposed multi-objective and uncertainty-based model. The LP-metric method provides a deterministic benchmark by transforming the multi-objective problem into a single-objective one through the use of weighted distances, facilitating comparative validation of metaheuristic results. The Multi-Objective Ant Lion Optimization (MOALO) algorithm was chosen for its strong exploration–exploitation balance and its proven capability in handling nonlinear and stochastic optimization problems. Meanwhile, the Multi-Objective Invasive Weed Optimization (MOIWO) algorithm offers fast convergence and high population diversity, which are advantageous for multi-modal search spaces commonly found in probabilistic hub location–routing problems. Together, these methods enable both accuracy (via LP-metric) and computational efficiency (via metaheuristics), ensuring robust performance under uncertainty.

To ensure reproducibility and transparency, the parameter settings and initialization rules for both meta-heuristic algorithms (MOALO and MOIWO) are summarized below. The configurations were selected based on preliminary pilot tests to balance exploration, convergence speed, and computational efficiency. Table 1 shows the summary of the algorithm.

Table 1. Parameter Settings and Initialization Rules for the Applied Meta-Heuristic Algorithms

Algorithm	MOALO	MOIWO
Population Size	50 ants and 50 ant lions	30 initial, up to 100 maximum
Iterations	500	500
Archive Size	100	100
Initialization Rules	Uniform random initialization within variable bounds; repair operator for capacity, coverage, and routing constraints	Uniform random initialization, feasibility repair for all constraints
Key	Elite retention, roulette-wheel selection, adaptive	Seeds per parent = 0–5, adaptive spread

Table 1. Parameter Settings and Initialization Rules for the Applied Meta-Heuristic Algorithms

Parameters	random-walk step	decay, Pareto-ranked seed allocation
Stopping Criteria	Max iterations = 500 or no hypervolume improvement in 50 iterations	Max iterations = 500 or no hypervolume improvement in 50 iterations
Tuning Approach	Grid search on 30–80 population, 300–800 iterations, 60–150 archive size	Grid search on 20–40 initial pop., 80–120 max pop., 3–7 seeds per parent

These settings provide a balanced trade-off between solution quality and computation time. Both algorithms demonstrated stable Pareto front convergence across all test instances under these parameter configurations.

5) Analysis of the Results

In this segment, the solution of the multi-objective demonstration of the scope hub location and the directing problem are discussed considering the simultaneous delivery and pickup inconceivable conditions based on the situation. For this reason and to appear the output of the over-show, a small numerical example has been outlined and the multi-objective problem has been solved utilizing the LP metric strategy. In the following, in order to solve the problem in larger sizes, MOALO and MOIWO algorithms are utilized, and statistical and non-statistical comparisons are performed on the results of this problem. Finally, the most efficient algorithm has been identified in terms of computational indicators and its performance compared to other algorithms.

5-1 Solving the Problem in Small Size

To appear the output of the model, a small size problem with 5 nodes and 2 vehicles in 3 different scenarios is considered. Other parameters obtained from the model are depicted in Table 2.

Table 2. The Lower and Upper Limits of the Deterministic Parameters Utilized Within the Model Based on Uniform Distribution

parameter	**Interval boundaries**	**parameter**	**Interval boundaries**
$D_{i,j}$	~U(50 ،70)	P	1
$Co_{i,j,v}$	~U(3 ،7)	Q	2
Fk_k	~U(5000 ،8000)	R_v	~U(250 ،350)
FV_v	~U(500 ،600)	$Capv_v$	~U(150 ،200)
$Capk_K$	~U(1000 ،1200)	α	0.7
parameter	The first scenario	The second scenario	The third scenario
$C_{i,j,s}$	~U(10 ،30)	~U(30 ،60)	~U(60 ،90)
$T_{i,j,s}$	~U(10 ،30)	~U(30 ،60)	~U(60 ،90)
$W_{i,j,s}$	~U(10 ،20)	~U(20 ،30)	~U(30 ،40)
P_s	0.1	0.4	0.5

As expressed within the Lp metric method, the most excellent esteem of each objective function ought to be primarily calculated from the individual optimization strategy, and based on these values, the compelling solutions of the three-objective problem ought to appear. Table 3 shows the optimal value and the calculated effective arrangements for each objective function.

