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Resilient Hub Network Design under Hub Availability Uncertainty: A Scenario-Based Bi-Objective Single-Allocation Hub Location with Direct Routing Capability

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Abstract

Strategic hub location decisions are fundamental to the architecture of transportation and supply chain networks, as they directly dictate cost-efficiency, operational flexibility, and overall network performance. This paper introduces a two-stage, bi-objective stochastic programming model designed to address the complexities of network planning. One of the key features of this model is its ability to take into account uncertainty in hub status, considering scenarios in which hubs may be operational or non-operational, while also allowing for direct shipments between selected origin–destination pairs to improve routing efficiency. Formulated as a mixed-integer programming problem, the model navigates uncertainty by evaluating a range of potential scenarios. The framework operates in two distinct phases: the first phase determines strategic hub placement, while the second optimizes tactical decisions, including flow allocation and demand management, within each scenario. This dual-layered approach not only enables a rigorous assessment of network risk and performance under varying conditions but also strikes a balance between minimizing capital and operational expenditures and maximizing service reliability. Our findings demonstrate that integrating hub-and-spoke connectivity with direct routing options yields a significantly more resilient and efficient network, capable of maintaining performance even when hubs become non-operational.

Keywords: Hub location-allocation, Uncertainty, Two-stage stochastic model, Supply chain network, Scenario.

1 | Introduction

Hub location problems are among the fundamental and widely studied problems in the fields of operations research, transportation network design, and supply chain management. Hubs function as intermediate nodes within a network, and their primary role is to consolidate, process, and distribute flows among different nodes. The use of hubs reduces the number of direct routes, decreases transportation costs, improves efficiency, and facilitates the management of goods and information flows. Over the past two decades, hub location has

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attracted considerable attention from researchers, as the optimal selection of hub locations can have a significant impact on overall network performance. In this context, various models have been proposed to address the problem from different perspectives, such as cost minimization, transportation time reduction, service level improvement, or a combination of these objectives. Despite significant advances in this field, several challenges remain unresolved. One of the most important challenges is uncertainty in key parameters, such as demand, transportation costs, and facility capacities. Ignoring such uncertainties may lead to unrealistic and impractical decisions. Therefore, stochastic models and scenario-based approaches have gained particular importance as effective tools for incorporating uncertain conditions into decision-making processes. Unlike direct transportation from origins to destinations, hub networks concentrate flows at central nodes and benefit from economies of scale. In this process, flows originating from different origins but sharing the same destination are consolidated at hubs, while flows from a single origin to multiple destinations are efficiently routed through the network. This mechanism reduces the number of direct routes between origin and destination nodes and enables demand satisfaction under limited resources [1].

The first study in this area was conducted by Hakimi [2], who investigated concepts similar to hub location problems. Later, in 1985, Toh et al. [3] examined the application of hub networks in airlines and the aviation industry, which is recognized as the first direct research contribution in this field. Subsequently, Campbell proposed several mathematical formulations for these problems and modeled them analogously to classical facility location problems [4]. Serious research in this area began with the pioneering work of O'Kelly [5], who introduced the first well-known mathematical model for minimizing total transportation costs, including time and distance, in air passenger transportation networks. In 1987, O'Kelly [6] introduced a dataset based on airline passenger flows among 25 U.S. cities, which was later validated by the Civil Aeronautics Board (CAB). Over time, this dataset became a primary benchmark in hub location research and has been widely used in the literature under the title of the CAB dataset. Hub networks can generally be classified into two main structures: single-allocation and multiple-allocation configurations. The distinction between these two structures lies in the way demand centers are connected to hubs. In the single-allocation model, each demand node is assigned to only one hub, and all its inbound and outbound flows pass through that hub. In contrast, in the multiple-allocation model, a node can send or receive portions of its flow through more than one hub [7]. O'Kelly et al. [8] demonstrated that the single-allocation problem is in fact a special case of the multiple-allocation model, obtained by adding a specific constraint. The development of multiple-allocation problems was largely shaped by Campbell's binary linear programming model, which laid the foundation for the idea of distributing flows among several hubs. In this class of models, each non-hub origin–destination pair can exchange flows through multiple hubs; a feature that, in practice, often results in allocation based on the nearest hub. In decision-making contexts, uncertainty is generally classified into two categories. In the first case, the source of instability cannot be described by probabilistic laws, making it difficult to model. In the second case, although the exact values of parameters are unknown, their behavior can be predicted using probability distributions. The latter category is commonly analyzed and controlled using stochastic methods [9].

