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以混合遺傳演算法求解整合性區位存貨、定址以及運輸路徑之兩階層供應鏈分銷網路設計

Incorporating Inventory, Location and Routing Decisions in Two-Echelon Supply Chain Network Design: A Hybrid Genetic Approach

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摘要

本研究探討兩階層供應鏈設計模式，其供應鏈層級包括單一的供應商、數個物流中心及顧客群，同時依顧客需求量的多寡，區分為大顧客群及小顧客群，分別以單點運送及多點運送的方式運輸貨物。本研究的目的係在成本最低的情形下，求取物流中心所在的位址、數量以及運輸的途徑。因為本研究模式包含定址-存貨整合問題以及車輛路徑問題，兩者均屬困難性的問題，故本研究運用三階段遺傳演算法求解，演算的結果證明本研究所提出的演算法可有效率的達到近似最適解，同時顯現在最低成本的要求下，在目標式中相關成本間相互抵換關係下，決定最適物流中心開設的數目、位址及車輛路徑等決策。

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關鍵詞: 兩階層供應鏈設計模式，定址-存貨整合問題，車輛路徑問題，遺傳演算法

Abstract

This study presents a two-echelon supply chain network design (2E-SCND) model consisting of a vendor, a number of potential distribution centers (DCs), and end customers. According to the demand size, we classify the end customers into two sets of clients, big and small, which are replenished by direct shipping and routing policies, respectively. Facility location is a strategic decision that requires vast capital investment. Failure to account for shipping costs for potential clients can lead to a sub-optimal facility location model. Therefore, this study aims not only to determine the number and location of DCs, but also to consider the distribution plan for big and small clients. The problem belongs to the class of NP-hard problems since it contains the location-inventory problem (LIP) and the multi-depot vehicle routing problem (VRP), both of which are NP-hard. The study develops a genetic algorithms-based three-phase heuristic approach to resolve this problem. The experimental results indicate that the proposed algorithms can efficiently yield near-optimal solutions and demonstrate the trade-off among the related costs.

Keywords: Two-echelon Supply Chain Network Design; Location-Inventory Problem; Vehicle-Routing Problem; Genetic Algorithms

1. Introduction

In today's fiercely competitive business environment, supply chain network (SCN) design is a critical issue with great potential to reduce cost and improve service quality. Traditionally, facility location is a strategic decision and significantly impacts tactical operations such as distribution and inventory management. The customer allocation and transportation problem should be solved after selecting the facility location. The distribution network on the downstream side of the supply chain is an important issue because it deals with the transportation of products from factories to each demand point. In general, the classical facility location models assume that each customer is served on a direct shipping policy, that is, one vehicle scheme serves only one customer. However, when customer demand is significantly below vehicle capacity, firms need a routing policy to visit multiple customers with one vehicle route. In fact, this phenomenon often occurs in urban areas.

This paper addresses the problem of two-echelon supply chain network design (2E-SCND), which deals with facility location and distribution issues in a two-echelon supply chain. From the distribution aspect, the network includes two levels of vehicle routes: in the first, the routes are added between the supplier and intermediate depots (e.g., distribution centers, DCs), the vehicles depart from the supplier and then unload their goods in the intermediate depot where the goods are stored and consolidated, then use appropriate size of vehicles to distribute these goods to the final destinations. Considering the economic scale, the most profitable firms use different sizes of vehicles at different levels of the supply chain to save transportation costs substantially (Dondo *et al.*, 2011). The problem also exists in urban logistics, which has less efficiency due to traffic congestion, pollution, and noise. For example, some cities in Europe developed an alternative transportation system where large trucks arrive at urban freight DCs from outside of the city and then goods are organized into smaller or environmentally friendly vehicles that satisfy the requests of some urban areas (Gonzalez-Feliu, 2008).

The remainder of this paper is organized as follows. Section 2 presents a review of related works. Section 3 describes the dual sales channel problem and formulates the mathematical model. Section 4 details the approach to resolving the problem, and Section 5 reports the computational results. The study concludes with recommendations for future research directions in Section 6.

2. Literature Review

Distribution network design problems typically comprise three sub-problems: facility location (FLP), vehicle routing, and inventory control. Among them, the FLP is a strategic decision because it requires vast capital investments and has a long-lasting effect. Therefore, the aim of the FLP determines the optimal number and location of facilities, as well as the allocation customers to specific facilities. Since the FLP is strongly related to inventory and shipment issues, failing to consider these issues can lead to a sub-optimal facility location model (Shen and Qi, 2007). Hence, many recent studies integrate two or three of these elements. Daskin *et al*. (2002) and Shen *et al*. (2003) introduced a joint location-inventory model with risk pooling that incorporates the inventory decision into the location problem. Shen and Qi (2007) modified the model and showed significant cost saving compared to the original optimization model. However, their model optimized only the inventory and location decisions and did not integrate distribution decisions. Miranda and Garrido (2009) incorporated unfulfilled demand penalty costs into their previous model (Miranda and Garrido, 2004) in a two-step formulation to update the service level to reach an equilibrium condition between an operations system and unfulfilled demand costs. Javid and Azad (2010) extended Shen and Qi’s (2007) work to propose a novel model that optimizes location, allocation, capacity, inventory, and routing decisions simultaneously in a stochastic supply chain and established a heuristic method based on Tabu Search and Simulated Annealing. Their work showed that the proposed heuristic was considerably efficient and effective for a broad range of problem sizes. Diabat *et al*. (2015) considered a multi-echelon joint inventory-location problem that integrates facility location, order assignment, and inventory decisions simultaneously. They developed an efficient Lagrangian relaxation-based heuristic to solve large instances of the problem. Gendron *et al*. (2016) considered a two-level uncapacitated FLP with single-assignment constraints and presented a Lagrangian relaxation approach to reduce the sub-problem to a single-level uncapacitated FLP, and then used a Lagrangian heuristic to solve a series of small uncapacitated FLPs.

