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An Integrated Model for Developing a Global Logistics Network Using Metaheuristic Algorithms

Reza KARIMI MEHRABADI, Emad ROGHANIAN*, Shahnaz PIROOZFAR, Abbas SHOJAIE

Abstract: The globalization of economies has heightened the importance of efficient logistics networks, particularly in the post-COVID-19 era where supply chain resilience is paramount. This study focuses on designing logistics hub networks to enhance global shipment flow management. A hub-based structure is adopted, aligned with existing global logistics frameworks. The research addresses key challenges such as optimizing warehouse and hub locations to streamline cargo delivery. An integrated model is developed for route planning, incorporating multi-modal transportation and cost-time trade-offs. The study employs metaheuristic algorithms including Strength Pareto Evolutionary Algorithm (SPEA-II), Non-Dominated Sorting Genetic Algorithm II (NSGA-II), and Multi-Objective Grey Wolf Optimization Algorithm to solve the proposed model. Detailed numerical analyses demonstrate the model's capability to generate optimal global solutions, underscoring its practical utility in real-world logistics management.

Keywords: global logistics; location allocation; logistics hubs; metaheuristic algorithms

1 INTRODUCTION

In today's global business environment, the increasing demands of customers for high-quality products, a diverse product range, and fast service have placed new challenges on organizations. Companies in the competitive landscape of today understand the significance of managing external factors alongside internal affairs to gain a competitive advantage and expand their market share. Functions such as supply and demand planning, procurement, production scheduling, service maintenance, inventory management, distribution, and customer service provision, which were once managed within individual companies, now span across the entire supply chain. Looking at functional topics in the supply chain literature and the outcomes of operational projects, it is evident that logistics network integration is a new concern for some global organizations in areas such as humanitarian logistics, commercial logistics, and tourism logistics [1-4]. For instance, consider the planning efforts of the United Nations Humanitarian Response Depot (UNHRD), which continuously works towards creating a global network to efficiently provide for needs during crises in different regions of the world [5]. Such initiatives improve the current supply conditions in various parts of the world. Another example is the global freight shipment network being developed by companies like Amazon, recognized as a major project in global commerce [6]. Amazon aims to respond to global demands quickly, although its current coverage is limited to parts of Europe, Southeast Asia, and North America.

Integrated logistics structures not only reduce strategic and operational costs but also enhance political relations between communities [7]. This foundation supports the expansion of international relations, particularly for underdeveloped nations that have significant logistical potential but lack investment opportunities [8].

In the global logistics structure, goods cannot be transported directly from supply centers to consumption points due to cost and time constraints. Hence, establishing hubs in key locations, preferably major global cities with maritime and air shipment infrastructures and warehousing capabilities, is essential to facilitate the delivery process. These hubs, shown in Fig. 1, serve as primary centers for receiving, sorting, and distributing goods. Customer regions worldwide are uniquely assigned to these hubs, ensuring smooth operations for sales market management, demand forecasting, cost management, and delivery management.

Figure 1 Map of some cities capable of becoming a global hub

This study aligns with the development of global logistics networks, utilizing commercial facilities like seaports, airports, and land shipment facilities for strategic, tactical, and operational planning. The key contributions of this study include: 1) Developing an integrated structure to coordinate maritime, air, and land shipment programs to reduce time and costs in the shipment management sector, potentially fostering global joint investments. For example, Amazon has made advancements in air and sea shipment logistics but aims to invest further globally for enhanced operational efficiency. 2) Integrated planning for infrastructure development related to ports, airports, and shipment routes through international joint investments. 3) Strategically locating logistics hubs based on global market demand to optimize system costs and operations.)

1.1 Literature Review

Focusing on container shipment in Myanmar, Yamaguchi et al. [9] suggest that fast economic growth rate of Myanmar is expected to multiply in the near future. This study simulates the effect of logistics policies in Myanmar on container shipment. Based on simulation results, the authors concluded that policies reducing border barriers and improving service levels at Dawei Port would also lead to Thailand using Myanmar's ports for its cargoes. Shah and colleagues [10] provided an overview of the existing and future capabilities of the Internet of Things (IoT) and its role in enhancing logistics management, especially during the digitalization era projected for 2050. Their research highlighted that logistics management is a dynamic process that is formulated, adjusted, and put into practice within the context of the supply chain. Jiang et al. [11] designed a multi-objective local logistics network for reducing CO_2 emissions and managing uncertain demands for cluster development. The system under investigation has been represented as a two-tier planning model, which was then translated into a mathematical programming with equilibrium constraints to illustrate the interactions between leaders and followers. To cope with uncertain demand environment, a robust and customizable optimization approach has been proposed, which includes individual control parameters and provides precise expression of maximum satisfaction.

Guerrero [12] focuses on modeling and policy making for global logistics network, quantification, and analysis for international shipment. First, main determinants of evolution of regions within Europe were reviewed through a literature review. In conclusion, there is a need for further advancement in development of a common framework despite the challenges of inter-regional comparisons. Lu et al. [13] addressed the optimal design of a hybrid recycling network that integrates both forward and reverse logistics simultaneously within multi-tier multi-product structures. To optimize this problem, a mixed integer fuzzy linear programming approach was used.

Yu et al. [14] proposed a novel multi-objective multi-level program for designing reverse logistics network during an epidemic outbreak to determine the best locations for temporary facilities and shipment strategies for effective management of increasing medical waste. The application of the model has been demonstrated through a case study based on outbreak of the COVID-19 virus in Wuhan, China in 2019. The results indicate that installation of temporary incinerators may be an effective solution for managing the significant increase in medical waste during the COVID-19 outbreak in Wuhan. However, locating these temporary incinerators is of considerable importance, which has been addressed using mathematical optimization. Guerrero-Lorente et al. [15] presented a hybrid integer programming model for design of an Omnichannel logistics network with integrated customer prioritization for delivery and return. This model manages online orders from retailers. The model formulation considers the effect of these collection points in consumer selection and maximum distance that customers walk to reach them. The model also takes into account realistic shipment costs, including long-term costs and delivery costs within a region. In their research, Wang et al. [16] developed a solution for a multi-depot logistics network issue involving vehicle routing with multiple shared warehouses. They incorporated the allocation of time windows to mitigate the impact of fluctuating time windows on operational expenses. A two-objective programming model was created in this investigation to enhance both the overall operational cost and the total count of delivery vehicles. To address this challenge effectively, the researchers introduced a heuristic hybrid algorithm that integrates K-means clustering, Clarke-Wright savings algorithm (CW), and Non-Dominated Sorting Genetic Algorithm II (NSGA-II).

Some previous studies discussed the global logistics network design problem as a conceptual problem, mainly focusing on defining development strategies in various political and financial domains, identifying and measuring development criteria for these networks, and proposing managerial solutions for implementation of the obtained results [17]. Therefore, there is sufficient access to infrastructure models and analytical studies. However, the less addressed subject is optimal design of a global logistics network for integrating strategic decisions such as facility location and development of port and airport infrastructures, as well as operational decisions such as coordinating maritime, air, and land shipment, taking into account real-world conditions through mathematical optimization tools and macro-level data analysis methods. While these tools are among the most effective management tools available for achieving highly reliable solutions [18]. The design of an integrated facility location structure can improve the performance of logistics system and ultimately reduce operational costs [19].