In this study, the objective is to develop a scenario-based, two-stage, bi-objective stochastic mathematical model that determines the optimal hub locations and allocates non-hub nodes to the selected hubs in the first objective, while the second objective allows for direct routing between nodes, thereby enabling the design of a hybrid transportation network. The proposed model is formulated as a Mixed-Integer Linear Programming (MILP) model and incorporates uncertainty through a set of probabilistically generated by scenarios that show hub conditions (operational and non-operational). In the first stage, strategic decisions, including hub location selection, are determined. In the second stage, tactical decisions, such as flow allocation and demand management under each scenario, as well as the possibility of direct shipment, are made. Furthermore, by employing a weighted aggregation of objective functions, the proposed approach enables risk assessment and performance comparison of the network under different conditions. On the one hand, it minimizes investment and operational costs, and on the other hand, it enhances the service level and network reliability.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on the hub location problem, as well as studies addressing reliability considerations. Section 3 presents the mathematical formulation of the proposed model. Section 4 reports the computational results obtained from solving the model using standard benchmark datasets commonly employed in the hub location literature. Finally, the paper concludes with a summary of the findings and suggestions for future research.

2 | Literature Review

Numerous studies have been conducted on hub location problems, a substantial portion of which has been devoted to the development of various models for analyzing different scenarios. Incorporating uncertainty into hub location optimization models can better reflect real-world conditions and improve the robustness and adaptability of decision-making schemes. For this reason, studies on hub networks have examined real-world constraints and attempted to incorporate such constraints into their models. In hub location problems, one of the fundamental challenges is the existence of uncertainty in key parameters, such as customer demand, transportation costs, facility capacities, and even the probability of network disruptions. Ignoring these uncertainties may lead to decisions that are not practically implementable under real conditions and may weaken network performance. Since many of these parameters are subject to variation in practice due to economic fluctuations, market volatility, climatic conditions, or other unpredictable factors, classical deterministic approaches are not capable of fully representing reality. In this regard, uncertainty-based models, including stochastic programming and scenario analysis, have been developed to evaluate network behavior under diverse and probable conditions. By considering probability distributions or a set of scenarios, these models enable risk analysis, the selection of more resilient hub locations, and the design of networks with higher flexibility. Accordingly, addressing uncertainty not only improves decision-making accuracy but also leads to the development of networks that operate more stably and efficiently against environmental changes. Shen et al. studied a reliable facility location problem in which facilities are subject to possible failures and customers assigned to a failed facility must be reassigned to other operational facilities. They formulated the problem as a two-stage stochastic programming model and proposed several heuristic approaches to obtain near-optimal solutions for this NP-hard problem [10]. Chaharsooghi et al. [11] investigated a reliable uncapacitated multiple-allocation hub location problem under hub disruptions. In their model, each hub may fail during operation and customers assigned to the disrupted hub are either reassigned to other operational hubs or incur a penalty if service cannot be provided. Momayezi et al. [12] proposed a hub location problem with modular capacitated single allocation under the probability of hub disruption, in which a limited number of capacitated transportation vehicles are used instead of fixed parameters. Soleimani et al. [13] developed a multi-objective mathematical programming model considering uncertainty in some parameters, particularly cost, represented as fuzzy numbers. In addition, backup hubs were selected for each primary hub to cope with disruptions and natural disasters and to prevent delays. Demir et al. [14] employed two metaheuristic approaches based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Archived Multi-Objective Simulated Annealing (AMOSA) method to solve the Multi-Objective Capacitated Multiple-Allocation Hub Location Problem (MOCMAHLP). Rahmati et al. [15] presented a two-stage robust optimization approach for the uncapacitated hub location problem, in which demand is uncertain. By introducing an expected aggregation function to adjust the uncertainty budget, they effectively improved the feasibility and reliability of the optimization strategy under uncertainty. In the proposed model, hub facility locations were determined in the first stage, while allocation decisions were made in the second stage. Ghaffarinasab et al. [16] addressed a single-allocation hub location problem using a risk-averse two-stage stochastic model, in which mean-CVaR was employed as the risk measure. They also proposed a new solution approach by combining Benders decomposition and scenario grouping. Wang et al. [17] introduced a two-stage mixed-integer programming model developed to address the proposed hub location-routing problem with hybrid logistics strategies. In the strategic stage, hub location and allocation decisions are made before the realization of uncertain demands in order to minimize total production and transportation costs. They then integrated third-party logistics into their self-built hub distribution network. Andaryan et al. [18] investigated a two-stage stochastic mathematical model for the capacitated single-allocation hub location problem under Bernoulli demand. Two strategies, namely facility outsourcing and customer outsourcing, were proposed. Guillot et al. [19] studied an extended version of this hub location problem with integrated fleet allocation decisions and proposed a two-stage stochastic integer programming hub location formulation for the problem. The first-stage variables represent hub location decisions, whereas the second-stage variables represent scenario-based transportation flows and fleet allocation decisions. Liu et al. [20] presented a two-stage stochastic optimization model aimed at intelligently deploying hub capacity to achieve timely delivery, high consolidation, and network flexibility, while minimizing the hub establishment budget and truck fleet cost.

