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Incorporating sales and marketing considerations into a competitive multi-echelon distribution network design problem with pricing strategy in a stochastic environment

G. Reza Nasiri [a,*], Hadi Deymeh [b], Behrooz Karimi [b], Elnaz Miandoabchi [c]

[a] Department of Industrial Engineering, Faculty of Engineering, Alzahra University, Tehran, Iran
[b] Department of Industrial Engineering and Management Systems, Amirkabir University of Technology, P.O. Box 15875-4413, Hafez Ave., Tehran, Iran
[c] Domestic Commerce Research Group, Institute for Trade Studies and Research, Ministry of Industry, Mine and Trade, Tehran, Iran

A R T I C L E I N F O

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A B S T R A C T

This paper presents a multi-echelon distribution network design problem with pricing strategy in a stochastic environment, where location, inventory, and pricing decisions in retail and wholesale channels are made simultaneously. The considered network is comprised of a central warehouse, a set of distribution centers, and a set of retailers and wholesalers. The objective of the problem is to maximize the supply chain profit. The decisions include the location of distribution centers and the allocation of retailers and wholesalers to them, order-size for each distribution center and product price at retail and wholesale channels for different payment conditions. A mixed-integer nonlinear mathematical model was formulated and solved using the Lagrangian relaxation method and a Genetic algorithm. Computational results indicate that Lagrangian relaxation algorithm has good performance in terms of objective function value and runtime, even in large sized problems.

1. Introduction

In today's world, due to the continuous expansion and rising complexity of production and trade networks, supply chain management has become an increasingly important topic. Distribution network design (DND) is an essential element of supply chain management which comprises topics such as inventory and transportation management (Perez Loaiza et al., 2017; Guimarães et al., 2019). Classically, distribution systems connect the producers to the customers, and act as channels for the movement of goods and provided services. In addition to the basic functions, they also perform various roles such as marketing, demand monitoring, market survey, collecting customer feedback for the producers, and supporting the backward flow of goods for returned, unsold, and recyclable goods and etc. Thus, distribution operations are of strategic importance in any supply chain (Nasiri et al., 2015).

Since distribution systems connect the customers to other tiers of supply chains, their proper design and planning has significant effect on the cost-efficiency and flexibility of supply chains, especially in Fast-moving Consumer Goods (FMCG) industry (Udokporo et al., 2020).

This article investigates the DND and planning problem which involves the decisions of locating the Distribution Centers (DCs), and allocating the retailers and wholesalers to them, and determining the inventory and pricing policy in retail and wholesale channels. Basically, the considered supply chain is categorized as the capacitated DND but each DC can be set up at a capacity level that is chosen among multiple available capacity levels.

Supply chain configuration significantly influences the realization of business strategies and gaining sustainable competitive advantage. In the past, strategic, tactical, and operational decisions were made in a hierarchical manner because of their different nature and scope (Fahimnia et al., 2013). This sometimes leads to contradictions and infeasible decisions, which requires multi-level decision making (Jabbarzadeh et al., 2014). Furthermore, in dynamic business environments, after developing operational and tactical plans, it may be necessary to revise the strategic decisions to improve the efficiency of the supply chain (Fahimnia et al., 2012).

Facility location as a strategic decision is mostly based on cost criteria (Farahani and Hekmatfar, 2009). Usually, the main cost elements include fixed facility setup costs, transportation, and inventory costs. In essence, trade-off between these costs is a major challenge in

* Corresponding author.
E-mail addresses: reza_nasiri@aut.ac.ir, grnasiri@alzahra.ac.ir (G.R. Nasiri), deymeh@aut.ac.ir (H. Deymeh), b.karimi@aut.ac.ir (B. Karimi), e.miandoabchi@itsr.ir (E. Miandoabchi).

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supply chain design problems (Pishvaee et al., 2009). A common approach in dealing with the complexities of facility location problems is to break down the large problem into smaller but simpler problems (Stadtler and Kilger, 2005).

The distribution network under consideration consists of a central warehouse, a set of candidate DCs, and a set of known retailers and wholesalers (Ouhimmou et al., 2019).

It is assumed that customer demand is price dependent and stochastic. The distribution network and pricing policy should be set such that retailers prefer to purchase directly from the producer (i.e. DC), instead of wholesalers. Otherwise, competition may arise between the two channels. Wholesalers also have their own retail channel, which is different from producer's distribution network. Another assumption is the demand leakage between the retailers and wholesalers. In this dual channel distribution network, product's price must be set so that minimum competition occurs between the sales channels. This matches the conduct seen in markets of FMCG industries in reality.

A review of previous studies shows that there is little research on integrated location, pricing, and inventory decisions in DND problems, which take into account marketing considerations, different sales channels and demand leakage between them. In this situation, cooperation pricing mechanisms among multiple channels is needed to be developed for integrating price strategy with location and inventory management decisions to improve system performance and competition advantage.

This paper complements the previous location-inventory-pricing researches by making the following contributions: (a) designing and price setting in distribution network with stochastic and price dependent demand; (b) estimating demand according to the population of retailer's and wholesaler's zones; (c) allowing different payment periods; (d) taking into account separate product pricing in retail and wholesale channels, considering demand leakage from the higher to the lower price channels; and finally, (e) determining upper and lower bounds of prices in both channels according to real world marketing considerations, competitor prices and unit product price, which provides a novel approach for price setting in distribution networks.

Proper pricing strategy and policy are crucial for the profitability of all enterprises. Generally, lower bound prices must be set such the income covers all supply, production and logistics costs. In other words, this bound dependents on the unit product cost. Upper bound price is more related to market conditions and competitors' prices, while for lower bound price, final product cost and marketing strategy are the major determinants. Usually, the general approach in setting the upper bound price is to use the average price value among the competitors. They can be different for each brand and product, but the selected competitors for price calculations must be in the same level in terms of product quality and price elasticity. The adoption of such pricing strategy dependents on the brand position in the market, which determines attainable level of market share for the brand.

A company with large market share will act as monopoly and usually will be able to set its upper bound price, higher than market average. When several companies have equal market shares, they act as competitors and set their upper bound price based on the average price in the market. In a company with small market share, lower prices must be set in order to attract the potential customers.

The reminder of the paper is organized as follows: section 2 provides a structured literature review. In section 3 the investigated problem and the mathematical model are discussed. Section 4 provides the developed algorithms for solving the proposed mixed-integer nonlinear model based on Lagrangian Relaxation (LR) and Genetic Algorithm (GA). Section 5 contains the computational results and discussions. In section 6, sensitivity analysis is conducted for the results, and finally conclusions and future research suggestions are made in section 7.

2. Literature review

The body of literature related to the subject of this paper can be classified into several groups. The first group of studies concentrates on location-inventory decisions. In location-inventory problems, by assuming the locations of suppliers to be known, the aim is to find the optimum number and location of DCs, to allocate them to the demand points, and to determine the optimum inventory levels in the centers (Cortinhal et al., 2019; Escalona et al., 2018). There is a vast body of literature on location-inventory problems. For instance, Daskin et al. (2002) studied the location-inventory problem and applied the LR method to solve it. Shu et al. (2005) studied a stochastic transportation-inventory supply chain problem involving one supplier and multiple retailers with uncertain customer's demand. Their objective function was minimization of DC location costs, inventory costs, and transportation costs. They presented heuristic method based on the column generation algorithm to solve the formulated problems. The generated computational results show the efficiency of their solution technique for wide-ranging of retailer numbers.

