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Hierarchical facility network planning model for global logistics network configurations

Jiuh-Biing Sheu [a,*], Alex Y.-S. Lin [b]

[a] Department of Business Administration, National Taiwan University, No. 1, Sec. 1, Roosevelt Road, Taipei 10617, Taiwan, ROC
[b] Institute of Traffic and Transportation, National Chiao Tung University, 4F, 118 Chung Hsiao W. Rd., Sec. 1, Taipei 10012, Taiwan, ROC

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ABSTRACT

This paper presents a novel hierarchical network planning model for global logistics (GLs) network configurations. The proposed method, which is based on the fundamentals of integer programming and hierarchical cluster analysis methods, determines the corresponding locations, number and scope of service areas and facilities in the proposed GLs network. Therein, a multi-objective planning model is formulated that systematically minimizes network configuration cost and maximizes both operational profit and the customer satisfaction rate. Particularly, potential risk-oriented costs, such as macro-environmental-risk and micro-operational-risk costs are considered in the proposed model. Numerical results indicate that the overall system performance can be improved by up to 11.52% using the proposed approach.

1. Introduction

Network configurations are critical issues in the area of global logistics (GLs) as they determine the performance of GLs operational strategies. With the rapid maturity of globalization, there is growing recognition that network configurations must be addressed prior to the operations of GLs strategies. Thus, the performance of GLs strategies and their functional integration should rely on elaborate network configurations to accomplish the goals of GLs management. Additionally, numerous international delivery firms (*e.g.* DHL, UPS, FedEx, and TNT) are now aware of the significance of constructing hierarchical GLs network via integration and classification of corresponding facilities, such as international hubs and depots, to enhance global competitiveness.

Despite the importance of GLs network design, planning a GLs hierarchical framework that integrates transnational facilities remains challenging in the area of GLs for the following reasons. First, from a practical point of view, efficiently coordinating activities of all transnational facilities, such as depot–depot, depot–hub and hub–hub shipment and transportation activities in a given GLs framework, is difficult due to the different functional relationships in both the spatial and temporal domains. To a certain extension, this difficulty is rooted in the fact that GLs operational networks are typically hierarchical, containing different nodes located in different network layers, where each node has its own operational goals and problems. Furthermore, existing models that are suitable for GLs hierarchical network planning are scarce. Instead, most of previous literature is likely to address the issue of GLs network configurations directly by mathematical programming, thus solving the induced facility location problems all in one phase without considering the hierarchical and geographic relationships among facilities in a comprehensive GLs network.

In reality, issues of general logistics network configurations have been addressed in some pioneering works [1–7]. For instance, Miller et al. [1] determined the best transport mode and rail network location strategy using a mixed integer

* Corresponding author. Tel.: +886 2 3366 1060; fax: +886 2 2362 5379.
E-mail address: jbsheu550921@yahoo.com.tw (J.-B. Sheu).

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programming model. Crainic [2] used a mathematical programming approach for inter-modal service network design. Crainic's model aims to seek for a set of interrelated decisions that ensure an optimal allocation and utilization of resources to achieve the economic and customer service goals of the company. Melkote and Daskin [3] formulated a combined facility location/network design problem using a mixed integer programming approach, where service capacities of facilities are considered. Cakravastia et al. [4] developed an analytical model of the supplier selection process in designing a supply chain network, where the capacity constraints associated with potential suppliers are considered in the supplier selection process. Jayaraman and Ross [5] proposed the Production, Logistics, Outbound, Transportation (PLOT) distribution network design system, which was characterized by functions of multiple distribution channel members and their corresponding locations. Drezner and Wesolowsky [6] introduced a novel network design problem which determines the links and facility locations, using several heuristic solution tools such as a descent algorithm, simulated annealing, tabu search, and a genetic algorithm. Ambrosino and Scutella [7] solved some complex distribution network design problems, which involve facility location, warehousing, transportation and inventory decisions. Nevertheless, the early works mentioned above seem to seek for one-shot solutions for general logistics network configurations, and thus are likely to have a common challenge in computational efficiency for large-scale network cases.

A few hierarchical network design studies have used algorithms [8–10]. For instance, Current et al. [8] formulated a hierarchical network design problem (HNDP) for identifying the shortest paths among facilities in a proposed two-level hierarchical network. This hierarchical network included a primary path from a predetermined start node to a predetermined terminal node. Additionally, each node without a primary path must be connected to a given node on the primary path via a secondary path. Sancho [9] developed a dynamic programming model to find a suboptimal solution for the HNDP with multiple primary paths. For all hierarchical network characteristic, the model still stresses the algorithm improvement to search better optimal solution in the proposed model. Furthermore, some researchers have applied the concept of hierarchical networks for vehicle routing and network design problems with time windows. For example, Lin and Chen [10] utilized a time-constrained hierarchical hub-and-spoke network to determine fleet size and schedules on primary and secondary routes to minimize total operating cost while meeting the desired service level. In spite of hierarchical concept in this model, the master–slave relationships of facilities are not considered in this paper.

Although certain advances have been made in general network design, studies regarding hierarchical GLs network configurations are rare. Particularly, the previous literature is limited to the scope of domestic logistics, and thus, issues of global logistics and influencing factors such as operational and investment risks characterizing uncertainties of transnational logistics activities remain unsolved. Accordingly, this paper presents a novel planning methodology for hierarchical GLs network that integrates cluster analysis and integer programming to solve the GLs network design problem. By taking advantage of related techniques for computational efficiency [11–18], this study uses hierarchical clustering to partition the demand dataset into a meaningful set of mutually exclusive hierarchical clusters. This is followed by GLs facility classification, where influencing factors such as GLs resources, facility size, and service area associated with each type of facility are considered. The integer programming methodology is then applied to address the resulting network design issues, where the corresponding facilities, including hubs, distribution centers and warehouse depots, are hierarchically structured. In formulating the proposed model, this study also considered multiple GLs channel members and related factors (*e.g.*, customs accessibility, transnational transportation and inventory costs, potential benefits, special susceptible area distribution restrictions, and long-term regional market demand conditions).

The remainder of this paper is organized as follows. Section 2 describes the development of a conceptual framework using the proposed methodology, where the corresponding GLs facilities are embedded in the network. The details of the model formulation are given in Section 3. In Section 4, a numerical study is used to demonstrate the feasibility of the proposed method; sensitivity analyses are also discussed in this section. Finally, concluding remarks and directions for future research are summarized in Section 5.

2. System specification

This section presents system specifications, which include system component definitions (*i.e.*, nodes), and the conceptual framework of the proposed model.

In the proposed model, three node types are defined—(1) hubs, (2) distribution centers, and (3) warehouse depots—based on the service-competence intensity (ρ) of the facility. The service-competence intensity (ρ) is composed of transshipment amount (α) and storage value (β) from each original demand spot, where $\rho = \alpha + \beta$.

In fact, the facility service-competence intensity (ρ) index is proposed to determine the types of candidate facilities in this work. Specifically, this indicator is used to assist the enterprise in appropriately allocating capital resources to improve the effectiveness of GL network configurations. If the types of facilities are not determined appropriately, the GL supply and demand sides cannot match each other properly, which may lead to serious operational problems, *e.g.*, the serious overstocks or idle facilities. Accordingly, three types of facilities are specified, and differentiated based on boundaries with respect to ρ using the following facility identification rules.

