Integrated Location-Inventory Retail Supply Chain Design: A Multi-objective Evolutionary Approach

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Abstract. A supply chain network system is to provide an optimal platform for efficient and effective supply chain management. There's increasingly competitive, multi-channel retail world calls for a radically new strategy for evaluating supply chain network design. Retailers must abandon past practices which look to optimize the number and placement of facilities within traditional networks. A multi-objective optimization procedure which permits a trade-off evaluation for an integrated model is initially presented. This model includes elements of total cost, customer service and flexibility as its objectives and integrates facility location and inventory control decisions. Inventory control issues include economic order quantity, safety stock and inventory replenishment decisions and consider the risk pooling phenomenon to be realized from collaborative initiatives such as vendor-managed inventory. The possibility of a multi-objective evolutionary approach is developed to determine the optimal facility location portfolio and is implemented on a real large retail supply chain in Taiwan to investigate the model performance. Some preliminary results are described.

Keywords: multiobjective evolutionary algorithm, retail supply chain, facility location problem, inventory control, integrated supply chain model.

1 Introduction

Today's increasingly competitive, multi-channel retail world calls for a radically new strategy for evaluating supply chain network design. Retailers must abandon past practices which look to optimize the number and placement of facilities within traditional networks where domestic distribution centers (DCs) touch all merchandise moving to stores. In recent years, two generic strategies for supply chain design emerged: efficient and responsive supply chains. Efficient supply chains aim to reduce operational costs; responsive supply chains, on the other hand, are designed to react quickly to satisfy customer demands and thus save costs. Therefore, it has become a challenge for firms to evaluate tradeoffs among the total costs (for efficiency) and customer service (for responsiveness).

Research on integrated location-inventory distribution supply chain network systems is flourishing. Nozick & Turnquist [1] proposed a joint location-inventory model to consider both cost and service responsiveness trade-offs based on the uncapacitated facility location problem. Miranda & Garrido [2] studied an MINLP model

K. Deb et al. (Eds.): SEAL 2010, LNCS 6457, pp. 533–542, 2010.

to incorporate inventory decisions into typical facility location models to solve the distribution network problem by incorporating a stochastic demand and the risk pooling phenomenon. Similarly, Gaur & Ravindran [3] studied a bi-criteria optimization model to represent the inventory aggregation problem under risk pooling. Daskin *et al.* [4] and Shen *et al.* [5] developed a single-commodity joint location-inventory model with risk pooling (LMRP) that incorporates inventory and safety stock costs at the facilities into the location problem. Liao & Hsieh [6] proposed a variation of the LMRP model: capacitated DCs and multi-objective performance metrics including customer service components. However, the single supplier assignment is usually not the practical case. When the number of suppliers increases, decisions that "where" and "which" suppliers should be identified were made. In this paper, we present an integrated location-inventory model with multiple suppliers. The basic premise of this paper is to consider inventory strategy together with facility location costs and distribution costs in determining the optimal location of suppliers and DCs, and the assignment of retailers to DCs. We consider a two-echelon location-inventory retail supply chain network design problem.

The paper is organized as follows. Section 2 describes our research problem and details the model formulation. Section 3 proposes an evolutionary algorithm for the model. Section 4 illustrates computational results of a real case problem. Finally, in section 5, we make the research conclusion.

2 Mathematical Formulation

2.1 Problem Description

Consider the problem of configuring a location-inventory distribution system, where a set of suppliers and distribution centers (DCs) are to be established to distribute various products to a set of retailers. It considers jointly both the strategic and tactical decisions in the supply chain system. The strategic decision involves the location problem, which determines the number and the locations of DCs and assigns retailers to DCs, whereas the tactical decision deals with the inventory problem which determines the levels of safety stock inventory at DCs to provide certain service levels to retailers. Fig. 1 shows our supply chain. It includes multiple suppliers (usually manufacturers but sometimes resellers or distributors) that support all retailers through DCs