In the next study Shu (2010) considered the inventory system for a multi-echelon case that warehouse and retailers coordinate their inventory replenishment activities to minimize the aggregated system costs. He proposed a heuristic greedy search algorithm to solve the model and demonstrated the performance of the solution approach. Snyder et al. (2007) proposed a stochastic location model with risk pooling under discrete scenarios for facility location and inventory decisions. They formulated the considered problem as a mixed-integer nonlinear programming model and solved it using the LR method. Nasiri et al. (2010a) addressed the DND problem in a multi-product supply chain with stochastic customer demand. The decisions of the model included location of DCs with multi-capacity levels, allocation and inventory policy decisions. LR and heuristic methods were used to solve the formulated model. Mousavi et al. (2015) developed a model for the multi-period location-allocation-inventory problem, which was solved using the modified fruit fly optimization, particle swarm optimization, and simulated annealing algorithms. Ahmadi et al. (2016) considered a multi-echelon DND problem for seasonal and non-seasonal products, including facility location and inventory decisions with transshipment between the DCs. They developed a bi-objective model for maximization of total profit and minimization of customer dissatisfaction. Production limits and inaccurate demand were considered and an interactive method was developed to solve the considered problem.

Motivated by environmental considerations, Wang et al. (2020) formulated a green integrated supply network problem under uncertainty and capturing carbon-trading decisions under the emission-trading regulation. They provided a stochastic model with the scenario-based property of uncertain market demand and volatile carbon price. Their study provided a new framework for the emission-compliance green supply network design and highlighted demand uncertainty effects on distribution facilities and regulators' perspective.

The second group of studies has incorporated pricing decisions into other supply chain decisions. For example, Ghomi-Avili et al. (2018) developed a bi-level fuzzy pricing model for closed-loop supply chain design with price dependent demand and random disruptions at suppliers echelon. Gao et al. (2016) considered a closed-loop supply chain consisting of a producer and a retailer, in which the producer set the rework process for the used products in its main production system. The remanufactured products were assumed to be similar to the new products, which could be sold with the same prices in the same market. They investigated collection and sales efforts and pricing decisions for different power channel structures. Taleizadeh and Nouri-Darian (2016) proposed a three-echelon supply chain consisting of a supplier, a producer and several retailers, in which the decision variables were supplier's price, producer's price, and number of shipments. Demand was assumed to be linearly dependent to the price and no shortage was allowed. The objective was to minimize the sum of costs for supplier, producer and retailers. Hajipour et al. (2016) addressed the bi-objective location-pricing problem within queuing framework, in which the main decision was to set up a facility in a zone. The problem was comprised of two networks and was solved using multi-objective vibration damping optimization method. User utility was a function of product or service price and the distance between the facilities and customers. Alfares and Ghaithan (2016) designed a model to optimize the inventory and pricing simultaneously, with price dependent demand, time dependent inventory holding cost, and quantity discounts. Demand variability, holding costs and purchasing costs were taken into account. Tavakkoli-Moghaddam et al. (2017) presented a model for facility location and pricing problem, assuming that immobile service facilities are congested with demand that followed $M/M/m/k$ queues. They solved the model using a multi-objective meta-heuristic algorithm. Finally, Avakh Darestani and Pourasadollah (2019) investigated a closed-loop supply chain design problem, with financial incentives for the customers to return the used products. Since the remaining value of the used products is the major incentive of a producer to purchase them, a dynamic pricing model was proposed to determine the purchase price of these products.

A distinct comparison between retail and wholesale decisions has been undertaken by Matsui (2020). He studied a dual-channel supply chain to determine the perfect timing for a producer to bargain a wholesale price with a retailer. He proposed a game theory-based model to formulate the considered problem in which the supplier could sell products in both channels. The outcomes of the study, give the managerial recommendation that in the dual-channel supply chain manufacturer can choose the perfect timing to negotiate the wholesale price with a retailer. The author pointed out that the results of his research contradict some previous articles on timing decision.

Duan et al. (2021) also studied the impacts of sales efforts and payment terms on a multi-echelon supply chain. Sales channels consist of a sales manager, a retailer, and an agent that operates both the wholesale and retail market. Moreover, they compared the equivalence decisions in three different situations especially selling quantity and payment modes.

The third group of studies has particularly focused on location-inventory-pricing problems (Nasiri et al., 2021). Ahmadi-Javid and Hoseinpour (2015a) proposed the location-inventory-pricing problem for multi-product supply chain with continuous review of inventory and price dependent demand with and without facility capacity limits. They used markup levels for pricing of the products and applied the LR method to solve the problem. In the other study, Ahmadi-Javid and Hossenipour (2015b) proposed a location-inventory-pricing model for DND with price dependent demand and facility capacity limits and solved it using the LR method. Kaya and Urek (2016) developed a location-inventory-pricing model in a closed-loop supply chain and solved it using a heuristic method. Their model integrated the reverse flow of used products with the distribution flow of new products. Ahmadzadeh and Vahdani (2017) investigated location-inventory-pricing decisions in a multi-echelon closed-loop supply network. They considered correlated demand across customer zones, periodical inventory review with allowed shortage. Finally, Nasiri et al. (2021), studied the fast-moving consumer goods network design with pricing policy in an uncertain environment with correlated demands.

The reviewed location-inventory-pricing studies from the literature and the present paper and compared in Table 1.

The present study belongs to the third group of studies, and it presents a number of contributions to the existing literature, by considering demand as stochastic and price dependent, allowing for different payment methods, pricing in retail and wholesale channels, and proposing a novel approach for pricing in distribution networks.

3. Problem definition and assumptions

The network under consideration in this study is a forward, single product logistics network which consists of a central warehouse, DCs, wholesalers and retailers. The products are sold to the customers from both retail and wholesale channels. Demand is price dependent and is stochastic in all channels. The supply chain is multi-echelon and can be a typical supply chain in FMCG industry. It is assumed that the distribution network in this problem is able to cover all demand points and to meet the demands in-time. The schema of the distribution network is

Table 1
Comparison of location-inventory-pricing studies in the literature with the present study.

Reference	Decisions	Costs	Type of pricing	Inventory policy	Demand characteristics	Demand uncertainty	Solution Method	
							Type	Algorithm
Ahmadi-javid and Hoseinpour (2015a, 2015b)	Location, Allocation, Order size, Price	DC setup, Ordering, Inventory Holding, Transportation	Discrete with markup levels	Continuous review	Price dependent	No	Exact-approximate	LR
Kaya and Urek (2016)	Location, Allocation, Inventory cycle time, Price, Incentive value	DC setup, Ordering, Inventory Holding, Holding of used products, Production	Continuous	Continuous review	Price and distance dependent	No	Meta-heuristic	SA-VNS[a] TS-VNS[b] GA-VNS[c]
Ahmadzadeh and Vahdani (2017)	Location, Allocation, Backlog, Incentive value, Inventory review period, Price	Production, Facility setup, DC Allocation, Production and transportation of new product, transportation of returned used products	Continuous	Periodical review	Price and location dependent	No, demand correlation between customer zones	Meta-heuristic	GA,ICA[d], FA[e]
Nasiri et al. (2021)	Location, Allocation, Inventory control policy, Retail and wholesale prices	DC setup, Transportation, Inventory holding in DC, ordering,	Continuous	Periodical review	Demand correlation between products	Yes	Meta-heuristic	Memetic Algorithm
This paper	Location, Allocation, Inventory replenishment policy, Retail and wholesale prices	DC setup, Transportation, Inventory holding in DC, ordering,	Continuous, Payment terms	Continuous review	Price and population dependent	Yes	Exact-approximate/ Meta-heuristic	LR, GA

[a] Simulated Annealing- Variable Neighborhood Search.
[b] Tabu Search- Variable Neighborhood Search.
[c] GA- Variable Neighborhood Search.
[d] Imperialist Competitive Algorithm.
[e] Firefly Algorithm.

