Multi-objective Dual-Sale Channel Supply Chain Network Design Based on NSGA-II

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Abstract. In this study, we propose a two-echelon multi-objective dual-sale channel supply chain network (DCSCN) model. The goal is to determine (i) the set of installed DCs, (ii) the set of customers the DC should work with, how much inventory each DC should order and (iv) the distribution routes for physical retailers or online e-tailers (all starting and ending at the same DC). Our model overcomes the drawback by simultaneously tackling location and routing decisions. In addition to the typical costs associated with facility location and the inventory-related costs, we explicitly consider the pivotal routing costs between the DCs and their assigned customers. Therefore, a multiple objectives location-routing model involves two conflicting objectives is initially proposed so as to permit a comprehensive trade-off evaluation. To solve this multiple objectives programming problem, this study integrates genetic algorithms, clustering analysis, Non-dominated Sorting Genetic Algorithm II (NSGA-II). NSGA-II searches for the Pareto set. Several experiments are simulated to demonstrate the possibility and efficacy of the proposed approach.

Keywords: Supply chain management, Integrated supply chain design, Dual sale channel, Multiple objective evolutionary algorithm, NSGA-II.

1 Introduction

In general prospective, there are two streams of research solving the integrated supply chain network (SCN) problem, one stream of study is based on the concept of the Location-Allocation Problem (LAP), and the other stream is based on the Location-Routing Problem (LRP). The LRP is defined to solve a facility location problem, but in order to achieve this we simultaneously need to solve a vehicle routing problem. The main difference of the LRP from the LAP is that, once the facilities have been placed, the LRP requires the visitation of demands nodes through tours, where the latter assumes straight-line or radial trips between the facilities and respective customers. The LRP considers three main decisions of difference levels simultaneously: location of depots - strategic level; allocation of customers to depots - tactical level and the routes to visit these customers - operational level. The interdependence between these decisions has

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been noticed by researchers long ago. Due to the complexity of both location and routing problems, they have been traditionally solved separately [1] and have made the proposed models too simple and led to sub-optimality.

In last few years, the advent of e-commerce (EC) has made retailing more complicated and more competitive. New channels for supply chains have attracted much interest. Since the internet made on-line shopping easy, it has become an important *internet-enabled* channel as well. Dual-channel supply chain design (DCSCN) is becoming more common. In DCSCN, customers select the channel through which to buy goods, so dual channels mean more shopping choices and potential cost savings to customers. Therefore, several models addressing these issues are developed. Especially, on-time delivery relies heavily on effective vehicle routing once the merchandise is out the supplier's door and on its way to the customer. The LRP has become more complicated in a B2C environment in dual-channel supply chains.

2 Literatures Reviews

In the last two decades, many LRP models have been proposed in the literature. Most of them are related to a simple distribution network with two layers (depots and customers) and are solved by either exact or heuristic solution methods. Only few exceptional studies addressed more complex distribution network design problems. [2] developed a four-tier integrated LRP made up of four layers (plants, central depots, regional depots and customers), with the aim of defining the number and the location of the different types of facilities. [3] proposed a three-layer distribution logistics model for the conversion from brick-and-mortar to click-and-mortar retailing by a static one-period optimization model. [4] considered four layer supply chains similar to [2]. A heuristic algorithm based on LP-relaxation was proposed. Research on dual channel environment problem is relatively rare. [5] considered ordering and allocation policies for multi-echelon systems with two sales channels. [6] reviewed an inventory equilibrium performance or the inventory control policy within dual sale channel. There are also very limited researches addressing the retail/e-tail routing operations in dual sale channel. [7, 8] both agreed that a quick-response vehicle dispatching system is more necessary in the B2C environment than in B2B. [3] solved a three-tier static location-routing-based problem that embraces the clicks-and-bricks strategy in their retail operations. Multi-objective optimization problems in SCN have been considered by different researchers in literature [9,10]. The evolutionary algorithms have been validated to have better computational efficiency on solving the optimization problems for SCN. In the last decade, there has been a growing interest to adopt Multi-objective evolutionary algorithms (MOEAs), such as Non-dominated Sorting Genetic Algorithm II (NSGA-II), to solve a variety of multi-objective SCN problems [11]. Through MOEAs, decision-makers can obtain Pareto optimal solutions.