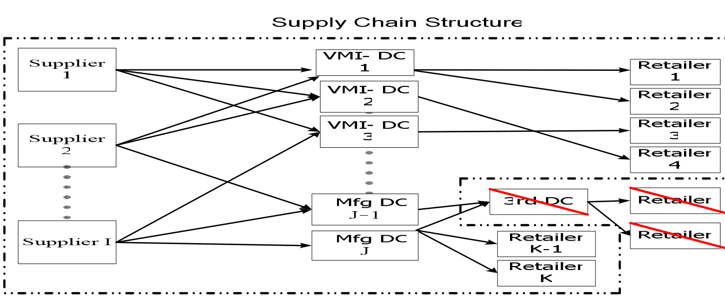


Fig. 1. Two-echelon retail supply chain network problem

of several types: supplier-owned (Mfg-DC), retailer-owned (VMI-DC) or third-party-owned (3rd-DC). Each retail-owned DC faces daily demand from the retailer's stores. The suppliers' DC receives daily orders from daily orders from retailers and places daily replenishment orders to specific suppliers. The dash-boxed area in the figure indicates our scope of interest. We tracked demand and inventory at the suppliers' DC and at the retailer's DC. We omitted third-party DC from the analysis since we were concentrating on VMI at the first-tier DC level.

2.2 Mathematical Model

Basic assumptions are used when modeling our problem. It is assumed that all the products are produced by a single supplier and one specific product for a retailer should be shipped from a single DC. Reverse flows, in-transit inventory, and pipeline inventory are not considered. All the retailers' demands are uncertain and the storage capacities of the supplier are unlimited but are capacitated at the open DCs. More assumptions will be stated when we illustrate the mathematical model. Here, the mathematical notation and formulation are as follows.

Indices. i is an index set for suppliers ($i \in$ I). j is an index set of potential DCs ($j \in$ J). k is an index set for retailers ($k \in$ K).

Decision Variables. $\boldsymbol{x}_{ij}$ is the number of units of products shipped from supplier i to DC j. $\mathbf{y}_{\mathrm{jk}}$ is a binary variable to decide if DC j serves retailer k. $\mathbf{w}_{\mathrm{i}}$ is a binary variable to see if supplier i is chosen or not. $\mathbf{s}_{\mathrm{j}}$ is a binary variable if DC j is opened or not. $\mathbf{Q}_{\mathrm{jk}}$ is the economic order quantity for retailer k at DC j.

Model Parameters. V_j is the capacity of *DC j*. P_i is the production capacity of supplier i. $\mathbf{d}_{\mathrm{k}}$ is the mean demand rate (daily) for retailer k. $\boldsymbol{\sigma}_{\mathrm{k}}$ is the standard deviation of daily demands for retailer k. $\mathbf{L}_{\mathrm{jk}}$ is the average lead time (daily) to be shipped from DC j to retailer k. $\mathbf{c}_{\mathrm{ij}}$ is the Unit cost of producing and shipping products from the supplier i to DC j and $\mathbf{t}_{\mathrm{jk}}$ is the unit transportation cost of shipping product from DC j to retailer k. $\mathbf{f}_{\mathrm{i}}$ is the fixed annual operating cost for supplier i and $\boldsymbol{g}_{\mathrm{j}}$ is the facility operating cost of locating at DC j. $\mathbf{h}_{\mathrm{j}}$ is the unit inventory holding cost at DC j. $\mathbf{o}_{\mathrm{jk}}$ is the ordering cost at DC j for retailer k per order. **dis**(i, j) and **dis**(j, k) are the distances between supplier i and DC j and between DC j and retailer k, respectively. $\mathrm{D}_{\max}$ is the maximal covering distance, *i.e.* retailers within this distance to an open DC are considered well satisfied. $\tau_k \stackrel{\Delta}{=} \{\mathrm{j} \in \mathrm{J} \mid \mathrm{dis(j, k)} \le D_{\max}\}$ is the set of DCs that could attend retailer k within $\mathrm{D}_{\max}$.

We assume that the daily demand for product k at each retailer i is independent and normally distributed, *i.e.* $\mathrm{N}(\boldsymbol{d}_{\mathrm{k}},\boldsymbol{\sigma}_{\mathrm{k}})$. Furthermore, at any site of DC j, we assume a continuous review inventory policy (Q_j, r_j) to meet a stochastic demand pattern. Also, we consider that the supplier takes an average lead time $\mathbf{L}_{\mathrm{jk}}$ (in days) for shipping product k from the supplier to DC j so as to fulfill an order. Considering centralized inventory system, if the demands at each retailer are uncorrelated, then the aggregate demands during lead time at the DC j is normally distributed and the total amount of safety stock pooled at any DC j is $z_{1-\alpha}\sqrt{\mathrm{L}_{jk}\sum_k \sigma_k^2 y_{jk}}$ where 1-α is referred to the level of service and $\mathrm{z}_{1-\alpha}$ is the standard normal value with $\mathrm{P}(\mathrm{z} \le \mathrm{z}_{1-\alpha}) = 1-\alpha$.