Table 3. The Optimal Value of Each Objective Function Based on the Individual Optimization Strategy and Effective Solutions

	OBF_1	OBF_2	OBF_3
The best amount	92433.03	214.78	2140
Solution 1	91761.66	237.94	24.61
Solution 2	92763.37	236.12	23.35
Solution 3	93746.42	235.50	23.30
Solution 4	94236.82	235.50	23.18
Solution 5	95219.13	230.84	22.40

According to the results presented in Table 2, with the reduction of the sum of contamination as well as the greatest travel time between the nodes, the entire costs of the network expands due to diverse situating and directing between the nodes. Figure 2 illustrates the Pareto front based on solving the problem.

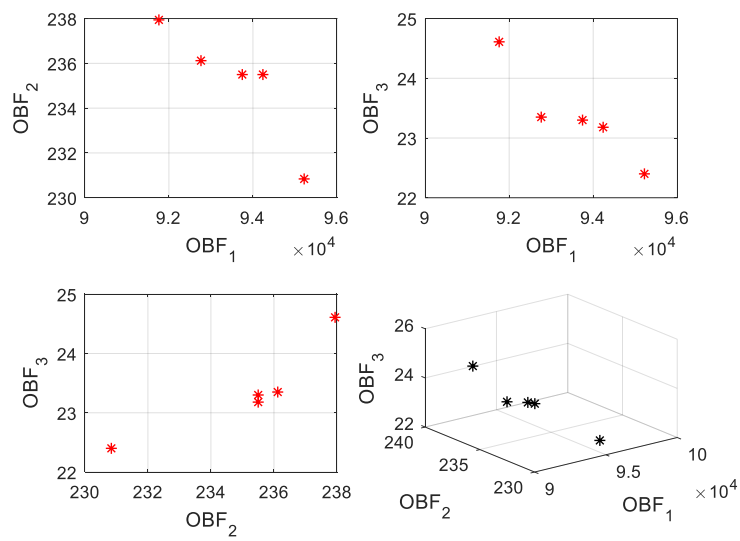

Figure 2. Pareto Front Obtained for Sample Problem

To illustrate the results of solving the problem, Figures 3 and 4 show the optimal location and routing problem of the covering hub for the objective functions of the problem and the most efficient solution, respectively.

