A Capacitated Inventory-Location Model: Formulation, Solution Approach and Preliminary Computational Results

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Abstract. Supply chain distribution network system provides an optimal platform for efficient and effective supply chain management. There are trade-offs between *efficiency* and *responsiveness*. In this research, a multi-objective capacitated location-inventory distribution network system is formulated which integrates the effects of facility location, transportation, and inventory issues and includes conflicting objectives. This model allows determining the optimal locations of distribution centers (DCs) and the assignment of buyers to DCs to find the set of Pareto optimal solutions. The possibility of a hybrid GA approach and its scenario analysis is investigated to understand the model performance and to illustrate how parameter changes influence its output.

Keywords: Location-inventory distribution network system, Multiobjective evolutionary algorithm, Scenario analysis.

1 Introduction

Enterprises are facing competitive environments by implementing new strategies and technologies in response to the challenges and customer demands. Recently, two generic strategies for supply chain design emerged: *efficiency* and *responsiveness*. Efficiency aims to reduce operational costs; responsiveness, on the other hand, is designed to react quickly to satisfy customer demands and save costs. In traditional distribution systems, minimizing costs or maximizing profits as a single objective is often the focus. However, very few distribution network systems are single objective problems. Multi-objective formulation has to be considered whose solutions will be a set of Pareto alternatives representing the tradeoffs among different objectives.

Recently, Daskin *et al.* [1] introduced a joint location-inventory model with risk pooling (LMRP) that incorporates inventory costs at the distribution centers (DCs) into the location problem. LMRP assumes uncapacitated DCs which is usually not practical. Capacity limitation may affect the number and locations of the facilities, the inventory that can be stored at the facilities and consequently the order frequency as

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well as the assignment of buyers to the facilities. Our model builds upon the initial LMRP model with some differences. First, a capacitated version of the similar model is established. Second, customer responsiveness and volume fill rate are incorporated as two extra performance metrics to make our contribution. With these considerations, we present a capacitated Multi-Objective Location-Inventory Problem (MOLIP) which results in a Mixed-Integer Non-Linear Programming (MINLP) formulation.

Evolutionary optimization algorithms are known to be efficient-solving and easy-adaptive, especially those where traditional methods failed to provide good solutions (*e.g.* MINLP). Recently, multiobjective evolutionary algorithms (MOEAs) have become prevailing since the pioneering work by Schaffer [2]. There are many efficient MOEAs that are possible to find Pareto optimal solutions as well as widely distributed sets of solutions, NSGA-II [3] is one of the most successful approaches. In our study, the well-known NSGA-II algorithm and a heuristic assignment procedure are incorporated that help to approximate the Pareto frontier for optimizing MOLIP.

This paper is organized as follows. Section 2 discusses relevant literature review. Section 3 details the model formulation. Section 4 proposes a hybrid genetic algorithm with a heuristic procedure for MOLIP. Section 5 illustrates computational results of simulated problems and considers scenario analysis to compare their performance, and finally, conclusions with some directions are provided in section 6.

2 Literature Review

Research on integrated location-inventory distribution network systems is relatively new. Nozick & Turnquist [4] proposed a joint location-inventory model to consider both cost and service responsiveness trade-offs based on the uncapacitated facility location problem. The analysis demonstrated an approximate linear safety-stock cost function in the framework and proposed a Lagrangean-based scheme. Miranda & Garrido [5] studied an MINLP model 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. A heuristic solution approach, based on Lagrangian relaxation and the sub-gradient method was presented. Sabri & Beamon [6] presented an integrated multi-objective multi-echelon stochastic model that simultaneously addresses strategic and operational planning decisions by developing an integrated two sub-module model. Similarly, Gaur & Ravindran [7] studied a bi-criteria optimization model to represent the inventory aggregation problem under risk pooling to find out the tradeoffs in costs and responsiveness.

Daskin *et al.* [1] and Shen *et al.* [8] present a LMRP model that incorporated safety stock placement into a location problem for a two-stage network. There are several variations of the LMRP model. Ozsen [9] presents a capacitated version of LMRP which determines the ordering policy at the DCs so that the inventory aggregation does not exceed DC capacities. A Lagrangian relaxation algorithm was applied to solve this problem. Shen & Daskin [10] extended LMRP to include the customer service component and proposed a nonlinear multi-objective model including both the cost and service objectives. They developed a weighting method and an efficient GA-based heuristic solution approach for quick and meaningful evaluation of cost/service trade-offs. From the survey, some innovative research aspects that are noteworthy have been incorporated in our research work as follows:

Multi-objective location inventory problem. Very few researches have addressed this problem. A multiobjective formulation should be required to provide the tradeoffs of Pareto optimal alternatives among total costs and customer service.