In our proposed model, the total cost of the system can be decomposed into the following items: (i) supplier's *operating cost*, which is the total cost incurred from the suppliers, (ii) DC's *operating cost*, which is the total cost of running DCs, (iii) *ordering cost*, which is the total annual expenses incurred in placing and order via VMI, which is the cost incurred from the suppliers, (iv) *cycle stock cost*, which is the cost of maintaining working inventory at the DCs, (v) *safety stock cost*, which is the cost of holding sufficient inventory at DCs in order to provide specific service level to their retailers, (vi) *inbound transportation cost*, which is the total cost of shipping products from suppliers to DCs, and (vii) *outbound transportation cost*, which is the total cost of shipping products from DCs to retailers. Hence, it can be represented as total cost function Z_1 as follows.

$$\begin{aligned} Z_1 = & \sum_{j\in J} f_i \cdot \mathrm{w}_i + \sum_{j\in J} g_j \cdot \mathrm{s}_j + \sum_{k\in K}\sum_{j\in J} o_{jk}\left(\frac{d_k \cdot y_{jk}}{Q_{jk}}\right) + \sum_{j\in J}\sum_{k\in K}\frac{\mathrm{h}_j \cdot Q_{jk} \cdot y_{jk}}{2} \\ & + \sum_{j\in J}\sum_{k\in K}\mathrm{h}_j \cdot \left(z_{1-\alpha}\sqrt{L_{jk}\sum_{k\in K}\sigma_k^2 \cdot y_{jk}}\right) + \sum_{i\in I}\sum_{j\in J} c_{ij}\cdot dis(i,j)\cdot x_{ij} \\ & + \sum_{j\in J}\sum_{k\in K} t_{ij}\cdot dis(j,k)\cdot d_k \cdot y_{jk} \end{aligned} \tag{1}$$

Based on Z_1, the optimal order quantity $\mathbf{Q}^*_{jk}$ for retailer k at DC j can be obtained through differentiating Z_1 in terms of $\mathbf{Q}_{jk}$, for $\forall$ j and k, and equaling to zero to minimize the total cost. We obtain $\mathbf{Q}^*_{jk}= \sqrt{2\cdot o_{jk}\cdot d_k \cdot y_{jk}/h_j}$ for every open DC j and every retailer k. Replacing $\mathbf{Q}^*_{jk}$ in the third and fourth terms of Z_1, we can obtain a non-linear cost function of Z_1. In the following, we propose our model.

$$\begin{aligned} \mathit{Min} \quad Z_1 = & \sum_{j\in J} f_i \cdot \mathrm{w}_i + \sum_{j\in J} g_j \cdot \mathrm{s}_j + \sum_{k\in K}\sum_{j\in J} o_{jk}\left(\frac{d_k \cdot y_{jk}}{Q_{jk}}\right) \\ & + \sum_{j\in J}\sum_{k\in K}\frac{\mathrm{h}_j \cdot Q_{jk} \cdot y_{jk}}{2} + \sum_{j\in J}\sum_{k\in K}\mathrm{h}_j \cdot \left(z_{1-\alpha}\sqrt{L_{jk}\sum_{k\in K}\sigma_k^2 \cdot y_{jk}}\right) \\ & + \sum_{i\in I}\sum_{j\in J} c_{ij}\cdot dis(i,j)\cdot x_{ij} + \sum_{j\in J}\sum_{k\in K} t_{ij}\cdot dis(j,k)\cdot d_k \cdot y_{jk} \end{aligned} \tag{2}$$

$$\mathit{Max} \quad Z_2 = \sum_{j\in J}\sum_{k\in K} d_k \cdot y_{jk} \Big/ \sum_{k\in K} d_k \tag{3}$$

$$\mathit{Max} \quad Z_3 = \sum_{j\in \tau_k}\sum_{k\in K} d_k \cdot y_{jk} \Big/ \sum_{j\in J}\sum_{k\in K} d_k \cdot y_{jk} \tag{4}$$

$$\text{s.t.} \quad \sum_{j\in J} \mathrm{x}_{ij} \le p_i \cdot w_i; \qquad \forall i\in I; \tag{5}$$