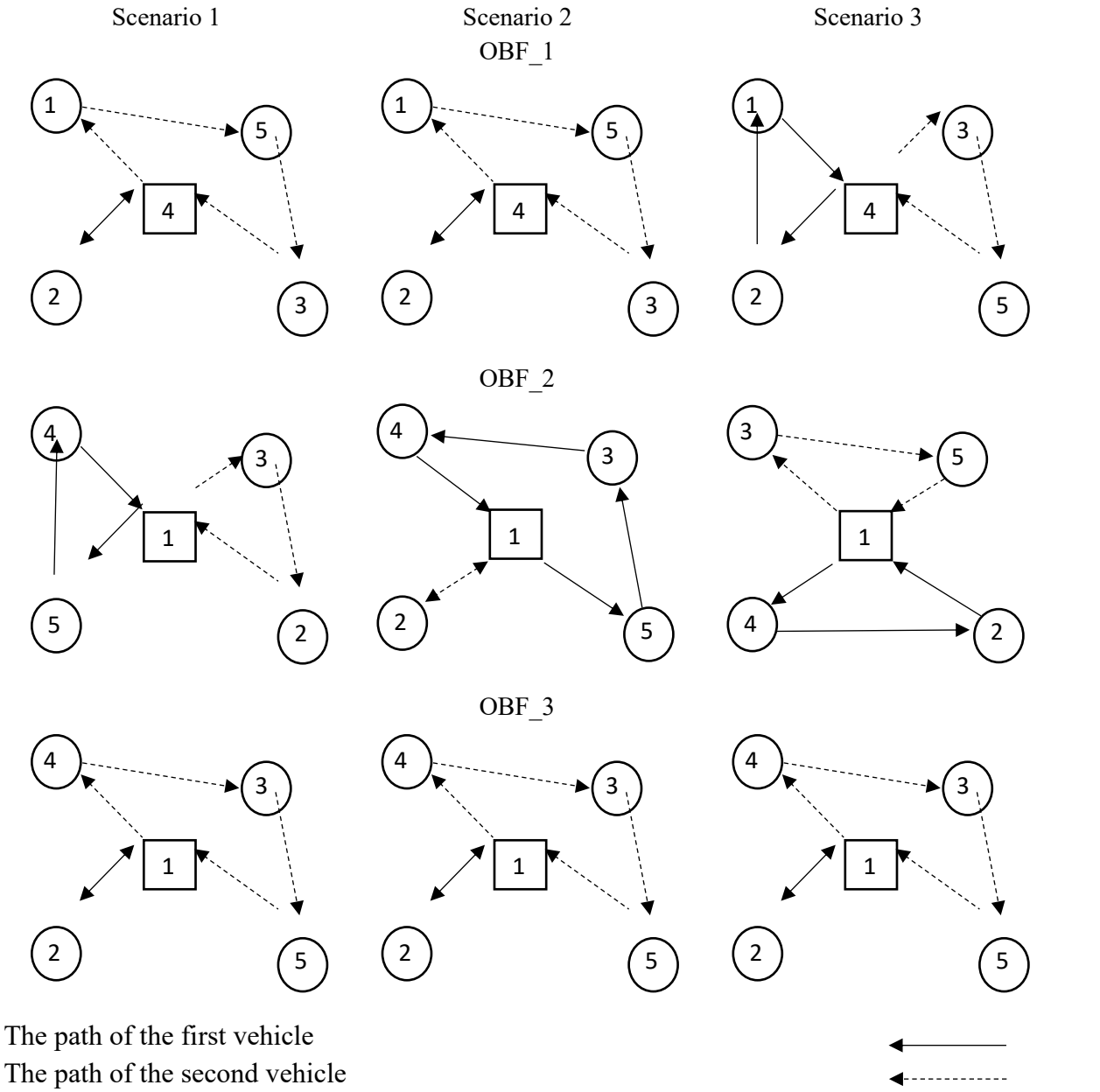

Figure 3. Locating the Hub and the Optimal Path Assigned by the Individual Optimization Method

According to Figure 3 for the primary objective work, it can be seen that node 4 is chosen as a hub and vehicles 1 and 2 have traveled diverse courses in numerous scenarios to meet customer demand. In Figure 3, for the second objective function, unlike the first objective function, node 1 is chosen as the hub; additionally, the vehicle routing has changed. This is due to considering the second objective function independently. In this figure, it can be seen that the positioning and routing of the vehicle have been determined in all scenarios.

If synchronous optimization is the objective, the optimal path and optimal routing will change. This problem has been solved for the first efficient solution by the LP metric method, as shown in Figure 4.

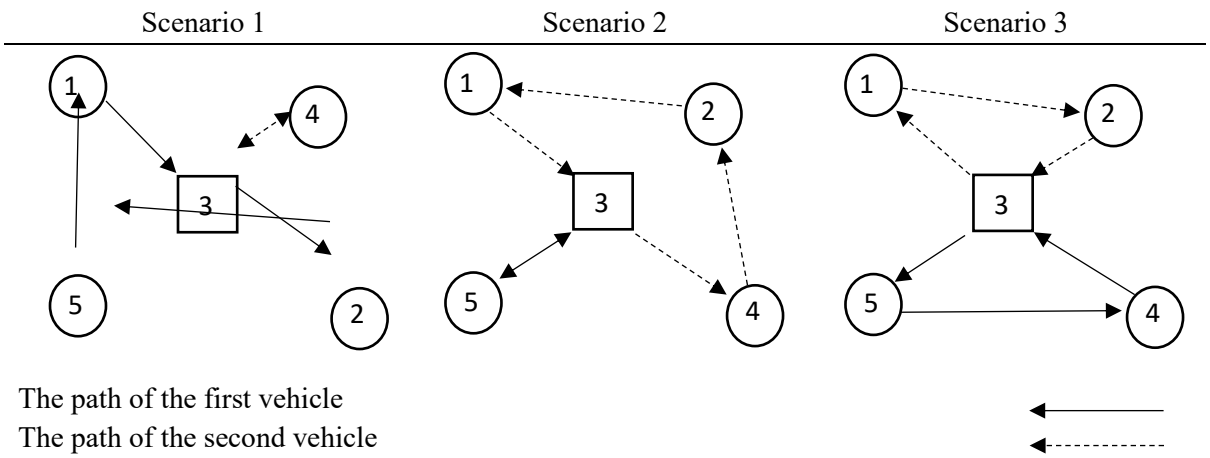

Figure 4. Locating the Hub and the Optimal Path Assigned by the Individual Optimization Method

Unlike Figure 3, in order to solve the multi-objective model and consider three objective functions at the same time, it can be seen that in Figure 4, node 3 is selected as a hub. While node 4 was chosen as the most optimal place to reduce costs, and node 1 was chosen as the most optimal place to reduce time and the amount of CO_2 emissions. Table 4 presents the values of the factors associated with the simultaneous pickup and delivery operations performed by vehicles. Figure 5 illustrates the optimal total pickup and delivery quantities for Effective Arrangement 1 in the first scenario. In addition, the demand between different nodes in the first scenario is presented in Table 5.