On the other hand, the location routing problem (LRP) uses integrated supply chain research in location analysis by paying special attention to the underlying issues of vehicle routing (Nagy and Salhi, 2007). Hence, LRP seeks to minimize the total cost by simultaneously locating the depots and designing the vehicle routes that satisfy each customer's demand at the same time. In the last two decades, many LRP models have been proposed in the literature. Most are related to a simple distribution network with two layers (Albareda-Sambola *et al*., 2005; Lin and Kwok, 2006). A few exceptional studies addressed more complex distribution network design problems. Ambrosino and Scutellà (2005) developed a four-layer (plants, central depots, regional depots, and customers) integrated LRP. Due to recent computing power increases, one stream uses mathematical tools to solve SCN problems. To define the number and location of different types of facilities, Aksen and Altinkemer (2008) proposed a three-layer distribution logistics model to convert bricks-and-mortar to click-and-mortar retailing with a static one-period optimization model and resolved it using Lagrangian relaxation. Lee *et al*. (2010) considered four-layer supply chains similar to Ambrosino and Scutellà (2005), and solved the location and vehicle routing problems simultaneously with a mixed integer programming model and a heuristic algorithm based on LP-relaxation. Recently, Govindan *et al*. (2014) introduced a multi-objective two-echelon location routing problem (2E-LRP) with time-windows for sustainable SCN design to optimize economic and environmental objectives in a perishable food SCN. They developed a hybrid particle swarm optimization and adapted multi-objective variable neighborhood search, with results indicating that the hybrid approach achieves better solutions than other common genetic algorithm (GA)-based metaheuristics. Vidović *et al*. (2016) presented a 2E-LRP for a logistics networks design with non-hazardous recyclables collection and a distance-dependent collection rate. They developed efficient heuristics to solve large problem instances within a reasonable time. Rahmani *et al*. (2016) considered a 2E-LRP in an SCN design model with multiple products, pickup, and delivery. They developed clustering-based approaches to solve the LRP. The computational experiments indicate that the clustering approach is very competitive when the system has less than 200 customers.

Although many prior studies seem to construct integrated SCN design models that coordinate inventory, transportation, and location issues simultaneously, most of these models either focus on FLP without considering the VRP or emphasize LRP while ignoring inventory policy. For the reason, we develop a 2E-SCND model that integrates the location-inventory problem (LIP) and VRP. Moreover, because we propose a model that is an NP-hard problem that cannot be easily resolved using existing optimization techniques, we formulate a mixed non-linear integer program. Consequently, we propose a GA that incorporates a three-phase heuristic approach to provide good solutions in a reasonable computational time. Our research offers two contributes. First, we consider the inventory and safety stock issue in the 2E-SCND model. Second, according to demand size, we classify end customers as big and small clients, and then use direct shipping and routing policies to satisfy their requirements.

3. Model Formulation

3.1 Problem Statement

This paper considers a three-level two-echelon integrated SCN design system depicted in Figure 1. The SCN design system consists of a vendor at the top level, potential locations of DCs in the middle, and two different types of consumers (big and small clients) at the bottom level. The vendor and DCs are situated at known and fixed locations and the vendor and DCs are owned and operated by a central decision maker responsible for managing product flows and inventory policy to meet uncertain demands that occur at the sales locations. From the inventory management perspective, we assume that each open DC carries enough safety stock to guarantee the desired client service levels to meet the risk pooling benefit. We assume that end customers carry negligible stock compared to the DC. On-hand inventory at each DC is controlled in the (Q, r) policy and the distribution network can be decomposed into two echelons. In the first echelon, the vendor ships products to a DC with a direct shipping policy, and then the products are consolidated, sorted in the DC, and await further transportation to clients through the second echelon. In our proposed model, there are into two types of clients, big and small, according to their demand amounts. Big clients (such as wholesalers) receive a direct shipping policy, while small clients (such as convenience shops), fit within the vehicle routing model, which is designed such that the vehicle visits each demand point only once by exactly one route and all routes start and end at the same DC.

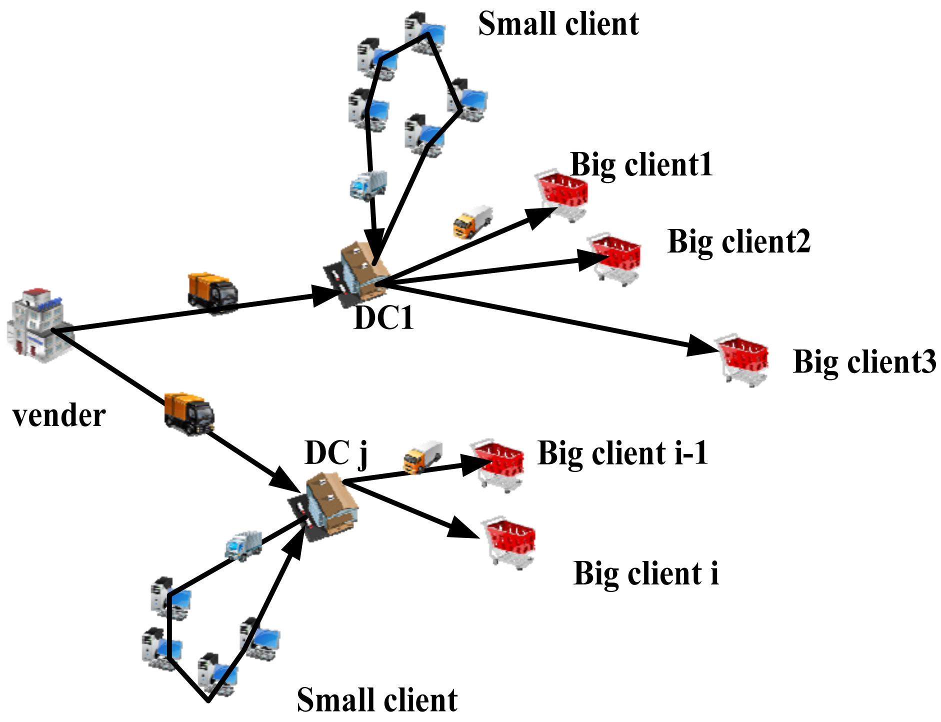

Figure 1. The 2E-SCND structure

Our study proposes to meet two goals: to minimize the total facility location and inventory-related costs in LIP and to minimize the total distribution costs. We then model the problem as a nonlinear integer program. We apply the following assumptions throughout the paper:

- The product is always available to clients through DCs, and clients pay identical prices.
- Both types of client have random demand and are identically independent and normally distributed.
- We consider a centralized inventory policy under the vendor-managed inventory (VMI) policy, where the vendor must keep safety stock pooled at DCs.
- A continuous inventory (Q_j, r_j) policy meets a stochastic demand pattern at any DC_j. Thus, when the inventory level at DC_j falls to or below a reorder point r_j, a fixed quantity Q_j is ordered from the vendor.
- Both the vendor and DCs have unlimited storage capacities.
- Each client's (big and small) order is fulfilled and delivered by a specific DC.