(1) a hub is specified when its service-competence intensity (ρ) is $\geqslant \delta_1$,
(2) a distribution center is a regional logistics facility identified when $\delta_2 \leqslant \rho < \delta_1$,
(3) a warehouse depot is a local logistics facility identified when $\rho < \delta_2$,

where δ_1 and δ_2 are two thresholds which can be determined by averaging the values suggested by GL enterprise managers in practical applications.

To formulate the hierarchical GLs network problem, a comprehensive conceptual model is proposed (Fig. 1), which involves the following three operational phases: (1) hierarchically clustering demand spots; (2) determining the number and type of nodes; and, (3) determining the location of nodes to design the proposed hierarchical GLs OR network. During phase 1, the original demand spots locations are identified, and then hierarchically clustered. Accordingly, the number and location of facility nodes for each demand group are determined in phases 2 and 3 using integer programming. Moreover, this study also considers several influential factors, such as investment costs and risks, logistics operational costs, potential benefits, transnational logistics restrictions, and regional demand variations, when formulating the proposed multi-objective function and to alleviate decision bias when configuring the hierarchical GLs network and locating the corresponding facilities. The corresponding models applied in these phases are described in Section 3.

To facilitate model formulation, we make the following four assumptions.

(1) Only three facility types, hubs, distribution centers and warehouse depots, are considered in the proposed model. These three facility types differ in their express cargo capacities.
(2) The demand quantity associated with each given original demand spot is known.
(3) The range of service-competence intensity associated with each node type in the proposed hierarchical GLs network is known.
(4) The proposed hierarchy is composed of three layers—hubs, distribution centers, and warehouse depots—where the facilities on a given layer are served by facilities of layer directly above. For instance, the hub layer only serves the distribution center layer, and similarly, the distribution center layer provides service only to the layer containing the warehouse depots.

3. Model development

Fig. 2 shows the scheme of the proposed planning model of the hierarchical GLs network; this model has three sequential phases. During the first phase, hierarchical cluster analysis is applied to classify demand spots into hierarchical demand groups. The next two phases are executed to determine appropriate number, types, and locations of GLs facilities using

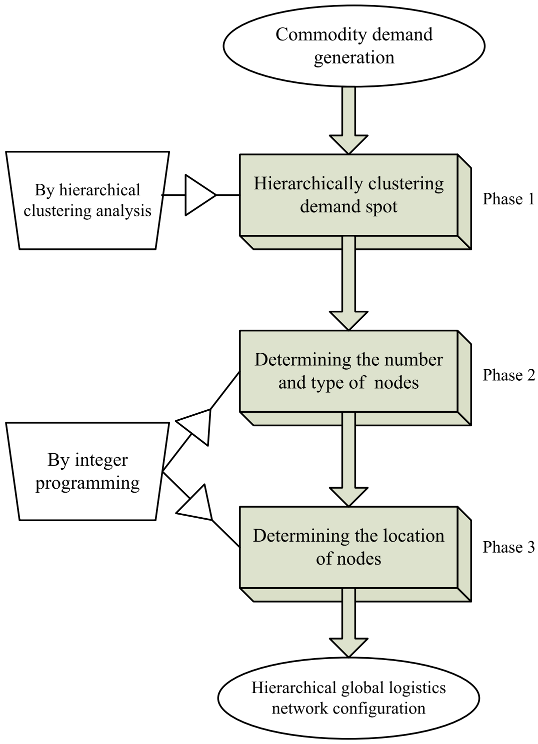

Fig. 1. Conceptual model.

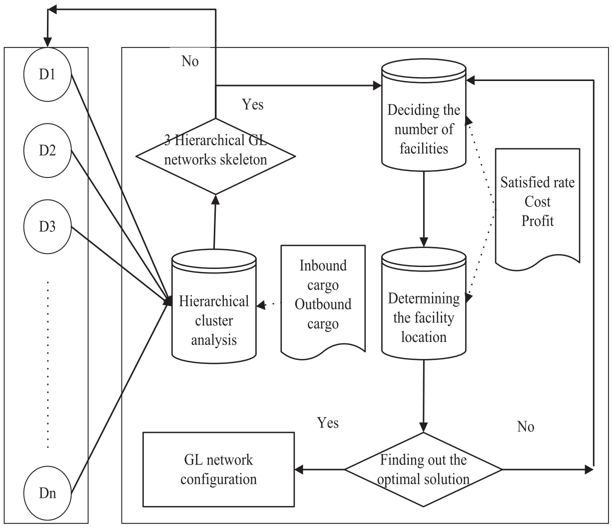

Fig. 2. Scheme of the proposed model.

the proposed integer programming model. The details of the developmental procedures associated with phases 1, 2, and 3 are presented in the following three subsections.

3.1. Demand-spot hierarchical cluster analysis

The hierarchical cluster analysis (Fig. 3) is composed of the following three steps: (1) selection of distance metrics; (2) variable standardization; and, (3) hierarchical clustering. The primary steps executed are as follows.

During the first step (*i.e.*, selection of distance metrics), hierarchical cluster analysis considers each given object i as a point in a multi-dimensional space characterized by two attributes—the amount of inbound (σ_i^1) and outbound (σ_i^2) cargo associated with object i. The distance between two objects is measured to determine the similarity among objects in terms of object attributes. Thus, the choice of a distance metric is the initial step in hierarchical cluster analysis. Although various distance metrics exist, such as Euclidean distance, Mahalanobis distance, city block distance, and Minkovski distance, Euclidean distance is utilized in this study as it is the most common and intuitive measure used in literature [19] when focusing on facility location.

The second step (*i.e.*, variable standardization) standardizes specified attributes. Variable standardization is an important step in hierarchical cluster analysis, since differences in units and magnitude of variance between attributes influence

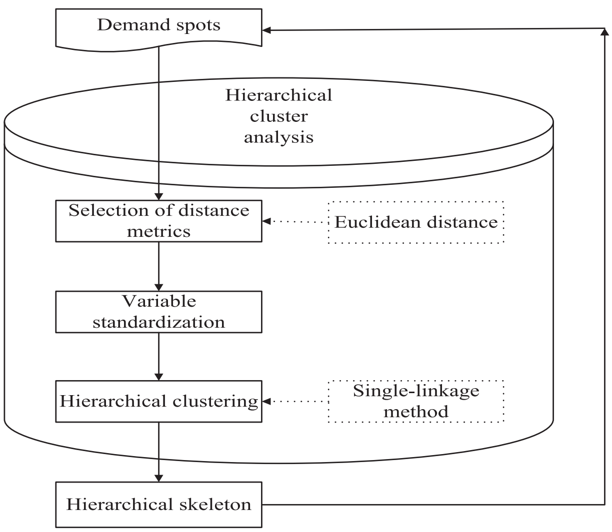

Fig. 3. Conceptual framework for cluster analysis.

computational results of distance metrics. Therefore, each attribute σ_i^p type is standardized; herein, the standardized attribute ($\tilde{\sigma}_i^p$) is given by

$$\tilde{\sigma}_i^p = \frac{\sigma_i^p - \sigma^{-p}}{S^p}, \tag{1}$$

where σ^{-p} and S^p are the mean and standard deviation of σ_i^p, respectively, and are given by

$$\sigma^{-p} = \frac{\sum_{i=1}^{N} \sigma_i^p}{N}, \tag{2}$$

$$S^p = \left[\frac{\sum_{i=1}^{N}(\sigma_i^p - \sigma^{-p})}{N-1}\right]^{\frac{1}{2}}, \tag{3}$$

where N is the number of customer demand spots from original data.