Table 4. Amount of Flow Demand Between the Problem Nodes in the First Scenario

Flow	Node 1	Node 2	Node 3	Node 4	Node 5
Node 1	0	19	16	13	13
Node 2	19	0	19	10	15
Node 3	16	19	0	18	11
Node 4	13	10	18	0	14
Node 5	13	15	11	14	0

Table 5. The Optimal Amount of Pickup and Delivery by Vehicles in the First Scenario

	Vehicle 1				Vehicle 2	
Flow	2→3	5→2	1→5	3→1	4→3	3→4
Node 1	[19,32]	[13,13]	-	[16,61]	[13,13]	-
Node 2	-	[15,63]	[19,48]	[19,29]	[10,10]	-
Node 3	[19,46]	[11,27]	[16,16]	-	[18,18]	-
Node 4	[10,37]	[14,27]	[13,13]	-	-	[18,55]
Node 5	[15,15]	-	[13,53]	[11,40]	[14,14]	-

For this case, Table 4 can be interpreted as follows for Node 1: the total demand between Node 1 and the other nodes is served by the vehicles, and the corresponding pickup and delivery quantities are represented in the table as [delivery quantity, pickup quantity]. Regarding the route associated with Node 1, the first vehicle collected 61 units of products from Node 1 and delivered 13 units to Node 3, 19 units to Node 2, and 13 units to Node 5. For the second vehicle, 13 units of products were collected and subsequently delivered to Node 4. Figure 5 provides a graphical illustration of these pickup and delivery flows.