$$\sum_{k\in K} d_k \cdot y_{jk} + z_{1-\alpha}\sqrt{L_{jk}\sum_{k\in K}\sigma_k^2 \cdot y_{jk}} \le V_j \cdot \mathrm{s}_j; \quad \forall j\in J \tag{6}$$

$$\sum_{i\in I} \mathrm{x}_{ij} = \sum_{k\in K} d_k \cdot y_{jk} + z_{1-\alpha}\sqrt{L_{jk}\sum_{k\in K}\sigma_k^2 \cdot y_{jk}}; \qquad \forall j\in J \tag{7}$$

$$\sum_{k\in K} y_{jk} = 1 \;\; ; \quad \forall k \in K \tag{8}$$

$$y_{jk} \;, \mathrm{w}_{\mathrm{i}}, \; \mathrm{s}_{\mathrm{j}} \in \{0,1\} \; ; \quad \forall j \in J; \qquad \forall k \in K \tag{9}$$

$$x_{ij} \;, Q_{jk} \geq 0 \;\; \text{integers}; \quad \forall i \in I; \qquad \forall j \in J; \qquad \forall k \in K \tag{10}$$

The objectives are referred to (2)-(4). Z_1 in (2) is to minimize the *total cost* (TC), Z_2 in (3) and Z_3 in (4) give the objectives referred to maximizing customer service by two measurements. Z_2 in (3) is referred to *volume fill rate* (VFR) which is defined as the fraction of total demand that can be satisfied from inventory without shortage. Z_3 in (4) is called *responsiveness level* (RL) which measures the percentage of fulfilled demand volume within a distance coverage for DCs. Equations in (5) and (6) are capacity restrictions on the suppliers and DCs, respectively, and permit the use of opened facilities only. Equations in (7) are product flow conservation equations at DCs, ensuring for every product that flows through the DC, a part of it is held in safety stock and the rest is used to satisfy demand at the retailers. Equations in (8) restrict a retailer's demand to be served by a single DC. Equations in (9) are binary constraints. Equations in (10) are integrality and non-negativity requirements.

3 Problem Solving Methodology

3.1 NSGAII-Based Evolutionary Algorithm

Multiobjective optimization problems give rise to a set of Pareto-optimal solutions, none of which can be said to be better than other in all objectives. Unlike most traditional optimization approaches, multiobjective evolutionary algorithms (MOEAs) work with a population of solutions and thus are likely candidates for finding multiple Pareto-optimal solutions simultaneously. Non-dominating Sorting GA (NSGA-II) [7] is one of the best techniques in MOEAs. For each solution, one has to determine how many solutions dominate it and the set of solutions to which it dominates. Thus, it ranks all solutions to form non-dominated fronts according to a *non-dominated sorting* process to classify the chromosomes into several fronts of nondominated solutions. The non-domination sorting updates a tentative set of Pareto optimal solutions by ranking a population according to non-domination. To maintain diversity in the population, NSGA-II also estimates the solution density surrounding a particular solution in the population by computing a crowding distance operator. During selection, individuals of equal non-domination rank are sorted according to their crowding distance. The selection operator selects the best individuals according to this ranking as the parents of the next generation, whereas crossover and mutation operators remain as usual. A NSGA-II-based evolutionary algorithm is proposed, as shown in Table 1. As we can see in Table I, chromosome fitness depends on the evaluation of the decoded solution in the objective functions and its comparison with other chromosomes in the selection process of the next generation. The *non-domination sorting* updates a tentative set of Pareto optimal solutions by ranking a population according to non-domination. After that, each individual p in the population is given two attributes: (1) non-domination rank in the optimization objectives; (2) local crowding distance in the objectives space directions. If both chromosomes are the same rank, the one with fewer chromosomes around in the front is preferred. Therefore, a partial order ($\geqq_n$) can be defined as follows. Let p, $q \in$ P(t) be two individuals in population P(t). We say that p is better fitted than q ($p \geqq_n q$), either if (p.rank < q.rank) or ((p.rank = q.rank) and ($p.distance$ > $q.distance$)).

