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MULTI-OBJECTIVE EVOLUTIONARY APPROACH FOR SUPPLY CHAIN NETWORK DESIGN PROBLEM WITHIN ONLINE CUSTOMER CONSIDERATION

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Abstract. Supply chain network design is one of the most important strategic decisions that need to be optimized for long-term efficiency. Critical decisions include facility location, inventory, and transportation issues. This study proposes that with a dual-channel supply chain network design model, the traditional location-inventory problem should be extended to consider the vast amount of online customers at the strategic level, since the problem usually involves multiple and conflicting objectives. Therefore, a multi-objective dual-channel supply chain network model involving three conflicting objectives is initially proposed to allow a comprehensive trade-off evaluation. In addition to the typical costs associated with facility operation and transportation, we explicitly consider the pivotal online customer service rate between the distribution centers (DCs) and their assigned customers. This study proposes a heuristic solution scheme to resolve this multi-objective programming problem, by integrating genetic algorithms, a clustering analysis, a Non-dominated Sorting Genetic Algorithm II (NSGA-II), and a Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Several experiments are simulated to demonstrate the possibility and efficacy of the proposed approach. A scenario analysis is conducted to understand the model's performance.

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1. Introduction

Supply chain management is a set of approaches that efficiently integrates suppliers, facilities, and customers so that merchandise is produced and distributed at the right quantities, to the right locations, and at the right time, to minimize system-wide costs while simultaneously meeting service level requirements. Supply chain network design is one of the most important strategic decisions in supply chain management. It determines the optimal configuration of the facilities as well as the production, distribution, and shipment of inventory in such a way to optimize both customer satisfaction and the value of the chain. Supply chain network design involves strategic decisions that also influence tactical and operational decisions, for instance, a decision on the location

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of facilities that fails to take into consideration the related inventory and transportation costs can lead to sub-optimality. For this reason, there is a new trend of research focuses on the integration of facility location, transportation, and inventory decisions.

Retail stores have always been the traditional channel in supply chains. However, since the advent of online shopping, the online channel has also become another important option for customers. Therefore, a dual-channel supply chain model comprising physical and online channels becomes more common, and this enables customers to select a specific channel. Dual channels mean more shopping choices and potential cost-savings for customers.

Traditionally, facilities location, inventory decision is a strategic policy, and transportation is a short term plan, Shin and Qi [27] stated "failure to take the related shipment costs into consideration when deciding the locations of facilities can lead to sub-optimality, since strategic location decisions have a big impact on shipment costs", moreover, the proposed paper discuss the dual channel supply chain network business model, if we only consider the retailer physical demand but ignore the online customer potential demand, could cause the DCs' location away these online customer lead to sub-optimality. the definition of potential customers demand in proposed model is not their actual order, but the rough data obtained by customers historical information, so, that don't need to be optimized each time the orders are to be delivered. This study addresses the problem of a dual-channel supply chain network which determines the facility locations, customer allocation, and inventory policy − a problem that has so far received limited attention. Since the explored problem integrates both location inventory and vehicle routing problems (VRPs), it is an NP-hard problem. This study attempts to provide an optimal solution to determine the distribution centers' (DCs) number, location, inventory, and distribution decisions. However, given that the integration of these decisions usually involve a trade-off among incompatible objectives, a single performance measure such as minimum cost or maximum profit would not capture the whole essence of the problem, as improving one objective may lead to the deterioration of others. Hence, three objectives are considered in this proposed model: (1) to minimize the operation cost comprising DCs' fixed cost and inventory holding cost; (2) to minimize the transportation cost comprising inbound point-to-point transportation and outbound vehicle routing conducted by outsourced providers; and (3) to maximize online customer service satisfaction. This therefore calls for the formulation of a multi-objective nonlinear integer programming model, as the problem cannot be easily solved by using existing optimization techniques. An approach that integrates NSGA-II [9] and TOPSIS [15] is proposed to resolve this problem. NSGA-II searches for a set of non-dominated solutions, where a non-dominated solution performs better than other solutions on at least one criterion. Subsequently, TOPSIS determines the best compromise solution for decision makers from the Pareto set.

The contribution of this study is in twofold. First, we establish a dual-channel supply chain network model which considers the issue of potential online customers within a traditional location-inventory problem, as this important strategic decision facilitates the transportation movement in a dual-channel supply chain configuration that would affect tactical and operational activities. Second, due to the inherent complexity of a supply chain network problem comprising various conflicting objectives, this study therefore develops a multi-objective model and presents a methodology solution to help the decision maker improve the decision quality through the evaluation of the trade-offs involved in incompatible goals.

The remainder of this paper is organized as follows. Section 2 presents a review of existing literature on related works. Section 3 describes the multi-objective dual sale channel problem and formulates the model. Section 4 details the approach for resolving the problem, and the computational results are reported in Section 5. The study is concluded with recommendations for the future direction in Section 6.

2. Literature review

Supply chain network design involves strategic decisions on the facility number, location, and customers' assignment, which influences tactical and operational decisions. As the supply chain network design is strongly related to inventory and transportation issues, a model that does not consider these issues can lead to sub-optimality. Daskin *et al.* [8] and Shen *et al.* [26] introduced a joint location-inventory model with risk pooling that incorporates the inventory decision into the location problem. Vidyarthi *et al.* [31] proposed a production-location-inventory integration problem in a three-level distribution network with multiple types of product consideration. In this study, they only considered the safety stock cost but not the on-hand inventory cost, while Özsen *et al.* [23] considered a location-inventory model subject to a restriction on the maximum possible inventory accumulation at DCs. Sourirajan *et al.* [29] analyzed a network design model where the supply lead time from a single supplier to capacitated DCs comprises load make-up, replenishment, and congestion time components. Gzara *et al.* [14] presented two integration network designs and inventory control problems in service parts logistic systems under demand uncertainty and highly nonlinear time-based service level constraints. Jin [17] proposed a distribution network design problem that considers an inventory management cost restricted by a given budget, and then used the Lagrangian relaxation method to solve the nonlinear integer program.

In contrast to the substantial number of studies discussing the physical channel supply chain network design, there is relatively little research on the problem with dual-sale channels. Dye [11] developed a deteriorating inventory model with a time-dependent backlogging rate, and then proposed an algorithm to find the optimal selling price and replenishment schedule. Mahar and Wright [21] established a "quasi-dynamic" policy to solve the online demand allocation problem, and assumed that the online demand is accumulated before being assigned to specific retailers/e-tailers, and the allocation decision is then made based on the expected inventory, shipping, and waiting costs. The experiment results indicated that total cost is significantly reduced after the proposed policy is applied. Bretthauer *et al.* [4] established a two-echelon facilities network which comprises a single central warehouse and several depots for both in-store and online sales, and one offsite depot for online sales only. The aim of this study is to determine the optimal inventory and allocation solution for satisfying both in-store and online demand. Widodo *et al.* [32] reviewed the inventory equilibrium performance and inventory control policy within dual-sale channels in terms of where and how much inventory should be allocated and held at each site to satisfy both in-store and online demand and minimize the total cost. Liu and Xu [20] developed a three-level, dual-channel supply chain network transactions model which integrates multi-period and multi-criteria decision-making that established the optimal conditions for the manufacturers and the retailers respectively, along with the behavior of the various decision makers.

Multi-objective optimization problems in supply chain network have been considered by different researchers in literature [6; 22; 25]. Farahani *et al.* [12] divided three categories consisting of classical approaches, pareto optimal approaches and Evolutionary algorithms (EAs) in their comprehensive review paper to solve multi-objective optimization problem. As they depicted, "if the problems in the first and second category are complex then those can be solved using EAs". EAs have been validated to have better computational efficiency in resolving the component assignment optimization problems of supply chain network, which is why there has been a growing interest to adopt Multi-objective evolutionary algorithms (MOEAs), such as NSGA-II, to resolve a variety of multi-objective supply chain network problems [2, 18]. While MOEAs can obtain a group of Pareto optimal solutions, those solutions need to be sorted according to decision-makers' preferences, which is a multi-attribute decision-making problem (MADM). Several novel hybrid approaches that combine various MOEAs and MADM techniques, such as the Analytic Hierarch Process (AHP) or TOPSIS have been proposed to resolve this type of problem. Taleizadeh *et al.* [30] developed a random fuzzy replenishment multi-product inventory model and proposed a hybrid intelligent algorithm to resolve multi-objective integer-non-linear problems, finally applied TOPSIS to rank the solutions. Goyal *et al.* [13] investigated the optimal machine selection for a reconfigurable manufacturing system. They applied NSGA II to provide the Pareto front solutions, and used the Shannon entropy weigh theory and TOPSIS approach to rank the solutions.