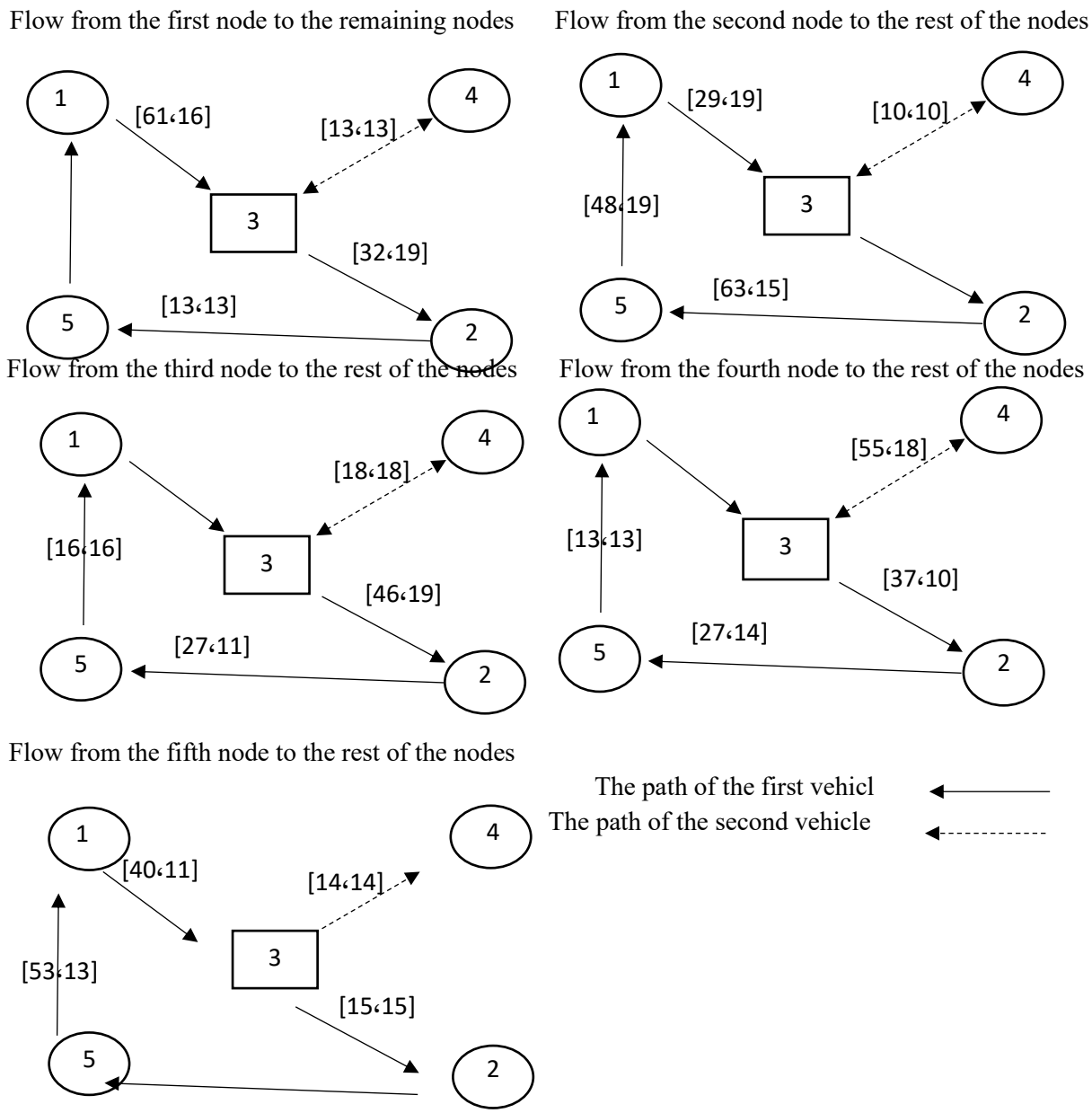

Figure 5. The Flow of Goods Between Nodes by Different Vehicles

There are different parameters within the problem that influence the value of the objective functions of the problem. One of the foremost vital parameters of the problem is the coefficient of economy of scale (α). According to the changes of this parameter in the problem, the values of the objective functions of the problem for the compelling solution number 1 is presented in Table 6.

Table 6. Changes in the Values of the Problem Objective Functions in Different Coefficients of Economy of Scale

α	OBF_1	OBF_2	OBF_3
0.9	93946.20	249.18	26.27
0.8	92568.66	237.94	24.61
0.7	91761.66	237.94	24.61
0.6	90524.36	237.94	24.61

α	OBF_1	OBF_2	OBF_3
0.5	89165.67	224.78	23.17
0.4	87485.68	224.78	23.17

The results presented in the table indicate that the total cost of the network decreases as the economy-of-scale coefficient changes. As the savings factor increases, modifications in the routing structure lead to reductions in both the maximum travel time and the total greenhouse gas emissions. This demonstrates the positive impact of economies of scale on the overall efficiency and sustainability of the distribution network. Furthermore, Figure 6 illustrates the variations in the values of the objective functions under different economy-of-scale coefficients, highlighting the relationship between scale effects and network performance.

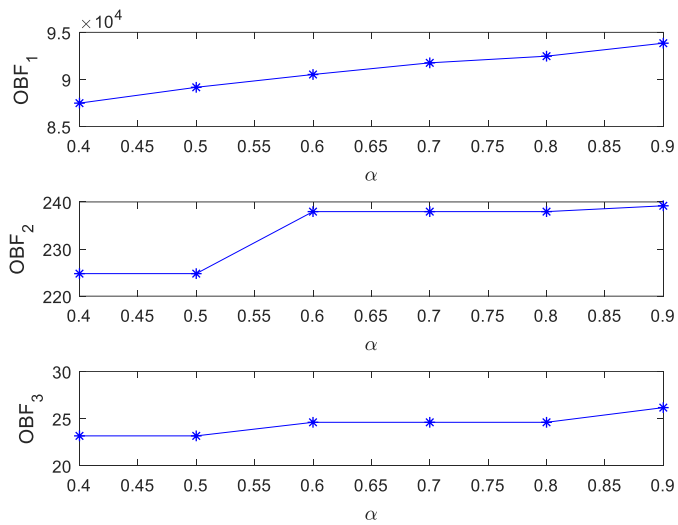

Figure 6. Changes in the Values of the Problem Objective Functions in Different Coefficients of Economy of Scale

After examining the mathematical model in small size, numerical examples in larger sizes with different solution methods have been analyzed.

In the LP-metric approach, the weight coefficients (θ_i) were assigned based on the relative importance of each objective function, as determined by managerial preference and sensitivity testing. Specifically, $\theta_1 = 0.5$ was assigned to minimize the total cost, $\theta_2 = 0.3$ to minimize the maximum travel time, and $\theta_3 = 0.2$ to minimize greenhouse gas emissions. These values were selected after preliminary experiments, indicating that this weighting structure maintains a balanced trade-off between economic efficiency and environmental performance. To verify robustness, additional tests were performed with varied weight distributions (e.g., 0.4–0.4–0.2 and 0.6–0.2–0.2), which showed less than 3% deviation in the Pareto front, confirming that the results are not highly sensitive to minor variations in θ_i. To demonstrate the necessity of incorporating uncertainty, the results of the proposed stochastic model were compared with those of a deterministic version of the same hub location–routing problem, in which all parameters (cost, time, and demand) were treated as fixed mean values. The deterministic model yielded a total network cost that was on average 6.8% lower than the stochastic model; however, its solutions were significantly less robust under fluctuating demand and travel-time conditions. In

contrast, the probabilistic model produced more stable hub allocations and vehicle routes with smaller performance deviation across scenarios. This highlights that although deterministic modeling may appear less costly under fixed conditions, it fails to capture real-world variability, making the stochastic approach more reliable and practical for uncertain logistics environments.