3 | Mathematical Modeling

Let G=(N,E) denote the graph representing the network, where N is the set of nodes and E\subseteq(N\times N) is the set of edges. In the hub network, J nodes out of the N nodes are selected as hubs, while the remaining N-J nodes are treated as non hub nodes (spokes) that must be assigned to the hub nodes. The variables and parameters used in the model are summarized in *Table 1*.

Table 1. Symbols and definitions.

Symbols	Definitions
i, j	Network nodes
k	The first hub node on the path i to j in the network
m	The second hub node on the path i to j in the network
f_k	Fixed cost of establishing a hub at node k
$I_k(\xi)$	A binary parameter that indicates the status of the problem hubs under a random event. If it is equal to 1, it means that hub k is operational and active, otherwise there is a non- operational in the hub.
w_{ij}	The amount of flow sent from origin node i to destination node j
c_{ij}	The cost of the flow sent from origin node i to destination node j
α	The discount factor for the cost of the flow between two hubs k and m, whose value is between zero and one.
c_{ijkm}	The cost of flow from node i to node j via hubs k and m
$X_{ijkm}(\xi)$	If flow i to j is transmitted via hubs k and m 1, otherwise 0
Z_k	1, if the hub at location k is open, otherwise 0
$Y_{ik}(\xi)$	1, if node i is assigned to the opened hub at location k, otherwise 0
$Y_{jm}(\xi)$	1, if node j is assigned to the opened hub at location m, otherwise 0
$V_{ij}(\xi)$	1, if node i is assigned to the node j directly, otherwise 0

Eq. (1) use for calculate the shipping cost.

$$c_{ijkm} = c_{ik} + \alpha c_{km} + c_{mj}. \tag{1}$$

Based on the variables and parameters in *Table 1*, the two-stage stochastic mathematical model is as follows.

First-stage

$$\min \sum_{k} f_k Z_k + E[Q(Z, \xi)], \tag{2}$$

Subject to

$$Z_k \in \{0,1\}, \qquad \forall k. \tag{3}$$

Second-stage

which the second stage includes:

$$Q_1(X, \xi) = \min \sum_{i} \sum_{j} \sum_{k} \sum_{m} w_{ij}\, c_{ijkm} X_{ijkm}(\xi), \qquad Q_2(X, \xi) = \min \sum_{i} \sum_{j} c_{ij}\, w_{ij} V_{ij}(\xi). \tag{4}$$

Subject to

$$\sum_{k} Y_{ik}(\xi) = 1, \qquad \forall i, \tag{5}$$

$$Y_{ik}(\xi) \leq Z_k, \qquad \forall i,k, \tag{6}$$

$$Y_{ik}(\xi) \leq I_k(\xi), \qquad \forall i,k, \tag{7}$$

$$\sum_{m} X_{ijkm}(\xi) \leq Y_{ik}(\xi), \qquad \forall i,j,k, \tag{8}$$

$$\sum_{k} X_{ijkm}(\xi) \leq Y_{jm}(\xi), \qquad \forall i,j,m, \tag{9}$$

$$\sum_{k}\sum_{m} X_{ijkm}(\xi) + V_{ij}(\xi) = 1, \qquad \forall i,j, \tag{10}$$