Multi-objective evolutionary algorithms (MOEAs). Most reviewed research works focused on traditional optimization techniques but few have performed successfully and efficiently. In the contrast, MOEAs have been successful developed for various optimization problems and enable the possibility for the proposed MOLIP.

3 Mathematical Formulation

3.1 Problem Description

Suppliers and distributors in general, route their products through DCs. Consider configuring a supply chain distribution network system, where a single supplier and a set of DCs are established and dispersed in a region to distribute various products to a set of buyers. The DCs act as intermediate facilities between the supplier and the buyers and facilitate the product shipment between two echelons. The supplier wishes to determine the opening DCs and to design the distribution strategy satisfying all DC capacities. Basic assumptions are used. It is assumed that all products are produced by a single supplier and one specific product for a buyer should be shipped from a single DC. Reverse flows and in-transit inventory are not considered. All demands of the buyers are uncertain. The capacities at the supplier are unlimited but capacitated at DCs. More assumptions will be stated when the mathematical model is illustrated.

Indices. *i is an index set for buyers ($i \in I$). j is an index set of potential DCs ($j \in J$). k is an index set for product classifications ($k \in K$).*

Decision Variables. Q_{wj}^{k} *is the aggregate economic order quantity for DC j for product k shipped from the supplier.* $Y_j = 1$ *if DC j is open (=0, otherwise).* $X_{ji}^{k} = 1$ *if DC j serves buyer i for shipping product k (=0, otherwise).*

Model Parameters. μ_j *is the capacity of DC j.* d_{ik} *is the mean demand rate for product k at buyer i.* σ_{ik} *is the standard deviation of daily demands for product k at buyer i.* ς_j^k *is the average lead time (daily) for product k to be shipped to DC j from the supplier.* ψ *is the number of days per year.* f_j *is the fixed annual facility operating cost of locating at DC site j.* h_j^k *is the annual inventory unit holding cost at DC j for product k.* o_j^k *is the ordering cost at DC j for product k per order.* tc_{ji}^k *is the unit variable transportation cost for shipping product k from DC j to buyer i.* rc_j^k *is the unit variable production and transportation cost for shipping product k from the supplier to DC j.* h_{ji} *is the distance between DC j and buyer i.* D_{wj}^k *is the expected annual demand for product k through DC j.* D_{max} *is the maximal covering distance, that is, buyers within this distance to an open DC are considered well satisfied.*

3.2 Mathematical Models

To begin modeling this problem, we also assume that the daily demand for product *k* at each buyer *i* is independent and normally distributed, *i.e.* $N(d_{ik},\sigma_{ik})$. 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 ς_j^k (in days) for shipping product *k* from the supplier to DC *j* so as to fulfill an order. From Eppen's inventory theory [11] considering the centralized inventory system, we assume that if the demands at different buyers are uncorrelated, the aggregate safety stock of the product *k* pooled at the DC *j* during lead time ς_j^k is normally distributed. Then, the total amount of safety stock for product *k* at any DC *j* with risk pooling is $z_{1-\alpha}\sqrt{\varsigma_j^k \sum_{i\in I}\sigma_{ik}^2 X_{ji}}$ where 1-α is referred to the *level of service* and $z_{1-\alpha}$ is the standard normal value with $P(z \le z_{1-\alpha}) = 1-\alpha$.

In our proposed model, the total cost can be decomposed into the following items: (i) *facility cost*, which is the cost of setting up DCs, (ii) *transportation cost*, which is the cost of transporting products from the supplier to the buyers via specific DCs, (iii) *operating cost*, which is the cost of running DCs, (iv) *cycle stock cost*, which is the cost of maintaining working inventory at DCs, and (v) *safety stock cost*, which is the cost of holding sufficient inventory at DCs in order to provide specific service level to their buyers. Hence, it can be represented as total cost function Z_1 as follows.