From the survey, some innovative research aspects that are noteworthy have been incorporated in our research work. This study incorporates two streams of SCN research, LAP and LRP, to solve an integrated DCSCN problem. We propose a nonlinear mix-integer Multi-Objective Location-Routing model with multiple objectives so as to minimize the total location cost and the routing cost simultaneously. We also provide a decision making approach via NSGA-II which is employed as a "filter" to approximate a set of Pareto-optimal solutions. Up to now, very few studies have applied similar problem-solving approaches in the same research context.

3 Problem Statement and Formulation

3.1 Problem Description and Assumptions

In this paper, we consider a multi-objective two-echelon DCSCN problem (see Fig 1.) that consists of a vendor with a warehouse at the top echelon, multi-distribution centers (DCs) in the middle echelon and the retailers from dual sale channels (either traditional or internet-enabled channels) at the bottom echelon. Our problem incorporates the Vehicle Routing Problem with Time Windows (VRPTW) which is the problem of designing least cost routes from one depot (say DC) to a set of geographically scattered points of e-retailers. The routes is designed in such a way that each point is visited only once by exactly one vehicle within a given time interval; all routes start and end at the same DC, and the total demands of all e-retailers on one particular route must not exceed the capacity of the vehicle. In addition, for each DC, there are two different delivery policies. A point-to-point policy is adopted for the shipment between DCs and retailers for the traditional channel. However, DCs have to quickly response to the online customer's requirements through the internet. A home delivery services guarantees that shipment should arrive during designated time window. In addition to the typical costs associated with LAP, we explicitly consider the pivotal routing costs between the DCs and their assigned customers incurred from VRP. Two objectives are provided to minimize the total facility location and the inventory-related costs in LAP as well as to minimize the total routing costs in VRP. Our problem then is modeled as a multi-objective nonlinear integer program.

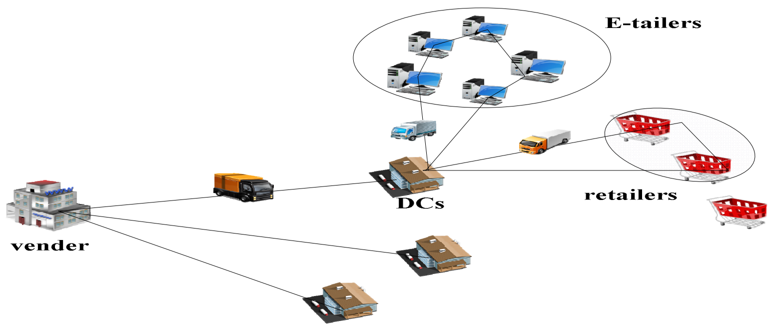


Fig. 1. Graphic representation of DCSCN model

The following assumptions are used throughout the whole paper. The product is always available to customers throughout both channels. The product price is identical for both channels. The system receives orders from both channels according to customers' preferences. The demands from both channels at each DC occurred randomly and are identically independent and normally distributed. The centralized inventory policy under the vendor managed inventory (VMI) mode is considered where the vendor is responsible for the safety stock pooled at DCs. At any DC j, we assume a continuous inventory revision, and a (Q_j, r_j) policy to meet a stochastic demand pattern. That is, when the inventory level at DC j falls to or below a reorder point r_j, a fixed quantity Q_j is ordered to the vendor. Each order is fulfilled and delivered by only a specific DC but the assignment of e-tailer/retailers to a DC is known a priori. For e-tailers, the last-mile home delivery within time windows is adapted to fulfill the quick response requirement. The vendor storage capacity is unlimited but each DC has capacity restriction for retailers but not for e-tailers due to the fact that the requirement of e-tailers is relatively small as compared to retailers. For retailers, therefore, the assignment rule is based on the DC's capability and distance coverage; for e-tailers, the routing distance is the only concern. Each DC possesses two types of vehicles' capacities for dual sale channels. Vehicles' capacities in the same channel are the same, and fleet type is homogeneous but the inter-dispatch shipping is prohibited. In addition, we integrate three decisions in a mathematical model under the aforementioned assumptions.

- *Location and allocation decisions*: how many DCs to locate, where to locate the opened DCs, and how to allocate the e-tailer /retailers to them.
- *Routing decisions*: how to build the vehicles' routes starting from an opened DC to serve its customers.
- *Inventory decisions*: how often to reorder, what quantity to replenish for each order at a DC from each retailer.

3.2 Mathematical Model

Before presenting the model, we depict the notation used throughout the paper.

Indices. j is an index set of potential DCs ($j \in$ J). i is an index set for retailers ($i \in$ I). n is an index set for e-tailers ($n \in$ N). r is an index set of all routes (vehicles) ; $\forall\, r \in$ R. v is an index set of vehicles ($v \in$ V). M is a merged set of e-tailers and potential DCs (N∪J). P is a merged set of e-tailers and potential DCs.