- For small clients, the DC adopts last-mile home delivery to fulfill the requirement of a fast response.
- Each DC holds a safety stock based on the risk-pooling strategy to buffer the system against stock-outs during lead times.
- Each DC possesses two types of homogeneous vehicles for big and small clients, respectively. The capacity of the vehicles can satisfy both types of clients' demand; however, inter-dispatch shipping is prohibited.
- The transportation cost from supplier to DC and DC to big clients depends on the shipping quantity, but the transportation cost from DC to small clients depends on both shipping quantity and distance.

3.2 Notation

We first present the notation used throughout the paper before presenting the model.

Indices:

j: index of candidate DC sites

J: set of all candidate DC sites; $\forall j \in J$

i: index of big clients

I: set of all big clients; $\forall\ i \in I$

n: index of small clients

N: set of all small clients; $\forall\ n \in N$

k: index of depots or small clients; $\forall$ k $\in J \cup N$

r: Index of routes

R: Set of all routes;　$\forall$ $r \in R$

Parameters:
B^r: number of nodes that the vehicle has visited in route r
d_i: mean of annual demand at big client i
u_n: mean of annual demand for small clients n
β_i: variance of annual demand for big clients i
δ_n: variance of annual demand for small clients n
f_j: annual fixed cost to open and operate DC_j
rc_j: unit transportation cost between the supplier and DC_j
tc_{ji}: unit transportation cost between DC_j and big clients i
vc_{nk}: unit transportation cost between node n and node k
$dist_{nk}$: distance from node n to node k
m: number of visits on each route in a year
D_{max}: the maximum shipping distance coverage
s_j: annual inventory holding cost per unit at DC_j
o_j: annual DC_j cost to order from the supplier
ζ_j: average lead time in days for shipment from DC_j from the supplier
z_α: left α-percentile of standard normal random variable Z

Decision Variables:
Y_j: 1 if DC_j is opened; 0 otherwise
X_{ji}: 1 if big clients i are assigned to DC_j; 0 otherwise
W_{jn}: 1 if small clients n are assigned to DC_j; 0 otherwise

V^r_{nk}: 1 if node n precedes node k in route r; 0 otherwise, $\forall n, k \in J \cup N$

M^r_l: auxiliary variable for sub-tour elimination constraints on route r, $\forall\ l \in N,$

$r \in R$

Q_j: order quantity at DC$_j$

3.3 Model Formulation

We formulate a mixed-integer programming model according to the notations and assumptions above, and describe the model formulation below. First, the objective function consists of the following cost components:

1. *Facility Operating Cost* (Eppen, 1979): the annual cost of operating facilities when the DCs are opened at different locations.

$$\text{FC}=\sum_{j \in J} f_j \times Y_j \tag{1}$$

2. *Expected Working Inventory Cost* (Axsäter, 1996): the expected cost of placing orders and carrying working inventory.

$$\text{WIC}= \sum_{j \in J} o_j \times \frac{[\sum_{i \in I}(d_i \times X_{ji}) + \sum_{n \in N}(u_n \times W_{jn})]}{Q_j} + \sum_{j \in J} s_j \times (Q_j / 2 \times Y_j)\,. \tag{2}$$

We adapted Ozsen *et al.*'s (2008) EOQ-approximation procedure as well as those of most typical LIP models (Daskin *et al.,* 2002; Shen *et al.*, 2003; Anderberg, 1997). The optimal order quantity Q^*_j at DC$_j$ can be obtained by differentiating Eq. (2) with respect to Q_j and setting it equal to zero to minimize total cost Z. Thus, we obtain the optimal solution of Q_j as follows:

$$Q^*_j = \sqrt{\frac{2 \times o_j \times (\sum_{i \in I} d_i \times X_{ji} + \sum_{n \in N} u_n \times W_{jn})}{s_j \times Y_j}} \tag{3}$$

3. *Safety Stock Cost* (SSC): the safety stock cost captures the cost of holding sufficient inventory to ensure a probability of stock out during a lead time of less than or equal to α. In other words, safety stock is maintained to

provide the specified service level to the buyer. Consider the centralized supply chain system under the VMI model, which means aggregating safety stock pooled at different DCs. Then, the total amount of safety stock at DC_j with risk pooling is

$$z_{1-\alpha}\left(\sqrt{\sum_{i\in I}\beta_i\cdot\zeta_j\cdot X_{ji}}+\sqrt{\sum_{n\in N}\delta_n\cdot\zeta_j\cdot W_{jn}}\right) \tag{4}$$

(Ozsen *et al*., 2008), where 1-α is the level of service for the system and $z_{1-\alpha}$ is the standard normal value with $P(z\le z_{1-\alpha})=1-\alpha$ .Therefore, the annual safety stock cost is

$$\text{SSC}=\sum_{j\in J}s_j[z_{1-\alpha}(\sqrt{\sum_{i\in I}\beta_i\cdot\zeta_j\cdot X_{ji}}+\sqrt{\sum_{n\in N}\delta_n\cdot\zeta_j\cdot W_{jn}})] \tag{5}$$

4. *Transportation Cost* (TC): the annual transportation cost includes inbound transportation cost, which is the cost to ship from the supplier to open DCs. The inbound transportation cost is quantity dependent and represented as $\sum_{j\in J}rc_j\times[\sum_{i\in I}(d_i\times X_{ji}+\sum_{n\in N}u_n\times W_{jn})]$. The outbound transportation cost, which consists of the cost to ship from the open DC to either big or small clients. The cost from DC to big client is $\sum_{j\in J}\sum_{i\in I}tc_{ji}\times d_i\times X_{ji}$, and depends on shipping quantities. The shipping cost from the DC to small client is $m\times\sum_{n\in J\cup N}\sum_{k\in J\cup N}vc_{nk}\times dist_{nk}\times u_n\times V_{nk}^r$, which depends on shipping quantity and distance. Thus, the total system cost will be FC + WIC + SSC + TC, as shown in Eq. (1).