Table 1. NSGA-II-based evolutionary algorithm

1: Random generating parent population P(0) of size L
2: *Non-domination* sorting P(0)
3: For each nondominated solution, assign a fitness (rank) equal to its nondomination.
4: Create a child population C(1) of size L, apply binary tournament selection, crossover, and mutation.
5: Evaluate C(1)
6: **while t** $\leq$ T do
7: Create the mating pool R(t) =P(t) $\cup$ C(t) of size 2L by combining the parent population P(t) and the child population C(t).
8: Sort R(t) using *non-domination sorting* $\geqq_n$
9: Select P(t+1) from the first L chromosome of R(t)
10: Generate C(t+1) from P(t+1), apply binary tournament selection, crossover, and mutation
11: Mutate and Evaluate C(t+1)
12: t $\leftarrow$ t + 1
13: **end while**

3.2 Hybrid Evolutionary Algorithm

Here, a hybrid evolutionary algorithm is proposed. Cycles of fitness evaluation, selection, crossover, and mutation repeat until some stopping criteria are met. However, our algorithm first focuses on fitness evaluation according to a partial order ($\geqq_n$) which is used to decide which chromosomes are fitter. Suppose that $Z_k(p)$ and $Z_k(q)$ and be the k-th objective function evaluated at two decoded chromosomes p and q, respectively. Here in our model, $Z_1(.)$ indicates *cost*, $Z_2(.)$ indicates *volume fill rate* and $Z_3(.)$ indicates *responsiveness level*. We say that $p \geqq_n q$ if $Z_1(p) \leq Z_1(q)$, $Z_2(p) \geq Z_2(q)$ and $Z_3(p) \geq Z_3(q)$; and $Z_1(p) < Z_1(q)$ or $Z_2(p) > Z_2(q)$ or $Z_3(p) > Z_3(q)$. The chromosome representation is represented in two parts as shown in Fig. 2. Each part has the same length m=|J| (where |J| is the number of DCs) with total length of chromosome 2J. The solution in the first part of chromosome is encoded in binary

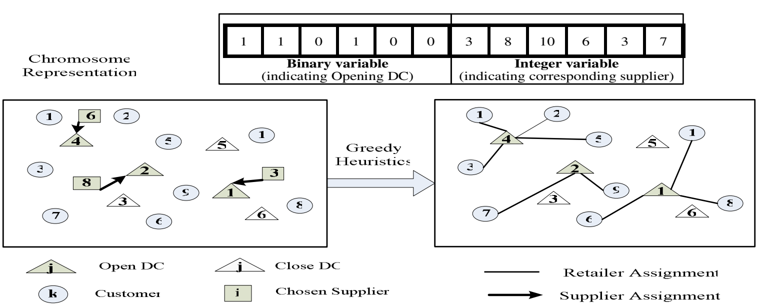


Fig. 2. Chromosome representation

variables (s_j) where the j-th position indicates if DC j is open (value of 1) or closed (value of 0). However, the second part of chromosome is encoded in integer variables where the value in it stands for the corresponding supplier that is assigned to it.

A solution also involves the assignments of retailers to open DCs (binary variables y_{jk}). This assignment is performed by a *greedy* heuristics used to obtain the single retailer-DC assignments. The retailers are firstly sorted in the descending order of their demand flows and then assign them in the sorted order to the DC according to the following rules:

Rule 1. If retailer i is covered (i.e., there are DCs within a coverage distance), it is assigned to a DC with sufficient capacity (if exists) which can serve it with the minimal difference between the remaining capacity of an open DC j and the demand flow of the retailer i through DC j. That is, the DC assignment attempts to be filled.

Rule 2. If the retailer i cannot be covered or there is no successful assignment from the coverage set τ_i, it is then assigned to the candidate DC (with sufficient capacity) that increases the total cost by the least amount, regardless of its distance to the DC.

4 Model Applications

4.1 An Illustrative Retail Supply Chain Example

C company, one of the world's largest retailer, is increased rapidly through the 1990s, and by 2010, the firm is currently 64 retail stores in Taiwan, most of them being hypermarkets. The company has set up several distribution centers in Taiwan, which distributes commodities through its national-wise retail chain. It also consigned vendor-managed inventories, consisting primarily of seasonal merchandise and such direct-to-store products as ice cream and soft drinks are held until needed. By asking them help manage inventory, the suppliers are asked to make new products available and to deliver products to stores ready to sell. It has illustrated clearly the benefits of such real-time stock management.