$$Z_1 = \sum_{j\in J} f_j \cdot Y_j + \psi\sum_{k\in K}\sum_{j\in J}\sum_{i\in I}(rc_j^k + tc_{ji}^k)\cdot d_{ik}\cdot X_{ji}^k + \sum_{k\in K}\cdot\sum_{j\in J} o_j^k \cdot \frac{\psi\cdot d_{wj}^k}{Q_{wj}^k}$$
$$+\sum_{k\in K}\sum_{j\in J} h_j^k \cdot \frac{Q_{wj}^k}{2}\cdot Y_j^k + \sum_{k\in K}\sum_{j\in J} h_j^k \cdot z_{1-\alpha}\sqrt{\zeta_j^k \sum_{i\in I}\sigma_{ik}^2 \cdot X_{ji}^k} \tag{1}$$

Based on Z_1, the optimal order quantity Q_{wj}^{k*} for product *k* at each DC *j* can be obtained through differentiating *eq.* (1) in terms of Q_{wj}^k, for each DC *j* and each product *k*, and equaling to zero to minimize the total supply chain cost. We can obtain $Q_{wj}^{k^*} = \sqrt{2\cdot o_j^k \cdot D_{wj}^k / h_j^k}$ for ∀ open DC *j*, ∀ *k*. In this case, there is not any capacity constraint for the order quantities Q_{wj}^k since we assume the storage capacity at the supplier is unlimited. Thus, replacing Q_{wj}^{k*} in the third and fourth terms of Z_1 in *eq.* (1), we can obtain a non-linear cost function of Z_1. In the following, we propose an innovative mathematical model for the Multi-Objective Location-Inventory Problem (MOLIP).

$$\text{Min } Z_1 = \sum_{k\in K}\sum_{j\in J} f_j \cdot Y_j^k + \sum_{k\in K}\sum_{j\in J}\sum_{i\in I}\Psi_{ji}^k \cdot X_{ji}^k + \sum_{k\in K}\cdot\sum_{j\in J}\left(\Gamma_j^k\sqrt{\sum_{i\in I} D_{ik}\cdot X_{ji}^k}\right)$$
$$+\sum_{k\in K}\sum_{j\in J} h_j^k \cdot \sqrt{\sum_{i\in I}\Lambda_{ji}^k \cdot X_{ji}^k} \tag{2}$$

$$\text{Max } Z_2 = \left(\sum_{k\in K}\sum_{i\in I} d_{ik} X_{ji}^k\right) \Big/ \sum_{k\in K}\sum_{i\in I} d_{ik} \tag{3}$$

$$\text{Max} \quad Z_3 = \left(\sum_{k \in K} \sum_{i \in I} d_{ik} \sum_{j \in \tau_i} X_{ji}^k \right) \Big/ \sum_{k \in K} \sum_{i \in I} d_{ik} X_{ji}^k \tag{4}$$

$$\text{s.t.} \quad \sum_{j \in J} X_{ji}^k \le 1 \qquad \forall i \in I \; ; \forall k \in K \tag{5}$$

$$X_{ji}^k \le Y_j \qquad \forall i \in I \; ; \; \forall j \in J \; ; \forall k \in K \tag{6}$$

$$\sum_{k \in K} \sum_{i \in I} d_{ik} \cdot X_{ji}^k + \sum_{k \in K} \sqrt{\sum_{i \in I} \Lambda_{ji}^k \cdot X_{ji}^k} \le u_j Y_j \quad \forall j \in J \tag{7}$$

$$X_{ji}^k \in \{0,1\}, \; Y_j \in \{0,1\}, \quad \forall i \in I \; ; \forall j \in J \; ; \forall k \in K \tag{8}$$

where $\Psi_{ji}^k = \psi \cdot (rc_j^k + tc_{ji}^k) \cdot d_{ik}$ $\qquad \Gamma_j^k = \sqrt{2 \cdot o_j^k \cdot h_j^k}$

$D_{ik} = \psi \cdot d_{ik}$ $\qquad \Lambda_{ji}^k = (z_{1-\alpha})^2 \cdot \zeta_j^k \cdot \sigma_{ik}^2$

Eqs. (2)-(4) gives the objectives. While *eq.* (2) of Z_1 is to minimize the total cost, *eq.* (3) of Z_2 and *eq. (*4) of Z_3 give the objectives referred to maximizing customer service by two performance measurements: (i) *volume fill rate* (VFR), defined as the satisfied fraction of total demands without shortage; (ii) *responsiveness level* (RL)*,* the percentage of fulfilled demand volume within specified coverage distance D_{max}. *Eq.* (5) restricts a buyer to be served by a single DC if possible. *Eq.* (6) stipulates that buyers can only be assigned to open DCs. *Eq.* (7) are the maximal capacity restrictions on the opened DCs to enable the capability of holding sufficient inventory for every product that flows through the DC, and also the part of safety stock so as to maintain the specified service level. *Eq.* (8) are binary constraints. The proposed MOLIP model would not only determine the DC locations, the assignment of buyers to DCs, but also find out endogenously both the optimal order quantities and safety-stock levels at DCs. Since two of the three objective functions (Z_1 and Z_3) are nonlinear, the formulation results in an intractable multi-objective MINLP model.