5-2- Analysis of Numerical Examples of Larger Size

In this section, 16 numerical examples in larger sizes have been designed according to Table 6 and various methods such as LP metric, MOIWO, and MOALO have been used to solve the problem. The data used in the modeling are in accordance with the data presented in Table 7.

Table 7. Size of Sample Problems in Different Sizes

Sample problem	N	V	S	Sample problem	N	V	S
1	10	5	3	9	80	28	5
2	15	8	3	10	100	32	6
3	20	10	3	11	120	35	6
4	25	12	4	12	140	40	6
5	30	15	4	13	160	45	7
6	40	18	4	14	180	50	7
7	50	20	5	15	200	55	7
8	60	23	5	16	220	60	8

After solving the test problems using different solution approaches, the performance of the multi-objective model was evaluated. The resulting outputs, including the Number of Pareto Fronts (NPF), Mean Ideal Solution (MIS), Spacing Metric (SM), and computational time, are presented in Table 8.

Table 8. Indices Obtained from Solving Numerical Examples in a Larger Size

	LP-Metrics				MOIWO				MOALO			
Numel examps	NPF	MSI	SM	$CPU-TIME$	NPF	MSI	SM	$CPU-TIME$	NPF	MSI	SM	$CPU-TIME$
1	8	3697.02	0.725	526.48	16	4996.41	.05	135.93	20	3751.62	0.781	143.61
2	12	3084.16	0.598	1266.48	30	3733.86	0.59	199.34	29	6157.36	0.766	217.83
3	13	5587.80	0.56	2974.64	28	4691.99	0.314	275.18	11	3220.97	0.376	299.36
4	-	-	-	-	11	3193.20	0.533	360.84	17	5678.24	0.617	392.17
5	-	-	-	-	16	6205.20	0.593	470.55	33	5523.75	0.535	509.52
6	-	-	-	-	33	3516.30	0.358	597.05	15	4017.45	0.324	643.07
7	-	-	-	-	19	3972.64	0.335	712.15	16	5462.81	0.473	778.19
8	-	-	-	-	17	6034.05	0.438	859.66	17	6380.34	0.73	923.63
9	-	-	-	-	28	5292.40	0.716	1037.55	31	3092.83	0.728	1108.88
10	-	-	-	-	31	6332.98	0.341	1257.48	31	3019.36	0.644	1330.42
11	-	-	-	-	27	3656.88	0.785	1489.75	26	5633.40	0.318	1581.77
12	-	-	-	-	30	5239.53	0.65	1796.30	19	5252.94	0.439	1878.48
13	-	-	-	-	29	3678.97	0.519	2089.54	32	5089.20	0.361	2201.75
14	-	-	-	-	10	3673.31	0.533	2493.10	32	5503.57	0.584	2604.12
15	-	-	-	-	12	5450.35	0.783	2967.18	18	4806.01	0.643	3103.62
16	-	-	-	-	29	5450.74	0.315	3715.48	26	3390.67	0.55	3899.14

Based on Table 7, it can be seen that the LP metric strategy was able to illuminate test problems number 1 to 3. This strategy has the most elevated problem tackling time among distinctive solution strategies, while meta-heuristic calculations near the LP metric strategy have unraveled

all the numerical cases. In these examinations, the greatest rate of relative contrast between the results of meta-heuristic calculations and the LP metric strategy was less than 3%. Moreover, on normal, MOALO has the most noteworthy NPF and the least SM and CPU time, while MOIWO has won the foremost MSI.

Figure 7 illustrates the Pareto front from diverse arrangement strategies for the primary numerical case of large size.