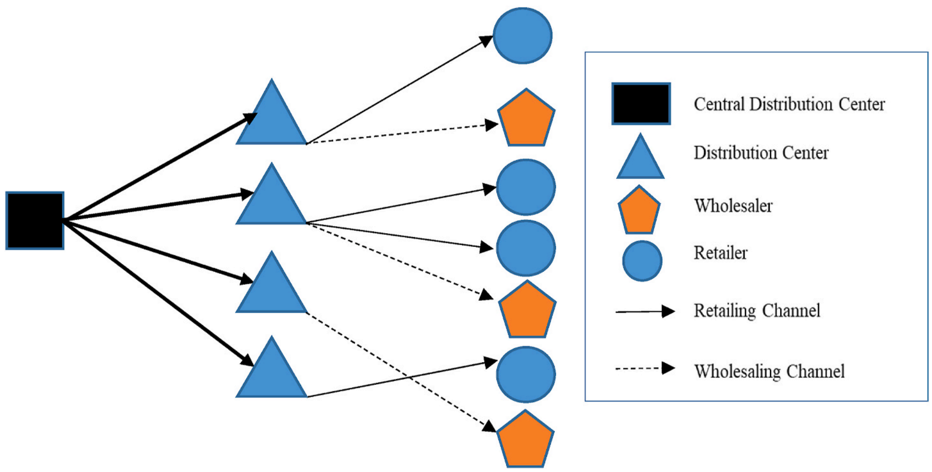

Fig. 1. General schema of the distribution network in this study.

depicted in Fig. 1.

In this paper, it is assumed that customers' demand in the wholesale channel is dependent to the wholesaler zone's population, suggested price to the wholesalers, demand leakage from retail channel, and payment terms.

3.1. Assumptions, parameters, and decision variables

The assumptions of the considered location-inventory-pricing problem are listed below:

- The locations of manufacturer and central warehouse are known and no inventory is hold by the manufacturer;
- The locations of retailers and wholesalers are known;
- The demands of retailers and wholesalers from DCs are stochastic and follows the Normal distribution with known mean and variance; thus the demand of DCs from the central warehouse is also stochastic;
- The demand of each retailer and wholesaler is supplied from only one DC;
- The capacity of each DC is limited, and a DC can be set up at a capacity level that is chosen among multiple available capacity levels;
- Lead time for all DCs is fixed and known;
- The mean demand of retailers and wholesalers from the DCs is dependent to the retail and wholesale prices and the population of customers;
- The variance demand of retailers and wholesalers are not price-dependent.

In the pricing strategy adopted in this study, it is attempted to control the demand leakage from retail channel to wholesale channel. There are lower and upper bounds for product price in both channels, which are defined according to the marketing policy, competitor prices, and internal considerations such as unit product cost. The ordering and inventory control system in each DC follows the continuous review policy (r, Q).

3.1.1. Sets and indices

I	Set of retailers i, $i \in I$
J	Set of candidate locations j for DCs, $j \in J$
H	Set of available capactity levels h for DCs, $h \in H$
W	Set of wholesalers w, $w \in W$
T	Set of allowed periods t for payment term, $t \in T$

3.1.2. Parameters

$TC2_{ji}$	Transportation cost per unit between central warehouse, DC j and retailer i
$\overline{TC2}_{jw}$	Transportation cost per unit between central warehouse, DC j and wholesaler w
F_{jh}	Setup cost of DC j with capacity level h
m_1	Elasticity of retailer's demand to the retail channel price
m_2	Elasticity of retailer's demand to the wholesale channel price
m_3	Elasticity of wholesaler's demand to the wholesale channel price
l_j	Lead time of DC j
r_j	DC j's inventory reorder point
σ^2_{it}	Variance of retailer i's demand with payment period t
$\overline{\sigma}^2_{wt}$	Variance of wholesaler w's demand with payment period t
$z_{1-\alpha}$	The z-score in standard normal distribution, with $p(z \le z_{\alpha_j}) = \alpha_j$, which 1- α is the service level of the distribution network
HC_j	Holding cost per unit for DC j
OC_j	Fix cost of ordering from central warehouse, for DC j
cap_{jh}	Capacity of DC j with level h
$pop1_i$	Average of population in retailer i's zone
$pop2_w$	Average of population in wholesaler w's zone
ε_1	Upper bound of the gap between retail and wholesale price, stated as percentage and defined according to marketing policies
ε_2	Lower bound of the gap between retail and wholesale price, stated as percentage and defined according to marketing policies
γ	Rate of demand leakage from the higher to the lower price channel
Pr_t^{UB}	Upper bound price in retail channel with payment period t
Pr_t^{LB}	Lower bound price in retail channel with payment period t
Pw_t^{UB}	Upper bound price in wholesale channel with payment period t
Pw_t^{LB}	Lower bound price in wholesale channel with payment period t
PH	Planning Horizon
ss_j	Safety stock at DC j
s	Space occupied by product unit in each DC

3.1.3. Decision variables

X_{jh}	Binary variable which equals 1 if DC j is established at capacity level h, and 0 otherwise
Y_{ji}	Binary variable which equals 1 if retailer i is allocated to DC j, and 0 otherwise
$\overline{Y}_{jw}$	Binary variable which equals 1 if wholesaler w is allocated to DC j, and 0 otherwise
pr_t	Product price offered by DC to retail channel with payment period t
pw_t	Product price offered by DC to wholesale channel with payment period t
Q_j	Order quantity in DC j
D_j	Mean of demand allocated to DC j
V_j	Variance of demand allocated to DC j
μ_{jit}	Mean of retailer i's demand from DC j with payment period t
$\overline{\mu}_{jwt}$	Mean of wholesaler w's demand from DC j with payment period t
ψ_j, η_w , β_i, τ_j	Lagrange multipliers

3.2. Mathematical model

Mathematically, the problem can be formulated as the following mixed-integer nonlinear model:

$$\begin{aligned} Max\ Z =& \sum_{j\in J}\sum_{i\in I}\sum_{t\in T} PH\cdot pr_t\cdot\mu_{jit} \\ &+\sum_{j\in J}\sum_{w\in W}\sum_{t\in T} PH\cdot pw_t\cdot\overline{\mu}_{jwt} - \sum_{j\in J}\sum_{i\in I}\sum_{t\in T} PH\cdot TC2_{ji}\cdot\mu_{jit} \\ &-\sum_{j\in J}\sum_{w\in W}\sum_{t\in T} PH\cdot\overline{TC2}_{jw}\cdot\overline{\mu}_{jwt} - \sum_{j\in J}\sum_{h\in H} X_{jh}\cdot F_{jh} - \sum_{j\in J} CH_j\cdot\sqrt{D_j} \\ &-\sum_{j\in J} CS_j\cdot\sqrt{V_j} \end{aligned} \tag{1}$$

S.T.

$$\sum_{j\in J} Y_{ji} = 1 \quad \forall i\in\{1,\ldots,I\} \tag{2}$$

$$\sum_{j\in J} \overline{Y}_{jw} = 1 \quad \forall w\in\{1,\ldots,W\} \tag{3}$$

$$D_j\cdot s \le \sum_{h\in H} cap_{jh}\cdot X_{jh} \quad \forall j\in\{1,\ldots,J\} \tag{4}$$

$$\sum_{h\in H} X_{jh} \le 1 \quad \forall j\in\{1,\ldots,J\} \tag{5}$$

$$\mu_{jit} = [pop1_i - m_1\cdot pr_t + m_2\cdot pw_t - \gamma(pr_t - pw_t)]\ Y_{ji} \quad \forall j\in\{1,\ldots,J\}, \forall i\in\{1,\ldots,I\}, \forall t\{1,\ldots,T\} \tag{6}$$

$$\overline{\mu}_{jwt} = [pop2_w - m_3\cdot pw_t + \gamma(pr_t - pw_t)]\overline{Y}_{jw} \quad \forall j\in\{1,\ldots,J\}, \forall w\in\{1,\ldots,W\}, \forall t\{1,\ldots,T\} \tag{7}$$

$$\sum_{i\in I}\sum_{t\in T}\mu_{jit}\cdot Y_{ji} + \sum_{w\in W}\sum_{t\in T}\overline{\mu}_{jwt}\cdot\overline{Y}_{jw} = D_j \quad \forall j\in\{1,\ldots,J\} \tag{8}$$

$$\sum_{i\in I}\sum_{t\in T}\sigma^2_{it}\cdot Y_{ji} + \sum_{w\in W}\sum_{t\in T}\overline{\sigma}^2_{wt}\cdot\overline{Y}_{jw} = V_j \quad \forall j\in\{1,\ldots,J\} \tag{9}$$

$$\varepsilon_1 \le \frac{pr_t - pw_t}{pr_t} \le \varepsilon_2 \quad \forall t\in\{1,\ldots,T\} \tag{10}$$

$$Pr_t^{LB} \le pr_t \le Pr_t^{UB} \quad \forall t\in\{1,\ldots,T\} \tag{11}$$

$$Pw_t^{LB} \le pw_t \le Pw_t^{UB} \quad \forall t\in\{1,\ldots,T\} \tag{12}$$

$$X_{jh}, Y_{ji}, \overline{Y}_{wi} \in \{0,1\},\ \mu_{jit}, \overline{\mu}_{jwt}, pw_t, pr_t, D_j, V_j \in R^+ \quad \forall j\in\{1,\ldots,J\},\ \forall h\in\{1,\ldots,H\},\ \forall i\in\{1,\ldots,I\},\ \forall w\in\{1,\ldots,W\},\ \forall t\in\{1,\ldots,T\} \tag{13}$$