4 A Genetic Approach for MOLIP

4.1 Solution Encoding

Each solution of MOLIP is encoded in a binary string of length m = |J|, where the *j*-th position indicates if DC *j* is open (= 1) or closed (= 0). This binary encoding only considers if a given DC *j* is open or closed (variables Y_j). A solution of MOLIP also involves the assignment of buyers to open DCs (variables X_{ji}). This assignment is performed by a *greedy* heuristics used to obtain the buyer-DC assignments where the buyers are sorted in the descending order of their demand flows and assign them in the sorted order to the DC according to the following rules:

Rule 1. If the buyer i is covered (i.e., there are DCs within a coverage distance), it is assigned to the 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 of the buyer i through DC j. That is, a DC is tried to be assigned as full as possible.

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

However, this assignment procedure cannot guarantee that each buyer can be assigned to a satisfiable DC due to DC's capacity limitations. Thus, the infeasible solution will degrade the supplier's volume fill rate and may cause business losses.

4.2 NAGAII-Based Genetic Algorithm for MOLIP

Nondominating Sorting GA (NSGA-II) [3] is one of the best techniques for generating Pareto frontiers 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. To allow the diversification, NSGA-II also estimates the solution density surrounding a particular solution in the population by computing a *crowding distance* operator. During selection, a *crowded-comparison* operator considering both the *non-domination rank* of an individual and its *crowding distance* is used to select the offspring without lost good solutions (*elitism*), whereas crossover and mutation operators remain as usual. We summarized the NSGAII algorithm as shown in Fig. 1.

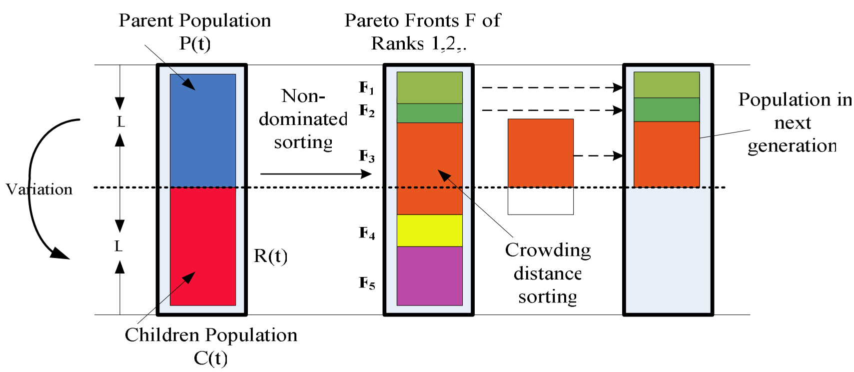

Fig. 1. Graphical Representation of the NSGA-II Algorithm

5 Computational Results and Scenario Analysis

In this section, a set of test problems similar to [12] are generated in the *base case* scenario. Then, two diverse capacity scenarios are established for scenario analysis.

5.1 Base Case Scenario (Scenario 1)

In our experiments, random sets from a square of 100 miles of width are used to generate the coordinates for DCs and buyers in all test problems. We especially establish the following parameters for the *base case* scenario. The unit transportation cost tc_{ji}

are set to 0.1 per mile. The unit production and shipping cost rc_j^k for product *k* from the supplier to DC *j* is generated uniformly on U(1,3). The average lead time ς_j^k is set to 5 days. The expected daily demands d_{ik} for product *k* at buyer *i* is generated uniformly on U(50,300). The daily inventory holding cost h_j^k at DC *j* for product *k* and the unit ordering cost o_j^k at DC *j* for product *k* are generated uniformly on U(5,10) and U(50,100), respectively. It is also assumed 365 working days ψ per year and the service level 1-α is 0.95. The maximal covering distance is 25 miles. The capacities of DCs are set to $\mu_j = cap_j \times \sum\sum d_{ik}/j$, j = 1,.,J, cap_j~U(4,6), where the values of cap_j vary DC's capacities. Here, we want to set the DC capacity to a multiple of the mean aggregate demand of a DC. The facility costs of DCs are set to $f_j = fac_j \times$ {U(500,1000)+ U(500,1000) $\times d_j^{0.5}$}, where $d_j = \sum\sum d_{ik}$ and the values of fac_j vary the facility operating costs. The concavity of f_j accounts for the economies of scale. In additions, the set of test problems is denoted by (*k*, *j*, *i*), where *k* is the number of products, *j* is the number of potential DCs, and *i* is the number of buyers. The values of the parameters are set to *k* = 1, 3; *j* = 5, 10, 15, 20; *i* = 30, 40, 50, 60.