In their study, Yuchi et al. [20] designed a reverse logistics network that takes carbon emissions into account. They framed this issue as a mixed-integer nonlinear programming model with dual objectives related to various technologies, operational modes, and shipping scenarios within the truck tire retreading sector. The enhanced non-dominated sorting genetic algorithm II (NSGA-II) was utilized to address this NP-hard problem with two objectives. Empirical data corroborates the effectiveness of the proposed model and the benefits of the enhanced NSGA-II algorithm compared to the original version. Furthermore, a thorough sensitivity analysis was carried out, leading to the derivation of several managerial insights.

Liao [21] introduced a comprehensive mixed-integer nonlinear programming model for establishing a multi-stage reverse logistics network aimed at maximizing total profit through product return strategies like repair, refurbishment, recycling, reuse, or disposal. To address this challenge, a hybrid genetic algorithm was presented. The effectiveness of the model was verified using a practical case study involving bulk waste recycling in Taoyuan City, Taiwan. Sensitivity analysis was conducted on different parameters to showcase the model's capabilities. Post-optimization analysis and comparison indicated that the proposed model surpasses existing reverse logistics operations, with the hybrid genetic algorithm proving efficient for solving intricate reverse logistics issues.

Wang et al. [22] addressed a multi-depot logistics network problem involving vehicle routing with multiple shared warehouses to minimize the impact of changing time windows on operational expenses. They devised a two-objective programming model to optimize total operational cost and the overall count of delivery vehicles. To tackle this issue, the researchers introduced a heuristic hybrid algorithm that incorporates K-means clustering, Clarke-Wright (CW) savings algorithm, and Enhanced NSGA-II for efficient problem-solving.

While previous studies have focused on defining development strategies in various domains and proposing managerial solutions, there is a lack of emphasis on the optimal design of a global logistics network that integrates both strategic and operational decisions. These decisions include facility location, port and airport infrastructure development, and coordination of maritime, air, and land shipment. The utilization of mathematical optimization tools and macro-level data analysis methods can provide highly reliable solutions in addressing real-world conditions. By incorporating a critical analysis of these limitations, this study aims to bridge the gap in the literature by offering a comprehensive approach to optimal global logistics network design.

2 MATHEMATICAL MODEL

In problems with current features, multiple factors in both real-world and mathematical contexts have a significant impact, including the number, capacity, and cost of facilities. Particularly in network design problems that focus on facility location, this aspect becomes even more pronounced. Regarding the number of facilities, several approaches can be taken. The first approach is to make decisions based on cost. The number of facilities is determined in a way that minimizes the cost for the implementers. This approach is widely used in mathematical models for logistic problems. In the second approach, the number of hubs is determined exogenously. Determining the number of hubs can be done in several ways; one common approach is to use top-level documents, which is considered as strategic framework of logistics decisions. The other approach is to use expert opinions in the field. The reason for this approach is their comprehensive understanding of the problem conditions and their more realistic perspectives. Accordingly, the number of each type of hubs, which are essentially logistics centers, is determined by flow structure between the hubs and network requirements. Certainly, the existing mathematical model focuses on the placement of diverse hub types, selection of supported shipment methods at these hubs, assignment of non-hub nodes to the hubs, determination of direct or hub-based shipment between node pairs, establishment of hub relationships, and network design with the aim of minimizing overall network expenses.

2.1 Model Assumptions

This study considers the problem of determining the logistics structure for delivering goods to service recipients and identifying suitable locations for warehouses and hubs, and ultimately implementing an appropriate routing for product delivery in an integrated model.

In general, assumptions of the mathematical model can be described as follow:

The quantity of regular nodes and potential hub candidates is specified;

The predetermined amount of hubs needed for each category is specified beforehand:

The locations of all nodes are identified;

The overall network structure is non-directed;

The connectivity network among the hubs is partial;

Hubs are not subject to capacity limitations;

Assignment of other nodes to hubs is conducted individually;

Budget is not a limiting factor;

Shipment methods are categorized and evaluated;

Direct communication between two non-hub nodes is permissible;

Inter-hub communication involves a time reduction factor;

Shipment between hubs is categorized as road-based or other methods.

Explanations follow below:

Symbols and Sets

$E, \{i\}$ = Supply centers set

$S, \{i\}$ = Set of centers

$V, \{v\}$ = Set of shipment vehicles determined by $v \in V$

$D,$ = Set of shipment warehouses

$D(v), \{i\}$ = Location of deployment for set of shipment vehicles $v \in V$

$N, \{i, j\}$ = Total set of points in item distribution process

$H, \{k, l\}$ = Set of candidate nodes for setting up a hub

$T, \{t\}$ = Set of different categories of hub facilities (urban, regional, and international)

$M', \{m\}$ = Set of shipment scenarios (g: road shipment)

Input Parameters

P^t = Quantity of hubs required for type t establishment

FH_k^{mt} = Constant cost of establishing a logistics hub of type t at candidate location k

f_{ij}^e = The quantity of commodity type e demanded between two nodes

$\hat{C}_{ij}$ = Shipment cost between two nodes in direct shipment

C_{ij}^m = Shipment cost between two nodes in inter-hub shipment using shipment method m

HL_{kl}^m = Cost of inter-hub network connectivity using shipment method m

cap^v = The load capacity of road shipment vehicle type v

CV^v = The expenses associated with utilizing road shipment vehicle type v

$Size^m$ = The maximum load capacity of the container utilized in shipment method m (excluding road shipment)

d_{kl}^m = The expenses incurred for unloading and loading the container utilized in shipment method m (excluding road shipment) during transportation between hubs k and l

tt_{ij}^m = Transportation duration between two nodes utilizing shipment method m

ot_k^m = The time needed for operation of shipment method m at hub k

α^m = Inter-hub time discount factor for shipment method m

SB_{ij} = The time gap for service between two nodes

$BigM$ = A sufficiently large quantity

C_{ij} = The time it takes to ship products from node $i \in N$ to node $j \in N$

S_i = The amount of supply of products from the supply center $i \in N$

d_i = The demand of centers $i \in S$ for products

b_i = Maximum time for goods to reach the demanding node $i \in S$

Cap_v = Vehicle capacity $v \in V$

Dt_i = Service time at node $i \in E \cup S$

$BigM$ = A sufficiently large positive number

Decision Variables

H_k^{mt} = If a hub of type t is established at potential site k with backing for shipment method m, then assign one; otherwise, assign zero.

$\hat{Y}_{ij}$ = If direct shipment occurs between two nodes, then assign one; otherwise, assign zero.

Y_{ijkl}^m = If shipment between two nodes is conducted via hub connection at k and l using shipment method m, then assign one; otherwise, assign zero.

Z_{kl}^m = If a hub link for shipment method m is created between two hubs k and l, then assign one; otherwise, assign zero.

X_{ik} = If node i is allocated to hub k, then assign one; otherwise, assign zero.

TFG_{kl}^m = The quantity of goods transported between hubs k and l using road shipment method

num_{kl}^v = The quantity of shipment vehicles of type v needed between hubs k and l

ICG_{kl}^m = Expense of transporting cargo between hubs k and l using road shipment method

TFM_{kl}^m = The quantity of goods transported between hubs k and l using alternative shipment methods (excluding road shipment)

ICM_{kl}^m = Expense of transporting cargo between hubs k and l using alternative shipment methods (excluding road shipment)

ST_{ij} = Service time of cargo shipment between two nodes

X_{ij}^v = It equals 1 when vehicle $v \in V$ travels from node $i \in N$ to node $j \in N$; otherwise, it is zero.