Some noteworthy innovative research aspects found from the survey have been incorporated in our research work Our study extends the traditional location-inventory problem to consider the vast amount of online customers at the strategic level. A nonlinear, mixed-integer, multi-objective location-routing model is proposed to minimize both the total location and routing costs. A systematic approach *via* the integration of NSGA II and TOPSIS is also provided. NSGA-II with a "filter" is employed to approximate a set of Pareto-optimal solutions. However, TOPSIS is then adopted to rank these solutions from the best to the worst once the subjective preferences of decision makers have been provided. To date, very few studies have applied similar problem-solving approaches in the similar research context.

3. Problem statement and formulation

3.1. Problem description and assumptions

This study presents a multi-objective dual-chain supply network model (depicted in Fig. 1) which comprises a vendor at the top level, multiple DCs at the middle level and customers from dual-sale channels, either physical retailers or internet-enabled channels, at the bottom level. A vendor receives an order either from physical retail stores or online customers directly, and both the vendor and DCs are owned and operated by a central decision maker who is responsible for the management of both the product flow and inventory policy. The vendor does not carry inventory and operates as a cross-decking facility that receives the consolidated loads from the manufacturer, and then delivers these products to the intermediate DC for serving downstream customers such as retailers or online customers, to meet uncertain demands that occur at the sales locations.

The problem incorporates a VRP with time windows, as the products are shipped from one DC to a set of geographically scattered downstream customers through the least costly routes. The routes must be designed in such a way that each point is visited only once by exactly one vehicle and all routes start and end at the same DC. In addition, the total demands of all customers on one particular route must not exceed the capacity of the vehicle. In addition, there are two different delivery policies for each DC. A point-to-point policy is adopted for shipments between DCs and retailers in a traditional channel. In contrast, a home delivery services guarantees that a shipment should arrive within a designated time window in an internet-enabled channel, since DCs need to respond quickly to online customers' requirements, and this is done by subcontracting to an outsourced carrier.

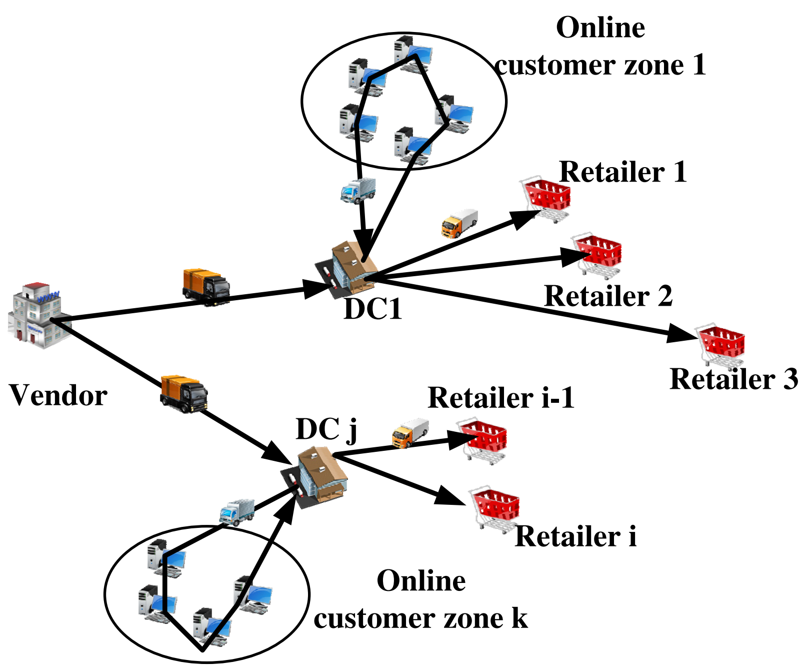

Figure 1. The dual channel supply chain distribution model.

In addition to the typical costs associated with a location-inventory problem, the pivotal routing costs between the DCs and their assigned customers incurred from a VRP are explicitly considered. Three objectives are provided; the first is to minimize the total facility location and inventory-related costs of a location-inventory problem, the second is to minimize the total routing costs in a VRP, and the third is to maximize the online customers' service level. The problem is then modeled as a multi-objective, nonlinear integer program. The following assumptions are made throughout the whole paper:

- The product is always available to customers through either physical or internet-enabled channels, and the product price is identical in both channels.
- The demands from both channels at each DC occur randomly and are identically independent and normally distributed.
- The centralized inventory policy with the vendor managed inventory is considered, the safety stock are pooled at DCs for the order of downstream customers.
- A continuous inventory (Q_j, r_j) policy is assumed to meet a stochastic demand pattern at any DC_j. This means that, 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 online customers/retailer's order is fulfilled and delivered only by a specific DC, but the assignment of online customers/retailers to the DC is known *a priori*.
- For online customers, the last-mile home delivery within time windows is considered and is conducted by outsource carriers, the time windows are divided into three time segment based on customers requirement.
- The vendor and DCs storage capacities are unlimited, the online customer's service level is constrained by specific DC maximum coverage distance.

3.2. Mathematical model

The notation used throughout the paper is predicted before presenting the model.

Indices:

j index of potential DCs;

J set of all potential DCs; $\forall\, jJ$

i index of retailer;

I set of all retailer; $\forall i \in I$

n index of online customer;

N set of all online customer; $\forall n \in N$

Parameters:

B number of online customer contained in set N, *i.e.* $B = N$

d_i mean of annual demand at retailer i

u_n mean of annual demand at online customer n

δ_i standard deviation of annual demand at retailer i

δ_n standard deviation of annual demand at online customer n

f_j annual fixed cost for opening and operating DC_j

rc_j unit transportation cost between the vendor and DC_j

tc_{ji} unit transportation cost between DC_j and retailer$i$

vc_{gh} unit transportation cost between node g and node n, $\forall\, g, h \in J \cup N$

a_h the earliest time to serve online customer h, $\forall\, h \in N$

b_h the latest time to serve online customer h, $\forall\, h \in N$

t_h the specified arrival time for online customer h, $\forall\, h \in N$

$D_{\max}$ maximal coverage distance

τ_n the set of DCs that could attend online customer n

$dist_{gh}$ distance from node$g$ to node h, $\forall g, h \in J \cup N$

sp Speed of vehicle

s_j inventory holding cost per unit time at DC_j

o_j inventory ordering cost per order to the supplier from DC_j

ζ_j average lead time in days to be shipped to 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 retailer i is assigned to DC_j; 0 otherwise

W_{jn} 1 if online customer n is assigned to DC_j; 0 otherwise

V_{gh} 1 if node g precedes node n; 0 otherwise, $\forall g, h \in J \cup N$

M_n auxiliary variable for online customer n for sub-tour elimination constraints

Q_j order quantity at DC_j

A multi-objective mixed-integer programming model is formulated according to the aforementioned notations and assumptions, as described below.

$$\begin{aligned} \text{Min} \sum_{j\in J} f_j \times Y_j + \sum_{j\in J} o_j \times \frac{\sum_{i\in I}(d_i \times X_{ji}) + \sum_{n\in N}(u_n \times W_{jn})}{Q_j} \\ + \left\{ \sum_{j\in J} s_j \times \left[\frac{Q_j}{2} \times Y_j + z_{1-\alpha}\left(\sum_{i\in I} \delta_i \sqrt{\zeta_j \times X_{ji}} + \sum_{n\in N} \delta_n \sqrt{\zeta_j \times W_{jn}} \right) \right] \right\} \end{aligned} \tag{3.1}$$

$$\text{Min} \quad \begin{aligned} & \sum_{j\in J} rc_j \times \left[\sum_{i\in I} (d_i \times X_{ji} + \sum_{n\in N} u_n \times W_{jn}) \right] + \sum_{g\in J\cup N} \sum_{h\in J\cup N} vc_{gh} \times dist_{gh} \times V_{gh} \\ & + \sum_{j\in J} \sum_{i\in I} tc_{ji} \times d_i \times X_{ji} \end{aligned} \tag{3.2}$$

$$\text{Max} \frac{\sum_{n\in N} u_n \times \sum_{j\in\tau_n} W_{jn}}{\sum_{n\in N} u_n \times W_{jn}} \tag{3.3}$$

subject to:

$$\sum_{j\in J} X_{ji}=1, \forall i \in I \tag{3.4}$$

$$X_{ji} \leqslant Y_j, \forall i \in I,\ \forall j \in J \tag{3.5}$$

$$\sum_{j\in J} W_{jn}=1,\ \forall n \in N \tag{3.6}$$

$$W_{jn} \leqslant Y_j,\ \forall n \in N, \quad \forall j \in J \tag{3.7}$$

$$M_l - M_n + (B \times V_{ln}) \leqslant B-1\,,\ l,\ n \in N \tag{3.8}$$

$$\sum_{h\in J\,\cup\,N} V_{gh} - \sum_{g\in J\,\cup\,N} V_{hg} = 0 \tag{3.9}$$

$$\sum_{g\in J\,\cup\,N}\ \sum_{h\in J\,\cup\,N} V_{gh} \leqslant 1 \tag{3.10}$$

$$-W_{jn} + j \sum_{u\in J\,\cup\,N} (V_{ju} - V_{un}) \leqslant 1, \forall j \in J,\ \forall n \in N \tag{3.11}$$

$$t_h = \left(t_g + \frac{\mathrm{dist}_{gh}}{sp}\right) \times V_{gh}\,,\ g \in J\,\cup\,N, h\,\in N \tag{3.12}$$

$$a_h \leqslant t_h \leqslant b_h\,,\ h \in N, \tag{3.13}$$

$$X_{ji} \in \{0,1\}\,, Y_j \in \{0,1\}\,, W_{jn} \in \{0,1\}\,, V_{gh} \in \{0,1\}\,. \tag{3.14}$$