$$\begin{aligned}Z=&\sum_{j\in J}f_j\times Y_j+\\&\sum_{j\in J}o_j\times\frac{[\sum_{i\in I}(d_i\times X_{ji})+\sum_{n\in N}(u_n\times W_{jn})]}{Q_j}+\sum_{j\in J}s_j({Q_j}/{2}\times Y_j)+\\&\sum_{j\in J}s_j[z_{1-\alpha}(\sqrt{\sum_{i\in I}\beta_i\cdot\zeta_j\cdot X_{ji}}+\sqrt{\sum_{n\in N}\delta_n\cdot\zeta_j\cdot W_{jn}})]\\&+\sum_{j\in J}\sum_{i\in I}tc_{ji}\times d_i\times X_{ji}+m\times\sum_{n\in j\cup N}\sum_{k\in J\cup N}vc_{nk}\times dist_{nk}\times u_n\times V_{nk}^r\\&+\sum_{j\in J}rc_j\times[\sum_{i\in I}(d_i\times X_{ji}+\sum_{n\in N}u_n\times W_{jn})]\end{aligned} \tag{6}$$

We obtain a non-linear cost function Eq. (7) by substituting Eq. (3) in Eq. (2),

$$
\begin{aligned}
\text{Min} \quad & \sum_{j\in J} f_j \times Y_j \\
& + \sum_{j\in J}\Big[\sqrt{2\times o_j \times s_j \times \Big(\sum_{i\in I} d_i \times X_{ji} + \sum_{n\in N} u_n \times W_{jn}\Big)\times Y_j}\,\Big] + \sum_{j\in J}\sum_{i\in I} tc_{ji} \times d_i \times X_{ji} \\
& + \sum_{j\in J} rc_j \times \Big[\sum_{i\in I}(d_i \times X_{ji}) + \sum_{n\in N}(u_n \times W_{jn})\Big] + m \times \sum_{n\in J\cup N}\sum_{k\in J\cup N} vc_{nk} \times dist_{nk} \times u_n \times V^r_{nk} \\
& + \sum_{j\in J} s_j \Big[z_{1-\alpha}\Big(\sqrt{\sum_{i\in I} \beta_i \cdot \zeta_j \cdot X_{ji}} + \sqrt{\sum_{n\in N} \delta_n \cdot \zeta_j \cdot W_{jn}}\Big)\Big]
\end{aligned}
\tag{7}
$$

s.t.

$$\sum_{j} X_{ji} = 1 \quad ,\forall i \in I \tag{8}$$

$$X_{ji} \le Y_j,\ \ \forall i \in I, \forall j \in J \tag{9}$$

$$\sum_{j} W_{jn} = 1 \quad ,\forall n \in N \tag{10}$$

$$W_{jn} \le Y_j,\ \ \forall n \in N,\ \ \forall j \in J \tag{11}$$

$$\sum_{r\in R}\sum_{k\in J\cup N} V^r_{nk} = 1,\ \forall n \in N \tag{12}$$

$$M^r_l - M^r_n + (B^r \times V^r_{ln}) \le B^r - 1\ ,\ \forall r \in R, ;\ l, n \in N \tag{13}$$

$$\sum_{k\in J\cup N} V^r_{nk} - \sum_{k\in J\cup N} V^r_{kn} = 0,\ \forall r \in R,\ \ n \in N \tag{14}$$

$$\sum_{j\in J}\sum_{n\in N} V^r_{jn} \le 1,\ \forall r \in R \tag{15}$$

$$-W_{jn} + \sum_{k\in J\cup N}(V^r_{jk} + V^r_{kn}) \le 1,\quad \forall j \in J,\ \forall n \in N,\ \forall r \in R \tag{16}$$

$$\sum_{n\in J\cup N}\sum_{k\in J\cup N} V^r_{nk} \times disk_{nk} \le D_{\max}, \forall\ r \in R \tag{17}$$

$$M^r_l \ge 0, \forall l \in N, r \in R \tag{18}$$

$$
\begin{aligned}
& X_{jn} \in \{0,1\}, Y_j \in \{0,1\}, W_{jn} \in \{0,1\}, V^r_{nk} \in \{0,1\} \\
& \forall i \in I, \forall j \in J, \forall n \in N, \forall k \in J \cup N, \forall r \in R
\end{aligned}
\tag{19}
$$

Eq. (8) restricts big clients to service from a single DC. Eq. (9) states that big clients can only be assigned to open DCs. Eq. (10) restricts small clients to service from a single DC. Eq. (11) states that small clients can only be assigned to open DCs. Eq. (12) ensures that each small client is placed on exactly one route. Eq. (13) is the sub-tour elimination constraint, which guarantees that each route must contain an origin DC, that is, each route must consist of a DC and some small clients (Desrochers and Laporte, 1991). Eq. (14) ensures flow conservation, indicating that whenever a vehicle enters a small client or DC node, it must leave again, and ensuring that the routes remain circular. Eq. (15) implies that each route is used at most once. Eq. (16) links the allocation and the routing components of the model: a small client is assigned to the DC only if a specific route starts its trip from the DC. Eq. (17) ensures that each route cannot exceed the maximum distance. Eq. (18) declares that auxiliary variables must take positive values. Eq. (19) enforces the integrality restrictions on the binary variables. Note that Miller *et al.*'s(1960) well-known sub-tour eliminate constraints requires n extra variables and roughly $n^2/2$ extra constraints, which make the problem very difficult to solve within a reasonable computing time. Therefore, we adopted a set of sub-tour eliminations that add a large number of auxiliary variables M^r_l, which results in a small number of constraints in the model (Wu *et al.*, 2002; Lee *et al.*, 2010; Selçuk, 2002). Interested readers can refer to Bektas (2006).

4. Solution Methodologies

The proposed model combines the LIP and the VRP, which results in an NP-hard problem. The complexity of these problems requires a computerized optimal procedure, though the time and computing resources to solve such problems repeatedly in practical applications are prohibitive. Exact methods can only tackle relatively small instances. Therefore, we apply a heuristic method as an alternative, which provide a multitude of heuristic solution techniques to provide good approximate solutions within a reasonable amount of time.