We report the performance solutions of 32 problem instances for the MOLIP model in terms of objective measurements, cost components and their respective percentage of total costs. Objective measurements include the optimal solutions of *total cost* (TC), *volume fill rate* (VFR), and *responsiveness level* (RL); the cost components provide the results of *facility cost* (FC), *transportation cost* (TrC), *inventory cost* (IvC) and *safety-stock cost* (SSC) and their respective percentages of total costs (%). All objectives and cost components are expressed by the average values of their Pareto solutions and are derived by computing the average solutions of each problem instance after several iterations (say 50) for computational robustness. Since the network structure with respect to test problems may be varied when the parameters *k, j, i* are changed, we establish an index called *competitiveness level* (CL) referred to a specific DC to measure the relative capacity ratio between *supply* ability provided by a DC and *demand* requirement incurred from the distribution network system. CL indicates computational difficulty of solving capacitated problems.

In order to explore the statistical associations on 32 problem instances, the Pearson correlations among DC's capacity CL and objective measurements have been derived. It is shown that there is a significant negative correlation between CL and TC with correlation coefficient of -0.639, implying that as CL increased, the average total cost decreased. However, there is not a similar correlation between CL and VFR or RL. The correlation coefficient between these groups for VFR was -0.167, and for RL was 0.191. It is concluded that the tightly capacitated network could have overall impacts on total cost but only little effects on its volume fill rate and responsiveness level.

Next, we measure the correlations among CL and cost components which have shown significant associations for three measured variables: transportation, inventory and safety-stock costs, with correlation coefficients of -0.722, -0.550 and -0.557, respectively. However, the facility costs are the least correlated among all cost components with CL. That is, the additional capacity available in the network system enables more reduction on transportation, inventory and safety-stock costs but has no significant impact on facility costs. In depicted in Fig. 2, it is observed that those tightly capacitated problems (with small CL values) hold significantly dominating transportation costs as compared to others; however, TrC decreases considerably in those problems when capacitated environment is loosened where FC takes the place as the major cost among others. It also reveals that transportation cost is the main factor for tightly capacitated problems but facility cost dominates gradually when additional DC capacity increases.

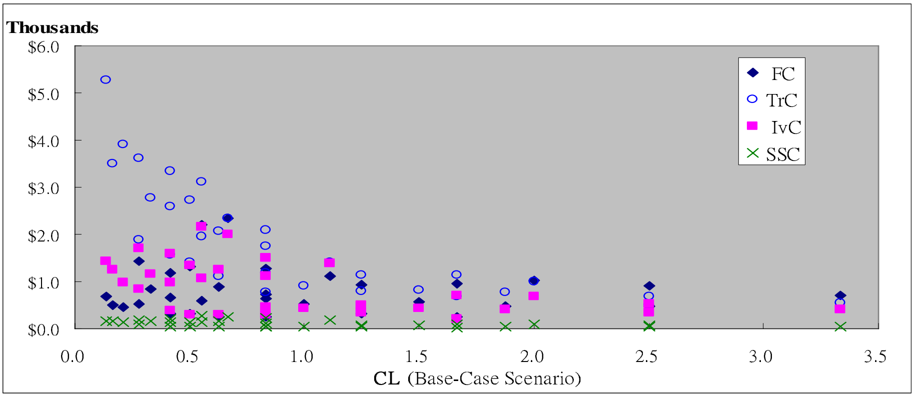

Fig. 2. Cost Components against Competitiveness Level (CL) for Scenario 1

5.2 Scenario Analysis

Our goal in this section is to illustrate the performance effects on the proposed solution procedure. We consider two diverse scenarios by changing the capacity scaling parameters of cap_j at a time as follows: cap_j ~U(2,4) for the *tight capacity* scenario (scenario 2) and cap_j ~U(6,8) for *excess capacity* scenario (scenario 3). In order to see the general effects of these scenarios to the *base case scenario* (scenario 1), the incremental gap is expressed as a *percentage gap* instead of an absolute solution, which is defined as ((*value of current scenario* − *value of scenario* 1) / *value of scenario* 1) × 100%. Also, an *improvement percentage* is used to find out the relative changes of the cost component proportions. In Table 2, comparative computational results for *capacity scenarios* to the *base case scenario* are illustrated.