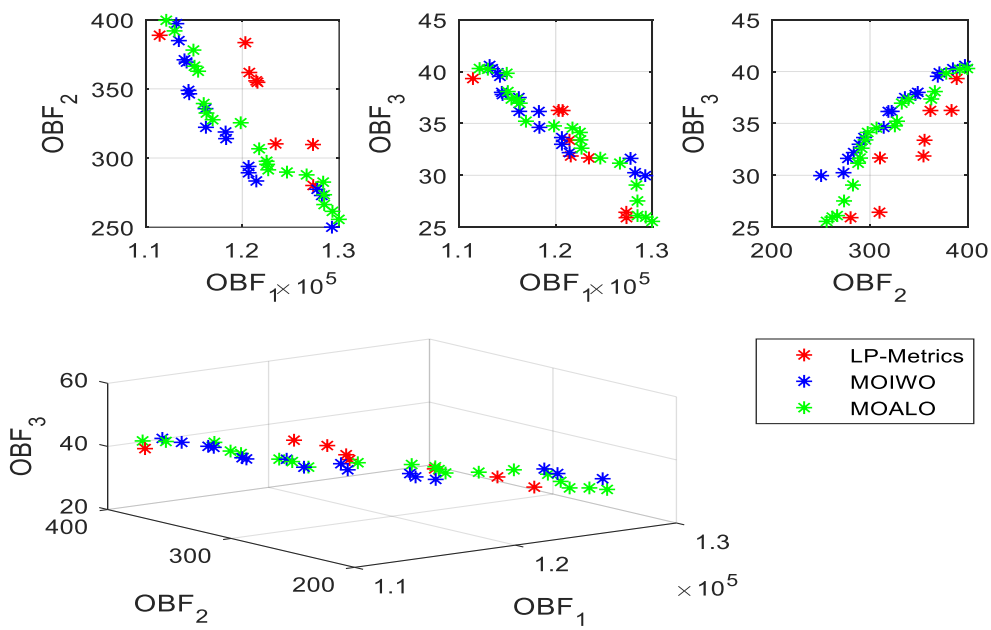

Figure 7. Pareto Front Comparison Between Different Solution in the First Sample Problem

Based on the fact that diverse arrangement strategies, including meta-heuristic calculations, have gotten diverse values of comparison lists, the significant distinction of these records between the two arrangement strategies was explored at the 95% confidence interval. The analyzes are presented in Table 9.

Table 9. The Results of the T-Test at the 95% Confidence Interval

Indicator	Mean difference	95% Confidence interval	T-Value	P-Value
NPF	0.44	(-5.12 5.99)	0.17	0.869
MSI	54	(-904 1012)	0.12	0.906
SM	0.0416	(-0.0755 0.1588)	0.76	0.461
CPU-time	71.2	(46.2 96.1)	6.07	0.000

Table 9 indicates that there is a noteworthy distinction among the pointers of computing time. In this manner, due to the brief arrangement time of the MOALO calculation, this calculation is chosen as a productive one. Figure 8 also presents the box graph comparing the midpoints of markers at the 95% confidence interval.