The objective of the model is to maximize the total supply chain profit. The first and second parts of objective function denote the incomes of retail and wholesale channels. The third and fourth parts indicate the total transportation cost between the central warehouse, DCs, and retailers or wholesalers. The fifth part is the total establishment cost of DCs. The last two parts denote the inventory and safety stock costs in DCs (See Appendix 2).

Constraints (2) and (3) imply that each retailer and wholesaler can be assigned to exactly one distribution respectively. Constraint (4) restricts the demand in each DC to its capacity, and constraint (5) restricts the capacity of each DC to the set of defined capacity levels. Constraints (6) to (7) calculate average demand and price levels in retail and wholesale channels. Expression $\gamma(pr_t - pw_t)$ is the amount of demand leakage from retail channel to wholesale channel. Here, $m_1\cdot pr_t$ captures the reverse effect of DC j's offered price on retailer i's demand with payment period t. Similarly, $m_2\cdot pw_t$ captures the effect of wholesaler w's price on retailer i's demand with payment period t. Constraints (8) to (9) calculate the mean and variance of demand in each DC, coming from the assigned retailers and wholesalers. Relation (10) implies the pricing strategy, according to which the retail channel price must be set such that the wholesaler's selling price to the retailer is not less than the price offered by DC. Otherwise, the retailer will purchase from wholesaler instead of DC. Relations (11) and (12) indicate the upper and lower price bounds for retail and wholesale channels, respectively. Finally, relation (13) defines the variable domains.

4. Proposed solution method

Since the well-known facility location problem is known to be NP-hard,with additional integrated decisions, formulated model is also NP-hard. Therefore, in this study, the LR method and a meta-heuristic algorithm are used to solve the proposed problem (Nasiri et al., 2010a), (Fahimnia et al., 2017). In the following sections the details of the two proposed algorithms are described.

4.1. LR algorithm

LR algorithm has been widely used in solving NP-hard combinatorial optimization problems, especially for location-inventory problems (Ahmadi-Javid and Hoseinpour, 2015b). The main idea of this method is to omit the challenging constraints from the main model and to introduce them into the objective function, using Lagrangian multipliers. The relaxed problem usually can be easily solved, and in maximization problems the obtained solution provides an upper bound for the original problem. Since a number of constraints are relaxed, so the solution for the relaxed problem may be infeasible for the original problem. To deal with this issue, a heuristic method is employed to generate a feasible solution which its objective function value is lower than the solution of relaxed model. This feasible solution itself requires to be improved, such that the gap between upper bound and best feasible solution is reduced. At each iteration, a certain value must be assigned to the Lagrange multiplier. Generally, a sub-gradient optimization method is applied to update the multiplier. Finally, the duality gap can be computed to assess the quality of the best solution found so far (Nasiri et al., 2010a). Fig. 2 illustrates the schema of the proposed LR algorithm.

4.1.1. Strong formulation and LR

In order to propose a relaxed version of the original model, constraints (14) and (15) are incorporated to the original problem:

$$\sum_{j\in J} D_j \le DT = \sum_{i\in I}\sum_{t\in T}\mu_{jit} + \sum_{w\in W}\sum_{t\in T}\overline{\mu}_{jwt} \tag{14}$$

$$\sum_{j\in J} V_j \le VT = \sum_{i\in I}\sum_{t\in T}\sigma^2_{it} + \sum_{w\in W}\sum_{t\in T}\overline{\sigma}^2_{wt} \tag{15}$$

The right hand sides of the constraints are the sums of means and variances of wholesalers' and retailers' demand assigned to DCs respectively. They imply that the total amount of demand assigned to all DCs must not exceed the total demand by all wholesalers and retailers. These constraints are redundant for the original problem, since they correspond to relations (8)–(9).

The demand allocation constraints (2)–(3) and the mean and variance calculation constraints (8)–(9) for demand are hard constraints; therefore, the next step is to relax them. With these constraints relaxation, the complexity of the problem is reduced. The model can be considered for each DC's capacity level separately. Since the objective function of the problem is profit maximization, by relaxing these constraints, an upper bound can be found for the optimum solution. By incorporating relations (2)–(3) and (8)–(9) into the objective function, with multipliers ψ_j، η_w ، $\beta_i$and τ_j respectively, relation (16) is obtained.

The optimum solution for the relaxed model may be infeasible since it may violate the relaxed constraints.

$$
\begin{aligned}
Z_{LR} &= Max\sum_{j\in J}\sum_{i\in I}\sum_{t\in T} PH.pr_t.\mu_{jit} \\
&+\sum_{j\in J}\sum_{w\in W}\sum_{t\in T} PH.pw_t.\overline{\mu}_{jwt} - \sum_{j\in J}\sum_{i\in I}\sum_{t\in T} PH.TC2_{ji}.\mu_{jit} \\
&-\sum_{j\in J}\sum_{w\in W}\sum_{t\in T} PH.\overline{TC2}_{jw}.\overline{\mu}_{jwt} - \sum_{j\in J}\sum_{h\in H} X_{jh}.F_{jh} - \sum_{j\in J} CH_j.\sqrt{D_j} \\
&-\sum_{j\in J} CS_j.\sqrt{V_j} + \sum_{i\in I}\beta_i^k - \sum_{j\in J}\sum_{i\in I}\beta_i^k.Y_{ji} + \sum_{w\in W}\eta_w^k \\
&-\sum_{j\in J}\sum_{w\in W}\eta_w^k.\overline{Y}_{jw} \\
&+\Bigg(\sum_{j\in J}\psi_j^k.D_j \\
&-\sum_{j\in J}\sum_{i\in I}\sum_{t\in T}\psi_j^k.\mu_{jit}.Y_{ji} - \sum_{j\in J}\sum_{w\in W}\sum_{t\in T}\psi_j^k.\overline{\mu}_{jwt}.\overline{Y}_{jw}\Bigg) \\
&+\left(\sum_{j\in J}\tau_j^k.V_j - \sum_{j\in J}\sum_{i\in I}\sum_{t\in T}\tau_j^k.\sigma_{it}^2.Y_{ji} - \sum_{j\in J}\sum_{w\in W}\sum_{t\in T}\tau_j^k.\overline{\sigma}_{wt}^2.\overline{Y}_{jw}\right)
\end{aligned} \tag{16}
$$

S.T. (4), (5), (6), (7), (10), (11), (12), (13), (14), (15).

The above model can be decomposed into three independent sub-models including location, inventory, and pricing decisions. Each of these sub-problems can be solved separately. For this purpose, at first the optimum solutions to the sub-problems are found. Next, their corresponding objective values are summed up to calculate an upper bound for the original problem. If the obtained solution is infeasible for the original problem, it is turned into a feasible solution and then is improved using a heuristic algorithm.