Over the past decades, heuristics have become important tools for solving various combinatorial problems encountered in many practical settings. Among the different methodologies, GA has become a very popular approach, especially in closed-loop supply chain problems that have an iterative procedure.

We use the following steps in the GA scheme:

1. Initialization: Generate the initial population randomly.
2. Evaluation: Compute fitness value, which is a measure of how well the individual optimizes the function. We sort the maximum fitness parameter for each population and store it as the local best.
3. Parent selection: Choose pairs of individuals from the population such that those with higher fitness will get more copies.
4. Crossover: Generate children from each pair of parents. Each parent contributes a portion of its genetic makeup to each child.
5. Mutation: Randomly change a tiny amount of the genetic information in each child.

A complete pass through of the steps above is defined as a generation, and after each generation is complete, a new one starts with the evaluation of each child. In our study, we decompose the heuristic method into constructive and improvement stages. Figure 2 depicts the solution scheme.

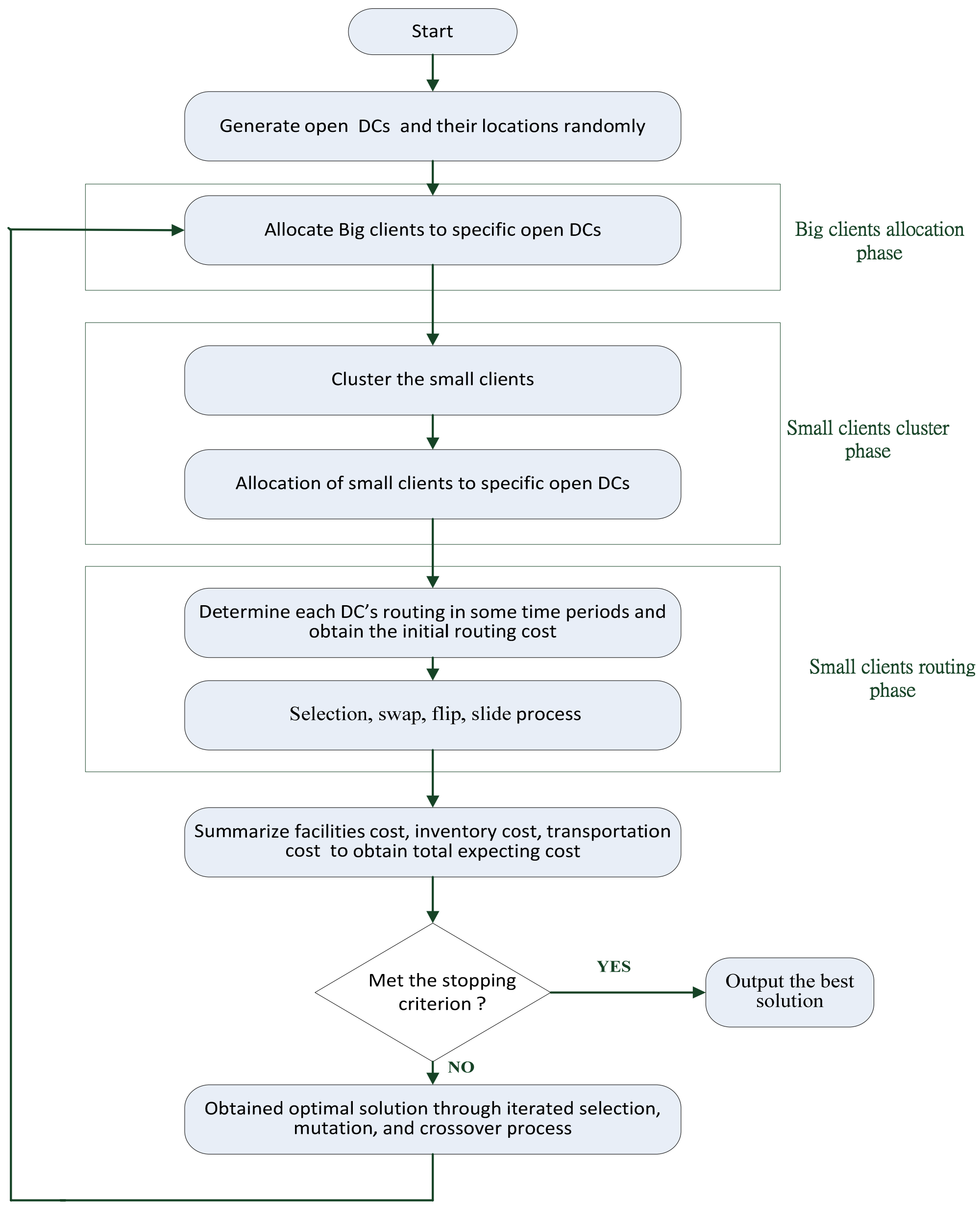

Figure 2 Flowchart of proposed heuristic method

4.1 Big Client Allocation Phase

The proposed algorithm starts by generating a random population P of size L. We define a chromosome with a binary string of length L, which implies the number of potential DCs. There is a gene Y_j representing a specific DC_j that will carry a value of 1 if it is open at the candidate site and 0 otherwise. This chromosome can be the basic condition that assigns big clients to one of the open DCs (variables X_{ji}) according to the minimal distance; a value of 1 indicates that big clients i were successfully assigned to an open DC_j, and 0 otherwise. Table 1 illustrates an example of the chromosome representation for a problem with 5 DCs and 5 big clients. Table 1 (a) shows the initial status of the DCs, indicating that DC1 and DC4 are closed, and the rest are open (i.e., Y_1=Y_4=0; Y_2=Y_3=Y_5=1). Tables 1 (b) and 1 (c) are the distance matrix between the DCs and big clients and the assignment tables after comparing the shortest distance between open DCs (Y_j=1) and each big client, respectively, where the value of X_{21}, X_{52}, X_{53}, X_{34}, and X_{25} is equal to 1; the remaining X_{ji} are equal to 0. For each chromosome in P, the algorithm evaluates its distance and coverage using the encoded solution expressions.