Y_i^v = It equals 1 when vehicle $v \in V$ is allocated to node $\in E \cup S$; otherwise, zero.

Z_v = It equals 1 when vehicle $v \in V$ is used; otherwise, zero.

Q_i^v = The number of items that are delivered to the demanding node $i \in S$ by vehicle $v \in V$

T_i^v = The arrival time of vehicle $v \in V$ at node $i \in N$

HU_k = It is equal to 1 if hub k is considered as destination hub; otherwise, zero.

$$Min \sum_{k,m,t} FH_k^{mt} H_k^{mt} + \sum_{k,l,m:k\neq l} HL_{kl}^m Z_{kl}^m + \sum_{i,j,e} f_{ij}^e \hat{C}_{ij} \hat{Y}_{ij} + \sum_{i,j:i\neq i\ ,k,l:k\neq l\ ,m,e} \left(C_{ik}^g + C_{kj}^g\right) Y_{ijkl}^m f_{ij}^e + \sum_{k,l:k\neq l\neq\ ,m=\{g\}} ICG_{kl}^g + \sum_{k,l:k\neq l\ ,m\neq\{g\}} ICM_{kl}^m \tag{1}$$

$$Min \sum_{k,m,t} EnH_k^{mt} H_k^{mt} + \sum_{k,l,m:k\neq l} EnL_{kl}^m Z_{kl}^m + \sum_{i,j,e} f_{ij}^e EnC_{ij} \hat{Y}_{ij} + \sum_{i,j:i\neq i\ ,k,l:k\neq l\ ,m,e} \left(EnC_{ik}^g + EnC_{kj}^g\right) Y_{ijkl}^m f_{ij}^e \tag{2}$$

Subject to:

$$\sum_{k,m} H_k^{mt} = P^t \qquad \forall t \in T \tag{3}$$

$$\sum_k X_{ik} = 1 \qquad \forall i \in N \tag{4}$$

$$\sum_i X_{ik} \le M \sum_t H_k^t \qquad \forall k \in H \tag{5}$$

$$\sum_t H_k^t \le M \sum_i X_{ik} \qquad \forall k \in H \tag{6}$$

$$\sum_i X_{ik} \le M X_{kk} \qquad \forall k \in H \tag{7}$$

$$2Z_{kl}^m \le H_k^{mt} + H_l^{mt} \quad \forall k,l \in H : k \neq l\ ,\ m \in M\ ,t \in T \tag{8}$$

$$2Z_{kl}^m \le \sum_t H_k^{mt} + \sum_t H_l^{mt} \quad \forall k,l \in H : k \neq l, m \in M \tag{9}$$

$$\sum_{l:l\neq k\ ,m} Z_{kl}^m \ge 1 + M\left(X_{kk} - 1\right) \qquad \forall k \in H \tag{10}$$

$$\sum_{k,l:k\neq l\ ,m} Y_{ijkl}^m = 1 - \hat{Y}_{ij} \qquad \forall i,j \in N : i \neq j \tag{11}$$

$$\sum_{l:l\neq k\ ,m} Y_{ijkl}^m - \sum_{l:l\neq k\ ,m} Y_{ijlk}^m = X_{ik} - X_{jk} \quad \forall i,j \in N : i \neq j\ ,k \in H \tag{12}$$

$$Y_{ijkl}^m + Y_{ijlk}^m \le Z_{kl}^m \quad \forall i,j \in N : i \neq j\ ,k,l \in H : k \neq l \tag{13}$$

$$TFG_{kl}^m = \sum_{i,j:i\neq j\ ,e} f_{ij}^e Y_{ijkl}^m \qquad \forall k,l \in H : k \neq l\ ,m = \{g\} \tag{14}$$

$$num_{kl}^v \ge \frac{TFG_{kl}^m}{cap^v} \qquad \forall k,l \in H : k \neq l\ ,m = \{g\}\ ,v \in V \tag{15}$$

$$ICG_{kl}^m = num_{kl}^v CV^v \quad \forall k,l \in H : k \neq l\ ,m = \{g\}\ ,v \in V \tag{16}$$

$$TFM_{kl}^m = \sum_{i,j\ :i\neq j\ ,e} f_{ij}^e Y_{ijkl}^m \qquad \forall k,l \in H : k \neq l\ ,m \in M \tag{17}$$

$$ICM_{kl}^{m} = \left(TFM_{kl}^{m} / Size^{m}\right)\left(C_{kl}^{m} + d_{kl}^{m}\right) \quad \forall k,l \in H : k \neq l, m \in M' \tag{18}$$

$$ST_{ij} = \left[\begin{array}{l} \sum_{k:k\neq i} tt_{ik}^{g} X_{ik} + \sum_{k.l:k\neq l,t} ot_{k}^{m} + \left(\alpha^{m} tt_{ij}^{m}\right) \\ + ot_{l}^{m} + \sum_{k:k\neq j} tt_{kj}^{g} X_{kj} \end{array}\right] Y_{ijkl}^{m} + tt_{ij}^{m} \hat{Y}_{ij} \quad \forall i,j \in N : i \neq j \tag{19}$$

$$ST_{ij} \leq SB_{ij} \quad \forall i,j \in N : i \neq j \tag{20}$$

$$H_{k}^{mt} \in \{0,1\} \quad \forall k \in H, m \in M', t \in T \tag{21}$$

$$X_{ik} \in \{0,1\} \quad \forall i \in N, k \in H \tag{22}$$

$$Z_{kl}^{m} \in \{0,1\} \quad \forall k,l \in H : k \neq l, m \in M' \tag{23}$$

$$Y_{ijkl}^{m} \in \{0,1\} \quad \forall i,j \in N : i \neq j, k,l \in H : k \neq l \tag{24}$$

$$\hat{Y}_{ij} \in \{0,1\} \quad \forall i,j \in N : i \neq j \tag{25}$$

$$TFG_{kl}^{m} \geq 0 \quad \forall k,l \in H : k \neq l, m = \{g\} \tag{26}$$

$$num_{kl}^{v} \geq 0 \quad \forall k,l \in H : k \neq l, m = \{g\} \tag{27}$$

$$ICG_{kl}^{m} \geq 0 \quad \forall k,l \in H : k \neq l, m = \{g\} \tag{28}$$

$$TFM_{kl}^{m} \geq 0 \quad \forall k,l \in H : k \neq l, m \in M' \tag{29}$$

$$ICM_{kl}^{m} \geq 0 \quad \forall k,l \in H : k \neq l, m \in M' \tag{30}$$

$$ST_{ij} \geq 0 \quad \forall i,j \in N : i \neq j \tag{31}$$

The first equation outlines the main goal of the initial problem, which consists of six different cost components. The initial cost component pertains to the expenses incurred in constructing facilities. Another cost component accounts for the expenses associated with establishing inter-hub infrastructure. The third component takes into consideration the expenses related to direct shipment. Finally, the fourth, fifth, and sixth components calculate the expenses involved in shipment through the hub network.

Eq. (2) deals with minimizing the environmental impacts, including the effects of facility construction, inter-hub infrastructure construction, and negative environmental impacts resulting from shipment operations in various scenarios.

Constraint (3) specifies the quantity of hubs built for each type in a given shipment scenario. Under Constraint (4), every non-hub node must be linked exclusively to one hub. Constraints (5) and (6) further outline how facility construction variables of different types are related to each other.