For this case study, 7 suppliers could be potentially chosen to make our procurement plan. According to the realistic data, there are 8 potential depots for its retail network. We also aggregate retailer's depots located in the same city or town. After aggregation, we ended up with 44 retailer stores. The maximal covering distance was set in D_{max}=150 km. Other key input parameters of the model are given in Table 2. The demand for retailer k ($\mathbf{d}_k$) is set equal 50 demands per day per million people in the population. For simplicity, Euclidean distance is used for measuring distribution distances. The company intended to determine both the number of opening DCs and its corresponding suppliers for retailer's order assignments. Such assignment will be affected by DC's capacity limitation and suppliers' production capacities. Therefore, the decisions are to evaluate tradeoffs among three criteria.

4.2 Computational Results

To obtain the Pareto front, we attempted to solve the specified problem using the evolutionary approach. The Pareto front is then evaluated to find out the 'optimal' solution. We define a reference point which is a vector formed by the single-objective optimal solutions. It is the best possible solution among the Pareto front that a multi-objective problem may have. Given a reference point, the problem can be solved by locating the alternative which has the minimum distance to the reference point. The reference point can simply be found by optimizing one of the original objectives at a time subjective to all constraints. Due to incommensurability among objectives, we measure this distance by using normalized Euclidean distance between two points in k-dimensional vector space to obtain the *score* function in *Eq.* (11).

$$score = \left\{ \sum_{t=1}^{k} w_t [(f_t^* - f_t) / f_t^*]^2 \right\}^{1/2} \tag{11}$$

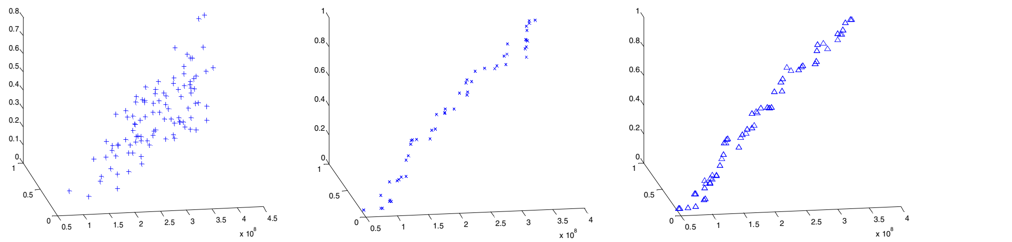
where f is an alternative solution in Pareto front, f^* is the reference point and $\boldsymbol{w}_t$ is the relative weight (given by prior) for the t-th objective. Then, all alternatives are ranked based on the value of d in descending orders. The highest ranked alternative (with the minimal value of *score*) is the 'optimal' solution. Input parameters are: cloning=20%; generation number=100; population size=50; crossover rate = 80%; mutation rate varies from 5% to 10%. The decision maker requires determining weights $\boldsymbol{w}_t$ by prior knowledge of objectives. The hybrid GA is evaluated with the illustrative example.

Table 2. Model parameters

Parameters	Value	Parameters	Value
Demands per unit population per day($\mathbf{d}_k$)	$50*10^{-6}$	Capacity of DC j ($\mathbf{V}_j$)	U($1.2*10^6$,$1.5*10^6$
Lead time (days) ($\mathbf{L}_{jk}$)	5	Prod. capacity of supplier i ($\mathbf{P}_i$)	U(1.8*106, $2*10^6$)
Unit ship. cost from supplier i to DC j ($\mathbf{c}_{ij}$)	\$0.2	Fixed ann. oper. cost for supplier i ($\mathbf{f}_i$)	U($50*10^6$, $80*10^6$)
Unit ship. cost from DC j to retailer k ($\mathbf{t}_{jk}$)	\$1	Fixed ann. oper. cost for DC j ($\boldsymbol{g}_j$)	U($35*10^6$, $65*10^6$)
Unit ordering cost at DC j ($\mathbf{o}_{jk}$)	U (0.5,1)	Unit inv. holding cost at DC j ($\mathbf{h}_j$)	\$1.2

Fig. 3 illustrates a good evolution approach for generating the Pareto front after 200 generations in our problem. It is revealed that the population curve converges shortly after 50 generations; they are nearly overlapped among themselves. Afterwards, no significant improvement is incurred. In order to illustrate the performance effects on the proposed solution procedure, we also consider four diverse scenarios by changing $\boldsymbol{w}_t$ parameters at a time as follows: (1) equal-weight scenario (S_1) with w_1=w_2=w_3=1/3; (2) cost-concerned scenario (S_2) with w_1=0.8, w_2=w_3=0.1; (3) responsive-level scenario (S_3) with w_2=0.8, w_1=w_3=0.1; (4) volume-fill-rate scenario (S_4) with w_3=0.8, w_1=w_2=0.1. Table 3 summarizes computational results of all scenarios.