Decision Variables. Q_j is the order quantity at DC j. Y_j is a binary variable to decide if DC j is opened. X_{ji} is a binary variable to decide if retailer i is assigned to DC j. W_{jn} is a binary variable to decide **i**f e-tailer n is assigned to DC j. R^r_{nh} is a binary variable to decide if node n precedes node h in the route r. F^v_{st} is a binary variable to decide if node s precedes node t in the route v. M_r is an auxiliary variable for sub-tour elimination constraints in route r. if DC j is opened; 0 otherwise see if RBC i is chosen or not. $\mathbf{v}_j$ is a binary variable if CBC j is opened or not.

Model Parameters. B is the number of e-tailers contained in set N, i.e. B = |N|. d_i is the mean of annual demand at retailer i. u_n is the mean of annual demand at e-tailer n. δ_i is the standard deviation of annual demand at retailer i. δ_n is the standard deviation of annual demand at e-tailer n. f_j is the annual fixed cost for opening and operating DC j. rc_j is the unit transportation cost between the vendor and DC j. tc_{st} is the unit routing cost between node s and node t; $\forall$ s, $t \in I \cup J$. vc_{nh} is the unit routing cost between node n and node h; $\forall\, n$, $h \in N \cup J$. a^r_n is the earliest time of route r to serve e-tailer n. b^r_n is the latest time of route r to serve e-tailer n. t^r_n is the specified arrival time of route r for e-tailer n. s_j is the inventory holding cost per unit time (annually) at DC j. o_j is the inventory ordering cost per order to the vendor from DC j. β is the weight factor associated with routing cost. Θ is the weight factor associated with inventory cost. ζ_j is the average lead time in days to be shipped to DC j from the vendor. z_α is the left α-percentile of standard normal random variable Z.

According to the mentioned notations and assumptions, we formulate a multi-objective mixed-integer programing model as follows.

$$\begin{aligned} \min \quad & \sum_{j\in J} f_j \times Y_j + \sum_{j\in J} (o_j \times \frac{\sum_{i\in I}\sum_{n\in N}(d_i \times X_{ji} + u_n \times W_{jn})}{Q_j}) \\ & + \theta \times \{\sum_{j\in J} s_j [{Q_j}/{2} \times Y_j + z_{1-\alpha}(\sum_{i\in I}\delta_i\sqrt{\zeta_j \times X_{ji}} + \sum_{n\in N}\delta_n\sqrt{\zeta_j \times W_{jn}})]\} \end{aligned} \tag{1}$$

$$\begin{aligned} \min \quad & \beta \times [\sum_{j\in J}\sum_{i\in I}\sum_{n\in N} rc_j \times (d_i \times X_{ji} + u_n \times W_{jn}) \\ & + \sum_{n\in M}\sum_{h\in M}\sum_{v\in V} vc_{nh} \times R^r_{nh} + \sum_{s\in P}\sum_{t\in P} tc_{st} \times d_i \times F^v_{st}] \end{aligned} \tag{2}$$

subject to :

$$\sum_j X_{ji} = 1 \tag{3}$$

$$X_{ji} \le Y_j \quad , \tag{4}$$

$$\sum_{h\in M} R^r_{nh} = 1 \tag{5}$$

$$\sum_{t\in P} F^v_{st} = 1 \tag{6}$$

$$M_n - M_h + (B \times R^r_{nh}) \le B - 1 \tag{7}$$

$$\sum_{h\in M} R^r_{nh} - \sum_{h\in M} R^r_{hn} = 0 \tag{8}$$

$$\sum_{j\in J}\sum_{n\in N} R^r_{jn} \le 1 \tag{9}$$

$$-W_{jn} + \sum_{h\in M}(R^r_{nh} - R^r_{jh}) \le 1 \tag{10}$$

$$a^r_n \times W_{jn} \le t^r_n \le b^r_n \times W_{jn} \tag{11}$$

$$X_{ji} \in \{0,1\} \quad Y_j \in \{0,1\} \quad W_{jn} \in \{0,1\} \quad R^r_{nh} \in \{0,1\} \tag{12}$$

The objective function Eq. (1) minimizes the facility location and inventory-related costs in LAP. The first term indicates the *facility operating* cost of DCs; the second term considers the *dual channel ordering* cost and the last one is the *holding cost at* DCs, including working inventory cost and safety stock cost. The objective function