$$Y_{ik}(\xi) \geq 0, \qquad \forall i,k, \tag{11}$$

$$X_{ijkm}(\xi) \geq 0, \qquad \forall i,j,k,m, \tag{12}$$

$$V_{ij}(\xi) \geq 0, \qquad \forall i,j. \tag{13}$$

Let ξ denote the random vector representing the operational hub status of nodes in the network, and let E denote its support, i.e., the set of all possible realizations of ξ. Each realization $\xi \in E$ corresponds to a specific hub-location scenario. *Objective Function (2)* minimizes the sum of the hub establishment costs in the first stage and the mathematical expectation of the transportation costs in the second stage. The distinctive feature of this model lies in its two-objective structure in the second stage, *Objective Function (4)*. While the first objective (Q_1) focuses on minimizing the expected costs resulting from the establishment of facilities and the flow of services, the second objective (Q_2) is minimizing the transmission cost by considering direct transmission between nodes. *Eq. (5)* states that each non-hub node i must be assigned to exactly one hub node. *Eq. (6)* ensures that each non-hub node i is not assigned to a node where a hub has not been established. *Eq. (7)* ensures that any non-hub node i is not assigned to a non-operational hub in the network. *Eqs. (8)* and (9) ensure that if a flow is sent from source i to destination j, it is sent through hubs k and m in the network. *Constraint (10)* enforces an exclusive routing choice at the origin–destination level, so that for each pair (i,j) the flow from i to j is either routed via hubs or sent directly between i and j, but not both. In other words, the model endogenously selects one of two mutually exclusive options for each origin–destination pair, namely hub-based routing or direct routing. *Eqs. (3)* and *(11)-(13)* indicate the range of variables in the mathematical model of the problem.

It is assumed that, in this mathematical model, the uncertainty in the operational and non-operational status of hubs is represented by a set of random scenarios $(s \in S)$, and the probability of occurrence of each scenario is denoted by P_s. The scenario parameters $I_k(\xi)$are also defined as $I_{k,s}$. After the uncertainty is revealed through the set of scenarios, the second stage is solved. In this stage, the allocation of demand to facilities (Y_{ik}^s), the flow of products or services (X_{ijkm}^s), and the auxiliary variables (V_{ij}^s) are determined in such a way that the constraints related to allocation, direct shipment, and service continuity are satisfied. Furthermore, by considering the two parameters $w_1$and $w_2$as the weights of the objective functions in the second stage of the mathematical model under scenarios, and by applying the convex weighted-sum method for combining the objective functions, the deterministic equivalent formulation of the two-stage stochastic programming model is presented as follows:

$$\min \ w_1\left(\sum_{k} f_k Z_k + \underbrace{\sum_{s} p_s\left(\sum_{i}\sum_{j}\sum_{k}\sum_{m} w_{ij}\, c_{ijkm}\, X_{ijkm}^s\right)}_{\text{first obj}}\right) + w_2\underbrace{\left(\sum_{s} p_s\left(\sum_{i}\sum_{j} c_{ij}\, w_{ij} V_{ij}^s\right)\right)}_{\text{second obj}}. \tag{13}$$

Subject to

$$\sum_{k} Y_{ik}^s = 1, \quad \forall i,s, \tag{14}$$

$$\mathrm{Y}_{\mathrm{ik}}^{\mathrm{s}} \leq \mathrm{I}_{\mathrm{ks}} \mathrm{Z}_{\mathrm{k}}, \quad \forall \mathrm{i,k,s}, \tag{15}$$

$$\sum_{\mathrm{m}} \mathrm{X}_{\mathrm{ijkm}}^{\mathrm{s}} \leq \mathrm{Y}_{\mathrm{ik}}^{\mathrm{s}}, \quad \forall \mathrm{i,j,k,s}, \tag{16}$$

$$\sum_{\mathrm{k}} \mathrm{X}_{\mathrm{ijkm}}^{\mathrm{s}} \leq \mathrm{Y}_{\mathrm{im}}^{\mathrm{s}}, \quad \forall \mathrm{i,j,k,s}, \tag{17}$$

$$\sum_{\mathrm{k}} \sum_{\mathrm{m}} \mathrm{X}_{\mathrm{ijkm}}^{\mathrm{s}} + \mathrm{V}_{\mathrm{ik}}^{\mathrm{s}} = 1, \quad \forall \mathrm{i,j,s}, \tag{18}$$

$$\mathrm{Y}_{\mathrm{ik}}^{\mathrm{s}}, \mathrm{Z}_{\mathrm{k}} \in \{0,1\}, \quad \forall \mathrm{i,k,s}, \tag{19}$$

$$\mathrm{X}_{\mathrm{ijkm}}^{\mathrm{s}} \geq 0, \quad \forall \mathrm{j,k,m,s}, \tag{20}$$

$$\mathrm{V}_{\mathrm{ij}}^{\mathrm{s}} \geq 0, \quad \forall \mathrm{i,j}. \tag{21}$$