After measuring the distance metrics and standardizing variables, the final step is hierarchical clustering. Since the purpose of hierarchical cluster analysis is to combine objects into groups or hierarchical clusters, some method-based rules are required to determine how to form these hierarchical clusters. In reality, some common centroid algorithms, such as the single-linkage method, the complete-linkage method, average-linkage method and Ward method, can be used for hierarchical clustering [20]. The single-linkage method is adopted as its computational process is generally shorter than that of the other methods. In the single-linkage method, the distance between two clusters is the minimum distance between all possible object pairs in two clusters. The Euclidean distance matrix (M) can then be constructed, as in Eq. (4), where each element (ω_{ij}) represents the distance between a given cluster pair such as i and j

$$M = \begin{bmatrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1i} \\ \omega_{21} & \omega_{22} & \cdots & \omega_{2i} \\ \ddots & \ddots & \vdots & \ddots \\ \omega_{i1} & \omega_{i2} & \cdots & \omega_{ij} \end{bmatrix}_{i\times j}, \quad \omega_{ij} - 0, \quad \text{if} \quad i = j, \quad \omega_{ij} = \omega_{ji}, \quad \text{if} \quad i \neq j. \tag{4}$$

To obtain a hierarchical skeleton, the Euclidean distance matrix (M) is calculated three times to find any arbitrary two demand spot minimum Euclidean distance by the single-linkage method. After the hierarchical clustering procedure, this study starts on layer 3 (*i.e.*, the bottom layer) to create the hierarchical tree (Fig. 4). The vertical axis of a hierarchical tree is the Euclidean distance where two objects or clusters merge to form a larger cluster.

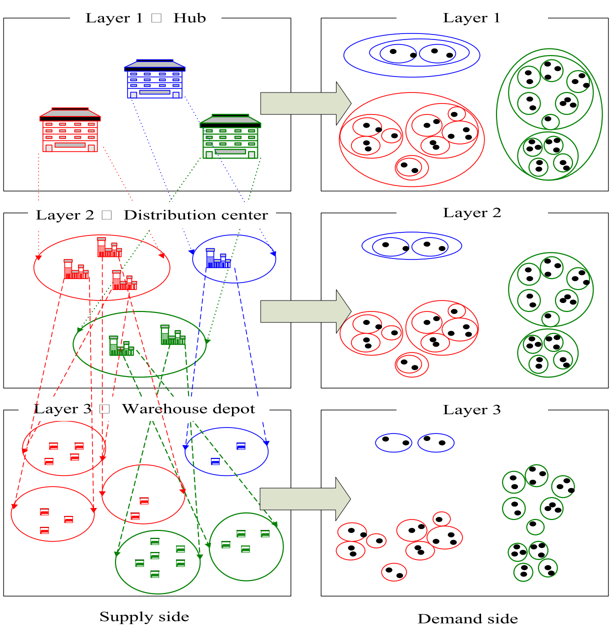

Fig. 4. Illustration of a hierarchical tree.

3.2. Facility network configurations

This subsection presents the second and third mechanisms utilized to construct facility networks via integer programming. Given the aforementioned assumptions, an integrated and composite multi-objective model is formulated to obtain optimal solutions with the goals of minimizing hierarchical GLs network investment cost ($\mathbf{\Theta}_1$), maximizing profit from hierarchical GLs network operations ($\mathbf{\Theta}_2$), and the aggregate satisfaction rate of customer demand ($\mathbf{\Theta}_3$). However, these three goals may be in conflict during the corresponding hierarchical GLs network configuration process. A typical example is the trade-off between minimizing hierarchical GLs network investment cost and maximizing operational profit. The mathematical formulation of the proposed model is as follows.

Fig. 5 presents the relationship between the composite multi-objective function ($\mathbf{\Theta}$), the three sub-objective functions ($\mathbf{\Theta}_1$, $\mathbf{\Theta}_2$, and $\mathbf{\Theta}_3$) and the affiliated factors of the three sub-objective functions.

After considering the effects of $\mathbf{\Theta}_1$, $\mathbf{\Theta}_2$, and $\mathbf{\Theta}_3$ on $\mathbf{\Theta}$, three corresponding weights, w_1, w_2, and w_3, are specified that are associated with $\mathbf{\Theta}_1$, $\mathbf{\Theta}_2$, and $\mathbf{\Theta}_3$, respectively. These three weights are also subject to the condition that the sum of w_1, w_2, and w_3 is 1.

Notably, the difference in measurement scales associated with $\mathbf{\Theta}_1$, $\mathbf{\Theta}_2$, and $\mathbf{\Theta}_3$ may also influence the determination of optimal solutions. Therefore, the proposed multi-objective functions are rewritten as a composite normalized form $\mathbf{\Theta}$ given by

$$Max \quad \mathbf{\Theta} = \sum_{\sigma=2}^{3} w_\sigma \times \frac{\Theta_\sigma^o - \Theta_\sigma^{\min}}{\Theta_\sigma^{\max} - \Theta_\sigma^{\min}} - w_1 \times \frac{\Theta_1^o - \Theta_1^{\min}}{\Theta_1^{\max} - \Theta_1^{\min}}. \tag{5}$$

That is, these three sub-objective functions, $\mathbf{\Theta}_1$, $\mathbf{\Theta}_2$, and $\mathbf{\Theta}_3$, can be expressed, respectively, as

$$\Theta_1 = \frac{\Theta_1^o - \Theta_1^{\min}}{\Theta_1^{\max} - \Theta_1^{\min}} \tag{6}$$

$$\Theta_2 = \frac{\Theta_2^o - \Theta_2^{\min}}{\Theta_2^{\max} - \Theta_2^{\min}} \tag{7}$$

$$\Theta_3 = \frac{\Theta_3^o - \Theta_3^{\min}}{\Theta_3^{\max} - \Theta_3^{\min}} \tag{8}$$

where $\Theta_1^{\max}$ and $\Theta_1^{\min}$ are the maximum and minimum values associated with the investment cost $\mathbf{\Theta}_1$ originating from hierarchical GLs network, respectively; and $\Theta_2^{\max}$ and $\Theta_2^{\min}$ are the maximum and minimum values associated with related profit $\mathbf{\Theta}_2$ originating from the hierarchical GLs network operations, respectively; and, $\Theta_3^{\max}$ and $\Theta_3^{\min}$ are the maximum and minimum values associated with the related satisfaction rate associated with customer demand, respectively. The components of $\mathbf{\Theta}_1$, $\mathbf{\Theta}_2$, and $\mathbf{\Theta}_3$ are further discussed as follows.