4.1.2. The three sub-problems and their solution methods

$SP1^k$, $SP2^k$ and $SP3^k$ denote the pricing, location/allocation, and inventory sub-problems respectively, where index k is iteration number in the LR algorithm. The three models are presented below.

$$
SP1^k = Max\sum_{j\in J}\sum_{i\in I}\sum_{t\in T} PH\cdot pr_t\cdot\mu_{jit} + \sum_{j\in J}\sum_{w\in W}\sum_{t\in T} PH\cdot pw_t\cdot\overline{\mu}_{jwt} \tag{17}
$$

S.T. (6), (7), (10), (11) and (12)

$$
\begin{aligned}
SP2^k &= Min\sum_{j\in J}\sum_{i\in I}\sum_{t\in T} PH.TC2_{ji}.\mu_{jit} + \sum_{j\in J}\sum_{w\in W}\sum_{t\in T} PH.\overline{TC2}_{jw}.\overline{\mu}_{jwt} \\
&+\sum_{j\in J}\sum_{h\in H} X_{jh}\cdot F_{jh} - \sum_{j\in J}\sum_{i\in I}\beta_i^k\cdot Y_{ji} - \sum_{j\in J}\sum_{w\in W}\eta_w^k\cdot\overline{Y}_{jw} \\
&+\sum_{j\in J}\sum_{i\in I}\sum_{t\in T}\psi_j^k\cdot\mu_{jit}\cdot Y_{ji} + \sum_{j\in J}\sum_{w\in W}\sum_{t\in T}\psi_j^k\cdot\overline{\mu}_{jwt}\cdot\overline{Y}_{jw} \\
&+\sum_{j\in J}\sum_{i\in I}\sum_{t\in T}\tau_j^k\cdot\sigma_{it}^2\cdot Y_{ji} + \sum_{j\in J}\sum_{w\in W}\sum_{t\in T}\tau_j^k\cdot\overline{\sigma}_{wt}^2\cdot\overline{Y}_{jw}
\end{aligned} \tag{18}
$$

S.T. (4), (5), (6), and (7)

$$
SP3^k = Min\sum_{j\in J} CH_j\sqrt{D_j} + \sum_{j\in J} CS_j\sqrt{V_j} - \sum_{j\in J}\tau_j^k V_j - \sum_{j\in J}\psi_j^k D_j \tag{19}
$$

S.T. (14), (15).

In the following, the solution method for each sub-problem is described.

4.1.2.1. Pricing sub-problem. Various factors influence the pricing approaches adopted by companies, which can include marketing objectives, consumer demand, product attributes, market conditions, and competitors' prices (Fattahi et al., 2018). In this study, two complementary factors are considered. The first one is the category of the concerned product, which is internal to the company. The second one is the product's brand position among the competitors in the market, which is an external factor. Different combinations of the two factors, lead to various product and market scenarios. In each of these scenarios,

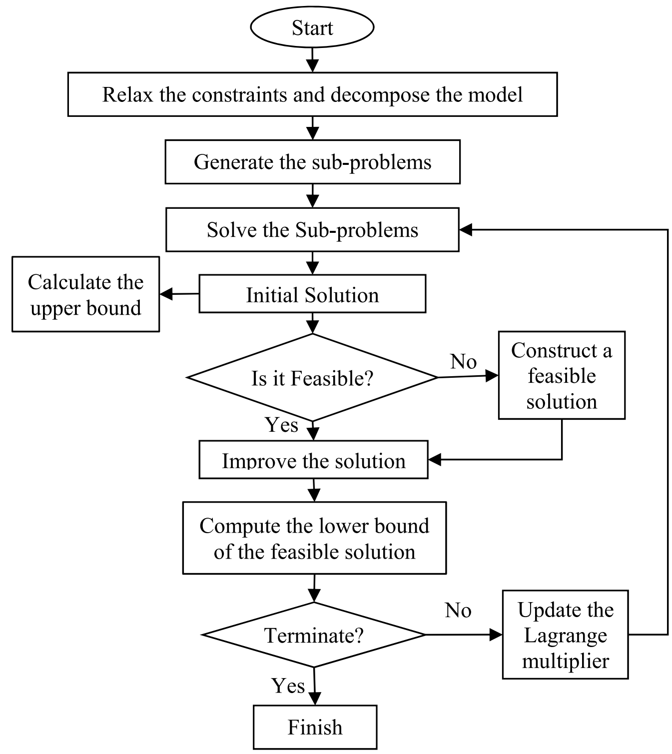

Fig. 2. Schema of the proposed LR algorithm.

the appropriate pricing strategy must be adopted. Regarding to this, in the present study three product categories (i.e. scenarios) are defined as follows:

- Leadership products: In this category of products, company is the market leader (i.e. has the largest market share). Market is in its maturity stage, with steady demand and high quality products. Price elasticity of product demand is usually low, which means that the increase of the price doesn't affect the demand significantly. Market is competitive, but the product has a high brand position in the market. Operating margin of the product is high and it generates majority of the company's profit.
- Commodity products: Market of these products is highly competitive, but unlike leadership products, here demand is highly sensitive to price. Operational margin of commodity products is low, but sales volume is high. Therefore, production and distribution capacities are fully utilized and the overhead costs are covered based on the economics of scale aspects.
- Newly-Launched Products: Products in this category have newly been released to the market, and thus no data and history exists for their demand and price. In the beginning, demand for the products is high, possibly due to extensive advertising, low number of competitors, and etc. If the newly launched product is not successful in attracting customers it will fail in the market. R&D (Research and Development) and Marketing departments are responsible for the development plan of new products.

Based on the above categorization, here eight scenarios are defined. The scenarios and their corresponding attributes and pricing strategies are illustrated in Table 2.

Table 2 shows a helpful scenario-based product categorization for defining the required model's parameters including Pr_t^{LB}, Pr_t^{UB}, Pw_t^{LB}, and Pw_t^{UB}. The generated pricing sub-problem is a nonlinear programing model, and can be solved using commercial software for the small sized problems. For larger problems, any meta-heuristic algorithms including GA could be applied. By solving this sub-problem, the prices are

Table 2
Product scenarios, their attributes and pricing strategies.

Scenario no.	Product category (company's perspective)	Market position of the brand	Proposed Pricing Strategy
1	Leadership product	Leader	Price is α% higher than average of competitors' price. Payment terms are flexible. Price sensitivity of demand is low. Credit payment is accepted.
2	Leadership product	Follower (Second/Third place among the leaders)	Price is α% lower than average of competitors' price. Payment terms are flexible. Price sensitivity of demand is low. Credit payment is accepted.
3	Commodity product	Leader	Price is equal to average of competitors' price. Payment terms are not flexible, and almost are not negotiable due to very low operational margin. Price sensitivity of demand is high. Payment is in cash, unless higher price is paid.
4	Commodity product	Follower (Second/Third place among the leaders)	Price is equal to average of competitors' price. Price sensitivity of demand is high. Payment is in cash, unless higher price is paid.
5	Commodity product	Follower	Price is α% lower than average of competitors' price. Payment is in cash, unless higher price is paid. Therefore, Payment terms may be negotiable.
6	Newly Launched product	Leader (in other products)	Price is α% higher than average of competitors' price. Volume of Production is determined by the R&D department.
7	Newly Launched product	Follower (low market share in other products)	Price is equal to average of competitors' price.
8	Newly Launched product	New and unknown brand	Price is α% lower than average of competitors' price. Product may be unprofitable.

obtained and then the amount of demand can be calculated according to the population of the zone.