The objective function equation (3.1) in the proposed model minimizes the facility location and inventory-related costs in a location-inventory problem. The first term indicates the facility operating cost of DCs, while the second term considers the dual-channel ordering cost and the last term is the holding cost at DCs, including working inventory and safety stock costs. The objective function equation (3.2) minimizes the transportation cost in a VRP. The first term indicates the inbound transportation cost from the vendor to DCs, while the second term represents the outbound transportation cost from DC to online customers, in this proposed model assume the transportation cost is distance depended. The third term represents the outbound transportation cost from DC to retailers, which is quantity depended. The objective function equation (3.3) maximizes the online customer's service satisfaction which is measured by the percentage of fulfillment for the demand within vehicle coverage distance. Equation (3.4) restricts a retailer to be serviced by a single DC. Equation (3.5) states that retailers can only be assigned to open DCs. Equation (3.6) restricts an online customer to be serviced by a single DC. Equation (3.7) states that online customers can only be assigned to open DCs. Equation (3.8) 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 online customers [10]. Equation (3.9) conducts the flow conservation indicating that whenever a vehicle enters an online customer or DC node, it must leave again, ensuring that the routes remain circular. Equation (3.10) implies that only one DC is included in each route. Equation (3.11) links the allocation and the routing components of the model: the online customer is assigned to the DC only if a specific route starts its trip from the DC. Equation (3.12) indicates the vehicle arrival time, equation (3.13) ensures that the DC delivery service for online customers can arrive during the designated time window, equation (3.14) enforces the integrality restrictions on the binary variables.

In equation (3.1) is convex in Q_j >0, the optimal order quantity Q_j^* can be obtained by differentiating equation (3.1) with respect to Q_j as follows in equation (3.15).

$$Q_j^* = \sqrt{\frac{2 \times o_j \times \left(\sum_{i\in I} d_i \times X_{ji} + \sum_{n\in N} u_n \times W_{jn}\right)}{s_j}}. \tag{3.15}$$

A non-liner cost function equation (3.16) is obtained by substituting equation (3.15) in equation (3.1).

$$\begin{aligned} \min \quad & \sum_{j\in J} f_j \times Y_j \ + \sum_{j\in J}\left[\sqrt{2 \times o_j \times s_j \times \left(\sum_{i\in I} d_i \times X_{ji} + \sum_{n\in N} u_n \times W_{jn}\right)}\right] \\ & + \sum_{j\in J} s_j \times z_{1-\alpha}\left[\sum_{i\in I} \delta_i \sqrt{\zeta_j \times X_{ji}} + \sum_{n\in N} \delta_n \sqrt{\zeta_j \times W_{jn}})\right] \end{aligned} \tag{3.16}$$

4. Solution methodologies

MOEAs are popular approaches to resolving multi-objective optimization for efficient-solving and easy-adaptive properties, especially for problems where traditional methods fail to provide good solutions [7]. However, the well-known MOEA called *Non-dominated Sorting Genetic Algorithm* II or NSGA-II is one of the most successful approaches as observed in the existing literature. In our study, a NSGA-II based evolutionary approach is proposed as illustrated in Figure 2.

```
Randomly generate P (1)
Apply GA1 for DCs location and allocation solution
Apply CA for online customers allocation
Conduct GA2 for online customers vehicle routing and service rate solution
Evaluate P (1)
Non-dominated sort P (1)
Generate C (1) form P (1), apply selection, crossover, and mutation
Evaluate C (1)
while t  T do
R(t) = P(t) ∪ C(t)
Non-dominated sort R(t)
Select P (t + 1) from the first L chromosome of R(t)
Generate C (t + 1) from P (t + 1), apply selection, crossover, and mutation
Evaluate C (t + 1)
t ← t + 1
end while
```

Figure 2. The NSGAII-based evolutionary approaches.

Furthermore, we proposed a heuristic procedure, as depicted shown in Figure 3, where a genetic approach incorporated with cluster analysis (CA) is used to resolve the dual-channel supply chain network model. The heuristic procedure is decomposed into location-inventory and vehicle-routing stages. In the first stage, a genetic-based heuristic procedure as represented by GA1 is firstly applied to determine the number and location of DCs, and assign the specific retailers to each DC. In the second stage, the procedure clusters the customers based on the number of open DCs *via* a K-means CA, and then determines the delivery routing with time windows by means of a hybrid heuristic as exemplified by GA2. All the costs incurred in the model are obtained *via* these heuristics, and subsequently, NSGA-II is adopted to search for the Pareto solutions before TOPSIS is finally applied to determine the best compromise solution.

4.1. A hybrid heuristic procedure

4.1.1. Genetic-based heuristic procedure (GA1) *for location inventory*

The major task of this GA1 procedure is to determine the number of potential DCs and the allocation of downstream retailers to specific opening DCs so as to minimize the initial cost in equation (3.1). Each individual of the initial population is generated by producing random strings of 0's and 1's of length |J| (the number of DC and $\forall j \in J$). Thus, a gene representing Y_j for every candidate location$j$ carries a value of 1 if a DC is open at that candidate's site and 0 otherwise. The procedure then conducts the assignment of retailers to one of the open DCs by a *minimal distance discipline*. That is, each retailer is allocated to a specific open DC based on the shortest distance between them. A value of 1 indicates that retailer i was successfully assigned to DC_j and 0 otherwise. Figure 4 illustrates an example of chromosome representation and allocation scheme for a problem with 5 DCs and 5 retailers. Figure 4a shows the chromosome and describes the initial status of DCs (*i.e.* $Y_1 = Y_4 = 0$; $Y_2 = Y_3 = Y_5 = 1$) indicating that DC1 and DC4 is close but DC2, DC3 and DC5 are open. Figure 4b depicts the distance matrix between DCs and retailers in our problem. Figure 4c represents an allocation table. A value of 1 in the table indicates the retailer i has the shortest distance to a specific open DC_j ($Y_j = 1$), therefore, DC_j is responsible for the distribution of retailer i.

4.1.2. Cluster procedure (CA) *for customers*

According to Jain and Dubes [16], "Clusters may be described as connected regions of a multi-dimensional space containing a relatively high density of points, separated from other such regions by a region containing a relatively low density of points." This definition of a group is an excellent reason to use a CA in the resolution of a location problem within a vehicle routing consideration. The potential of a CA for the problem has been recognized by prior research [3]. K-means, a least-square partitioning method that resolves many well-known clustering problems, is applied in this study to classify customers into k online customer zones according to the number of open DCs given priori. After clustering customers into k customer zones, the next process is to allocate each customer zone to specific opening DCs based on the shortest distance between DCs and the zone's centroids. The cluster procedure is depicted in Figure 5.

4.1.3. Genetic-based heuristic procedure (GA2) *for online customer's VRP with time window and fulfillment rate*

The purpose of the VRP with time window and fulfillment rate procedure is to determine the delivery route plan from each DC to each online customer group that is performed by a GA2 procedure. In this procedure, a genetic algorithm is applied again and obtained the initial transportation cost and online customers' fulfillment rate from the objective functions equations (3.2) and (3.3). Owing to the fact that the supply chain network design discussed in this study is a strategic decision, rather than an assumption of the customers expecting to receive their goods at an exact time at the traditional VRP with time window, three daily time periods representing morning, afternoon, and evening of the customers receiving the goods are considered in our problem. The algorithm is conducted by randomly clustering each group of online customers into three sub-groups, with each sub-group representing one of three time windows. Further, the chromosome is encoded in an integer string of length N, where N is the number of online customers allocated to a specific DC within selected time windows.