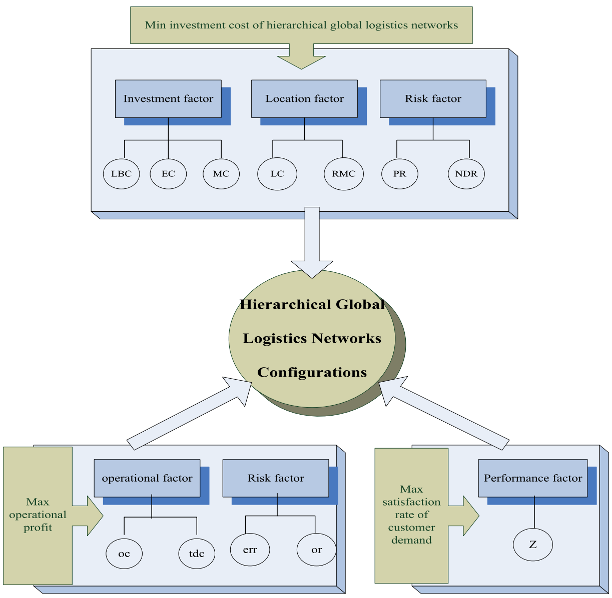

Fig. 5. Conceptual framework for the composite multi-objective function.

The hierarchical GLs network investment cost ($\boldsymbol{\Theta}_1$) is measured by adding such corresponding costs as building cost (BC), land cost (LC), asset input cost (AIC), and related risk cost (RRC), as expressed by Eq. (9)

$$\boldsymbol{\Theta}_1 = BC + LC + AIC + RRC. \tag{9}$$

Therein, BC is further decomposed into raw material cost (RMC) and labor cost (LBC). For the AIC, costs are considered in terms of machine cost (MC) and equipment cost (EC). For risk-induced cost (RERC), the corresponding political risk (PR) and natural disaster risk (NDR) are considered. In this objective function, $X_{i_h^s j}$ is a 0–1 decision variable representing the decision of whether to locate the ith facility in the sth area of the hth layer to serve the jth demand spot. Accordingly, $\boldsymbol{\Theta}_1$ (see Eq. (9)) can be further expressed as

$$\begin{aligned}\boldsymbol{\Theta}_1 &= \sum_{\forall s}\sum_{\forall h}\sum_{\forall i_h^s}\sum_{\forall j}\left(BC_{i_{h,j}^s} + LC_{i_{h,j}^s} + AIC_{i_{h,j}^s} + RERC_{i_h^s}^{\Theta_1}\right)\times X_{i_{h,j}^s}\\ &= \sum_{\forall s}\sum_{\forall h}\sum_{\forall i_h^s}\sum_{\forall j}\left[\left(RMC_{i_{h,j}^s} + LBC_{i_{h,j}^s}\right) + LC_{i_{h,j}^s} + \left(MC_{i_{h,j}^s} + EC_{i_{h,j}^s}\right) + \left(PR_{i_h^s} + NDR_{i_h^s}\right)\right]\times X_{i_{h,j}^s}.\end{aligned} \tag{10}$$

Similarly, the profit from the hierarchical GLs network operations ($\boldsymbol{\Theta}_2$) is based on total revenues (r) across the three-layer hierarchical GLs network minus the sum of induced costs, which include operational cost (oc), transportation and distribution cost (tdc), and operational risk-oriented cost (rorc) for the operations of the hierarchical GLs network, as expressed in Eq. (11)

$$\boldsymbol{\Theta}_2 = r - oc - tdc - rorc = \sum_{\forall s}\sum_{\forall h}\sum_{\forall i_h^s}\sum_{\forall j}\left(r_{i_{h,j}^s} - oc_{i_{h,j}^s} - tdc_{i_{h,j}^s} - rorc_{i_{h,j}^s}^{\Theta_2}\right)\times X_{i_{h,j}^s}\times Y_{i_{h,j}^s} \tag{11}$$

where $Y_{i_h^s j}$ is a decision variable representing the amount distributed from the ith facility located in the sth area of the hth layer to the jth demand spot. In terms of the operational *rorc*, this study considers the costs induced by exchange rate risk (*err*) and human risk (*hr*); thus, Eq. (11) can be rewritten as

$$\boldsymbol{\Theta}_2 = \sum_{\forall s}\sum_{\forall h}\sum_{\forall i_h^s}\sum_{\forall j}\left[r_{i_{h,j}^s} - oc_{i_{h,j}^s} - dc_{i_{h,j}^s} - \left(err_{i_{h,j}^s} + hr_{i_{h,j}^s}\right)\right]\times X_{i_{h,j}^s}\times Y_{i_{h,j}^s}. \tag{12}$$

The last sub-objective function ($\boldsymbol{\Theta}_3$), *i.e.*, the aggregate satisfaction rate of customer demand ($\boldsymbol{\Theta}_3$), accounts for the proportion (Z) of potential consumer demands (D) that can be served by the logistics distribution amount (Y) planned within a preset upper bound of delivery time ($\bar{t}$). Thus, $\boldsymbol{\Theta}_3$ is given by

$$\boldsymbol{\Theta}_3 = \sum_{\forall s}\sum_{\forall h}\sum_{\forall i_h^s}\sum_{\forall j} Z_{i_h^s j}\times X_{i_h^s j} = \sum_{\forall s}\sum_{\forall h}\sum_{\forall i_h^s}\sum_{\forall j}\left(t_{i_h^s j}\times\frac{Y_{i_h^s j}}{D_j}\right)\times X_{i_h^s j}. \tag{13}$$

3.3. Related model constraints

The required conditions of decision variables $X_{i_h^s j}$ and $Y_{i_h j^s}$, either caused by corporate regulations and law or limited by operating capacities, 11 groups of constraints are specified, as in Eqs. (14)–(24).

$$\sum_{\forall s}\sum_{\forall h}\sum_{\forall i_h^s} X_{i_h j^s} = 1, \quad \forall j, \tag{14}$$

$$\sum_{\forall j} Y_{i_h^s j} \leqslant \overline{Y}_{i_h^s}, \quad \forall (i_h^s, h, s), \tag{15}$$

$$0 \leqslant t_{i_h j^s} \leqslant \bar{t}, \quad \forall (i_h^s, j, h, s), \tag{16}$$

$$\underline{U}_{i_h^s} \sum_{\forall j} Zi_h, j^s \leqslant \overline{Z}_{i_h^s}, \quad \forall (i_h^s, h, s), \tag{17}$$

$$\sum_{\forall s}\sum_{\forall h}\sum_{\forall i_h^s} Y_{i_h j^s} \geqslant D_j, \quad \forall j, \tag{18}$$

$$\sum_{\forall s}\sum_{\forall h}\sum_{\forall i_h^s} Z_{i_h j^s} \geqslant G_j, \quad \forall j, \tag{19}$$

$$RERC_{i_h^s}^{\Theta_1} \leqslant \delta_{i_h^s}^{\Theta_1}, \quad \forall (i_h^s, h, s), \tag{20}$$

$$rorc_{i_h^s}^{\Theta_2} \leqslant \delta_{i_h^s}^{\Theta_2}, \quad \forall (i_h^s, h, s), \tag{21}$$

$$X_{i_h j^s} \in \{0, 1\}, \quad \forall (i_h^s, j, h, s), \tag{22}$$

$$Y_{i_h j^s} \geqslant 0, \quad \forall (i_h^s, j, h, s), \tag{23}$$

$$Z_{i_h j^s} \geqslant \underline{Z}_j, \quad \forall (i_h^s, j, h, s). \tag{24}$$

In Eq. (14), decision variable $X_{i_h^s,j}$ is specified to ensure that any demand spot is served by only one facility to avoid squandering facility resources. Eq. (15) represents the corresponding upper bound limitation of the decision variable $Y_{i_h^s,j}$. Eqs. (16) and (17) are the upper and lower bounds associated with derivative decision variable $Z_{i_h^s,j}$ and parameter $t_{i_h^s,j}$ while considering potential governmental regulations and basic requirements for international express delivery enterprise distribution resource allocation. Eqs. (18) and (19) represent the basic requirements for service levels in terms of in-bound logistics and satisfaction rate of the customer associated with each given demand spot. Eqs. (20) and (21) are specified for the concerns of the maximum external and internal risks tolerated by enterprises. For example, the transnational investment of an enterprise may account for varied potential risks caused by uncertainties associated with either natural and artificial events such as natural disasters, anomalous variations in exchange rates, and political risks. Therefore, the upper bounds of the RERCs are specified in the model.