The proposed model is a two-stage stochastic programming model developed to support decision-making under uncertainty. In the first stage, strategic decisions are made before the realization of uncertainty and are associated with fixed costs, which are reflected in the first objective function. In the second objective function of the second stage, the variable $\mathrm{V}_{\mathrm{ij}}^{\mathrm{s}}$ represents direct shipment. By considering this second objective, the model simultaneously focuses on economic efficiency, service reliability, and service resilience across all possible scenarios. This bi-objective structure enhances the practical validity of the model, as it jointly covers the economic and robustness-related dimensions of decision-making under uncertainty. In this model,. *Eq. (14)* operates in the same manner as *Eq. (5)*. *Inequality (15)* is a combination of *Eqs. (6)* and *(7)*, which specifies the allocation of nodes. In this inequality, Z_{k} represents the hubs in the network, whose value is determined by the model, whereas I_{ks}, as a binary parameter, indicates the status of the hubs (operational or non-operational) selected by the model in the network, which can be observed in *Table 2*. *Inequalities (16)* and *(17)* are analogous to *Inequalities (8)* and *(9)*. *Constraint (18)* enforces the routing choice at the origin–destination level by requiring that, for each pair $(\mathrm{i,j})$ and scenario s, the total flow routed via hubs plus the flow sent directly must sum to one, that means one of them can be happened.

Table 2. random scenarios for CAB data set.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
S (1)	1	0	1	0	0	1	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
S (2)	1	1	0	1	0	0	1	1	1	0	0	0	1	1	0	1	1	1	0	0	1	1	1	1	0
S (3)	0	1	0	0	1	0	1	0	0	0	0	0	1	0	1	1	1	1	0	0	1	1	0	1	0
S (4)	1	1	1	1	0	1	0	0	1	0	0	1	1	1	0	0	0	0	1	0	1	1	0	1	0
S (5)	0	0	0	1	1	0	0	1	1	0	1	0	0	1	1	0	0	1	0	1	1	0	0	0	1

4 | Numerical Results

To evaluate the efficiency of the mathematical model, computational experiments were conducted using widely used datasets available in the literature on the hub location problem, and the results are presented in this section. The dataset used for the computations is the CAB dataset, which is based on air travel data among 25 different cities in the United States. Since the CAB dataset does not include fixed costs for establishing hubs, three values were considered for the fixed-cost parameter, namely 100, 150, and 200. The discount factor parameter $\alpha$was set at three levels, 0.2, 0.6, and 1, in accordance with commonly used values in the related literature. The mathematical model was solved using the CPLEX solver in GAMS 24.7. All computations were performed on a computer equipped with an Intel Core i7-12700H CPU with a clock speed ranging from 2.3 to 4.7 GHz and 16 GB of RAM, under the Windows 11 operating system. The obtained results are reported in *Table 3*.

Table 3. Numerical results for CAB data set.