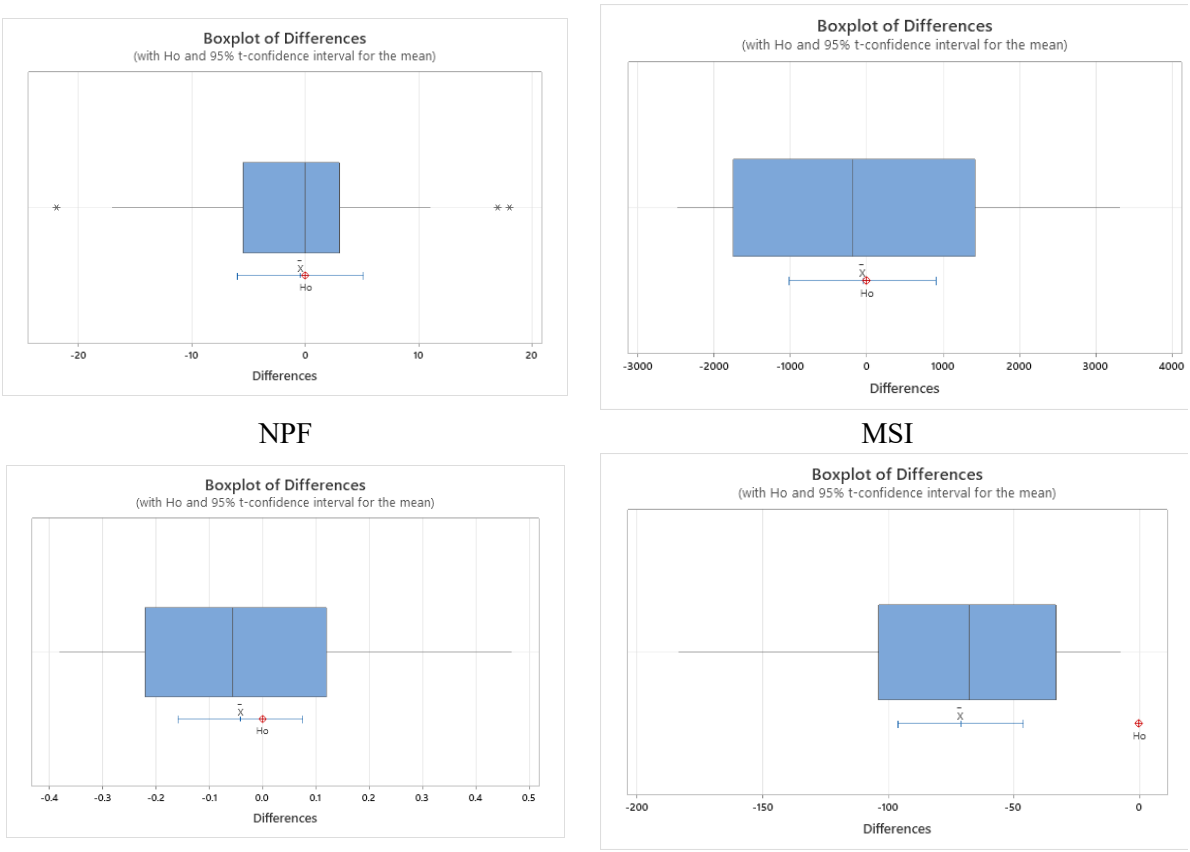

Figure 8. Box Diagram Comparing the Average Indicators at the 95% Confidence Interval

6) Conclusion

In this article, the modeling and tackling of positioning-routing problem in the covering hub, by considering the synchronous securing and collecting under uncertainty, were investigated. The non-determinism of the problem information is driven by the utilization of the two-level probabilistic programming strategy to control the non-deterministic parameters. The outlined model took diverse vital choices, such as center area, and strategic choices, such as vehicle directing, at the same time. Analysis of the model's findings using the LP metric strategy demonstrated that arrangement costs escalate with reductions in greenhouse gas emissions and optimal vehicle operating times. Additionally, an examination of the economy of scale calculation showed that a decrease in this value incentivizes vehicles to utilize hubs, consequently lowering total network costs. This alteration in vehicle routing patterns leads to a reduction in both greenhouse gas emissions and their overall volume.

MOIWO and MOALO algorithms were used to analyze larger-scale numerical examples and evaluate different solution methods. Comparisons of these solution methods across various numerical examples revealed a trade-off among objective functions: as the time objective and the third objective decreased, the first objective increased. Moreover, the solution time of these methods was significantly lower than that of the LP-metric method. The LP-metric method was unable to solve numerical cases of very large scale; based on the findings, it was only able to

solve test problems 1 through 3. In contrast, metaheuristic algorithms—which produced results close to those of the LP-metric method—solved all numerical examples. In these comparisons, the maximum relative difference between the results of the metaheuristic algorithms and the LP-metric method was less than 3%.

On average, MOALO achieved the highest NPF and the lowest SM and CPU-time, while MOIWO performed best in terms of MSI. Furthermore, analysis of the significant relationship between the mean values of the indicators revealed a statistically significant difference between the average computing times of the two proposed algorithms.

The implications of this model can assist supervisors in fleet planning by helping them manage the costs of the entire network, reduce merchandise delivery time, and mitigate harmful environmental impacts. Furthermore, the incorporation of a two-level stochastic planning approach enables supervisors to analyze different scenarios and evaluate their effects on strategic and tactical decisions. Due to the high efficiency of the solution methods proposed in this article, managers can apply MOIWO and MOALO to achieve the desired results for larger-scale cases.

The limitations of this study, such as the exclusion of queueing systems in the distribution and collection of items, may be considered as directions for future research. In addition, the application of uncertainty control methods, such as fuzzy robustness, could further enhance the richness of the numerical model.

Ethics Statement: The author affirms that this research was carried out in compliance with recognized ethical standards and principles. All information sources have been appropriately cited and credited. Where required, ethical clearance was granted, and informed consent was obtained from all participants. No instances of plagiarism, data fabrication, or falsification were involved in this study.

Use of Artificial Intelligence: The author confirms that AI-based tools were employed exclusively for language polishing and grammatical correction. All AI-generated assistance was thoroughly examined, validated, and revised by the author, who bears full responsibility for the precision, authenticity, and integrity of the final manuscript. AI tools were not utilized to produce or alter research data or to substitute essential scholarly reasoning.

Conflicts of Interest: Any possible conflicts of interest, including financial or personal relationships that might affect the research, are disclosed. The author states that there are no competing interests.

Compliance with Regulations: The author verifies that this study adhered to all relevant institutional, national, and international rules, and that all required permissions for data usage and reproduction were secured.

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