Table 1 (a) Initial DCs open status

DC1	DC2	DC3	DC4	DC5
0	1	1	0	1

Table 1 (b) Distance matrix

	B1	B2	B3	B4	B5
DC1	1	2	3	4	5
DC2	2	3	4	5	1
DC3	3	4	5	1	2
DC4	4	5	1	2	3
DC5	5	1	2	3	4

Table 1 (c) Assignment table

	B1	B2	B3	B4	B5
DC1	0	0	0	0	0
DC2	1	0	0	0	1
DC3	0	0	0	1	0
DC4	0	0	0	0	0
DC5	0	1	1	0	0

4.2 Small Client Cluster Phase

Cluster analysis (Anderberg, 1997) examines the division of entities in groups based on some characteristics. In our model, we define the group characteristic as the distance among the small clients, which are geographically dispersed in a connected area. Prior research recognized the potential for cluster analysis for LRPs (Barreto *et al.*, 2007). K-means, which is a least-square partitioning method, resolves many well-known clustering problems. We apply it here to classify small clients into k groups according to the number of open DCs obtained in the previous big client allocation phase. Table 2 presents the clustering procedure in the proposed method for small clients. After clustering small clients into k groups, the next process is the DC-Group allocation procedure to allocate each open DC to one of the groups based on the shortest distance between the DC and the group centroids.

Table 2 Small client cluster procedure

1: Specify a certain number of *k* groups a priori
2: Place one point inside each group as the initiated centroid
3: **Repeat**
4: Assign each small client to the group with the closest centroid
5: Re-compute the new centroid in each group
6: **Until** all centroids do not swift

4.3 Small Client Routing Phase

The purpose of the small client routing phase is to estimate the distribution cost between the DCs to small clients. Because the SCN design is a strategic decision, it is difficult to know small clients' exact demand when we develop the SCN; hence, rather than using some complicated VRP models, we apply a traveling salesperson problem model in this phase based on demand data collected from the clients' past purchase history. The main idea is to find a near optimal solution for the shortest route (least distance for the salesperson to travel to each city exactly once and return to their starting locations). We assume that the vehicle has a distance limitation, so it can return to the depot in a certain time and prepare for next period's shipping. Therefore, each route restricts $\sum_{n \in J \cup N} \sum_{k \in J \cup N} V_{nk}^{r} \times disk_{nk} \leq D_{\max}, D_{max} = s \times p$, where s is the vehicle cruise speed and p is the time limit for the route. In contrast to the big client allocation phase, which uses a binary variable representation, the GA chromosome representation here is encoded in an integer string; the value of each gene denotes a specific small client, and the gene sequence of the chromosome represents the vehicle routing in small client transportation. The GA involves encoding solutions as chromosomes. We create a new population with the selection, crossover, and mutation operator. The best chromosome should survive and become the original breed for the next generation.

We evaluate the fitness of these chromosomes by computing the routing cost (distance) of each complete route. Then, we use tournament selection to choose parents from the crossover pool. The three mutation operators of flip, swap, and slide aim to make modifications that are more likely to improve the best solutions. Figure 3 illustrates an example of how the reproduction scheme of each operator is implemented. As shown in Figure 3, there are six small clients in a chromosome in each row of the table. The genetic sequence of a chromosome represents a vehicle route plan indicating the small client visitation sequence. In this example, we assume that the second chromosome has the best fitting value in the initial solution. Then, the mutation operator randomly selects two points among these nodes. Afterward, we apply the flip, swap, and slide processes to obtain another three new chromosomes. Finally, the four vehicle schemes with the best fit are combined to form a new parent set.

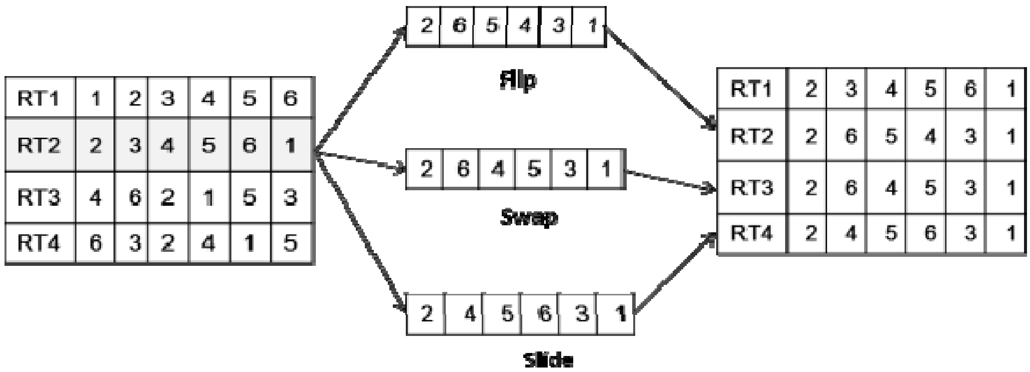

Figure 3 Example flip, swap, and slide mutation operators

The old population is replaced by a new one. We repeat these steps for a number of generations. In the end, the best chromosome is decoded to obtain a solution. When the generation number t reaches the maximum T, the algorithm stops. Table 3 depicts the small client vehicle routing scheme.

Table 3 Small client vehicle routing scheme

1: t=0

2: initialize P(t)	//Randomly generate an initial population of small client routing sequences in each group.
3: Evaluate P(t) P(t).	// Calculate the fitness in the population
4: Output the best solutions	
5: While t< max_generation T	// Do the following steps when critical T is not met.
6: For i = 1…n/4	// Divide the population solution into the n/4 sub-group.
7: Selection (p(u_i); p(n/4))	// Select the highest ranking individuals in each subgroup.
8: Mutation (p(u_i); p(n/4))	// Generate three offspring p(u') from p(u) with slide, swap, and flip processes.
9: P(t+1) = p (u_i)∪p(u_i')	//Generate the next population by combining the highest ranking individuals and their offspring in each sub-group.
10: End	
11: t=t+1	
12:End while	

4.4 Improvement Stage

The improvement stage includes the selection, crossover, and mutation operations. First, the algorithm applies binary tournament selection (to form the crossover pool). We choose two parents randomly from the population P(t) and select the best fitting one by the operator $\geq n$. After this selection, a copy of this chromosome becomes part of the crossover pool of parents. The selected chromosomes join the tournament in P(t). Therefore, the chromosome has a higher opportunity to be selected several times. For simplicity, we implement uniform crossover with both children having equal probabilities of receiving a given gene from a given parent. We then perform single point mutation on randomly chosen members of the population, where the mutation point is random and all members of the population and all genes of a chromosome vector have an equal probability of selection to generate the child population C of size L. Once initialized, the main body of the algorithm repeats for *T* generations. During the process of selecting the next generation, the chromosome fitness depends on the evaluation of the decoded solution in the objective functions and its comparison with other chromosomes.