Table 2. Comparative Results of Capacity Scenario Analysis

Scenarios	Objectives			Percentage Gaps				Improvement Percentage			
	TC	VFR	RL	FC	TrC	IvC	SSC	%FC	%TrC	%IvC	%SSC
S_2 vs S_1	-19.3%	-21.6%	-28.8%	-22.2%	-13.9%	-21.4%	-24.9%	-1.3%	2.4%	-0.8%	-0.2%
S_3 vs S_1	6.1%	8.1%	32.8%	17.7%	0.4%	12.7%	11.81%	1.69%	-3.1%	1.27%	0.1%

The first row of S_2 vs. S_1 in Table 2 provides the comparative computational results under scenario 2 as compared to scenario 1. All the objective measurements tend to statistically decrease where TC reduced by 19.3% (in average), VFR reduced by 21.6% and RL reduced by 28.8%. As compared to scenario 1, the general effect of scenario 2 is explained that the model is simultaneously reducing the objectives due to

DC capacities shortage. The most influenced objective by DC capacity tightness is RL since the buyers could be possibly assigned to a DC that is not satisfied within the coverage distance if there are still additional capacities available. Nevertheless, if tightness causes insufficient capacities, the supplier will gradually lose his orders from buyers. That is the reason why VFR is also reduced. Contrarily, the second row of S3 vs. S1 in Table 2 provides comparative computational results under scenario 3 as compared to scenario 1, where TC increased by 6.1% (in average), VFR increased by 8.18% and RL increased by 32.8%. With sufficient capacity, the supplier can not only satisfy as many as his customers but also are capable of assigning them to nearer DCs according the *greedy* heuristic. That is why both VFR and RL are increasing at the same time and especially RL shows the largest increase of gaps among others.

The general effect on cost components is that all relevant costs are optimized in *tight capacity scenario* (scenario 2). First, FC is decreased because the optimal number of DCs is reduced. Second, TrC should have increased because it is inversely related to the number of opening DCs. The fact can be identified that only TrC has the positive improvement percentage (2.4% in Table 2) among others. However, scenario 2 reduces the buyer's willingness to place orders so as to reduce VFR. Thus, TrC is decreased for the sake of sales loss. Third, IvC is also reduced for the similar reason of the decreasing amount of opening DCs and the reduction of sales. Finally, tight capacity causes strong effects on the SSC as well. The relationship between safety stock and the number of opening DCs is explained by the square root law and the portfolio effects [13]. Tight capacity enables less risk-pooling that makes worse inventory aggregation. The larger amount of safety stock was no longer required. However, scenario 3 is contrarily different from scenario 2 that the model occurs to increase all relevant costs.

6 Concluding Remarks and Research Directions

This paper presented the MOLIP model initially represented as a multi-objective optimization formulation which examines the effects of facility location, transportation, and inventory issues. The MOLIP model via a GA approach has been successfully applied for providing promising solutions on a set of test problems and enhances the possibility of including realistic facility transportation, inventory costs in this model. The scenario analysis illustrates that excess capacity in network design is beneficial for volume fill rate and responsiveness level and has only little expense of total costs. The computational results above imply that network capacity tightness needs to be adjusted when new buyers are introduced or demand changes so as to capture the tradeoff between costs and customer service levels. The model proposed in this research is helpful in adjusting the distribution network to these changes.

An implication of this research is particularly relevant for firms seeking to increase DC's capacity flexibility in their distribution networks. To gain more benefits from their volume fill rate and responsiveness level, the firms might face the problem of increasing total cost, especially the transportation cost. However, firms could be suggested to use the services of third parties to manage down the facility costs and the transportation costs because that allows for faster facility changes in response to market or demand changes. As a result, the relative importance of facility cost in the network design declines. This proposed model can be extended in a number of ways. First, inclusion of other inventory and distribution decisions, such as inventory order policy, frequency and size of the shipments, would be a direction worth pursuing. Second, inventory at the buyers has to be explicitly modeled. Third, it is likely to include stockout and backorder costs in the model.

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