In addition to the aforementioned constraints, all decision variables should be subject to the non-negative domain to meet the basic requirement of a feasible solution. Correspondingly, all decision variables should be restricted to the real-value domain that is $\geqslant 0$, and the others are 0–1 binary decision variables, as in Eqs. (22)–(24). Therefore, according to the proposed model, the optimal solutions of decision variables together with these updated functions will determine the best location and optimal distribution amount for each layer under the optimized system for hierarchical GLs network.

4. Numerical study

4.1. Experimental design and data collection

The numerical study is focused on the case of an international express delivery company, DHL. Its current international express cargo capacity is more than 1 billion ton, accounting for nearly 30% of all international express cargo. Additionally, the DHL global network has four head offices. Each head office has 2–5 hubs in operation; thus, 12 hubs are considered. Based on the study scope and limitations in acquiring real data, we assume the international express delivery demands are from Taiwan, China, and the USA, which, as mentioned, are the three dominant international express delivery cargo sources worldwide. Furthermore, as cross-strait direct shipping is prohibited, transnational cargo transportation between Taiwan and China is not considered in this case study.

This case study considered three regions, Taiwan, China, and the USA, for the GLs network configurations. Therein, 15 original demand spots are located in Taiwan, 116 original demand spots are in China, and 260 original demand spots in the USA where these demand spots are determined using local population data. The thresholds δ_1 and δ_2 associated with the facility service-competence intensity index (ρ) were determined by averaging the values suggested by GL enterprise managers were used in the case study. Based on the predetermined thresholds and proposed facility identification rules, 3 original demand spots in Taiwan (*e.g.* Taipei, Taichung, and Kaohsiung) were chosen as candidates for the consideration of locating hubs. Similarly, there are 15 and 36 original demand spots chosen as candidates for locating hubs in China and the USA, respectively. Accordingly, the problem scope has 3429 decision variables subject to 1068 constraints.

The local express-delivery demand was estimated based on input data. Notably, the primary purpose of this numerical study is to demonstrate the applicability of the proposed approach to a simplified case (DHL). Due to difficulties in collecting real demand data for each demand spot, this study utilized a simple data processing procedure. Processed demand data were then used as the common database to assess the relative performance of the proposed model by comparing it with the existing performance of DHL.

First, this study collected data for local populations of these demand spots and the corresponding gross domestic product (GDP) data from databases in Taiwan, China, and the USA. International express delivery demand associated with each original demand spot was then approximated using a proportion of GDP and the corresponding local population.

The next step generated a four-tier GLs hierarchical network, including the three main regions (first tier), sub-regions (second tier), the local area (third tier), and original demand spots (fourth tier) based on geographical relationships. Table 1 presents hierarchical cluster results.

Notably, errors in demand data approximation may exist. However, this issue may not be of major concern based on study scope and its primary purpose.

4.2. Setting parameters

Model parameters estimated in this scenario are classified into (1) cost-related parameters, (2) risk-related parameters, and (3) boundary conditions. These parameters were estimated using interview survey data and corresponding statistics.

Practically, estimating cost-related parameters, such as unit operational cost, directly from reported statistical data is difficult due to business confidentiality and security concerns. Therefore, interviews with key staff in express operations and logistics-related sectors of DHL were conducted to collect real data. The interviews utilized both open-ended and closed questions regarding existing strategies in express air delivery and logistics management, as well as potential limitations. A questionnaire was designed based on the need to estimate cost-related parameters of the model. For example, given a cost item, the corresponding survey respondent was asked to measure unit cost within an acceptable range. Analytical results of interviews were then processed to determine unit operational costs and boundaries using uniform distributions with ranges

Table 1
Hierarchical cluster results of the proposed GLs network.

1st tier Region	2nd tier Sub-regions	3rd tier Local area (Original demand spots)
Taiwan	1. Northern	Taipei (6), Keelung (1), Taoyuan (2), Hsinchu (1)
	2. Central and southern	Taichung (1), Chiayi (1), Tainan (1), Kaohsiung (2)
China	1. Northern China	Beijing (1), Tianjin (1), Hebei (10), Shanxi (3), Inner Mongolia (2)
	2. Central China	Henan (9), Hubei (3), Hunan(7)
	3. Southern China	Guangdong (10), Hainan (1), Hong Kong (1), Macao (1), Guangxi (3)
	4. Eastern China	Shanghai (1), Shandong (5), Jiangsu (11), Anhui (6), Zhejiang (3), Jiangxi (1), Fujian (3)
	5. Nothern-east China	Liaoning (11), Jilin (3), Heilongjiang (5)
	6. Northern-west China	Shaanxi (2), Gansu (1), Qinghai (1), Ningxia (1), Xinjiang (2)
	7. Southern-west China	Chongqing (1), Sichuan (3), Yunnan (1), Guizhou (2), Tibet (1)
The USA	1. New England	Connecticut (5), Maine (1), Massachusetts (5), New Hampshire (1), Rhode Island (1), Vermont (1)
	2. Atlantic	Delaware (1), District of Columbia (1), Florida (17), Georgia (5), Maryland (1), New Jersey (4), New York (5), North Carolina (7), Pennsylvania (4), South Carolina (2), Virginia (9), West Virginia (1)
	3. Mid-west	Illinois (7), Indiana (4), Iowa (2), Michigan (7), Minnesota (2), Nebraska (2), North Dakota (1), Ohio (6), South Dakota (1), Wisconsin (3)
	4. South	Alabama (4), Arkansas (1), Kentucky (2), Kansas (5), Louisiana (4), Mississippi (1), Missouri (4), Oklahoma (3), Tennessee (5), Texas (25)
	5. Rockies	Arizona (9), Colorado (9), Idaho (1), Montana (1), New Mexico(1), Utah(2), Wyoming (1)
	6. Pacific	Alaska (1), California (62), Hawaii (1), Nevada (4), Oregon (3), Washington (5)

Note: the number inside parentheses in the third-tier column is the number of original demand spots.

Table 2
Estimated parameters of the minimum cost objective function.

Region	Type of cost (US$)						
	$RMC_{i_h^s j}$	$LBC_{i_h^s j}$	$LC_{i_h^s j}$	$MC_{i_h^s j}$	$EC_{i_h^s j}$	$PR_{i_h^s j}$	$NDR_{i_h^s j}$
Taiwan	3	2	100	8	6	50	85
China	6	6	110	4	9	35	60
The USA	5	4	100	9	7	40	75

bounded by the estimated upper and lower bounds in the profit-maximization objective function and corresponding constraints, respectively.