α	f_k	w_1	w_2	With Direct Routing		With Panilty	
				opt	Hubs	opt	Hubs
0.2	100	0.1	0.9	141.76	6,12,18,21,22	141.76	6,12,18,21,22
		0.25	0.75	354.41	6,12,18,21,22	354.41	6,12,18,21,22
		0.5	0.5	708.8	6,12,18,21,22	708.8	6,12,18,21,22
		0.75	0.25	1037.97	6,18,21,22	1062.62	6,12,18,21,22
		0.9	0.1	1172.8	6,18,21,22	1224.85	6,18,21,22
	150	0.1	0.9	162.7	6,18,21,22	162.7	6,18,21,22
		0.25	0.75	406.77	6,18,21,22	406.77	6,18,21,22
		0.5	0.5	812.28	6,18,21,22	813.54	6,18,21,22
		0.75	0.25	1187.97	6,18,21,22	1216.18	6,18,21,22
		0.9	0.1	1342.89	6,18,21	1403.09	6,18,21
	200	0.1	0.9	182.7	6,18,21,22	182.7	6,18,21,22
		0.25	0.75	456.77	6,18,21,22	456.77	6,18,21,22
		0.5	0.5	912.28	6,18,21,22	913.54	6,18,21,22
		0.75	0.25	1314.98	6,18,21	1365.57	6,18,21
		0.9	0.1	1433.05	9,13	1538.09	6,18,21
0.6	100	0.1	0.9	161.27	6,18,21,22	161.27	6,18,21,22
		0.25	0.75	403.17	6,18,21,22	403.17	6,18,21,22
		0.5	0.5	805.07	6,18,21,22	806.34	6,18,21,22
		0.75	0.25	1161.77	6,18,21	1205.4	6,18,21,22
		0.9	0.1	1269.99	6,21	1350.01	6,18,21
	150	0.1	0.9	177.47	6,18,21	177.47	6,18,21
		0.25	0.75	443.67	6,18,21	443.67	6,18,21
		0.5	0.5	886.09	6,18,21	887.35	6,18,21
		0.75	0.25	1267.06	6,21	1325.03	6,18,21
		0.9	0.1	1359.99	6,21	1477.08	6,21
	200	0.1	0.9	192.47	6,18,21	192.47	6,18,21
		0.25	0.75	481.17	6,18,21	481.17	6,18,21
		0.5	0.5	952.99	6,21	962.35	6,18,21
		0.75	0.25	1342.06	6,21	1435.24	6,21
		0.9	0.1	1419.99	6,21	1567.82	6,21
1	100	0.1	0.9	171.79	6,18,21	171.79	6,18,21
		0.25	0.75	429.47	6,18,21	429.47	6,18,21
		0.5	0.5	857.63	6,18,21	858.95	6,18,21
		0.75	0.25	1202.12	6,21	1282.42	6,18,21
		0.9	0.1	1282.22	6,21	1398.78	6,21
	150	0.1	0.9	183.98	6,21	183.98	6,21
		0.25	0.75	459.96	6,21	459.96	6,21
		0.5	0.5	909.81	6,21	919.92	6,21
		0.75	0.25	1277.12	6,21	1370.48	6,21
		0.9	0.1	1372.22	6,21	1488.78	6,21
	200	0.1	0.9	193.98	6,21	193.98	6,21
		0.25	0.75	484.96	6,21	484.96	6,21
		0.5	0.5	959.81	6,21	969.92	6,21
		0.75	0.25	1352.12	6,21	1445.48	6,21
		0.9	0.1	1462.22	6,21	1578.78	6,21

In *Table 3*, the term penalty means that, instead of shipping through direct transportation at its corresponding direct cost, a fixed penalty value ($\theta = 1000$) is considered. The results presented in the table indicate that changes in the weights of the objectives have a direct effect on the network structure and the objective function value. When the weight associated with the fixed costs of establishing hubs (w_1) increases, the model tends to select fewer hubs in order to avoid a sharp increase in capital costs. This issue is particularly observable at higher weights, where the combination of selected hubs is reduced to smaller sets. In contrast, when the weight of operational costs (w_2) is higher, the model prefers to keep more hubs active in order to reduce ongoing costs and cover flows through shorter routes, even if this decision leads to a relative increase in capital costs. For example, in the case where the two objectives are considered with equal weights ($w_1 = 0.5$ and $w_2 = 0.5$), the objective function value increases noticeably because both cost components are simultaneously influential. On the other hand, increasing the fixed cost of hub establishment (f_k) leads to changes in the selected hub configuration and an increase in the objective function value. By increasing this cost level from 100 to 150 and 200, the model becomes less inclined to keep all initial hubs open, and the selected configuration shifts toward smaller and more centralized sets, for instance, selecting only two or three hubs instead of the initial five hubs. This behavior is logical, because under conditions of increased capital costs, maintaining multiple hubs is not economically viable, and the model prefers to cover the network with a smaller number of hubs; although this change may lead to an increase in operational costs. Furthermore, the comparison of the results under the two cases of "considering the penalty θ" and "allowing direct shipment" shows that incorporating direct shipment has led to a reduction in the objective function value in many cases.