5. Experiment Results

Our method above formulates a problem consisting of LIP and VRP issues. There are different benchmarks to evaluate LIP or VRP models, though these are not suitable for our proposed integrated model. This section attempts to evaluate the performance of the overall solution scheme for the proposed model by providing some computational results.

5.1 Evaluation Instances

We construct test problems by generating examples of problems in a SCN with 30 potential DCs that are randomly dispersed in a square of 50 distance units of width. For simplicity, we use Euclidean distance to measure the distribution of distances. Table summarizes the remaining model parameters. There are 9 different problem sets representing different sizes of problem instances in the distribution network to evaluate the proposed model.

In addition, we consider various transportation and inventory holding cost scenarios to evaluate how these costs affect the DC location decisions. In this experiment, we generate 3 sets of problem instances, which represent different sizes of problem instances ranging from 50 big clients and 300 small clients, to 100 big clients and 600 small clients (problem sizes *m_n*: 50_300, 70_400, and 100_600). All instances are randomly generated and uniformly distributed; all big and small clients are located within a square of 50 distance units of width for the coordinates. Moreover, there are two types of transportation cost structures (T1 to T2) and two types of inventory holding cost scenarios (S1 to S2), where T2 and S2 represent a high cost instance, and T1 and S1 present a low cost instance. Each problem instance is named in the following format: P_*m*_*n*_(T1 to T2)_(S1 to S2). For example, the problem instance P_50_300_T1_S1 represents the problem with 50 big clients and 300 small clients who are uniformly distributed within the square area of width 50 distance units.

Table 4 Model parameters of the problem instances

Parameter	Value

d_i	U(10,15)
u_n	2
β_i	U(2,4)
δ_n	U(0.5,0.7)
f_j	U(600,650)
rc_j	U(20,40)
tc_{ji}	2
vc_{nk}	1(T1); 3(T2)
m	300
s_j	U(4,6)(S1); U(8,10)(S2)
o_j	U(1,3)
ζ_j	U(2,4)

5.2 Computational Results

We use the following input parameters for the hybrid GA implementation: population size = 100; cloning = 20%; crossover rate = 80%; and mutation rate varies from 5% to 10% as the number of generations increase. We encode the program in MATLAB 7 and execute it on an INTEL I5 2.40 GHz processor. We modify the generation size until each solution converges. Figure 4 reveals that the population curve converges shortly after 16 generations in the P_50_300_T1_S1 problem. No significant improvement occurs thereafter.

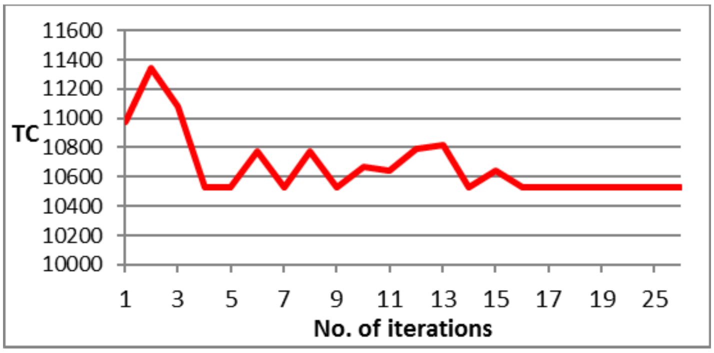

Figure 4 The P_50_300_T1_S1 problem convergence trends

We perform 10 runs for each algorithm on each data set. To evaluate the trade-offs between related costs when the number of open DCs changes, we run the GA process using a given open number of DCs from five to ten in the P_50_300_T1_S2 problem instances. We do this by presetting the open DC number at begin of the GA process. Therefore, the chromosome will be restricted at a specific number, but the location will be random, and the rest of process will remain the same. Table 5 shows how the number of open DCs affects supply chain-related costs.

Table 5 Computational results for P_50_300_T1_S2

# of DCs	Percentage of costs (%)					
	FC	TC	OC	IC	RC	TOTAL COST
5	15.71	22.22	21.53	13.64	26.9	66,761
6	16.61	21.34	21.57	15.61	24.87	79,812
7	16.12	21.11	22.45	17.35	22.97	85,165
8	16.45	20.18	23.12	17.89	22.36	93,467
9	16.89	19.74	23.78	18.42	21.17	102,319
10	17.03	19.21	23.41	19.86	20.49	111,176

FC: Fixed Cost; TC: Transportation Cost (DC to big clients); OC: Ordering Cost; IC: Inventory cost; RC: Routing Cost (DC to small clients)

Figure 5 also depicts the trade-offs among these cost components when the number of open DC increases. We see that when the number of open DCs increases, the facility cost (FC), ordering cost (OC), and inventory cost (IC) also increase. However, transportation cost (TC) and routing cost (RC) decreases.

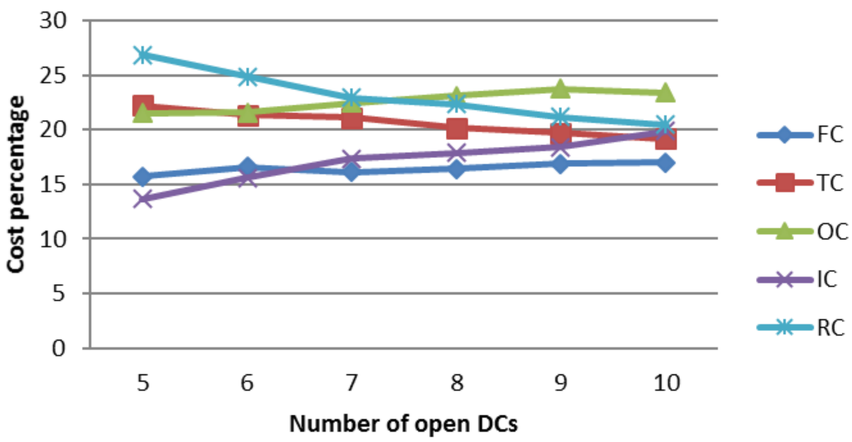

Figure 5 Trade-off trends among costs in P_50_300_T1_S2 problem

The results are consistent with Shen *et al.*'s (2003) findings, and imply that the more potential DCs open, the higher the chance that it is closer to the big / small clients' locations, which decreases transportation cost. However, more open DCs will increase the facility, ordering, and inventory costs. There are also multiple trade-off effects as the number of big /small clients serviced increases. Table 6 summarizes the computational results for the optimal number of DCs and their different costs percentages. Figure 6 illustrates the solutions for the nine problems.