Risk-related parameters estimated in this scenario aim at the unit increments of money (m) risks for environmental risk cost and operational risk cost induced by the hierarchical GLs network configuration. Corresponding parameters are classified into and associated with the following five activities: (1) government stability ($m^{gs}_{i^s_h}$); (2) earthquake ($m^{e}_{i^s_h}$); (3) flood ($m^{f}_{i^s_h}$); (4) exchange rate ($m^{er}_{i^s_h}$); and (5) personnel skills ($m^{ps}_{i^s_h}$). Among these risk-related parameters, $m^{gs}_{i^s_h}$ and $m^{ps}_{i^s_h}$ are associated with the corresponding artificial organization and behavior; the others are influenced by natural disasters and operational situations in the resulting hierarchical GLs network. As mentioned, a unit increase in risk-induced penalty refers to the monetary value of a particular penalty caused by the unit of a given physical amount associated with a particular activity.

According to literature, a democratic or communist regime may affect aspirations and freedoms related to business secrets for an international express delivery enterprise. Conveniently, $m^{gs}_{i^s_h}$ was derived from comparative measures of freedom developed by the Freedom House and Business Environment Risk Intelligence [21].

To estimate unit incremental risks $m^{e}_{i^s_h}$ and $m^{f}_{i^s_h}$ for natural disasters, this study first averaged aggregate earthquake and flood damage costs of these three regions over the last 30 years using historical data provided by central governments. Second, aggregate damage costs caused by earthquakes and floods were measured using the averaged aggregate earthquake and flood damage costs multiplied by the ratio of natural disaster frequency over the last 30 years.

Conversely, exchange rate risk (*err*) may depend on foreign reserves, exchange law, and foreign debt. Therefore, this study estimated the exchange-oriented risk ($m^{er}_{i^s_h}$) by approximating the corresponding comparative measures of exchange risk from BERI, which is similar to the concept of political risk cost for the three regions. Here, according to the proposed method, exchange risk can be expressed by the amount of foreign debt divided by the amount of foreign reserves. In this case study, statistics for foreign debt and foreign reserves for these three governments were used to estimate the corresponding exchange risk.

Similar to risks induced by the government stability, personnel skill risk (*ps*) can be caused by either Democracy or Communism. Accordingly, ($m^{ps}_{i^s_h}$) was estimated using comparative measures of freedom developed by the Freedom House and

BERI for workers and society. Notably, parameter $m_{i_h^s}^{ps}$ may vary with race; particularly, whites currently have an advantageous position worldwide.

Accordingly, cost- and risk-related parameters of the proposed composite multi-objective function ($\boldsymbol{\Theta}$) were estimated. Tables 2 and 3 show the parameters in the hierarchical GLs network based the cost-minimum function ($\boldsymbol{\Theta}_1$) and profit-maximum function ($\boldsymbol{\Theta}_2$), respectively. Additionally, other primary parameters, such as upper and lower bounds of logistics-related facilities, were also specified using the collected data and corresponding corporate regulations in Table 4.

4.3. Analysis of numerical results

This section introduces the numerical results to demonstrate the applicability of the proposed hierarchical GLs network based on the model for planning and the operations of coordinated air cargo express delivery, given the predetermined data for international express delivery cargo demand and estimated parameters. Numerical studies consider two different test scenarios for different purposes. The first test scenario involves evaluating the performance of the proposed model in comparison with existing performance (*i.e.*, express delivery enterprise case without coordination of three facilities, including hubs, distribution centers, and warehouse depots). In the second test scenario, this work conducts sensitivity analyses aiming at several target parameters including the weights (w_1, w_2, and w_3) associated with these three sub-objective functions, and boundaries associated with the facility service-competence intensity indexes. Notably, all the other parameters preset in Tables 2–4 remain the same in the test scenarios. The sensitivity analyses are mainly used to realize what the most important parameters are in the enterprise and assist in enterprise resource planning. The Lingo 9.0 software package, which is a commercial optimization package widely used for solving optimization problems [22], is employed to search for optimal solutions to the formulated problems in these two scenarios.

In the first test scenario, we generated optimal solutions using the proposed model, and then compared the resulting aggregate profit with existing operational performance. According to analytical results of the interview surveys of high-level decision-makers at the Taiwan branch of DHL, the existing GLs network of DHL are primarily driven by operational strategies to maximize profit. To compare with the existing operational strategy, the weight (*i.e.*, w_2) associated with the sub-objective function of profit-maximization is set to 1 in this test scenario to conform to the existing operational strategy. Table 5 presents the comparison results with respect to system performance.

Overall, numerical results (Table 5) indicate that the proposed model is likely to outperform the existing strategy by comparing the overall system performance. As can be seen in Table 5, the overall system performance is improved by 11.52%, which is mainly attributed to the relative improvement (16.58%) in aggregate profit. Such an analytical result also implies that the existing GL network configurations and corresponding operational strategy leave room for improvement.

Table 3
Estimated parameters of the maximum profit objective function.

Region	Type of cost (US$)				
	$r_{i_h^s,j}$	$oc_{i_h^s,j}$	$tdc_{i_h^s,j}$	$err_{i_h^s,j}$	$hr_{i_h^s,j}$
Taiwan	17	3.8	5	20	22
China	12	2.7	4	25	17
The USA	13	3.5	4.5	12	18

Table 4
Primary constraint parameters.

Region	Parameters							
	$\bar{t}_{i_h^s,j}$	$\bar{Y}_{i_h^s}$	$\bar{Z}_{i_h^s}$	$\underline{Z}_{i_h^s}$	$\delta_{i_h^s}^{\Theta_1}$	$\delta_{i_h^s,j}^{\Theta_2}$	G_j	$\underline{Z}_j$
Taiwan	3	60,000	0.85	0.8	350	450	0.6	0.55
China	5	85,000	0.9	0.85	550	300	0.65	0.6
The USA	4	55,000	0.85	0.8	500	400	0.7	0.55

Table 5
Evaluation of relative system performance using the proposed model.

Evaluation criteria	Aggregate profit (US$$10^9$)	Aggregate cost (US$$10^9$)	Risk
The proposed model	12.15	0.88	0.75
The existing operational strategy	10.42	0.96	0.83
Increase in net profit/decrease in cost	1.73	0.08	0.08
Relative improvement (%)	16.58	8.33	9.64
Overall improvement (%)	11.52		
CPU times (in seconds)	372.18		

Table 6
Results of sensitivity analysis with respect to δ_1.