4.1.2.2. Location-allocation sub-problem. As mentioned before, this sub-problem is related the location of potential DCs and allocating retailers and wholesalers to them. It takes into account the costs of transportation between the central warehouse, DCs, and retailers or wholesalers, and the fixed costs of DCs establishment. The sub-problem itself can be decomposed into an allocation (SP2-1) and a location sub-problem (SP2-2). The formulations are given below:

$$(SP2-1)^k(j,h) = VC_{jh} = Min\sum_{j\in J}\sum_{i\in I}\sum_{t\in T}\left(PH\cdot TC2_{ji}\cdot\mu_{jit} - \beta_i^k + \psi_j\cdot\mu_{jit} + \tau_j\cdot\sigma_{it}^2\right)\cdot Y_{ji} + \sum_{j\in J}\sum_{w\in W}\sum_{t\in T}\left(PH\cdot\overline{TC2}_{jw}\cdot\overline{\mu}_{jwt} - \eta_w^k + \psi_j\cdot\overline{\mu}_{jwt} + \tau_j\cdot\overline{\sigma}_{wt}^2\right)\cdot\overline{Y}_{jw} \tag{20}$$

S.T.

$$\left(\sum_{i\in I}\sum_{t\in T}\mu_{jit}\cdot Y_{ji} + \sum_{w\in W}\sum_{t\in T}\overline{\mu}_{jwt}\cdot\overline{Y}_{jw}\right)\cdot s \le cap_{jh}\ \forall j\in\{1,\dots,J\}, h\in\{1,\dots,H\} \tag{21}$$

$$0 \le Y_{ji}, \overline{Y}_{jw} \le 1 \quad \forall j\in\{1,\dots,J\}\ ,\ \forall i\in\{1,\dots,I\}\ ,\ \forall w\in\{1,\dots,W\} \tag{22}$$

$$(SP2-2)^k(j) = Min\sum_{j\in J}\sum_{h\in H}F_{jh} + VC_{jh} \tag{23}$$

S.T.

$$s\cdot D_j \le \sum_{h\in H}cap_{jh}\cdot X_{jh} \quad \forall j\in\{1,\dots,J\} \tag{24}$$

$$\sum_{h\in H}X_{jh} \le 1 \quad \forall j\in\{1,\dots,J\} \tag{25}$$

$$X_{jh}\in\{0,1\}\ \forall j\in\{1,\dots,J\},\ \forall h\in\{1,\dots,H\} \tag{26}$$

For solving these sub-problems, first the allocation problem and then the location problem are solved. SP2-1 model is similar to the knapsack problem, with distance being the single influencing factor in it. This means that it suffices to allocate the retailers and wholesalers according to their distance from the DCs. Then SP2-2 can be solved based on the output of allocation problem, and by minimizing the setup cost. It is noted that X_{jh}values are equal to 1 unless the capacity of the selected distribution center is less than the total required space to accommodate the total customer demand. For solving these problems, the method devised by Nasiri et al. (2010a) is applied.

4.1.2.3. Inventory sub-problem. This sub-problem optimizes the inventory holding costs in DCs subject to the capacity constraints, and can be further decomposed into two sub-problems, namely optimization of average holding cost of inventory on hand (SP3-1) and optimization of holding cost of safety stock (SP3-2). To solve these problems, the proven theorem in Miranda and Garrido's work is applied (Miranda and Garrido, 2004).

$$(SP3-1)^k = Min\sum_{j\in J}CH_j\sqrt{D_j} - \sum_{j\in J}\psi_j^k D_j \tag{27}$$

$$S.T.\ (14) \tag{28}$$

$$(SP3-2)^k = Min\sum_{j\in J}CS_j\sqrt{V_j} - \sum_{j\in J}\tau_j^k V_j \tag{29}$$

$$S.T.\ (15) \tag{30}$$

4.1.3. Obtaining a feasible solution for the original problem

By solving the above mentioned five sub-problems, a solution is obtained for the Lagrangian problemZ_{LR}, which is proved to be an upper bound for the original problem Z:

Proposition:

$$Z^{UB} = SP1^k + (SP2-1)^k + (SP2-2)^k + (SP3-1)^k + (SP3-2)^k \tag{31}$$

Proof:

Sub-problem SP1 is a nonlinear model, in which the competitive price interval for retail and wholesale channels is determined according to the scenarios in Table 2. Then price variables pr_t and pw_t, and demand variables μ_{jit} and $\overline{\mu}_{jwt}$ are calculated according to constraints (6)–(7), and (10)–(12). In fact, SP1 computes the maximum obtainable income. Since the problem is single product, sub-problem SP2-1 can be decomposed into J sub-problems, equivalent to the number of potential DCs. These models can be solved using Dantzig's bound (Dantzig, 1957). Meanwhile, because the binary domains of allocation variables $Y_{ji}, \overline{Y}_{wi}$ are substituted with $0 \le Y_{ji}, \overline{Y}_{jw} \le 1$, a smaller objective function value will be obtained. Similarly, the solution for sub-problem SP2-2 is an upper bound for the location problem.

It is likely that the solution obtained by solving the generated five sub-problems, is an infeasible upper bound for the original problem. Therefore, the next step will be to transform it to a feasible solution and improving it. In this study, the proposed method by Nasiri et al. (2010a) is employed. The algorithm consists of a method for generating a feasible solution, and three improvement procedures for the allocation of retailers and wholesalers, location of DCs and defining their capacity.

4.1.4. Updating Lagrangian multipliers

After obtaining the upper and lower bound solutions, the termination condition is checked. If the condition is satisfied, the algorithm has reached the end and the upper and lower bounds contain the optimal solution of the original problem. Otherwise, the Lagrangian multipliers are updated and the algorithm is executed for the next iteration. Termination condition is usually defined as reaching a specific number of iterations or a certain duality gap, or having no improvement for a defined number of iterations. The duality gap between the initial and dual problems is always a positive number for mixed-integer nonlinear problems, and is calculated using the following formula:

$$Duality\ Gap = \frac{Z^{UB} - Z^*}{Z^{UB}} \tag{32}$$

Where Z^* is the best feasible solution found so far, which is obtained by implementing the previously mentioned procedures at the end of section 4.1.3. Z^{UB} is the upper bound value and is calculated from relation (16) and Proposition (32) i.e. the relaxed model.

To compute the values of Lagrangian multipliers ψ_j, η_w, $\beta_i$and τ_j in iteration k+1, the sub-gradient method proposed by Amiri (2006) is applied as follows:

$$U_1^k = max\left[0, \beta_i^k - stepsize1^k\left(\sum_{j\in J} Y_{ji} - 1\right)\right] \quad \forall i = \{1,\dots,I\} \tag{33}$$

$$U_2^k = max\left[0, \eta_w^k - stepsize2^k\left(\sum_{j\in J} \overline{Y}_{jw} - 1\right)\right] \quad \forall w = \{1,\dots,W\} \tag{34}$$

$$U_3^k = \left(\sum_{j\in J}\sum_{i\in I}\sum_{t\in T}\psi_j^k\cdot\mu_{jit}\cdot Y_{ji} + \sum_{j\in J}\sum_{w\in W}\sum_{t\in T}\psi_j^k\cdot\overline{\mu}_{jwt}\cdot\overline{Y}_{jw} - \sum_{j\in J}\psi_j^k\cdot D_j\right) \forall j=\{1,\dots,J\} \tag{35}$$

$$U_4^k = \left(\sum_{j\in J}\sum_{i\in I}\sum_{t\in T}\tau_j^k\cdot\sigma_{it}^2\cdot Y_{ji} + \sum_{j\in J}\sum_{w\in W}\sum_{t\in T}\tau_j^k\cdot\overline{\sigma}_{wt}^2\cdot\overline{Y}_{jw} - \sum_{j\in J}\tau_j^k\cdot V_j\right) \forall j=\{1,\dots,J\} \tag{36}$$

The step length is computed using the following formulas:

$$stepsize^k = \rho^k \frac{\overline{Z}_k^{UB} - Z_k^*}{\|U_1^k\|^2 + \|U_2^k\|^2 + \|U_3^k\|^2 + \|U_4^k\|^2} \tag{37}$$

$$\overline{Z}_k^{UB} = min\left(\overline{Z}_{k-1}^{UB}, Z_k^{UB}\right) \tag{38}$$

Where $\overline{Z}_k^{UB}$ is the value of upper bound for the original problem which is found by solving the relaxed model, i.e. objective function (16). At the first the value of parameter ρ is set between 0 and 2. If there is no improvement in two consecutive iterations, its value is halved. This process continues until the termination condition is satisfied. Finally, Lagrangian multipliers are update using the relations (39)–(42).

$$\beta_i^{k+1} = \beta_i^k - stepsize^k\cdot U_1^k \quad \forall i = \{1,\dots,I\} \tag{39}$$

$$\eta_w^{k+1} = \eta_w^k - stepsize^k\cdot U_2^k \quad \forall w = \{1,\dots,W\} \tag{40}$$

$$\psi_j^{k+1} = Max\left\{0, \psi_j^k + stepsize^k\cdot U_3^k\right\} \quad \forall j = \{1,\dots,J\} \tag{41}$$

$$\tau_j^{k+1} = Max\left\{0, \tau_j^k + stepsize^k\cdot U_4^k\right\} \quad \forall j = \{1,\dots,J\} \tag{42}$$

4.2. Proposed GA

In this section the proposed GA is presented to compare the objective function and runtime obtained by LR algorithm.