Eq. (2) minimizes the transportation cost in VRP. The first term indicates the *inbound transportation cost* from the vender to DCs; the second and the third terms refer to the o*utbound routing costs* incurred by the orders of *retailers* and *e-tailers* respectively. We split the total cost into these objectives for the sake of concerning the association of costs incurred between LAP and VRP. In Eq. (1) and Eq. (2), β and θ denote the weights of different scenarios corresponding to their impacts on inventory and routing factors, respectively. Eq. (3) restricts a retailer to be serviced by a single DC. Eq. (4) states that retailers can only be assigned to open DCs. Eq. (5) ensures that each e-tailer is assigned on exactly one vehicle route at a time. Eq. (6) ensures each retailer is placed on only one vehicle at a time. Eq. (7) is the sub-tour elimination constraint which guarantees each tour must contain a DC from which it originates, i.e. each tour must consist of a DC and some e-tailers. Eq. (8) carries out the flow conservation saying that whenever a vehicle enters an e-tailer or DC node, it must leave again and ensuring that the routes remain circular. Eq. (9) implies that only one DC is included in each route. In Eq. (10), the e-tailer is assigned to the DC only if a specific route starts its trip from the DC. Eq. (11) ensures the DC delivery service meets the e-tailer's time requirement. Eq. (12) enforces the integrality restrictions on the binary variables. Since the order quantity Q_j in Eq(1) is convex in Q_j >0, the optimal order quantity Q_j^* is obtained by differentiating Eq. (1) with respect to Q_j.

$$Q_j^* = \sqrt{\frac{2 \times o_j \times (\sum_{i \in I} d_i \times X_{ji} + \sum_{n \in N} u_n \times W_{jn})}{s_j}} \tag{13}$$

4 Solution Methodologies

Our proposed model combines the location-allocation problem (LAP) and the multi-depot vehicle routing problem (VRP) in dual sales channel environments that results in NP-hard. Due to the complexity of the problems that exact methods can only tackle relatively small instances, as an alternative, a heuristic procedure is applied. Fig. 2 depicts the solution scheme of our heuristic procedure.

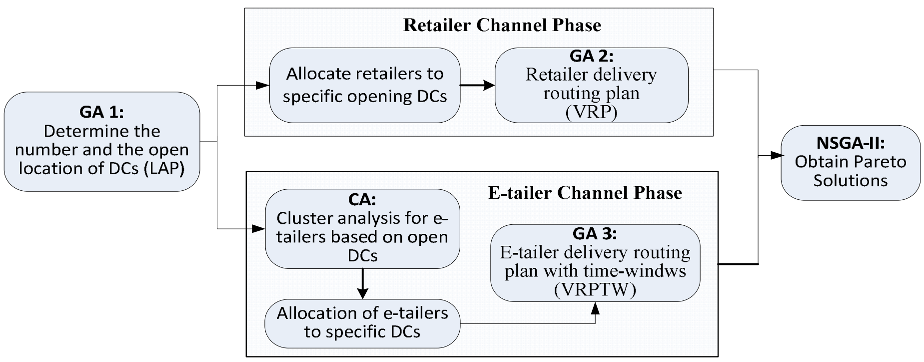


Fig. 2. The solution scheme of proposed heuristic procedure for DCSCN

As we can see in the heuristic procedure in Fig. 2, genetic algorithms (GA) and cluster analysis (CA) are integrated to solve our DCSCN model. The heuristic procedure is decomposed into LAP and VRP stages. In the LAP stage, a genetic-based heuristic procedure (GA1) is first applied to determine the number, location of DCs, assignment of specific retailers to each of DC. In the VRP stage, the procedure is then decomposed into two phases: retail channel phase and e-tail channel phase. The former mainly arranges retailer' delivery routing plan between each opened DC to their allocated retailers by a second genetic-based heuristic (GA2) , the latter clusters the e-tailers based on open DCs and also makes delivery routing by time-windows by a hybrid heuristic via a K-means cluster analysis (CA) and a genetic algorithm (GA3). Vis those heuristics, we obtain all costs incurred in the proposed DCSCN model problem. Subsequently, NSGAII is adopted to search for the Pareto solutions.