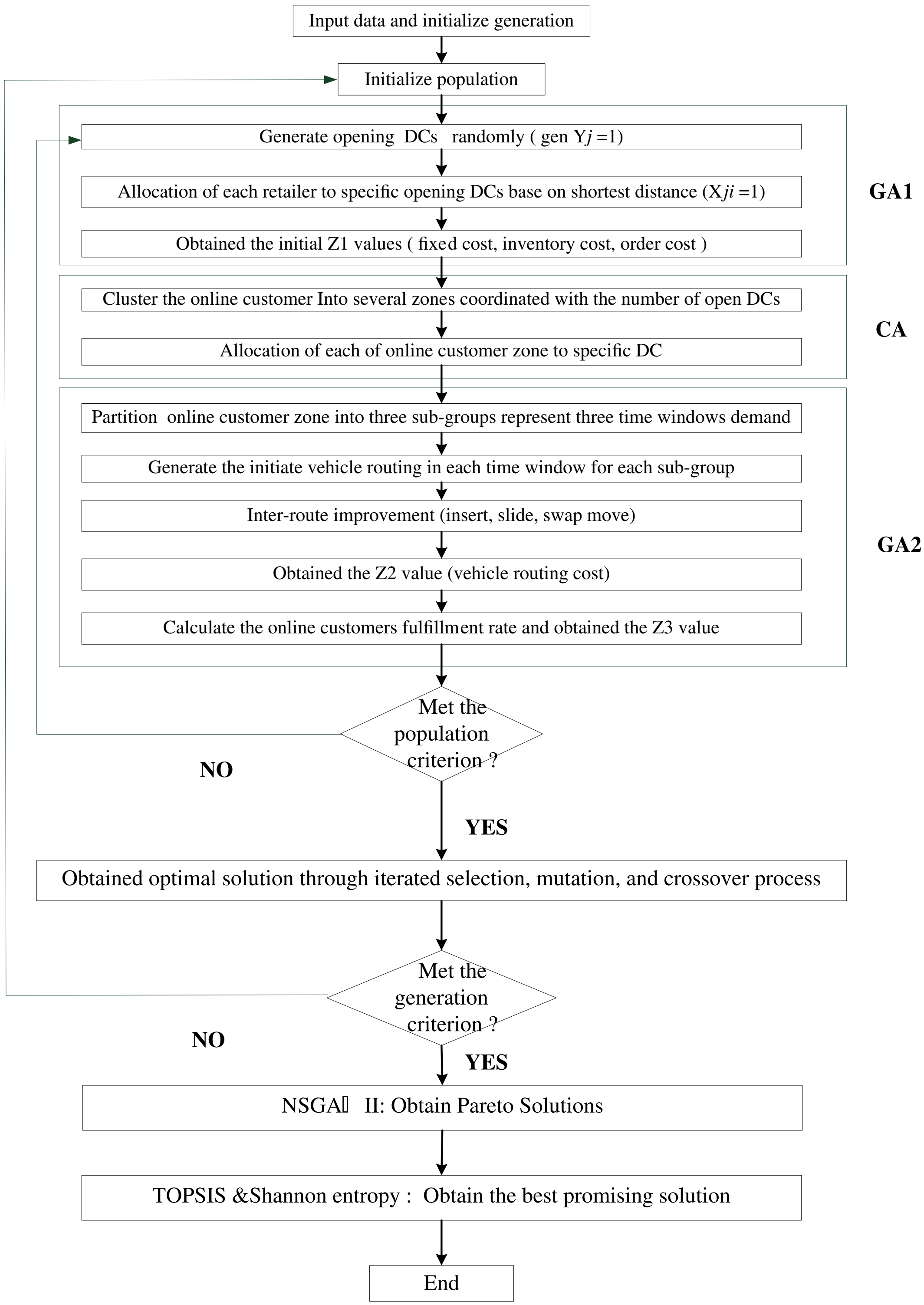

Figure 3. The flow chart of the proposed heuristic procedure.

	R1	R2	R3	R4	R5
DC1	0	0	0	0	0
DC2	1	1	1	1	1
DC3	1	1	1	1	1
DC4	0	0	0	0	0
DC5	1	1	1	1	1

(a) The initial DCs open status

	R1	R2	R3	R4	R5
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

(b) The distance matrix

	R1	R2	R3	R4	R5
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

(c) The assignment table

FIGURE 4. DC Allocation scheme for GA1.

```
Specify a certain number of k groups a priori
Place one point inside each group as the initiated centroid
Repeat
    Assign each small client to the group with the closest centroid
    Re-compute the new centroid in each group
Until all centroids don't swift
```

FIGURE 5. The online customers' clustering procedure in CA.

The value of each gene denotes a specific online customer, and the genetic sequence of the chromosome represents the vehicle visiting order. The online customers' vehicle inter-route improvement procedure is depicted as follows in Figure 6. Once the route plan is determined *via* above routing algorithms, the value for objective of Z_3 is then obtained by accounting the number of online customers within the scheme and compare to the number of customers in the group that plan to visit.

Similar to other evolutionary algorithms, GA2 randomly generated the individuals in the initial population. Then, a vehicle's inter-route improvement procedure is activated based on two schemes: *tournament selection* and *reproduction*. The tournament selection scheme with a 75% selection rate to select the individuals from the population is used to choose parents from the cross-over pool. In other words, the better fit individuals have a 75% chance of being selected. However, a simple cross-reproduction scheme is not valid since some gen values are repeated while others are missed. A remedy for this problem is to apply flip, swap and slide cross-over operators to the original parents to reproduce new offspring. Figure 7 illustrates an example how the reproduction scheme of three operators is implemented in GA2. As shown in Figure 7, for example, there are six online customers in a chromosome in each row of the table. The genetic sequence of a chromosome represents a vehicle route plan indicating the visiting order of the online customer. In this example, it is assumed that the second chromosome

1: Randomly generate an initial population P(1) of online customers routing sequence within each sub-group
2: Fitness evaluation of the population according to the routing cost
3: While t $\leq$ T do
4: Generate offspring C(t) from P(t) by applied *tournament selection* and *reproduction* (slide, swap and flip processes)
5: New parent P(t+1) = parent P(t)∪offspring C(t)
6: End

FIGURE 6. Genetic-based heuristic procedure (GA2) for online customer's VRP.

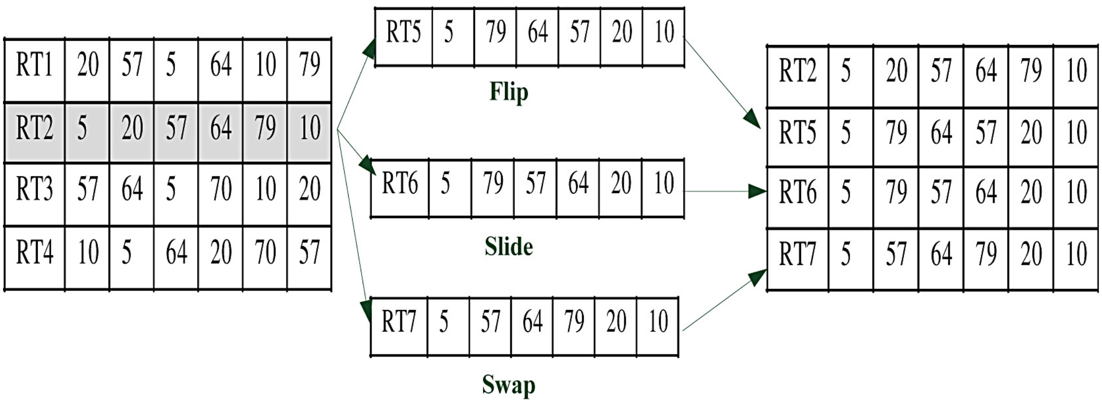

FIGURE 7. A reproduction scheme of three operators for GA2.

which has the best fitting value in the initial solution. Therefore, the mutation operator is conducted to randomly select two points among these nodes. Afterward, flip, swap, and slide processes are applied respectively to obtain another three new chromosomes. Finally, four vehicle schemes including the best fitting one are combined to form a new parent set.