The possibility of directly transferring flows between some origin–destination pairs without the need to pass through two hubs provides the model with greater flexibility and, under conditions where the number of active hubs is reduced, results in savings in operational costs. This feature becomes particularly more important when hub-to-hub routes are limited, and it contributes to balancing capital and operational costs. Therefore, it can be concluded that, in the design of real-world networks, direct shipment can play an effective role as a complementary strategy in improving network efficiency and resilience. For further analysis, we presented the figures related to allocations in this study. In these figures, the blue points represent the nodes, the red stars indicate the hubs, the black lines represent the connections between hub nodes and non-hub nodes, and the red lines indicate the connections between hubs. In addition, we identified the direct shipments between nodes using yellow lines.

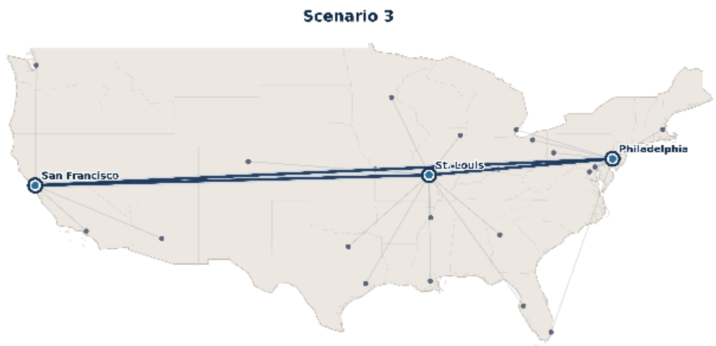

Fig. 1. Hub allocations and direct routing ($\alpha = 0.2$, $f_k = 150$, $w_1 = 0.25$, $w_2 = 0.75$).

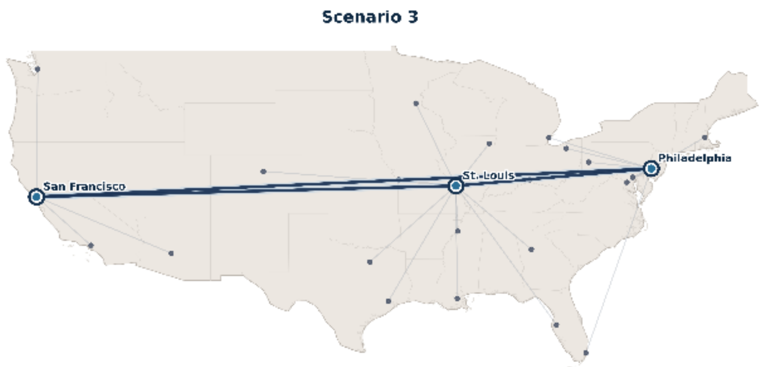

Fig. 2. Hub allocations and direct routing with penalty ($\alpha = 0.2$, $f_k = 150$, $w_1 = 0.25$, $w_2 = 0.75$).

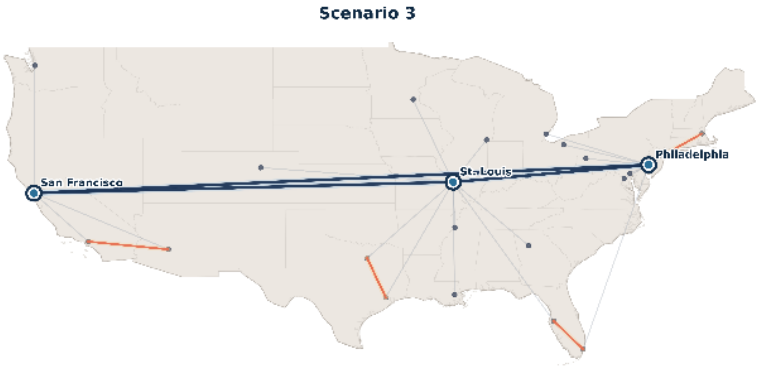

Fig. 3. Hub allocations and direct routing ($\alpha = 0.2$, $f_k = 150$, $w_1 = 0.75$, $w_2 = 0.25$).