In Fig. 4, we display graphically the geographical locations of three components: DCs(△) and their corresponding suppliers (□) and retailers (○). All corresponding retailer assignments and supplier selections of a specific DC are represented in the same color. Fig. 4(a) illustrates the optimal assignment of alternative 27 for scenario S1 with minimal TC \$1,078,800,000, maximal VFR 73.71% and maximal RL 65.14%, respectively, where 5 out of 8 potential DCs are aggregated. Most of these DCs look close to their assigned retailers. However, there are about 26.29% unassigned retailers (especially the retailers located in southern Taiwan), indicating sales loss percentage. There are also 34.86% aggregated retailers assigned to DCs farther than the coverage distance. Fig. 4(b) represents the cost-concerned scenario. Fig. 4(c) shows the optimal assignment of alternative 6 for scenario S_3 and S_4, where 7 DCs are aggregated. The results shows that it is possible to increase VFR 13.12% and RL 17.23%, if only the percentage over TC increases 17.23% where the number of open DCs increased from 5 to 7. That is, it is necessary to spend extra costs to open DCs up to 7 to enhance customer's VFR and also to increase RL at the same time.

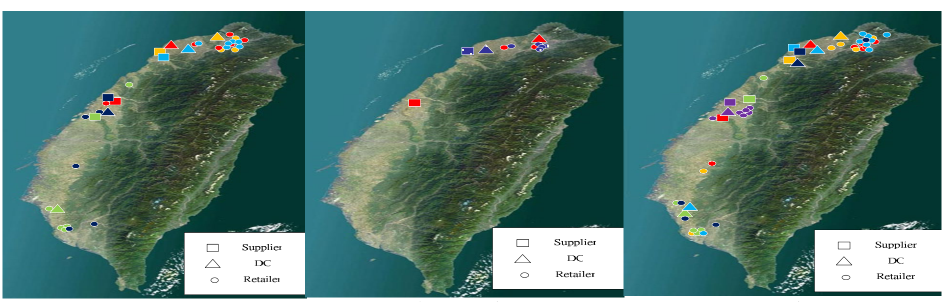


(a) First Generation (n=1) (b) Generation (n=50) (c) Generation (n=200)

Fig. 3. Evolutionary approach for generating Pareto front

Table 3. Summary of computational results

Scenarios	Objectives			Optimal solution			
	TC (million)	VFR	RL	Alter-native	# of open DC	DC (vs. supplier)	Retailer (vs. DC)
S_1	1,078.8	73.71%	65.14%	27	5	2(4) 3(7) 4(3) 5(5) 7(2)	3(5) 4(2) 5(5) 6(3) 8(3) 9(5) 10(2) 11(5) 12(3) 15(3) 16(2) 18(5) 19(3) 20(5) 22(4) 23(3) 28(7) 30(7) 32(7) 34(4) 38(4) 39(4) 40(7) 43(4) 44(7)
S_2	388.46	28.51%	28.51%	19	2	2(2) 3(5)	3(3) 5(3) 6(3) 8(2) 13(3) 19(2) 20(3)
S_3 & S_4	1,549	90.94%	78.26%	6	7	1(6) 3(3) 4(7) 5(5) 6(1) 7(2) 8(5)	1(5) 2(5) 3(5) 4(5) 5(3) 6(3) 7(3) 8(5) 9(3) 10(1) 11(3) 12(5) 13(6) 15(5) 16(1) 18(3) 19(1) 20(1) 22(4) 23(7) 24(7) 25(7) 27(7) 28(7) 30(7) 32(1) 33(3) 34(4) 35(6) 38(4) 39(4) 40(1) 41(6) 42(8) 43(4) 44(6)



(a) scenario 1 (b) scenario 2 (c) scenarios 3 & 4

Fig. 4. Graphical display of the 'optimal' solution under scenarios

5 Conclusion

This research presented an integrated location-inventory retail supply chain network design problem which examines the effects of facility location, distribution, and inventory issues. The goal of this research is to realize the application of multi-objective evolutionary approaches to real problems. The possibility of a hybrid MOEA is developed to efficiently determine the optimal facility location portfolio and is successfully implemented on a real large retail supply chain in Taiwan to investigate the model performance. The proposed model is helpful in adjusting the distribution network to these changes.

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