Table 6 Computational results for the nine sample problems

Instances	# of DCs	Percentage of costs (%)				
		FC	TC	OC	IC	RC
P_50_300_T1_S1	6	19.97	27.88	17.77	8.48	25.9
P_50_300_T1_S2	5	15.71	22.22	21.53	13.64	26.9
P_50_300_T2_S1	9	19.25	27.59	16.28	7.89	28.99
P_70_400_T1_S1	7	16.54	25.77	17.2	9.41	31.08
P_70_400_T1_S2	5	8.87	28.57	15.88	12.15	35.54
P_70_400_T2_S1	10	15.97	17.93	14.89	9.31	41.89
P_100_600_T1_S1	8	18.2	29.16	13.88	8.58	30.18
P_100_600_T1_S2	7	13.6	24.58	17.22	16.67	27.92
P_100_600_T2_S1	12	20.49	16.77	12.1	8.32	42.33

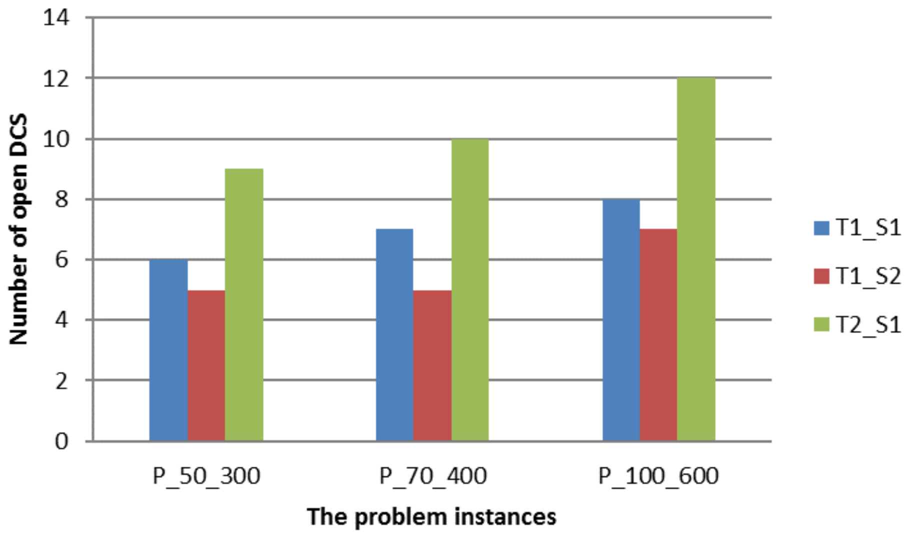

Figure 6 Number of open DCs under various cost scenarios

We observe when the number of sales points (big or small clients) increases, the number of DCs also increases, and each problem has similar cost structures, regardless of the number of sale points or cost changes. Moreover, compared to problems P_70_400_T1_S1 and P_70_400_T1_S2, the number of open DCs decreased in the high inventory cost circumstance (S2), which dropped from 6 to 5; but the number of open DCs significant increased from 6 to

10 in the high transportation cost circumstance (T2). This phenomenon indicates that the trend of open DCs is more sensitive to transportation cost than inventory cost, possibly because small clients who are typically scattered across large geographic areas require more open DCs once transportation cost increases in order to shorten the distance between the DCs and small clients and balance the additional cost. Therefore, location decisions that only consider big clients and neglect small clients, as is the case in many traditional 2E- LRP studies, could lead to a biased optimization. To keep the scope of the paper within reason, we focus on the location-allocation decision, and without loss of generalization, we assume the customers' demand for both big clients and small clients are known, and that their purchase preferences between both channels are independent of price and service factors. Furthermore, in the GA operation, the population encompasses a range of possible outcomes. Solutions are identified on a fitness level, when solutions closer to the global optimum will have higher fitness values. Successive generations improve the fitness until the optimization convergence criterion is met. Due to this probabilistic nature, GA cannot guarantee the optimal solution. This is another limitation in our model. Since we propose dealing with two different transportation methods simultaneously in the inventory location model, it is difficult to find a benchmark in past studies to verify the performance of the proposed algorithms. We aim to develop multiple algorithms for comparison in future studies.

6. Conclusion

This study proposes a 2E-SCND model consisting of a vendor, DCs, and end customers, with a network configuration designed based on the facility location and distribution problems. In the location decision, we consider inventory-related issues, including risk pooling and safety stock with a guaranteed service level. On the other hand, in terms of distribution, we first classify the end customers into a set of big and small clients according to their demand sizes, and then use direct shipping and routing policies for transportation. The objective of the study is to situate DCs to serve end customers to minimize the sum of the fixed, inventory, order, and transportation costs. We propose a systematic GA-based approach to resolve this problem. In the experiments, the proposed approach shows good results for the near-reality data and yields a near-optimal solution in a stochastic demand environment. We also conduct a sensitivity analysis to evaluate how DC selection affects transportation, inventory, and routing costs. We find several interesting phenomena.

In future work, the model can be extended in several realistic and practical directions. We can extend the proposed single-echelon inventory to a multi-echelon inventory structure. Furthermore, a detailed sensitivity analysis could determine the crucial parameters with respect to different assignments in the 2E-SCND structure. Moreover, the proposed genetic procedure provides a variety of options and parameter settings worth a full examination. It would also be interesting to develop more effective and elegant decomposition methods to resolve the integrated model. For example, the model could be decomposed into location-allocation with an inventory stage and vehicle routing and examine a highly computationally efficient heuristic method to coordinate the problem.

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