Constraint (7) specifies that a time node can only be assigned to a hub if the hub has been built. Constraint (8) ensures that an inter-hub connection in a non-road shipment scenario can only be established if both nodes are selected as hubs and can accommodate the specific scenario. In the road shipment scenario, this link is separate from the supported scenario in the hubs because a road link, different from situations involving rail and air transportation, this particular scenario does not require any specific communication systems or equipment for loading and unloading.

Constraint (9) addresses the possibility of establishing a road connection between two hubs regardless of the supported shipment scenario, as long as both hubs are present at their respective locations. Constraint (10) states that a designated hub location must be linked to another hub through an inter-hub connection. Decision-making is required in Constraint (11) to choose between direct shipping and hub-connected shipping methods. Meanwhile, Constraint (12) enforces flow balance among nodes to select the appropriate inter-hub link for moving goods between two nodes. Constraint (13) ensures that goods are only transported through designated hub links. Constraint (14) calculates the total amount of goods transported between two hubs using road shipping. Constraint (15) determines the required quantity of vehicles for each category, while Constraint (16) computes the expenses associated with transporting goods between hubs via road. Constraint (17) determines the overall volume of products transported between hubs for different shipping options (excluding transportation by road), whereas Constraint (18) evaluates the expenses associated with this mode of transportation between two hubs. Constraint (19) dictates the total amount of time for servicing between two nodes while Constraint (20) establishes the maximum limit for this time. Constraints (21) through (31) define the range of possible values for decision variables.

2.2 Solution

Given that the logistics hub network design problem falls within the category of NP-hard problems, this research employs metaheuristic algorithms to address numerical instances of moderate to large scales. One of the crucial aspects in utilizing metaheuristic algorithms is selecting the appropriate algorithm based on their nature and operational structure in finding the final solutions.

2.3 Multi-Objective Genetic Algorithm (NSGA-II)

NSGA-II is widely recognized as a powerful algorithm frequently used to attain optimal solutions, which has been proven to be efficient in solving various problems.

The process and overall algorithm of NSGA-II can be outlined as follows:

- Create an initial population.
- Calculate fitness indexes.
- Sorting the population based on their dominance.
- Crowding distance calculation.
- Selection: After arranging the initial population according to dominance criteria, the calculation of crowding distance will commence, followed by the

selection process starting from the initial population. This selection is based on two elements:
  - Population Ranking: The selection process begins with populations in lower ranks being chosen first.
  - Distance calculation: When p and q belong to the same rank, the member with a greater crowding distance is selected. It is important to note that the selection priority is primarily determined by rank, followed by crowding distance.
- Crossover and mutation: New offspring are generated through binary selection.
- Incorporation of the initial population with the population resulting from crossover and mutation.
- Substitution of the parent population with the top members of the merged population: Initially, members from lower ranks replace the previous parents; subsequently, they are organized based on crowding distance.

These steps are repeated until the desired generation (or optimal conditions) are achieved.

2.4 Strength Pareto Evolutionary Algorithm, Version II (SPEA-II)

SPEA2 is an enhanced iteration of the multi-objective evolutionary optimization technique SPEA. It is widely acknowledged as a leading and frequently applied algorithm for optimization endeavors, with widespread practical, scientific, and engineering applications.

N_E : The upper limit of the archive containing non-dominated solutions E.

N_F : Population size

K: Parameter for calculating density $K = \sqrt{N_E + N_F}$

Step 1: Generate an initial solution population, P_0, and establish $E_0 = \varnothing$ as an empty set.

Step 2: Determine the fitness of each solution i in the combined set $P_t \cdot E_t$.

Step 3: Copy all non-dominated solutions from the set $P_t \cdot E_t$ to P_{+1}.

Step 4: If the termination conditions are met, the algorithm stops and returns the solutions E_{t+1}.

Step 5: Using the binary competition, parents are selected from the set E_{t+1}.

Step 6: The parents undergo crossover and mutation operations, resulting in the production of N_p offspring. These offspring are copied to the set P_{t+1} and the counter is incremented by one ($t = t + 1$). The algorithm then returns to Step 2.

2.5 Grey Wolf Algorithm

Drawing inspiration from the social behavior of grey wolves during hunting, this algorithm operates on a population, follows a straightforward procedure, and can be readily adapted to address high-dimensional problems. Within the Grey Wolf Optimization (GWO) framework, the top solution is denoted as alpha, while the second and third best solutions are referred to as beta and delta, respectively. The remaining solutions are collectively known as omega. In GWO, the leadership in the hunting process is assumed by alpha, beta, and delta, with the omega solution trailing behind these three wolves.

As the wolves encircle their prey and come to a halt, the assault commences under the guidance of the alpha wolf. This process is simulated using the attenuation vector a. Decreasing the value of a results in a reduction of the coefficient vector A, as A is a random vector within the range [$-2a$, $2a$]. If $|A|$ is less than 1, the alpha wolf (and other wolves) move closer to the prey; if $|A|$ exceeds 1, the wolf (and others) move away from the prey. In the Grey Wolf algorithm, all wolves are required to update their positions based on the positions of the alpha, beta, and delta wolves.

In the hunting phase, grey wolves encircle their prey. The mathematical formulation for this encircling behavior is described by the following equations, where t signifies the current iteration, A and C denote coefficient vectors, X_P represents the position vector of the prey, and X represents the position vector of the grey wolf.

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right|$$
$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D}$$

The vectors A and C are determined as:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a}$$
$$\vec{C} = 2.\vec{r}_2$$

Here, the variable a decreases linearly from 2 to 0 across iterations, while r_1 and r_2 are random vectors within the range [0, 1].

In the mathematical model of Grey Wolf Optimization, it is assumed that alpha, beta, and delta possess superior awareness of the potential prey's position. The three top solutions are retained, while the remaining wolves are required to adjust their positions based on the positions of the leading wolves they are pursuing. This adjustment process adheres to the equations provided below.

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|$$
$$\vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|$$
$$\vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right|$$
$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$$

The search stage is the inverse of the attack phase: in the search phase, the wolves distance themselves from one another to trail the prey ($|A| > 1$). Conversely, once the prey is located, the wolves draw closer to each other during the attack phase. This phenomenon is recognized as divergence during search and convergence during attack.

3 ANALYSIS OF NUMERICAL RESULTS USING METAHEURISTIC ALGORITHMS FOR MULTI-OBJECTIVE PROBLEMS

Since the logistics hub network problem is a NP-hard problem, metaheuristic algorithms are commonly used to solve numerical instances with medium to large sizes. However, one of the most important challenges in using metaheuristic algorithms is selecting the appropriate algorithm based on their nature and functional structure to find the final solutions. According to literature review, population-based metaheuristic algorithms and swarm-based algorithms generally exhibit better performance compared to other response-based algorithms. Therefore, this study used population-based and swarm algorithms. Among the algorithms proposed in recent years, the Grey Wolf Algorithm has had very high computational power and has been used in almost all problems, showing relative or absolute superiority to other algorithms. The multi-purpose version of these algorithms also has very high efficiency and can perform well in the Exploration phase and then enter the Exploitation phase, reporting appropriate final solutions. Therefore, this study used algorithm. Additionally, the genetic family, in general, has shown good performance in all optimization problems and can be used as a reliable benchmark. In this family, NSGA-II is considered the most prominent multi-objective algorithm in all optimization domains. Evolutionary-based algorithms such as SPEA-II can also create appropriate solutions for problems. Therefore, this study compared the results of the proposed algorithms with NSGA-II and SPEA-II algorithms to report the best results. Structure of each of the proposed algorithms will be explained below.