4.2.1. Chromosome representation of solutions

Chromosome presentation of decision variables is an important element of GA. The problem under consideration includes both independent and dependent variables. Dependent variables can be calculated using the values of independent variables. So, only independent variables are used in chromosome representation. Here, each solution is encoded using three types of chromosomes, which are relevant to the decision variables of retailer-DC allocation, wholesaler-DC allocation, and DC location.

Suppose that 5 retailers are to be assigned to DCs 1 and 2. Figs. 3 and 4 illustrate the typical values of allocation decision variables and their chromosome representation respectively.

The Same approach is used to encode the allocation of wholesalers to DCs. In fact, each solution is depicted by two chromosomes with length of I and W (i.e. number of retailers and number of wholesalers), which are filled with integer values that corresponded to the assigned DC's number (i.e. 1 to J).

For representation of DC locations, a chromosome with length of J is used, which is filled with integer numbers between 0 and H (i.e. maximum capacity level of DCs). If the candidate DC is established, the number will be between 1 to H. Otherwise, the number will be zero. Thus, the encoding automatically considers constraint (5), which limits the capacity level of located DCs.

Fig. 5 depicts a typical chromosome representation for the location of 6 DCs.

Other operators of the GA such as crossover, mutation, and selection are adopted from Nasiri et al. (2010b).

4.2.2. Parameter setting

The values of the algorithm parameters were adjusted using Taguchi-based design of experiments (DOE). DOE is a systematic method to determine the relationship between the influencing factors of a process and its outputs. The information required for implementing DOE depends on the number of experiments and the relevant data. The size of the data is important since it is the major determinant of time and cost of implementing experiments.

Here, the Signal-to-Noise (S/N) ratio is used in Taguchi method, to find the parameter values that produce the best possible results for the GA with minimum variability. Signal refers to the desired values (response variable), and Noise refers to the undesired values (coefficient of variation). Therefore, Signal to Noise ratio denotes the degree of variations in response variable, and the objective is to maximize it. The ratio is calculated using relation (43):

$$\frac{S}{N} = -10\ log_{10}\left[\left(\frac{1}{n}\right)\cdot\sum_{a\in N}\frac{1}{y_a^2}\right] \tag{43}$$

		Retailer No.				
		1	2	3	4	5
DC No.	1			1	1	
	2	1	1			1

Fig. 3. Typical allocation of retailers to DCs.

Retailer No.	1	2	3	4	5
DC No.	2	2	1	1	2

Fig. 4. Typical chromosome representation of allocations.

Where, n denotes the number of experiments for the problem, and y_a is the value of response variable. Response variable is the ratio of objective function value to the runtime of GA. In the developed GA, four parameters including number of generations, population size, and crossover and mutation probabilities with three values are considered, as stated in Table 3. Note that the values for number of generations and populations size are selected such that their product always remains constant.

Experiments were conducted using Minitab software for the test problem No.5 in TableA2. The problem was solved 5 times, and the average values of its objective function and runtime were used to compute the S/N ratio. The results are depicted in Fig. 6. Symbols A, B, C, and D, correspond to *MaxIter*, *PopSize*, P_c, P_m respectively.

Based on the results of Fig. 6, the best parameter values are given in Table 4.

5. Computational results and discussions

The considered problem in this article is a mixed-integer nonlinear programming model which is of relatively high complexity. The model was solved using the Baron system in GAMS 24.8.3 optimization software. LR and GA were coded using MATLAB R2016b. Both GAMS and MATLAB were run on a PC with a Core i7@ 2.1 GHz CPU and a 6G RAM.

In total, 35 test problems were developed and solved using GAMS, LR algorithm and GA. The numbers of retailers, wholesalers, and DCs were set between 4 and 200, 1 to 40, and 1 to 40 respectively. The important attributes of designed test problems are stated in Appendix1 Tables A1, A2. In order to achieve reasonable level of confidence about the performance of the proposed solution algorithms each test problem was solved 5 times with same structure and different input parameters.

Table 5 illustrates the average of computational results of solving the test problems with the proposed algorithms. Note that for GAMS, a runtime limit of 4 hours (14,400 seconds) was set.

It is observed that runtimes of GAMS are below 14,400 seconds only for test problems 1–6, and for larger problems it could not achieve a feasible solution in the defined time limit. As can be seen from Table 5, the relative gaps in objective function values of GA to LR are between −2 and −10 percent. Runtimes of LR are also lower than that of GA in all problems, not exceeding 308.68 s (see Fig. 7).

In order to compare the runtimes of LR algorithm and GA, the analysis of variance (ANOVA) with an alpha of 0.05 is used. The results of the designed tests are indicated in Table 6. According to normality conditions, since P-value < 0.05, it can be concluded that there is significant difference between runtimes of the two proposed algorithms.

To assess the efficiency of capacity planning for DCs in the obtained solutions, the Warehouse Utilization Ratio (W.U.R.) is used. W.U.R. is calculated as formula 44.

DC No.	1	2	3	4	5	6
Capacity Level	1	5	0	0	4	2

Fig. 5. Typical chromosome representation for the location of DCs.

Table 3
Selected levels of GA parameters for parameter setting.

Parameter	Level 1	Level 2	Level 3
MaxIter: Number of Generations	320	240	160
PopSize: Population size	75	100	150
P_c: Crossover probability	0.6	0.7	0.8
P_m: Mutation probability	0.01	0.04	0.07

$$W.U.R._j = \frac{Sum\ of\ demands\ allocated\ to\ DC\ j}{Capacity\ of\ DC\ j} \tag{44}$$

The average of W.U.R. for the three algorithms among test problems 1 to 6 are indicated in Table 7. It is seen that the resulting average values for LR are higher than the values obtained with the other two algorithms.

6. Sensitivity analysis of the results

In this section, sensitivity analysis is conducted in order to assess the impact of various parameters on the objective function value and the suggested prices. The analysis includes assessing the impact of demand leakage, capacity of DCs, lead time, elasticity of retailer's demand to the retail and wholesale prices, elasticity of wholesaler's demand to the wholesale price, on the objective function value, for a problem with 4 retailers, 4 wholesalers, and 4 DCs.

Fig. 8 depicts the results of sensitivity analysis for demand leakage rate. It is observed that objective function is highly sensitive to this parameter, and has inverse relationship with it.

Fig. 9, indicates the impact of DC capacity level on the objective function value. According to this Figure, supply chain profit increases as the capacity level is increased. There is a significant drop in the curve, from −20% to −25% of the maximum capacity level. The reason maybe that for a very low capacity level, the prices offered by DCs are set higher so as to ensure the profitability. But higher prices lead to decreased levels of demand allocated to the DCs which as a result, significantly decreases supply chain profit.

In contrast, when capacity level is reduced to 5, 10, 15 or 20%, profit decreases smoothly. This means that, capacity and demand reduction are compromised with higher prices.

When the capacity level is increased above the initial value, the network tends to be set for fewer DCs with higher capacity levels. This is maybe because of the lower cost of establishing fewer but larger DCs, than setting up larger number of smaller DCs.