4.2. NSGA-II for Pareto solutions

NSGA-II is adopted to search for the Pareto solutions. In the selection process for the next generation, chromosome fitness depends on the evaluation of the decoded solution in the objective functions and its comparison with other chromosomes. First, 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: (i) non-domination rank in the optimization objectives (p.rank); (ii) local crowding distance in the objectives space directions (p.distance). If both chromosomes are at the same non-domination rank, the one with fewer chromosomes around in the front is preferred. Thus, a partial order ($\geqq_n$) defined in Definition 4.1 is used to guide the selection process of the algorithms to decide among two chromosomes which one is fitter.

Definition 4.1. Let $p, q \in R(t)$ be two chromosomes in population $R(t)$. 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)).

Suppose that $Z_{\mathrm{k}}(p)$ and $Z_{\mathrm{k}}(q)$ be the kth objective function evaluated at two decoded chromosomes p and q, respectively. In the our NSGA-II approach, $Z_1(\bullet)$ indicates the facility location and inventory-related costs

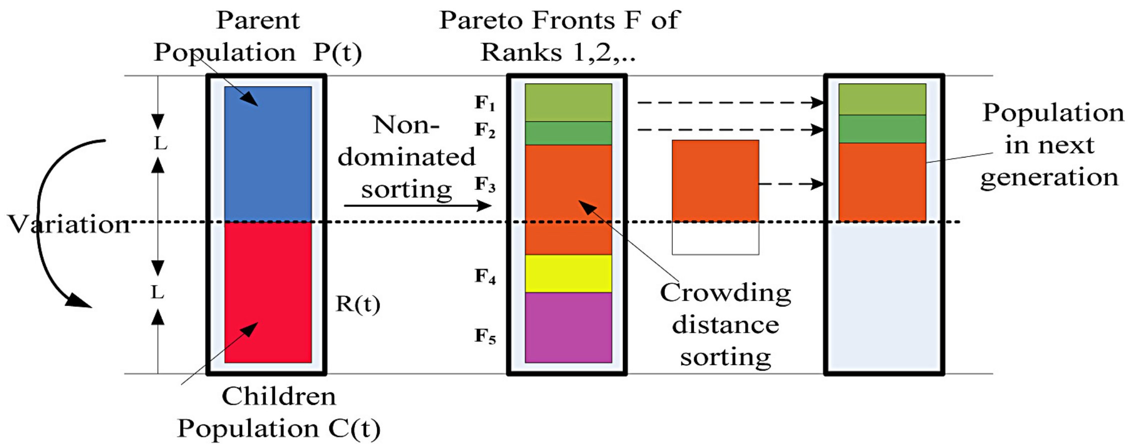

FIGURE 8. The NSGA-II solution scheme.

obtained by CA1, $Z_2(\bullet)$ indicates the transportation cost and $Z_3(\bullet)$ indicates the online customer's service satisfaction rate obtained by CA2. 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 that considers 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.

The NSGA-II solution scheme for Pareto solutions is illustrated in Figure 8. The procedure begins by generating a random population $P(1)$ of size L. The algorithm evaluates the cost of each chromosome in $P(1)$ using an encoded solution expression. Then, it applies non-dominated sorting to $P(1)$ and assigns a front to each chromosome to which it belongs. Next, the algorithm applies a binary tournament selection (to form the cross-over pool), crossover, and mutation operators to generate the child population $C(1)$ of size L. After that, a combined population $R(1) = P(1) \cup C(1)$ of size $2L$ is sorted according to the aforementioned elitism strategy. Therefore, a new parent population $P(2)$ is formed by adding solutions from the first front until the size exceeds L. Once initialized, the algorithm is repeated for T generations.

4.3. TOPSIS and Shannon entropy for the best compromise solution

Although NSGA-II is usually applied to generate Pareto solutions, it is crucial for decision makers to find the best compromise solution from the Pareto set as an ultimate goal. Inspired by [5,13,19], our research uses TOPSIS to find the best compromise solution. TOPSIS, introduced by Hwang and Yoon [15], is used to rank the given alternatives of the Pareto solutions obtained by NSGA-II. The basic concept of TOPSIS determines the positive ideal solution (PIS or $\mathbf{S}^+$), as well as the negative ideal solution (NIS or $\mathbf{S}^-$), and then finds the best compromise solution which is closest to $\mathbf{S}^+$ and furthest from $\mathbf{S}^-$ from the Pareto set according to the decision makers' objective weights.

The process of TOPSIS to determine the best compromise solution is presented as follows:

Step 1: Input the decision matrix X, where the element $x_{ij}\, of X$ is the jth objective value of the ith alternative. That is, X is composed of the Pareto solutions based on three objectives $Z1$, $Z2$ and $Z3$ of equation (3.1), equations (3.2) and (3.3) which are generated by NSGA-II.

Step 2: Calculate the normalized decision matrix $P = [p_{11,}p_{12,}p_{13};p_{21,}p_{22,}p_{23};\ldots;p_{n1,}p_{n2,}p_{n3}]$ of X to transform different scales of attributes into common measurable units. Shin *et al.* [28] had classified the normalization methods as vector, liner and non-monotonic normalization, furthermore, Chakraborty and Yeh [5] compared the performance of vector and various liner normalization in terms of ranking consistency and weight sensitivity, the result show the vector normalization has better performance than others methods, for the reason, this paper adopted the vector normalization which is the initial form presented in the original manuscript of Hwang and Yoon [15]. X is normalized to be P according to equation (4.1).

$$p_{ij} = \frac{x_{ij}}{\sqrt{\sum\limits_{i=1}^{n} (x_{ij})^2}}, i = 1.2 \ldots, n, j = 1, 2, 3. \tag{4.1}$$

Step 3: Decide the objective weights based on the concept of Shannon entropy in information theory [34]. The *entropy* value (e_j) of the attribute A_j is determined by equation (4.2). Let $d_j = 1 - e_j$ represents the inherent contrast intensity of the attribute A_j. The higher the value of d_j, the more important the attribute A_j is. Finally, the objective weight for each attribute can be obtained by equation (4.3)

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln p_{ij}, \quad j = 1, 2, 3 \tag{4.2}$$

$$w_j = -\frac{d_j}{\sum_{j=1}^{3} d_j}, \quad j = 1, 2, 3. \tag{4.3}$$

Step 4: Construct the weighted normalized decision matrix $\hat{S} = [\hat{s}_{11,}, \hat{s}_{12}, \hat{s}_{13}; \hat{s}_{21,}, \hat{s}_{22}, \hat{s}_{23}; \ldots; \hat{s}_{n1,}, \hat{s}_{n2}, \hat{s}_{n3}]$ using equation (4.3).

$$\hat{s}_{ij} = w_j \cdot p_{ij}, i = 1, \ldots, n \text{ and } j = 1, 2, 3. \tag{4.4}$$

Step 5: Use equations (4.5) and (4.6) to determine the positive ideal solution (PIS or $\mathbf{S}^+$) as well as the negative ideal solution (NIS or $\mathbf{S}^-$).

$$\mathbf{S}^+ = (\min(\hat{s}_{11}, \hat{s}_{21}, .., \hat{s}_{n1}), \ \min(\hat{s}_{12}, \hat{s}_{22}, .., \hat{s}_{n2}), \ \max(\hat{s}_{13,}, \hat{s}_{23,}, .., \hat{s}_{n3})) \tag{4.5}$$

$$\mathbf{S}^- = (\max(\hat{s}_{11}, \hat{s}_{21}, .., \hat{s}_{n1}), \ \max(\hat{s}_{12}, \hat{s}_{22}, .., \hat{s}_{n2}), \ \min(\hat{s}_{13,}, \hat{s}_{23,}, .., \hat{s}_{n3})). \tag{4.6}$$

Step 6: Calculate the separation measures h_i^+ and h_i^- for each alternative. The separation measures $h_{\mathbf{i}}^+$ in equation (4.7) and h_i^- in equation (4.8) are the Euclidean distances of alternative i from PIS ($\mathbf{S}^+$) and NIS ($\boldsymbol{S}^-$) respectively.

$$h_i^+ = \sqrt{\sum_{j=1}^{3} \left(\hat{s}_{ij} - s_j^+\right)^2}, \qquad i = 1, \ldots, n \text{ and } s_j^+ \in \mathbf{S}^+, \quad j = 1, 2, 3 \tag{4.7}$$

$$h_i^- = \sqrt{\sum_{j=1}^{3} \left(\hat{s}_{ij} - s_j^-\right)^2}, \qquad i = 1, \ldots, n \text{ and } s_j^- \in \mathbf{S}^-, \quad j = 1, 2, 3. \tag{4.8}$$

Step 7: Calculate relative closeness C_i for each Pareto solution according to equation (4.9).

$$C_i = \frac{h_i^-}{h_i^+ + h_i^-}, i = 1, \ldots, n. \tag{4.9}$$

Step 8: Choose the best compromising solution whose relative closeness C_i is the closest to 1.