3.1 Criteria for Comparing the Performance of Multi-Objective Algorithms

DNS: The number of points in the Pareto front.

NDNS: The ratio of the number of points in the Pareto front for each algorithm obtained from synergy of all solutions obtained from solving different algorithms.

QM: The initial proposed algorithm is independently run multiple times. Then, all the obtained solutions, along with the Pareto front of other algorithms, are collected into a set. Now, the percentage of Pareto points that match the front of that algorithm is considered as quality of that algorithm.

Max Spread: Uniformity index of this criterion tests uniformity of distribution of obtained Pareto solutions on solution front. This index is defined as:

$$s = \frac{\sum_{i=1}^{N-1} \left| d_{mean} - d_i \right|}{\left(N-1\right) \times d_{mean}}$$

where, d_i represents the Euclidean distance of the i-th member of the Pareto front from the optimal boundary. Additionally, d_{mean} indicates the average value of these distances. Now, the results of the algorithm solutions will be explained. However, the numerical results must be applied to different numerical examples. For this purpose, 150 numerical instances were generated with random and hypothetical data. These instances are divided into 30 categories; within each category, the size of the problems is divided into small, medium, and large based on the number of points assigned to the problems. Additionally, each category is designed with a predetermined number of potential centers. For example, Tab. 1 considers 30 numerical instances with 5 potential hubs. In fact, in all these 30 instances, the number of potential hubs is equal to 5, and only the number of demand points and input parameters changed.

Table 1 Comparison of efficiency of algorithm for 5 potential hubs

		SPEAII				NSGAII				MOGWO			
	Problem Size (nodes)	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread
Small	10	8.1	7.51	0.15	48788.8	7.2	6.25	0.21	39881.9	9.77	6.26	0.64	39661.2
	11	8.62	10.65	0.25	31056.7	6.66	8.32	0.09	57048.9	10.23	8.55	0.66	35664.9
	12	9.33	10.87	0.03	44599.8	11.82	10.86	0.21	29032.1	7.04	6.65	0.76	46152.1
	13	12.67	7.99	0.15	51314.9	8.52	10.21	0.1	47453	10.69	6.98	0.75	31382.4
	14	10.73	6.47	0.12	29000.7	6.92	13.57	0.1	31958.8	10.7	13.95	0.78	30112.8
	15	7.17	12.89	0.15	46418.8	8.47	13.61	0.26	53342.3	6.24	9.16	0.59	46588
	16	15.73	15	0.36	36588.9	15.26	12.99	0	10592.3	9.64	13.7	0.64	55707.8
	17	11.09	15.01	0.19	27768.9	13.07	6.98	0.03	28619.5	15.1	8.06	0.78	32748.1
	18	8.6	16.05	0.21	45145.4	10.08	8.68	0.24	12452.6	7.2	10.54	0.55	27856.1
	19	14.12	14.23	0.24	37831	15.23	10.87	0.05	55333.4	10.82	13.6	0.71	27422.9
Medium	20	16.38	6.64	0.23	37507.3	6.79	18.51	0.19	54608.2	17.1	12.83	0.58	43285.5
	21	19.66	10.51	0.19	51004.1	9.39	9.69	0.01	27790.6	12.03	8.04	0.8	33811.9
	22	6.65	8.95	0.19	12722.7	17.31	8.59	0.25	36660.6	21.77	19.92	0.56	14023.3
	23	7.33	8.29	0.15	34499.8	17.4	11.08	0.31	22244.2	19.02	17.52	0.54	44992.4
	24	22.58	7.32	0.15	10706.8	13.34	17.54	0.11	11060.3	13.86	14.66	0.74	23623.1
	25	22.74	15.67	0.05	53339.7	8.58	18.32	0.33	40223.2	17.25	12.13	0.62	45805
	26	24.47	12.49	0.21	27179.4	12.53	24.26	0.1	24779.5	22.03	22.02	0.69	38920.3
	27	9.02	9.33	0.24	24421.4	19.37	12.44	0.02	23451.4	21.7	14.86	0.74	25442.3
	28	13.44	9.81	0.01	40504.5	7.23	22.67	0.39	22252.5	23.81	19.25	0.6	56176.6
	29	22.18	16.44	0.21	14636.4	9.92	25.89	0.16	43974.2	10.65	10.08	0.63	20552.1
Large	30	21.16	7.36	0.17	52625	8.91	27.91	0.3	19492.8	23.09	24.53	0.53	40213.5
	31	15.94	26.03	0.27	12439.2	11.57	10.08	0.01	32489.4	15.54	30.53	0.72	31986.1
	32	16.54	28.01	0.05	43022.7	30.65	22.14	0.16	40656.9	30.92	25.13	0.79	57911.4
	33	16.72	31.8	0.01	46809.3	23.55	32.65	0.43	49008.3	28.97	24.52	0.56	30906
	34	10.63	31.39	0.26	33825	30.42	30.28	0.24	58090.2	30.87	6.82	0.5	57788.3
	35	28.1	21.09	0.18	46910.8	26.12	21.23	0.13	17922.4	12.27	13.43	0.69	39359
	36	26.71	17.39	0.04	39218.8	8.49	8.41	0.38	22681.2	6.41	22.95	0.58	53739.4
	37	35.35	33.56	0.17	23619.9	15.22	14.5	0.08	40548.8	23.55	14.51	0.75	14040.8
	38	16.03	14.72	0.22	16419.2	19.75	24.25	0.03	44121.7	12.13	9.34	0.75	36466.9
	39	8.54	26.26	0.32	29331.7	8.61	16.15	0.02	29060.9	29.24	26.6	0.66	23596.7