Country	Threshold δ_1 increment (%) Variations in service-competence intensity				
	−50%	−25%	0	+25%	+50%
Taiwan	Kaohsiung, Keelung, Taichung, Taipei 4	Kaohsiung, Taichung, Taipei 3	Kaohsiung, Taichung, Taipei 3	Kaohsiung, Taipei 2	Taipei 1
China	Harbin, Shenyang, Changchun, Chongqing, Shanghai, Nanjing, Chengdu, Wuhan, Changsha, Beijing, Tianjin, Xi'an, Taiyuan, Guangzhou, Hong Kong, Dalian, Jinan, Hangzhou, Jilin, Shijiazhuang 20	Harbin, Shenyang, Changchun, Chongqing, Shanghai, Nanjing, Chengdu, Wuhan, Changsha, Beijing, Tianjin, Xi'an, Taiyuan, Guangzhou, Hong Kong, Dalian, Hangzhou, Shijiazhuang 18	Harbin, Shenyang, Changchun, Chongqing, Shanghai, Nanjing, Chengdu, Wuhan, Changsha, Beijing, Tianjin, Xi'an, Taiyuan, Guangzhou, Hong Kong 15	Harbin, Changchun, Chongqing, Shanghai, Nanjing, Chengdu, Beijing, Tianjin, Xi'an, Taiyuan, Guangzhou, Hong Kong 12	Chongqing, Shanghai, Nanjing, Beijing, Tianjin, Guangzhou, Hong Kong 7
The USA	New York, Philadelphia, Washington, Baltimore, Detroit, Indianapolis, Columbus, Milwaukee, Minneapolis, Omaha, Chicago, Los Angeles, San Diego, San Jose, Portland, San Francisco, Seattle, Charlotte, Virginia Beach, Louisville-Jefferson, Memphis, Nashville, Jacksonville, Oklahoma City, Austin, El Paso, Fort Worth, Houston, San Antonio, Dallas, Boston, Phoenix, Tucson, Las Vegas, Denver, Albuquerque, Atlanta, New Orleans, Long Beach, Oakland, Kansas City, St. Louis, Buffalo, Colorado Springs, Honolulu, Miami 46	New York, Philadelphia, Washington, Baltimore, Detroit, Indianapolis, Columbus, Milwaukee, Minneapolis, Omaha, Chicago, Los Angeles, San Diego, San Jose, Portland, San Francisco, Seattle, Charlotte, Virginia Beach, Louisville-Jefferson, Memphis, Nashville, Jacksonville, Oklahoma City, Austin, El Paso, Fort Worth, Houston, San Antonio, Dallas, Boston, Phoenix, Tucson, Las Vegas, Denver, Albuquerque, Atlanta, New Orleans, Long Beach, Oakland, Kansas City, St. Louis 42	New York, Philadelphia, Washington, Baltimore, Detroit, Indianapolis, Columbus, Milwaukee, Minneapolis, Omaha, Chicago, Los Angeles, San Diego, San Jose, Portland, San Francisco, Seattle, Charlotte, Virginia Beach, Louisville-Jefferson, Memphis, Nashville, Jacksonville, Oklahoma City, Austin, El Paso, Fort Worth, Houston, San Antonio, Dallas, Boston, Phoenix, Tucson, Las Vegas, Denver, Albuquerque 36	New York, Philadelphia, Washington, Baltimore, Detroit, Indianapolis, Columbus, Milwaukee, Minneapolis, Chicago, Los Angeles, San Diego, Portland, San Francisco, Seattle, Charlotte, Oklahoma City, Houston, Dallas, Boston, Phoenix 21	New York, Philadelphia, Washington, Detroit, Columbus, Chicago, Los Angeles, San Diego, Portland, San Francisco, Seattle, Houston, Boston 13

In the second test scenario, we conducted sensitivity analyses with respect to the following four parameters—(1) the threshold (δ_1) associated with the facility service-competence intensity index for determination of hub locations, (2) original demand (D_j), (3) upper and lower bounds of the satisfaction rate of customer demand ($\underline{Z}_{i_h^s}, \overline{Z}_{i_h^s}$), and (4) the weights associated with the three sub-objective functions. Therein, the combination of $w_1 = w_2 = w_3 = \frac{1}{3}$ was chosen for all cases except for the sensitivity analysis with respect to these weights. We summarized the results of sensitivity analysis with respect to δ_1 in Table 6, and the others in Table 7. The following implications are provided based on the analytical results of Tables 6 and 7.

(1) A GL enterprise is allowed to loosen the facility allocation threshold by choosing a lower value of δ_1 for the determination of hub locations if the enterprise has enough capital and human resources allocated in GL network configurations. As can be seen in Table 6, the numbers of hubs that can be located in Taiwan, China, and the US increase up to 4, 20, and 46, respectively, when the threshold δ_1 decreases by 50%.
(2) The reduction of original demands may contribute significantly to the aggregate improvement in system performance. The aggregate cost of the hierarchical GLs network can be improved by 32.93% when original demands are reduced by 50%.
(3) Given the necessity of increasing the satisfactory rate of customer by 50% to replace other situations, the aggregate performance of the proposed hierarchical GLs network improves 31.45% than original situation.
(4) As revealed by sensitivity analysis, adjusting the corresponding weights associated with the three sub-objective functions have a significant effect on enhancing overall improvement. The weights associated with the profit sub-objective function w_2 is equals 1, then the aggregate profit is 12.15×10^9 US dollars and is larger than the other situation.

Overall, numerical results are indicative of the potential advantages of the proposed hierarchical GLs network, and the importance of appropriate hierarchical GLs network configuration strategies in determining system performance.

Table 7
Sensitivity analysis results.

Parameter	Parameter increment (%)			
	−50%	−25%	+25%	+50%
	Variations in aggregate hierarchical GL networks costs			
D_j	15.89 (−32.93%)	18.95 (−20%)	29.67 (25.24%)	30.43 (28.45%)
$\underline{Z}_{i_h^s}, \overline{Z}_{i_h^s}$	17.02 (−28.16%)	19.26 (−18.7%)	28.75 (21.36%)	31.14 (31.45%)

Designed cases Weight setting			Aggregate cost (US$ 10^9)	Aggregate profit (US$ 10^9)	Overall improvement (%)
w_1	w_2	w_3			
The proposed model					
1	0	0	0.69	10.32	12.94
0.5	0.5	0	0.71	11.17	1.81
$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	0.79	10.9	10.49
0	0.5	0.5	0.84	11.52	6.83
0	1	0	0.88	12.15	19.18

5. Conclusions

This work has presented a novel approach that integrates hierarchical cluster analysis and integer programming to formulate a hierarchical GLs network model for dealing with the facility location problem by minimizing total costs and maximizing operational profit and the satisfaction rate of customers. By specifying a three-layer hierarchical GLs facility network framework, risk associated with critical activities and corresponding state variables, and a composite multi-objective function combined with the operational constraints is formulated.

Compared to literature on facility location and network design problems, the proposed method has two unique features. First, the corresponding integrated supply and demand sides of a specified three-layer hierarchical GLs network are formulated using a generalized mathematical form; thus, the proposed method can readily solve hierarchical facility location problems for an international express delivery enterprises. Such a methodology is rare in literature, and has potential advantages in addressing elaborate hierarchical GLs network problems. Second, internal and external factors (*e.g.*, fundamental investment cost requirements, basic requirements of operational costs, related operational and disaster risks, and the satisfaction rate of customers) are considered by the proposed model, thereby improving performance of hierarchical GLs network configurations.

Case results indicate that Taipei is the most suitable site for locating a hub for international express delivery enterprises in Taiwan. The most appropriate locations of hubs in China are Shenyang, Beijing, Shanghai, Chongqing, and Hong Kong. In the USA, Los Angeles, Phoenix, Dallas, Houston, Chicago, New York, and Boston are the prime locations for hubs.