5. Numerical experience

This section attempts to evaluate the performance of the overall solution scheme for a dual-chain supply chain network by providing some computational results.

5.1. Data generation

The proposed multi-objective dual-chain supply chain network model involves the three aforementioned subproblems. However, to the best of our knowledge, there are no similar instances in the public domain, nor has any benchmarking been made available in previous studies. Thus, we develop a baseline problem to explore the decision dimension. The test problems are constructed by generating examples of problems in a supply chain network with 25 potential DCs, 80 retailers, and 500 online customers in a square of 50 distance units of width. In other words, Euclidean distance is used to measure the distribution distances. The vehicle maximum reach distance is 250 km, the average travel speed is 50 km/h, the transportation cost from vendor to DCs is distance and volume dependent which is set as 40 per unit distance and 1 per unit volume, but DCs to retailers and to online customers are only distance dependent which is set as 50 and 10 per unit distance, respectively. The remaining model parameters are depicted as follows:

u_k is uniformly drawn from [150,200].
δ_i and δ_k are uniformly drawn from [2,4].
f_j is uniformly drawn from [900,1000].
s_j is uniformly drawn from [16,32].
o_j is uniformly drawn from [1,3].
ζ_j is uniformly drawn from [2,4].

The approach program is coded in MATLAB 7 and executed on an INTEL I5 2.40 GHz processor. We use the following input parameters for the hybrid GA implementation: population size of GA1 = 1000; population size of GA2 = 100; maximum number of generations = 200; cloning = 20%; crossover rate = 80%; mutation rate varies from 5% to 10% as the number of generations increase.

5.2. Computational results

The non-dominated solution set of a dual-chain supply chain network obtained by applying NSGA-II is illustrated in Table 1, where 40 alternatives of non-dominated solutions are listed. Each alternative contains the number of opening DCs, the objective function values for operation cost in a location-inventory problem (Z_1), the transportation cost in a VRP (Z_2), as well as the online customer service level (Z_3). The best values for Z_1, Z_2, and Z_3 are demonstrated in bold and italic text, and the values Z_1, Z_2, and Z_3 obtained from Table 1 are used to form a decision matrix $\mathbf{X}$ for the TOPSIS process. Thereafter, the computational results of the TOPSIS and Shannon entropy information theory are depicted in Table 2. The relative closeness C_i and its corresponding rank among the five top-ranking solutions are also highlighted. Hence, the decision maker may select one of the top-ranked solutions based on the practical market environment. From Tables 1 and 2, we observe that decision makers will not choose an inefficient alternative by considering a single performance measurement of either cost minimization or service level maximization. Instead, they might choose a compromised but satisfied solution. Figure 9 indicates the results of the Pareto-fronts using NSGA-II for the baseline problem in two and three dimensions, respectively.

5.3. Sensitivity analysis

To evaluate the magnitude of the impact of online customers on the DC location decision for the proposed model, we establish three different problem instance sets based on size – representing small, medium, and large – of online customer groups scattered in a specific area. In addition, various inventory holding and transportation costs are considered again. Subsequently, two different types of transportation cost components (T1 or T2) and two different types of inventory holding cost scenarios (S1 or S2) are introduced; where S1, T1 stand for low-cost

Table 1. Non-dominated solution set from NSGA-II.

Alternative	# of Open DCs	Operation cost (Z_1)	Transportation cost (Z_2)	Fill rate (Z_3)	Alternative	# of Open DCs	Operation cost (Z_1)	Transportation cost (Z_2)	Fill rate (Z_3)
1	5	$191 486	$324 203	38.40%	21	8	$265 784	$334 188	65.20%
2	6	$217 848	$328,083	45.60%	22	9	$263 876	$338 284	71.40%
3	6	$207 436	$327 375	43.60%	23	9	$264 156	$338 095	74.00%
4	10	$299 966	$338 629	86.60%	24	11	$319 546	$340 812	89.00%
5	12	$366 262	$332 668	86.20%	25	9	$275 320	$333 720	66.80%
6	6	$194 276	$332 859	46.60%	26	9	$263 876	$338 726	71.80%
7	9	$291 995	$333 608	73.00%	27	12	$338 780	$333 235	82.20%
8	7	$243 199	$332 917	56.80%	28	8	$274 528	$333 846	63.60%
9	6	$231 475	$331 224	53.40%	29	9	$293 822	$332 945	71.20%
10	6	$207 436	$323 823	38.80%	30	9	$277 792	$333 746	74.80%
11	8	$242 550	$336 134	62.80%	31	9	$264 156	$336 091	73.80%
12	6	$207 436	$329 110	44.40%	32	13	$385 346	$333 198	90.40%
13	8	$256 901	$332 298	60.40%	33	12	$311 480	$338 028	84.60%
14	12	$331 409	$336 130	85.80%	34	13	$368 025	$334 824	88.80%
15	8	$272 160	$331 212	58.00%	35	12	$366 262	$336 509	91.20%
16	13	$367 780	$335 744	88.80%	36	6	$194 276	$330 004	46.20%
17	8	$261 818	$337 073	68.60%	37	10	$311 709	$334 302	81.20%
18	7	$248 778	$334 837	59.20%	38	7	$243 199	$332 903	56.40%
19	11	$286 807	$344 729	83.60%	39	6	$207 436	$329 598	44.60%
20	12	$332 839	$335 320	83.20%	40	8	$242 550	$341 392	73.00%

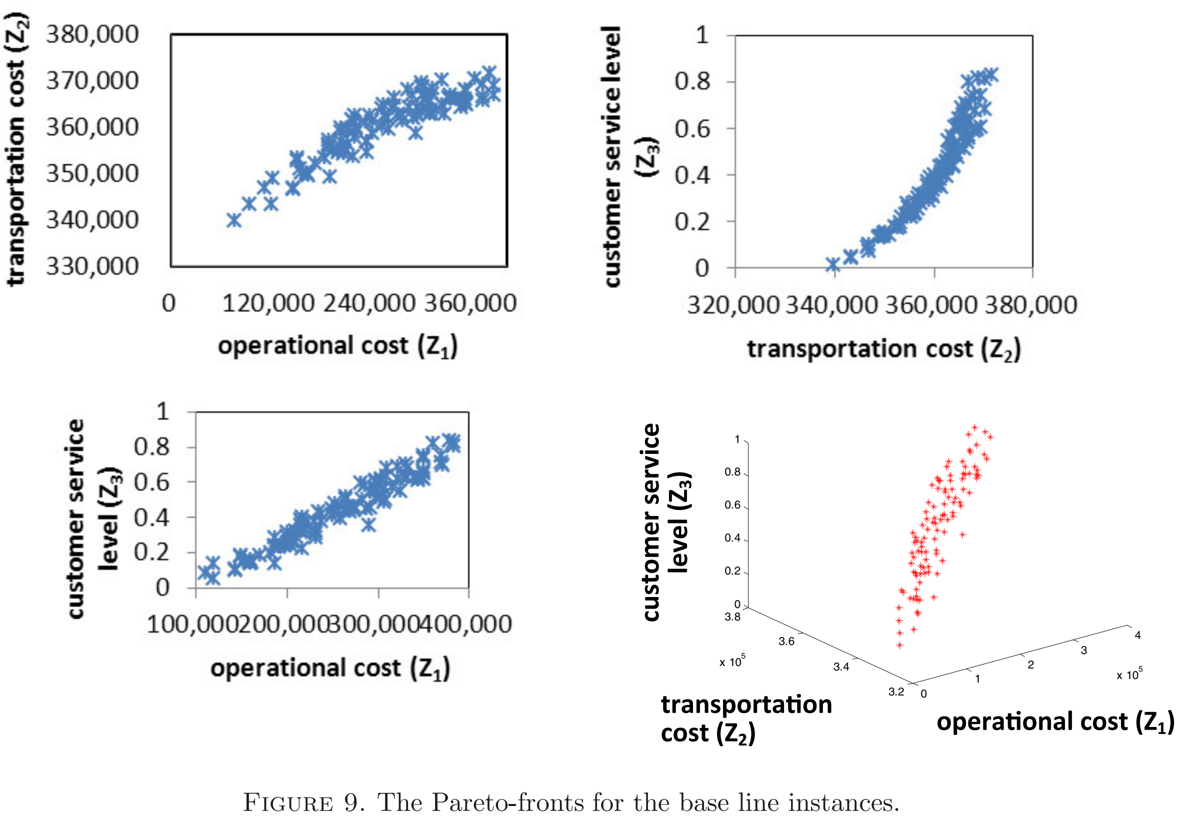

Figure 9. The Pareto-fronts for the base line instances.