Table 2 Comparison of efficiency of algorithm for 10 potential hubs

		SPEAII				NSGAII				MOGWO			
	Problem Size (Facilities)	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread0
Small	20	11.72	14.01	0.08	40198.9	15.33	8.67	0.37	35078.6	15.39	12.03	0.23	52726.4
	21	18.22	18.42	0.42	51810.1	18.76	19.12	0.33	30225.3	17.66	20.28	0.31	45716.7
	22	16.88	19.71	0.24	34656.4	18.24	11.08	0.18	15377.3	9.43	17.07	0.24	25968.8
	23	11.72	6.94	0.19	26512.9	19.6	13.45	0.17	59852.1	19.66	14.13	0.25	49656.9
	24	17.65	18.41	0.1	52755.7	20.14	23.25	0.35	33828.7	19.38	22.74	0.18	35529
	25	19.69	7.84	0.07	32047.9	6	17.77	0.09	57302.9	13.83	21.44	0.3	16563.3
	26	8.02	22.89	0.43	10620.8	19.35	22.11	0.07	48394.2	22.67	14.24	0.25	31894.2
	27	18.27	18.98	0.35	17418.3	20.43	25.84	0.19	47959.4	10.15	26.07	0.21	50629.1
	28	14.69	24.88	0.45	30621.2	17.34	22.55	0.44	47925.4	14.24	11.61	0.09	34476.9
	29	10.92	7.71	0.37	23731.3	8.33	6.17	0.22	11621.8	18.85	27.94	0.32	32493.2
Medium	30	11.02	12.43	0.24	50183.2	21.64	15.42	0.21	26226.8	24.32	21.8	0.21	30505.3
	31	18.47	30.46	0.09	48511.7	13.97	26.35	0.23	33028.6	24.46	28.58	0.08	30239.3
	32	29.26	12.9	0.36	49016	6.23	13.02	0.12	22728.6	24.25	8.3	0.11	26432.9
	33	30.54	7.14	0.3	49285.2	27.57	30.35	0.43	21285.1	30.6	28.11	0.3	36489.8
	34	26.78	8.97	0.09	23864.2	8.47	25.2	0.16	47772.7	26.15	30.15	0.35	50839.1
	35	23.54	32.3	0.26	26426.8	12.09	16.01	0.25	42492.3	7.25	21.63	0.22	16636.4
	36	29.77	28.38	0.21	36421.7	21.26	6.68	0.41	37991.9	29.56	16.2	0.32	26899.8
	37	32.49	31.41	0.35	56227.5	28.43	19.41	0.4	56005.7	35.01	24.6	0.42	14753.6
	38	19.92	20.78	0.16	41276.7	11.12	7.74	0.25	37941.3	17.88	6.3	0.42	15972.3
	39	34.2	28.15	0.23	22813.7	16.16	35.5	0.25	54296	18.89	27.65	0.2	58277.7
Large	40	38.09	11.59	0.38	14970.1	16.86	15.89	0.22	40624	23.86	34.3	0.4	57918.8
	41	10.27	22.95	0.19	15451.4	12.8	22.32	0.23	23571.3	35.51	35.37	0.35	28736.7
	42	26.52	22.32	0.36	25480.3	23.03	22.33	0.09	51955	32.91	29.28	0.32	16332.4
	43	23.06	10.39	0.19	24520.2	33.55	13.8	0.35	39173.2	28.58	23.87	0.25	54987.8
	44	17.14	12.24	0.22	32061.6	16.81	10.24	0.37	16617.1	40.85	21.04	0.45	48201.9
	45	19.06	25.56	0.25	23720	33.31	38.49	0.38	16282.5	13.67	43.8	0.23	27887.5
	46	45.6	38.91	0.18	26668	28.55	19.24	0.07	27565.9	34.95	32.27	0.07	22153.6
	47	20.79	30.66	0.14	30141.9	29.13	36.45	0.08	59886.7	16.83	35.12	0.28	25536.3
	48	38.1	35.2	0.38	37921.7	41.26	36.06	0.42	48955.6	39.27	38.96	0.3	31329.6
	49	35.62	47.55	0.12	56755.6	19.01	7.01	0.24	51143.7	30.68	6.56	0.09	31852.2

Table 3 Comparison of efficiency of algorithm for 15 potential hubs

		SPEAII				NSGAII				MOGWO			
	Problem Size (Facilities)	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread
Small	30	22.8	11.48	0.37	52406.8	24.78	7.86	0.14	24746.1	26.72	28.34	0.44	35798.2
	31	8.21	23.57	0.42	17361.9	28.6	6.76	0.37	59566.3	15.51	12.48	0.16	17643.2
	32	13.87	21.24	0.36	30889.1	13.86	19.2	0.19	14154.8	25.8	26.58	0.16	21690.4
	33	18.65	9.07	0.27	26146.5	20.14	15.47	0.22	25748.7	29.14	7.34	0.37	12488.6
	34	14.33	25.84	0.43	53056.5	23.15	11.86	0.11	35025.9	15.74	21.35	0.11	20669.3
	35	17.58	17.29	0.22	28415.2	9.52	23.55	0.4	32608.7	25.13	11.14	0.25	27992.1
	36	26.79	27.66	0.35	56016.6	33.69	35.24	0.21	10165.6	30.05	35.99	0.34	41203.4
	37	20.74	35.31	0.22	11973.4	11.14	27.23	0.34	49606.1	20.77	32.3	0.22	56314
	38	29.23	18.43	0.13	24093.6	31	19.59	0.16	20244.8	21.42	22.1	0.31	53651.3
	39	36.19	13.48	0.17	58942	7.4	9.08	0.14	22738.6	7.88	31.44	0.21	11686.8
Medium	40	20.4	39.21	0.32	15146.8	32.54	35.21	0.28	20356.1	26.44	20.42	0.36	42955.1
	41	36.82	31.96	0.12	21425.5	38	21.88	0.16	20150.4	7.33	39.14	0.25	59240.3
	42	7.96	12.44	0.16	21390.4	6.25	6.22	0.26	13329.2	37.29	20.89	0.09	42613.2
	43	27.11	28.81	0.22	58284.5	18.87	23.33	0.3	59823.8	37.24	35.92	0.43	18544.5
	44	8.64	43.14	0.3	36355.9	38.44	34.42	0.28	56510.3	36.12	13.54	0.17	39762.2
	45	26.63	42.05	0.26	28613.7	37.48	24.16	0.11	52846.5	44.81	36.81	0.4	32898.4
	46	12.32	23.42	0.32	50711.2	36.63	28.71	0.19	25134.1	40.3	40.37	0.33	21620.7
	47	21.34	40.34	0.36	57628.1	17.05	35.51	0.17	50134.3	30.33	18.74	0.41	45470.1
	48	29.13	23.65	0.08	36778.3	34.43	38.98	0.16	33808.1	7.59	34.68	0.37	13820.2
	49	15.25	46.23	0.18	44543.9	46.63	31.29	0.19	12035.8	39.9	23.04	0.32	21865.1
Large	50	23.17	20.6	0.21	19250.1	8.45	27.9	0.35	31963.6	10.57	6.45	0.1	52642.9
	51	21.66	36.72	0.08	31806.5	41.47	29.71	0.21	48717.3	16.53	38.26	0.35	55493
	52	25.69	25.86	0.3	21066.9	32.31	15.14	0.09	35618.2	24.46	31.89	0.17	21921
	53	18.58	44.9	0.07	43105	29.15	34.51	0.1	15869.7	38.08	18.61	0.09	25866.9
	54	17.77	24.15	0.35	52026.9	40.28	46.2	0.34	59331.3	25.48	26.49	0.44	42079.6
	55	38.4	6.98	0.29	25827.1	29.84	51	0.34	50604.5	9.29	33.49	0.44	38121.9
	56	31.68	48.55	0.07	22961.8	11.05	21.01	0.45	43083.3	12.38	28.13	0.15	27592.7
	57	13.93	37.8	0.21	31544.6	36.26	31.13	0.28	23847.1	45.58	35.9	0.35	13861
	58	44.23	34.01	0.4	48147.6	40.71	26.03	0.14	55041.2	42.4	51.64	0.33	26599.6

Table 4 Comparison of efficiency of algorithm for 20 potential hubs

		SPEAII				NSGAII				MOGWO			
	Problem Size (Facilities)	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread
Small	40	27.96	18.75	0.36	17045.7	9.69	14.64	0.2	32394.9	14.69	24.43	0.15	22522.5
	41	19.51	40.11	0.18	50708	19.29	8.97	0.08	33523.4	36.14	24.48	0.25	25588
	42	22.61	29.58	0.35	28447.2	40.29	30.34	0.43	10522	39.26	32.14	0.29	32214.1

Table 5 Comparison of efficiency of algorithm for 20 potential hubs (continuation)