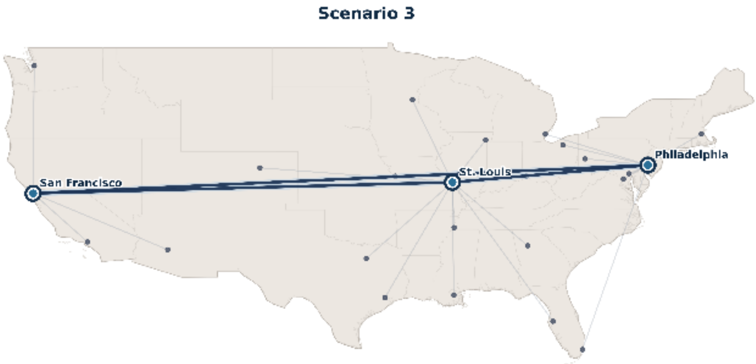

Fig. 4. Hub allocations and direct routing with penalty ($\alpha = 0.2$, $f_k = 150$, $w_1 = 0.75$, $w_2 = 0.25$).

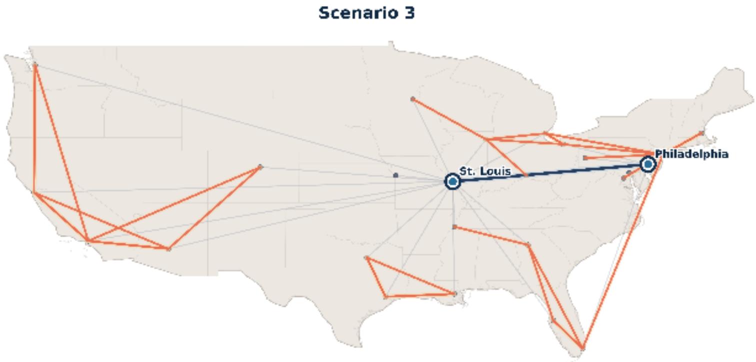

Fig. 5. Hub allocations and direct routing ($\alpha = 0.2$, $f_k = 150$, $w_1 = 0.9$, $w_2 = 0.1$).

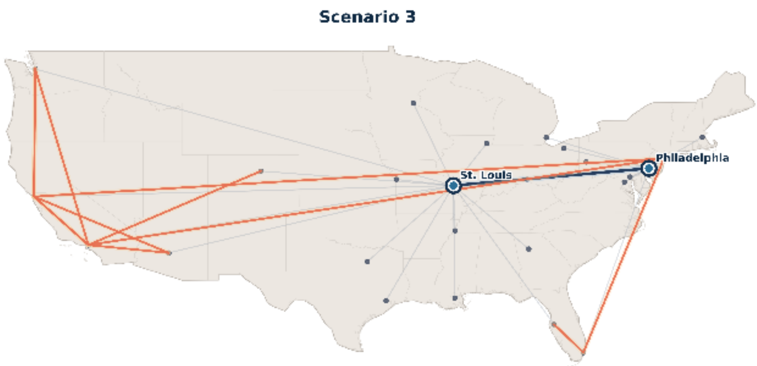

Fig. 6. Hub allocations and direct routing with penalty ($\alpha = 0.2$, $f_k = 150$, $w_1 = 0.9$, $w_2 = 0.1$).

According to *Figs. 1, 3,* and *5*, as (w_2) increases, the amount of direct shipment also increases, because the model shows a greater tendency to cover flows through shorter routes. It can also be stated that the direct allocations in the penalty case, shown in *Figs. 2, 4,* and *6*, differ from those in the direct-shipment case. This is due to the nature of the model, which compares the transportation cost through hubs with the penalty value. Overall, it can be concluded that, in the design of real-world networks, direct shipment can play an effective role as a complementary strategy in improving network efficiency and resilience.

5 | Conclusion

In this study, a bi-objective single-allocation hub location model was proposed by considering uncertainty in hub availability and the possibility of direct shipment. The proposed approach demonstrated that combining flows routed through hubs with direct shipments between some origin–destination pairs can lead to the design of a more efficient and resilient network. Accordingly, the network not only benefits from the advantages of centralization and economies of scale arising from flow consolidation at hubs, but also achieves greater flexibility in dealing with demand variations and potential disruptions through the use of direct routes.

The obtained results indicate that direct shipment can play an important complementary role in network design and can contribute to cost reduction and improved stability under different conditions. This capability becomes particularly important when there are limitations on the number of hubs and flows need to be managed through alternative routes. Therefore, the proposed hybrid approach can provide an effective decision-making framework for the design of real-world networks, especially in transportation and distribution industries.

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Data Availability

Sufficient data is available upon request.

Conflict of Interest

No potential conflict of interest was reported by the authors.

Consent for Publication

All authors have provided their consent for the publication of this manuscript.

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