TABLE 2. Computational results incurred from TOPSIS.

Alternative	Normalized decision Matrix S			Weighted normalized decision matrix $\hat{S}$			Separation measures		C_i	Ranking
	p'_{i1}	p'_{i2}	p'_{i3}	$\hat{s}_{i1}$	$\hat{s}_{i2}$	$\hat{s}_{i3}$	h_i^+	h_i^-		
1	0.1082	0.1534	0.0868	0.0359	0.0523	0.0288	0.0396	0.0365	0.4796	38
2	0.1231	0.1553	0.1031	0.0409	0.0529	0.0342	0.0346	0.0320	0.4806	37
3	0.1172	0.1549	0.0985	0.0389	0.0528	0.0327	0.0358	0.0337	0.4847	36
4	0.1695	0.1603	0.1957	0.0563	0.0546	0.0650	0.0208	0.0396	0.6557	3
5	0.2069	0.1574	0.1948	0.0687	0.0537	0.0647	0.0330	0.0361	0.5222	26
6	0.1098	0.1575	0.1053	0.0364	0.0537	0.0350	0.0335	0.0364	0.5209	28
7	0.1650	0.1579	0.1650	0.0548	0.0538	0.0548	0.0233	0.0314	0.5734	15
8	0.1374	0.1576	0.1284	0.0456	0.0537	0.0426	0.0276	0.0301	0.5214	27
9	0.1308	0.1568	0.1207	0.0434	0.0534	0.0401	0.0294	0.0310	0.5140	33
10	0.1172	0.1533	0.0877	0.0389	0.0522	0.0291	0.0394	0.0335	0.4597	40
11	0.1370	0.1591	0.1419	0.0455	0.0542	0.0471	0.0234	0.0325	0.5807	14
12	0.1172	0.1558	0.1003	0.0389	0.0531	0.0333	0.0352	0.0338	0.4893	35
13	0.1451	0.1573	0.1365	0.0482	0.0536	0.0453	0.0262	0.0293	0.5277	25
14	0.1872	0.1591	0.1939	0.0621	0.0542	0.0644	0.0266	0.0370	0.5815	13
15	0.1538	0.1568	0.1311	0.0510	0.0534	0.0435	0.0292	0.0259	0.4705	39
16	0.2078	0.1589	0.2007	0.0690	0.0542	0.0666	0.0332	0.0380	0.5338	22
17	0.1479	0.1595	0.1550	0.0491	0.0544	0.0515	0.0216	0.0324	0.6003	11
18	0.1406	0.1585	0.1338	0.0467	0.0540	0.0444	0.0264	0.0300	0.5326	24
19	0.1620	0.1632	0.1889	0.0538	0.0556	0.0627	0.0191	0.0386	0.6695	2
20	0.1881	0.1587	0.1880	0.0624	0.0541	0.0624	0.0272	0.0351	0.5627	16
21	0.1502	0.1582	0.1473	0.0498	0.0539	0.0489	0.0240	0.0302	0.5566	17
22	0.1491	0.1601	0.1614	0.0495	0.0546	0.0536	0.0203	0.0337	0.6243	8
23	0.1492	0.1600	0.1672	0.0495	0.0546	0.0555	0.0189	0.0351	0.6498	4
24	0.1805	0.1613	0.2011	0.0599	0.0550	0.0668	0.0242	0.0399	0.6223	9
25	0.1556	0.1579	0.1510	0.0516	0.0538	0.0501	0.0242	0.0297	0.5513	19
26	0.1491	0.1603	0.1623	0.0495	0.0547	0.0539	0.0200	0.0339	0.6282	6
27	0.1914	0.1577	0.1858	0.0635	0.0538	0.0617	0.0285	0.0340	0.5445	21
28	0.1551	0.1580	0.1437	0.0515	0.0539	0.0477	0.0260	0.0281	0.5202	29
29	0.1660	0.1576	0.1609	0.0551	0.0537	0.0534	0.0244	0.0301	0.5519	18
30	0.1570	0.1580	0.1690	0.0521	0.0538	0.0561	0.0204	0.0340	0.6250	7
31	0.1492	0.1591	0.1668	0.0495	0.0542	0.0554	0.0190	0.0350	0.6483	5
32	0.2177	0.1577	0.2043	0.0723	0.0538	0.0678	0.0364	0.0390	0.5176	32
33	0.1760	0.1600	0.1912	0.0584	0.0545	0.0635	0.0232	0.0373	0.6172	10
34	0.2079	0.1585	0.2007	0.0690	0.0540	0.0666	0.0332	0.0380	0.5335	23
35	0.2069	0.1593	0.2061	0.0687	0.0543	0.0684	0.0328	0.0398	0.5478	20
36	0.1098	0.1562	0.1044	0.0364	0.0532	0.0347	0.0338	0.0364	0.5186	30
37	0.1761	0.1582	0.1835	0.0585	0.0539	0.0609	0.0238	0.0350	0.5949	12
38	0.1374	0.1576	0.1275	0.0456	0.0537	0.0423	0.0279	0.0299	0.5178	31
39	0.1172	0.1560	0.1008	0.0389	0.0532	0.0335	0.0351	0.0338	0.4904	34
40	0.1370	0.1616	0.1650	0.0455	0.0551	0.0548	0.0169	0.0373	0.6880	1

scenarios and S2, T2 represent high-cost scenarios. These are implemented in each of the problem sets, namely, T1_S1, T1_S2 and T2_S1. The rest of model parameters are kept the same as the baseline problem.

Tables 3–5 summarize the computational results for the various problem sets discussed above. These tables contain the optimal number of DCs, the percentage of cost components, the closeness C_i and the five top-ranking solutions among the alternatives. As mentioned in reference [33], when increasing the number of opening DCs, the facility and inventory costs also rise in the different problem sets, but the inbound transportation cost from the supplier to DCs is reduced. This phenomenon indicates that when more potential DCs are opened, there are more opportunities to locate them close to the retailers/online customers' locations to decrease the transportation cost; these results support prior studies [1, 27]. However, as this study assumes that the amount

TABLE 3. Computational results of 5 top-ranking solutions for P25_500.

Scenarios	Cost component percentage					Objectives			# of open	Score	Rank
	FC	IC	OC	TC	RC	Z_1	Z_2	Z_3	DC	C_i	
T1_S1	16.1	32.1	3.87	41.9	5.97	\$242 550	\$341 392	73.00%	8	0.688	1
	17.3	31.1	3.83	41.8	5.86	\$286 807	\$344 729	83.60%	11	0.6695	2
	17.4	31.1	3.71	41.9	5.73	\$299 966	\$338 629	86.60%	1	0.6557	3
	17.0	32.5	3.98	40.9	5.38	\$264 156	\$338 095	74.00%	9	0.6498	4
	16.2	32.3	3.90	42.1	5.45	\$264 156	\$336 091	73.80%	9	0.6483	5
T1_S2	13.5	30.4	4.35	44.9	6.79	\$298 841	\$389 800	75.80%	10	0.6608	1
	15.8	28.9	4.44	44.4	6.22	\$340 367	\$392 341	84.40%	11	0.6458	2
	14.9	29.4	4.26	45.2	6.08	\$301 574	\$389 475	74.00%	9	0.6450	3
	14.7	30.8	4.40	44.2	5.79	\$293 513	\$388 408	72.20%	8	0.6444	4
	14.1	27.8	4.41	46.7	6.80	\$342 047	\$391 241	83.20%	12	0.6385	5
T2_S1	16.1	22.6	3.10	52.4	5.70	\$242 223	\$479 317	75.80%	9	0.6864	1
	13.9	23.3	3.31	53.2	6.09	\$234 110	\$479 867	71.80%	7	0.6758	2
	15.8	24.1	3.24	51.3	5.50	\$279 480	\$481 131	84.60%	10	0.6595	3
	16.1	22.7	3.10	52.4	5.63	\$273 274	\$479 867	81.40%	9	0.6572	4
	15.8	24.1	3.25	51.4	5.33	\$275 465	\$478 718	81.80%	10	0.6551	5

FC: facility Cost; IC: inventory cost; OC: ordering Cost; TC: distribution cost from vendor to DCs and DCs to retailers, RC: routing cost from DCs to customers.

TABLE 4. Computational results of 5 top-ranking solutions for P25_800.