		SPEAII				NSGAII				MOGWO			
	Problem Size (Facilities)	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread
Small	43	17.5	6.94	0.45	59903.4	37	7.86	0.07	32672	28.4	40.54	0.19	12287.5
	44	37.31	25.05	0.43	52985.8	21.61	31.12	0.12	58049.1	27.63	22.29	0.09	32261.8
	45	18.95	8.19	0.45	37443.3	18.82	14.64	0.31	37568.8	27.52	31.52	0.45	34085.4
	46	23.86	35.72	0.12	45288.5	37.89	8.16	0.29	40041.1	20.98	41.96	0.32	16298.2
	47	39.74	19.59	0.35	11336.1	38.18	28.1	0.22	51625.2	24.02	36.17	0.11	52240.3
	48	32.13	33.74	0.33	12674.3	41.29	11.65	0.18	14137.9	37.28	8.38	0.4	56332.5
	49	15.83	21.3	0.41	22989.5	12.49	7.21	0.35	51485.1	30.16	26.48	0.2	35294.4
Medium	50	20.92	37.13	0.36	17266.9	48.73	39.74	0.09	29851.2	27.9	40.65	0.13	29014.3
	51	8.7	40.93	0.15	25360.9	31.6	49.3	0.12	47811.7	46.29	35.38	0.14	47048.1
	52	25.95	18.59	0.17	38150.5	46.92	21.99	0.45	22184.5	48.57	29.15	0.45	15354.9
	53	12.52	14.11	0.29	56999.2	8.97	18.36	0.09	33055.6	36.64	22.16	0.34	44829.2
	54	53.1	10.82	0.15	54931.3	9.37	46.9	0.12	12914.1	46.75	39.69	0.31	17949.6
	55	28.7	50.24	0.4	55283.8	42.59	28.88	0.2	32419.5	33.29	11.25	0.41	39194.8
	56	10.52	44.86	0.25	50840.2	51.46	27.52	0.16	33630.1	51.09	30.61	0.31	19031.3
	57	32.3	19.16	0.15	44028.3	55	50.61	0.36	33548.1	37.37	20.39	0.39	38148.4
	58	14.62	52.73	0.23	43728.2	24.46	47.78	0.42	35020.1	56.41	47.75	0.1	58864.9
	59	34.85	53.84	0.16	41659.1	56.15	48.67	0.25	54085	27.55	36.92	0.15	36065.9
Large	60	50.89	40.85	0.38	52196.1	34.48	55.67	0.07	41930.7	47.04	24.56	0.29	17452.3
	61	60.48	60.45	0.35	22729.5	23.08	37.92	0.25	47983.4	26.02	14.89	0.27	12738.6
	62	41.41	52.22	0.22	53238.5	43.8	56.56	0.32	24050.6	41.66	13.94	0.25	48393.8
	63	18.78	22.94	0.12	29575	32.15	21.2	0.26	12778.6	60.8	30.38	0.33	16045.9
	64	35.82	6.18	0.09	21219.1	29.99	63.81	0.13	38264.9	45.51	38.6	0.29	40330
	65	32.76	36.88	0.39	33202.1	38.54	6.66	0.25	24476.2	47.22	12.98	0.2	17419.5
	66	37.51	62.82	0.4	58909.1	13.64	15.23	0.22	36470.5	19.08	6.76	0.26	47047
	67	6.61	55.06	0.15	12475.6	13.95	15.17	0.3	29867.4	38.89	23.2	0.25	14376.6
	68	55.9	11.73	0.39	23843.6	64.66	46.84	0.28	21068	9.91	67.49	0.25	45457.3
	69	53.56	7.52	0.1	15968.4	62.68	28.99	0.09	51517.6	14.9	57.81	0.1	29518.2

Table 6 Comparison of efficiency of algorithm for 25 potential hubs

		SPEAII				NSGAII				MOGWO			
	Problem Size (Facilities)	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread	DNS	ADNS	QM	Max Spread
Small	50	30.55	23.29	0.17	55639.8	17.53	12.12	0.17	18811.4	25.47	28.78	0.17	38269.6
	51	22.79	27.09	0.21	44680.7	27.57	49.12	0.42	35656	33.56	35.55	0.17	52207.1
	52	13.62	35.49	0.44	44839.6	14.25	48.97	0.18	17440.3	17.41	27.26	0.44	10310.9
	53	17.36	46.13	0.3	52876.7	8.76	17.73	0.27	44587.8	42.46	41.8	0.37	54040
	54	47.22	46.94	0.16	21509.5	8.59	25.06	0.45	57691.6	19.49	22.32	0.28	23684
	55	9.92	10.52	0.09	35610.7	45.98	35.88	0.11	15143	30.36	43.7	0.16	38674.1
	56	51.67	45.14	0.12	17703.6	39.14	54.63	0.43	56353	52.86	31.78	0.13	57774.9
	57	40.37	50.07	0.13	36941	50.93	23.56	0.18	52532.3	10.89	45.58	0.32	14261.4
	58	40.94	17.96	0.29	42110	12.9	7.94	0.26	54328.2	17.09	32.01	0.11	41148.1
	59	26.69	14.26	0.43	33751.7	54.29	41.23	0.28	45133.8	11.67	12.15	0.41	51151.7
Medium	60	46.08	48.88	0.38	13069.3	33.38	12.09	0.3	11805.1	53.25	34.45	0.45	24298.4
	61	20.52	14.91	0.39	31862	27.07	45.53	0.14	33450.7	53.87	35.29	0.33	28694.1
	62	45.03	50.14	0.11	31560.6	47.18	26.81	0.4	16806.1	16.56	8.72	0.22	20131.6
	63	8.82	18.03	0.25	54507	20.22	36.34	0.09	47031.8	24.89	59.76	0.26	51073.8
	64	47.91	41.44	0.44	54760	63.16	9.79	0.41	37265.4	63.96	28.91	0.34	38013
	65	34.82	30.82	0.33	11522.7	36.17	24.81	0.45	39641.1	29.52	34.61	0.27	10932.3
	66	24.06	65.44	0.33	30815.7	33.29	64.52	0.14	16420.5	53.38	13.83	0.35	59567.7
	67	33.71	27.8	0.37	58693.7	38.62	59.41	0.14	12199.6	43.59	16.7	0.16	45816.2
	68	17.01	66.51	0.26	39548.5	20.82	43.92	0.21	56718.6	66.57	39.35	0.3	26715.8
	69	25.18	50.77	0.26	38438.1	26.72	38.67	0.14	47378.3	33.41	65.17	0.27	54882.1
Large	70	22.13	8.93	0.16	38742.2	40.43	61.39	0.29	29858.9	50.67	63.98	0.08	50796.2
	71	18.25	37.74	0.09	54338.3	17.87	20.12	0.45	23030.7	6.32	58.99	0.33	44297.2
	72	42.9	56.92	0.41	13780.5	29.73	58.93	0.34	20700.3	50.39	68.7	0.09	44233.8
	73	63.99	35.98	0.39	51929.8	8.52	69.59	0.12	18490.6	70.41	34.73	0.08	38535.4
	74	18.08	41.14	0.27	37472.9	30.78	26.4	0.18	49611.5	8.05	57.45	0.4	29738.6
	75	23.94	69.43	0.41	18587.6	60.97	14.2	0.25	44096.1	11.81	21.96	0.43	51073.5
	76	73.73	60.55	0.31	37937.7	61.58	53.5	0.45	26791	42.2	55.34	0.24	11796.3
	77	67.5	22.82	0.16	33462.2	27.27	62.19	0.36	48602.8	67.12	67.77	0.18	14969.7
	78	20.59	34.55	0.28	30826	23.84	43.57	0.39	50759.6	40.1	23.35	0.13	36793.6
	79	20.3	10.98	0.16	22248.9	12.37	56.59	0.18	31277.4	17.16	19.77	0.25	11065.3