- GA1 for LAP: the major task of this procedure (GA1) is to determine the number of potential DCs will be opened and the allocation of downstream retailers to specific opening DCs, the solution is encoded in a binary string of length $|J|$ (the number of DC and $\forall j \in J$).
- GA2 for VRP: this procedure is to decide the retailer's delivery routing plan for DCs.
- CA for e-tailers: this procedure is to classify e-tailers into k groups according to the number of open DCs given priori by k-means. After clustering, the DC-Group *allocation* procedure is performed to allocate each opening DC to one of the groups based on the shortest distance between DCs and the group centroids. Due to DC capacity restrictions, it is allowed for a specific group to select the secondary closest DC, if its closest DC cannot afford sufficient capacity for all e-tailers in the same group, until every group has been assigned.
- GA3 for e-tailer's VRPTW: this procedure is to determine the e-tailer's delivery routing plan within time windows for DCs. The process of GA3 is quite similar to GA2 except for delivery time requirements. In practice, on-line delivery service allows its customers to choices favorite time periods to receive orders instead of exact arriving time. For this reason, we randomly divide each group of e-tailers into three sub-groups with respect to different time requirements of delivery service.

4.1 NSGAII for Pareto Solutions

NSGA-II [12] is one of the best techniques for generating "good" solutions in MOEAs in which two primary goals should be achieved: (i) convergence to a Pareto-optimal set, and (ii) maintenance of population diversity in a Pareto-optimal set. First of all, for each solution in the population, one has to determine how many solutions dominate it and the set of solutions to which it dominates. Then, it ranks all solutions to form non-dominated fronts according to a *non-dominated sorting* process, hence, classifying the chromosomes into several fronts of non-dominated solutions. To allow for 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 losing good solutions (*elitism* strategy). However, the crossover and mutation operators remain the same as usual.

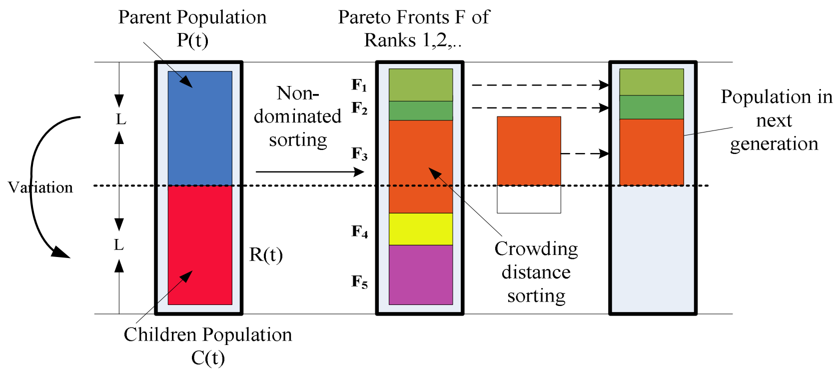
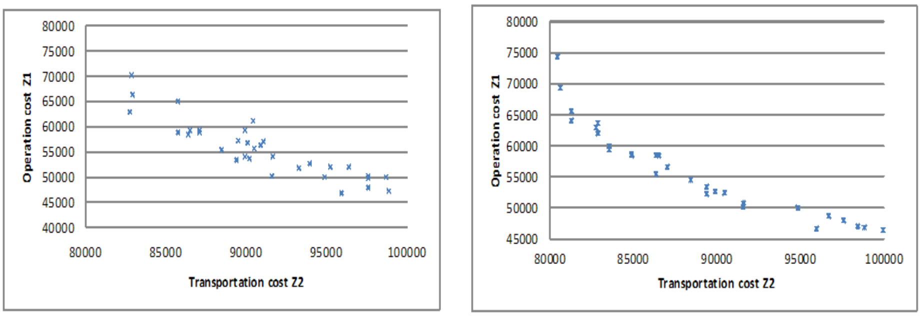


Fig. 3. NSGA-II solution scheme

Based on NSGA-II, a hybrid evolutionary algorithm is proposed for our model. The solution scheme is graphically represented as in Fig. 3. This algorithm starts by generating a random population P(1) of size *L*. For each chromosome in P(1), the algorithm evaluates its costs using the encoded solution expressions. Then, it applies *non-dominated sorting* on P(1) and assigns to each chromosome a front to which it belongs. Next, the algorithm applies binary tournament selection (to form the crossover pool), crossover, and mutation operators to generate the children population C(1) of size *L*. After that, a combined population R(1)=P(1)∪C(1) of size 2*L* is sorted according to the *elitism strategy* aforementioned . Therefore, a new parent population P(2) is formed by adding solutions from the first front till the size exceeds *L*. Once initialized, the algorithm repeats for *T* generations.