Scenarios	Cost component percentage					Objectives			# of open	Score	Rank
	FC	IC	OC	TC	RC	Z_1	Z_2	Z_3	DC	C_i	
T1_S1	18.7	27.1	3.68	41.6	8.80	\$333 389	\$392 390	79.25%	13	0.6434	1
	18.8	26.6	3.64	41.7	9.13	\$375 110	\$395 609	88.88%	15	0.6304	2
	19.2	29.4	3.90	39.7	7.64	\$323 773	\$392 640	71.25%	13	0.6114	3
	17.6	28.2	3.76	42.0	8.25	\$375 110	\$391 752	83.13%	15	0.6107	4
	17.5	28.7	3.65	41.9	8.03	\$324 975	\$389 162	70.75%	11	0.6072	5
T1_S2	19.5	30.5	4.68	37.1	8.07	\$333 164	\$376 870	78.00%	12	0.7102	1
	19.7	29.7	4.50	37.9	8.01	\$333 164	\$375 074	71.75%	12	0.6693	2
	17.7	30.9	4.49	38.4	8.39	\$375 562	\$373 859	81.63%	14	0.6667	3
	18.0	29.3	4.45	39.0	9.14	\$346 484	\$374 060	72.50%	12	0.6557	4
	18.7	31.6	4.65	37.6	7.32	\$370 307	\$372 331	75.63%	12	0.6430	5
T2_S1	10.6	15.9	2.19	63.8	7.36	\$242 223	\$479 317	75.80%	9	0.6864	1
	11.5	22.4	3.11	56.6	6.17	\$234 110	\$479 867	71.80%	7	0.6758	2
	9.61	16.5	1.99	65.4	6.40	\$279 480	\$481 131	84.60%	10	0.6595	3
	13.1	23.1	2.88	54.5	6.34	\$273 274	\$479 867	81.40%	9	0.6572	4
	7.23	19.2	2.24	65.7	5.48	\$275 465	\$478 718	81.80%	10	0.6551	5

of delivery from each DC to specific online customer zones is restricted by vehicle capacity, more opening DCs would imply that more products need to be delivered, which in turn will increase the routing cost. Hence, the magnitude of objective function value Z_2 affected by the number of opening DCs is dependent on the trade-off between inbound and outbound transportation costs. Moreover, we observe that when holding costs increase (T1_S2 *versus* T1_S1) in each problem set of online customers, it is noteworthy that the number of opening DCs also simultaneously increases among the top five alternatives. This phenomenon could be explained as follows: the scope of each alternative is obtained from a balance of the three objective function values. Hence, when the alternative containing the value of Z_1 remains constant, the higher inventory cost decreases the number of opening DCs, causing the value of Z_3 to also fall. In contrast, the higher weight of Z_3 compared with Z_1 brings down the alternative's ranking on the list of top-ranking solutions. Conversely, the other alternatives

TABLE 5. Computational results of 5 top-ranking solutions for P25_1000.

Scenarios	Cost component percentage					Objectives			# of open	Score	Rank
	FC	IC	OC	TC	RC	Z_1	Z_2	Z_3	DC	C_i	
T1_S1	22.2	28.1	3.73	36.8	8.95	$350 303	$669 466	84.20%	15	0.6585	1
	19.9	27.2	3.74	39.2	9.83	$347 256	$666 417	77.40%	14	0.6391	2
	19.7	28.0	3.88	38.7	9.63	$376 338	$664 708	79.00%	15	0.6162	3
	20.0	26.7	3.63	39.3	10.1	$304 744	$666 377	63.70%	12	0.6137	4
	21.0	30.0	3.98	36.5	8.49	$392 845	$666 723	81.30%	16	0.6091	5
T1_S2	25.9	37.3	5.77	20.2	10.7	$368 146	$221 202	74.00%	13	0.6619	1
	27.1	35.3	5.53	21.1	10.9	$413 756	$226 381	82.40%	17	0.6564	2
	26.1	37.5	5.80	20.3	10.1	$360 504	$225 476	70.70%	13	0.6446	3
	26.9	37.6	5.72	20.0	9.66	$387 381	$222 079	74.30%	14	0.6429	4
	26.9	37.6	5.72	20.0	9.65	$428 064	$230 490	83.10%	16	0.6429	5
T2_S1	18.8	28.7	3.51	41.6	7.29	$381 010	$494 818	79.50%	13	0.6657	1
	18.8	28.8	3.52	41.7	7.06	$369 260	$494 457	74.50%	13	0.6512	2
	17.0	28.0	3.38	44.1	7.98	$369 260	$492 797	73.30%	13	0.6439	3
	16.3	27.5	3.22	44.9	7.21	$441 315	$495 919	87.10%	16	0.6318	4
	17.0	28.1	3.38	44.2	7.43	$369 260	$488 608	71.30%	13	0.6311	5

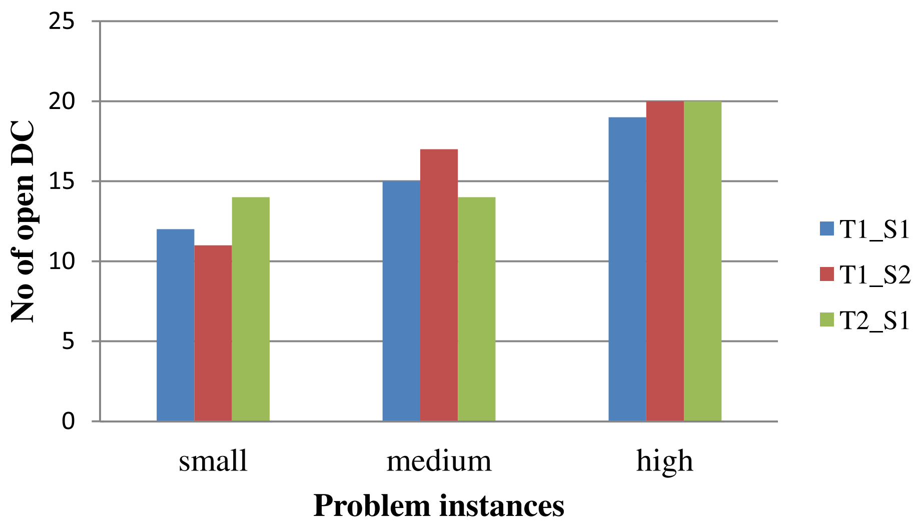

FIGURE 10. The number of open DCs for various problem top ranking.

which contain more opening DCs will have a higher scope and may rank higher in the list of top-ranking solutions. A similar phenomenon is also observed in high transportation problem sets (T2_S1 *versus* T1_S1). Furthermore, Figure 10 demonstrates how as the number of online customers increases, more DCs will need to be set up to extend their coverage to meet these customers' requirements. In summary, the results from the above experiment suggest that the proper number and location of DCs is a critical factor that has a significant impact on the supply chain network performance. If a facility location decision only considers the physical store but ignores the steady growth of web shoppers, this could result in DCs being located far away from web customers, and lead to inefficiencies in the whole supply chain network.

6. Conclusion

This study considers a multi-objective dual-sale channel supply chain network model comprising a single vendor, multiple DCs, and a set of customers − either physical retailers or online customers. A novel formulation which integrates three issues within supply chain, namely facility location, inventory, and vehicle routing, is developed. A two-stage NSGA-II and TOPSIS-based approach is proposed to resolve this problem. In the first stage, NSGA-II is applied to determine a finite set of non-dominate Pareto solutions. In the second stage, the Shannon entropy information theory from the decision makers' perspective is first applied to weigh both the cost and service satisfaction criteria, and then TOPSIS is used to determine the best compromise solution. The feasibility of the developed model is evaluated by presenting several small-sized random instances. In the experiments, the proposed approach displays good behavior on the near-reality data and yields a near-optimal solution in a stochastic demand environment. The benefit of this proposed study is twofold. First, it develops a dual-chain supply chain network model that considers the issue of online customers within a traditional location-inventory problem that so far only involves a physical retail sale channel. Second, it presents a multi-objective method that involves both financial and service performance indicators. A sensitivity analysis is performed to evaluate the way in which DC selection impacts transportation, inventory, and routing costs, and several interesting phenomena were perceived.

As for future work, the model can be extended in several realistic and practical directions. In recent years, increasing number of studies are dealing with environmental issues and the integration of forward and reverse supply chains, therefore a consideration of the closed-loop aspect of this proposed dual-chain supply chain network model can be an attractive future research direction. Moreover, it would be interesting to develop more effective and elegant heuristic methods to resolve the integration model. In addition, determining the weight of the attributes in the model is an important but complex process. Comparative research could adopt a structured technique, such as an AHP or Analytic Network Process, to determine the weight to evaluate its influence on these objectives.

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