Managers of international express delivery enterprises can conveniently employ the proposed model as a decision-making support tool to assist in strategically determining precedence for locating the corresponding facilities, according to operational goals and overseas investment resources. In future research, the proposed model can be extended to determine dynamic multi-resource allocation based on hierarchical GLs network configurations problems. Moreover, in-depth identification of qualitative and quantitative factors, such as demand variation, risk uncertainty, and the time difference between different zones, also warrant further research. Utilization of elaborate measures for demand data aggregation is suggested in further research to demonstrate the applicability of the proposed method.

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Appendix A

A.1. Definitions of model variables and parameters

Definitions of variables and parameters shown in the proposed method are summarized below.

Notation	Definition
$X_{i_h^s j}$	the decision variable representing the decision whether to locate the ith facility in the sth area of the hth layer to serve the jth demand spot
$Y_{i_h^s j}$	the decision variable representing the distribution amount from the ith facility located in the sth area of the hth layer to the jth demand spot

Appendix A (*continued*)

Notation	Definition
$Z_{i_h^s,j}$	the derivative decision variable about the satisfied rate of customer demand associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$BC_{i_h^s,j}$	the building cost associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$LC_{i_h^s,j}$	the land cost associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$AIC_{i_h^s,j}$	the asset input cost associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$RERC_{i_h^s,j}^{\Theta_1}$	the related environment risk cost induced in Θ_1 associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$RMC_{i_h^s,j}$	the raw material cost associated with the *i*th facility in the sth area and the *h*th layer for the *j*th demand
$LBC_{i_h^s,j}$	the labor cost associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$MC_{i_h^s,j}$	the machine cost associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$EC_{i_h^s,j}$	the equipment cost associated with the ith facility in the sth area and the hth layer for the *j*th demand
$PR_{i_h^s,j}$	the political risk associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$NDR_{i_h^s,j}$	the natural disaster risk associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$r_{i_h^s,j}$	the aggregate revenue associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$oc_{i_h^s,j}$	the aggregate operational cost associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$dc_{i_h^s,j}$	the aggregate distribution cost associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$rorc_{i_h^s,j}^{\Theta_2}$	the related operational risk cost induced in Θ_2 associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$err_{i_h^s,j}$	the exchange rate risk associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$hr_{i_h^s,j}$	the human risk associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$t_{i_h^s,j}$	the unit upper bound time during the plan period to guarantee and content customer demand associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
D_j	the *j*th original demand for amount of distribution
$\bar{Y}_{i_h^s}$	the upper bound providing distribution amount with the *i*th facility in the *s*th area and the *h*th layer
$\bar{Z}_{i_h^s}$	the upper satisfied rate bound of customer demand associated with the *i*th facility in the *s*th area and the *h*th layer
$\underline{Z}_{i_h^s}$	the lower satisfied rate bound of customer demand associated with the *i*th facility in the *s*th area and the *h*th layer
G_j	the *j*th lower bound of the satisfaction rate of customer demand
$\delta_{i_h^s,j}^{\Theta_1}$	the upper bound for the related environment risk cost induced in Θ_1 associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$\delta_{i_h^s,j}^{\Theta_2}$	the upper bound the related operational risk cost induced in Θ_2 associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$\underline{Z}_j$	the lower satisfied rate bound of the *j*th customer demand
$m_{i_h^s}^{gs}$	the money risk for government stability associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$m_{i_h^s}^{e}$	the money risk for earthquake associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$m_{i_h^s}^{f}$	the the money risk for flood associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$m_{i_h^s}^{er}$	the the money risk for exchange rate associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand
$m_{i_h^s}^{ps}$	the the money risk for personnel skill associated with the *i*th facility in the *s*th area and the *h*th layer for the *j*th demand

References

[1] T. Miller, D. Wise, L. Clair, Transport network design and mode choice modeling for automobile distribution: a case study, Location Sci. 4 (1996) 37–48.
[2] T.G. Crainic, Service network design in freight transportation, Eur. J. Oper. Res. 122 (2000) 272–288.
[3] S. Melkote, M.S. Daskin, Capacitated facility location/network design problems, Eur. J. Oper. Res. 129 (2001) 481–495.
[4] A. Cakravastia, I.S. Toha, N. Nakamura, A two-stage model for the design of supply chain networks, Int. J. Prod. Econ. 80 (2002) 231–248.
[5] V. Jayaraman, A. Ross, A simulated annealing methodology to distribution network design and management, Eur. J. Oper. Res. 144 (2003) 629–645.
[6] Z. Drezner, G.O. Wesolowsky, Network design: selection and design of links and facility location, Transp. Res. Part A 37 (2003) 241–256.

[7] D. Ambrosino, M.G. Scutella, Distribution network design: new problems and related models, Eur. J. Oper. Res. 165 (2005) 610–624.
[8] J.R. Current, C.S. Revelle, J.L. Cohon, The hierarchical design problem, Eur. J. Oper. Res. 27 (1986) 57–66.
[9] N.G.F. Sancho, The hierarchical network design problem with multiple primary paths, Eur. J. Oper. Res. 96 (1996) 323–328.
[10] C.C. Lin, S.H. Chen, The hierarchical network design problem for time-definite express common carriers, Transp. Res. Part B 38 (2004) 271–283.
[11] Y.W. Wan, R.K. Cheung, J. Liu, J.H. Tong, Warehouse location problems for airfreight forwarders: a challenge created by the airport relocation, J. Air Transp. Manage. 4 (1998) 201–207.
[12] C.C. Lin, Y.J. Lin, D.Y. Lin, The economic effects of center-to-center directs on hub-and-spoke for air express common carriers, J. Air Transp. Manage. 9 (2003) 255–265.
[13] M. Wasner, G. Zapfel, An integrated multi-depot hub-location vehicle routing model for network planning of parcel service, Int. J. Prod. Econ. 90 (2004) 403–419.
[14] A.A. Chaves, L. Lan, Hybrid algorithms with detection of promising areas for the prize collecting traveling salesman problem, in: International Conference on Hybrid Intelligent Systems, IEEE Computer Society, 2005.
[15] J.-B. Sheu, A novel dynamic resource allocation model for demand-responsive city logistics distribution operations, Transp. Res. Part E 42 (2006) 445–472.
[16] K.-M. Osei-Bryson, T.R. Inniss, A hybrid clustering algorithm, Comput. Oper. Res. 34 (2007) 3255–3269.
[17] A. Nagurney, D. Matsypura, Global supply chain network dynamics with multicriteria decision-making under risk and uncertainty, Transp. Res. Part E 41 (2005) 585–612.
[18] B. Groothedde, C. Ruijgrik, L. Tavasszy, Towards collaborative, intermodal hub networks: a case study in the fast moving consumer goods market, Transp. Res. Part E 41 (2005) 567–583.
[19] D. Afshartous, Y. Guan, A. Mehrotra, US Coast Guard air station location with respect to distress calls: a spatial statistics and optimization based methodology, Eur. J. Oper. Res. 196 (2009) 1086–1096.
[20] H. Ankara, S. Yerel, Determination of sampling errors in natural stone plates through single linkage cluster method, J. Mater. Process. Technol. 209 (2009) 2483–2487.
[21] Business Environment Risk Intelligence (BERI), Business Risk Service Annual Report, vol. 3, December, 2008.
[22] Lindo Systems Inc., LINGO user's guide, LINDO SYSTEMS INC., 2004.