5 Numerical Experience

To evaluate the performance of the DCSCN consisting of LAP and VRP issues, we provide some computational experiments. For the best of our knowledge, there are no similar instances in the public domain, nor have any benchmarking available in previous studies. To explore DCSCN, we developed a test problem by generating problem instances with 25 potential DCs, 100 retailers and 500 e-tailers in a square of 50 distance units of width. For simplicity, Euclidean distance is used for measuring distribution distances. For the hybrid GA implementation, we used the following input parameters: population size = 100; maximum number of generations = 200; cloning = 20%; crossover rate = 80%; mutation rate varies from 5% to 10% as the number of generations increases. The approach program was coded in MATLAB. In Fig. 4, we represent the solution evolutionary process of our optimization scheme visually from a variety of feasible solutions to a non-dominated solution set through NSGAII. The non-dominated solution set of DCSCN is obtained by applying NSGAII is illustrated in Table 2, where 30 alternatives of non-dominated solutions are listed. Each alternative contains the number of opening DCs, the operation cost in LAP (Z_1) as well as the transportation cost in VRP (Z_2).



(a) Feasible solutions for DCSCN (b) Pareto non-dominated solutions through NSGA-II

Fig. 4. The solution evolutionary process of optimization scheme

Table 1. Non-dominated solution set from NSGAII

Al-terna-tive	# of Open DCs	Operation cost in LAP (Z1)	Transporta-tion cost in VRP (Z2)	Alter-native	# of Open DCs	Operation cost in LAP (Z1)	Transpor-tation cost in VRP (Z2)
1	4	\$80,493.74	\$74,397.86	16	13	\$96,676.35	\$48,711.52
2	14	\$99,943.45	\$46,537.74	17	14	\$98,420.11	\$46,942.34
3	7	\$83,545.31	\$59,497.13	18	9	\$91,568.61	\$50,742.70
4	6	\$80,616.50	\$69,302.92	19	7	\$86,520.80	\$58,509.21
5	7	\$84,929.02	\$58,530.48	20	7	\$84,929.02	\$58,743.14
6	7	\$81,315.94	\$64,184.07	21	13	\$98,859.08	\$46,907.06
7	8	\$86,356.81	\$55,498.99	22	10	\$89,393.85	\$53,304.12
8	9	\$88,438.25	\$54,549.90	23	5	\$82,909.69	\$63,657.47
9	10	\$89,393.85	\$52,289.53	24	9	\$87,058.17	\$56,529.38
10	5	\$82,909.69	\$62,103.26	25	8	\$89,914.31	\$52,583.65
11	12	\$95,947.76	\$46,701.68	26	10	\$90,491.93	\$52,466.75
12	7	\$82,764.15	\$63,051.12	27	7	\$83,545.31	\$59,979.49
13	9	\$91,568.61	\$50,246.43	28	13	\$97,618.28	\$47,885.84
14	11	\$94,872.27	\$50,086.08	29	8	\$86,356.81	\$58,523.08
15	7	\$82,315.94	\$65,645.07	30	9	\$88,438.25	\$55,496.18

6 Conclusion

In this study, we attempt to propose a two-echelon multi-objective dual sale channel supply chain network model regarding a single vender, multiple distribution centers (DCs), as well as a set of customers (physical retailers or online e-tailers). We develop a novel formulation which integrates three issues, LAP, inventory and VRP, of

SCN. This study attempts to find the location and the number of open DC, the allocation of DCs to customers, inventory replenishment and also the distribution routes for physical retailers or online e-tailers of with minimal facility and inventory operation cost and minimal transportation cost for DCSCN. NSGA-II is applied to determine a finite set of non-dominate Pareto solutions. Feasibility of the developed model was checked by presenting several small-sized random instances and solving them by proposed GA approaches. In our experiments, the proposed approach displays good behavior on the near-reality data and yields a near-optimal solution in stochastic demand environments. Several interesting phenomenon are perceived.

The model can be extended in some practical directions. Detailed sensitive analysis should be adopted to find the crucial parameters with respect to different assignments, resulting in the maximum increases/decreases on this DCSCN structure. Moreover, the proposed heuristic procedure genetic provides a variety of options and parameter settings that are worth fully examined. It is also interesting to develop more effective and elegant heuristic methods to solve the integrated model problem. For example, model can be solved by other meta-heuristic algorithms. In additions, determining the weights of the attributes in the model is important but complex. Sorting Pareto solutions is also required according to decision-makers' preferences by using multi-attribute decision making (MADM) techniques, such as Analytic Hierarch Process (AHP) or Technique for Order Preference by Similarity to Ideal Solution (TOPSIS).

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