The number of demand points for network design varies in each of Tabs. 1 to 5, as can be seen, but the number of hubs remains constant. It can be observed that as dimensions of the problem increase and different solutions are generated, each of which can be a member of the Pareto front, the criteria of DNS and ADNS also increase. In fact, considering that these two criteria are directly dependent on the number of members in the Pareto front generated, their values also increase with the increase in dimensions of the problem. However, this growth rate in the Grey Wolf algorithm is significantly higher compared to other algorithms. In other words, the Grey Wolf Optimizer algorithm has a higher capability of finding Pareto solutions in various instances. The Genetic

Algorithm also exhibits the lowest growth rate, indicating insufficient capability in generating final solutions. Similar analysis can be presented regarding the quality metric (QM). As observed, the Grey Wolf Optimizer algorithm exhibits higher percentages for this criterion. In fact, this scenario has the ability to generate fairly similar solutions in independent runs, ultimately increasing the percentage of compatible solutions. In terms of run time, this scenario also demonstrates the ability to find solutions and converge to final results in a shorter period. Based on the results obtained, it can be observed that the presented algorithms exhibit satisfactory efficiency, as the observed differences in performance of the Grey Wolf Optimizer algorithm compared to other algorithms are reasonable.

3.2 Sensitivity Analysis of the Superior Algorithm

For a more detailed examination of the behavior of the Grey Wolf Optimizer algorithm, chosen as the superior algorithm in analyses, sensitivity analysis is conducted on varying values of demand parameter. To this end, a numerical instance is considered in large scale with 50 potential hubs and 200 demand points.

Considering that implementing the results of the proposed model depends on behavior of decision variables against changes in some important parameters such as cost of establishing distribution centers and flow rate between points, appropriate analyses are presented by defining different values for each of these parameters and examining the changes in the Pareto front for each of them (Tab. 6).

Table 7 Variations in parameters of establishment costs and customer demand

Scenario 1	Scenario 2	Scenario 3	Scenario 4
40% reduction	20% reduction	20% increase	40% increase

As seen in Fig. 2, variations in the problem costs only affect the value of the first objective function. It is quite evident that the upper and lower bounds of the Pareto front only change for the first objective function, while there is little change in the upper and lower bounds of the second front. This is because ultimately the model tended to consider facility establishment and logistics operations in a way that minimizes changes in the environmental objective function. In such circumstances, managers should focus on cost reduction, and environmental criteria take a secondary priority.

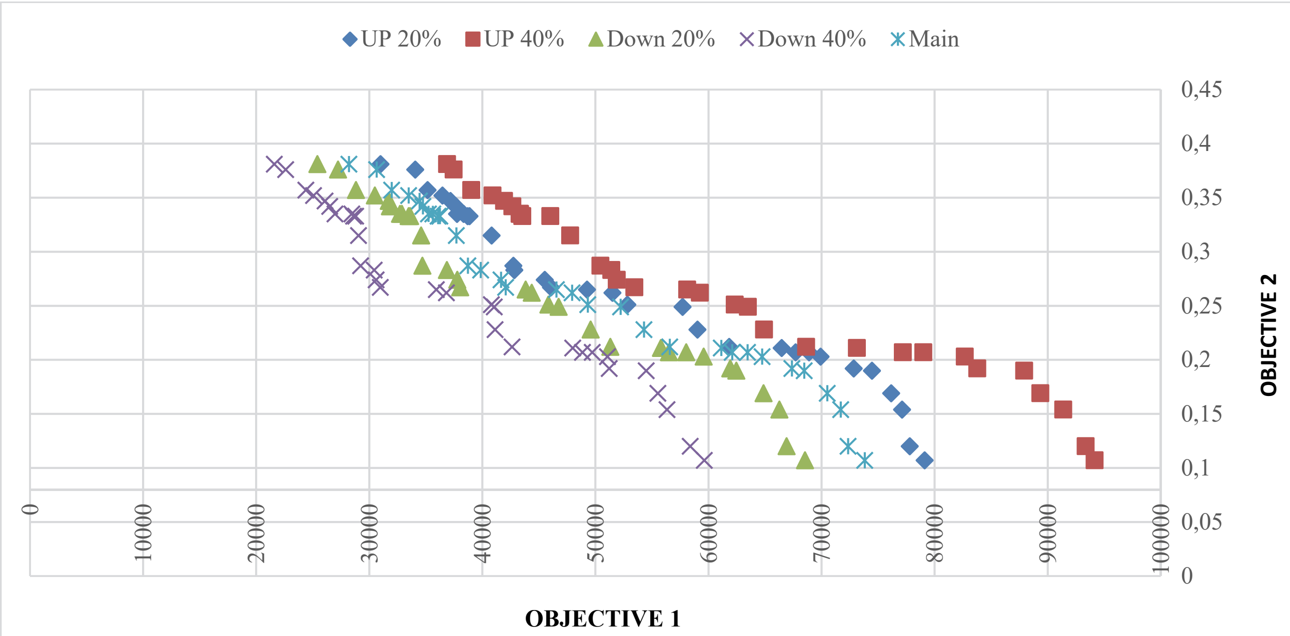

Figure 2 Variations in pareto front versus different scenarios of establishment costs and logistics operations

4 CONCLUSION

This study has contributed significantly to the field by developing a robust logistics hub network designed to operate at a global scale using advanced mathematical optimization techniques. By employing various metaheuristic algorithms, including the SPEA-II, NSGA-II, and Multi-Objective Grey Wolf Optimization Algorithm, this research has effectively optimized the management of goods flow among customer points within complex global supply chains. The developed logistics hub network system offers valuable tools for managers and decision-makers in the global transportation industry. It enhances flow management and productivity by strategically locating hubs and optimizing transportation routes. The application of three distinct models and a range of analytical tools underscores the versatility and practical utility of the approach.

To better elucidate the benefits of this research, future studies should emphasize the comprehensive advantages of optimized logistics networks. This includes not only cost reductions but also enhanced environmental sustainability and resilience, particularly in the face of disruptive events like the COVID-19 pandemic.

In practical terms, the developed model equips global transportation managers and decision-makers with invaluable tools for improving flow management efficiency and productivity. Moving forward, expanding the model's capabilities could involve:

- Developing exact solving algorithms to scale the solution for larger networks, ensuring global optimality.

- Incorporating support hubs into the model to enhance operational flexibility and responsiveness.
- Extending performance analysis to include metrics of resilience and sustainability, thereby evaluating network robustness under adverse conditions [23].

By addressing these avenues, future research can further advance both the theoretical foundations and practical applications of global logistics network optimization.

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Contact information:

Reza KARIMI MEHRABADI
Department of Industrial Engineering,
South Tehran Branch, Islamic Azad University,
Tehran, Iran

Emad ROGHANIAN
(Corresponding author)
Department of Industrial Engineering,
K. N. Toosi University of Technology,
Tehran, Iran
E-mail: e_roghanian@kntu.ac.ir

Shahnaz PIROOZFAR
Department of Industrial Engineering,
South Tehran Branch, Islamic Azad University,
Tehran, Iran

Abbas SHOJAIE
Department of Industrial Engineering,
South Tehran Branch, Islamic Azad University,
Tehran, Iran