The impact of different lead time values on objective function value is shown in Fig. 10. It can be seen that the objective function value decreases slightly as the lead time increases. This matches the conduct seen in markets of commodity products in reality. For strategic products, interpretations must be made with caution.

Fig. 11 illustrates curves of lead time, DC capacity, and holding costs in a single chart. Note that trends of ordering and holding costs are very similar. According to this Figure, DC capacity level is the most influential parameter. This means that more profit can be gained by increasing the DC capacity levels, than by increasing the other parameters. Therefore, in this study decision makers need to focus on capacity

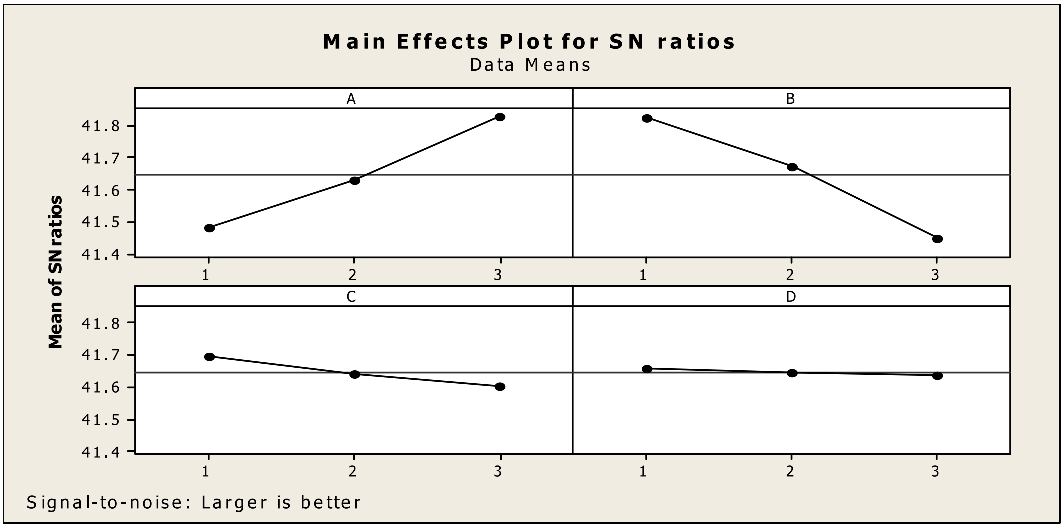

Fig. 6. Average S/N ratios obtained for the GA parameters.

Table 4
Optimum parameters values for the GA.

Parameters	Selected value
MaxIter: Number of Generations	160
PopSize: Population size	75
P_c: Crossover probability	0.6
P_m: Mutation probability	0.01

planning at DCs location and establishment to improve system performance.

In Fig. 12, the impacts of the four demand parameters including γ, m_1, m_2, and m_3 on the objective function are illustrated. These parameters are demand leakage, elasticity of retailer's demand to the retail and wholesale channel prices, and elasticity of wholesaler's demand to the wholesale channel price respectively. As can be seen from the mentioned curves, objective function value is most sensitive to m_1 and m_3. Note that

Table 5
Summary of computational results.

Problem No.	Lagrangian Duality Gap	Relative Gap in Objective Function (%)			Runtime (seconds)		
		GAMS vs. LR	GAMS vs. GA	GA vs. LR	GAMS	LR	GA
1	0.50	11.2	6.53	−7.99	0.22	0.74	7.59
2	0.64	6.25	3.15	−8.22	5.10	0.89	11.06
3	0.61	5.20	2.77	−8.10	12.31	1.14	13.47
4	0.91	4.79	1.03	−3.51	27.83	1.23	25.50
5	0.53	7.47	1.36	−7.42	83.65	1.47	27.34
6	1.19	11.93	4.37	−8.69	4,844.27	1.87	33.68
7	0.50	–	–	−8.34	–	2.09	44.58
8	0.54	–	–	−9.17	–	2.46	52.03
9	0.55	–	–	−4.82	–	3.24	61.84
10	0.61	–	–	−7.99	–	4.04	70.57
11	1.38	–	–	−4.48	–	5.12	77.51
12	1.05	–	–	−7.31	–	6.53	86.66
13	0.86	–	–	−5.48	–	7.84	96.72
14	0.50	–	–	−9.76	–	10.69	107.28
15	0.70	–	–	−7.41	–	13.45	128.74
16	1.01	–	–	−5.82	–	17.68	137.35
17	1.57	–	–	−6.72	–	22.61	139.38
18	1.28	–	–	−5.82	–	24.10	149.92
19	1.24	–	–	−5.93	–	26.32	164.16
20	1.36	–	–	−2.14	–	30.54	176.89
21	1.22	–	–	−7.41	–	34.44	188.72
22	1.07	–	–	−9.17	–	43.89	200.38
23	1.83	–	–	−7.75	–	50.90	218.94
24	2.19	–	–	−6.15	–	62.04	228.51
25	1.74	–	–	−7.52	–	71.35	242.68
26	1.63	–	–	−5.04	–	73.84	257.75
27	1.57	–	–	−2.14	–	95.69	278.42
28	1.77	–	–	−4.38	–	103.58	284.18
29	2.16	–	–	−6.87	–	109.11	307.25
30	2.01	–	–	−9.40	–	118.33	318.33
31	1.91	–	–	−8.91	–	147.25	391.48
32	2.34	–	–	−7.73	–	163.29	418.83
33	3.16	–	–	−8.19	–	198.45	482.30
34	3.23	–	–	−8.62	–	247.32	563.09
35	3.41	–	–	−9.63	–	308.68	638.87
Ave.	1.39	7.81	3.20	−6.97	828.90	57.49	189.49

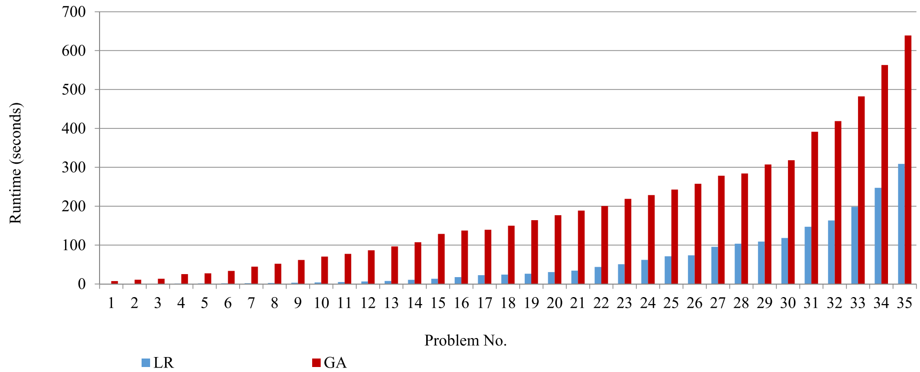

Fig. 7. Comparison of runtimes of LR and GA.

Table 6
ANOVA results for LR and GA runtimes.

Source	Degree of Freedom	Sum of Squares	Mean Square	F-value	P-value
Between	1	304,892	304,892	19,39	0.000
Within	68	1,069,343	15,726	–	–
Total	69	1,374,235	–	–	–

Table 7
Comparison of average W.U.R. for the three algorithms.

Problem No.	LR	GA	GAMS
1	87.84	86.47	85.26
2	89.18	87.58	85.38
3	89.74	88.19	87.04
4	92.97	89.89	88.75
5	94.32	90.01	87.96
6	89.72	87.52	86.07
Average	90.63	88.28	86.74

as m_3 decreases, the demand for wholesaler increases and supply chain profits will increase consequently.

Also, 3D Fig. 13 shows the effect of m_1 & m_3 parameters on the objective function.

Consequently, demand leakage in the multi-channel system is a very important issue that must be controlled according to the marketing considerations to achieve competitive success.

7. Conclusions and recommendations

In this paper a model is proposed for the design of a multi-echelon DND with different distribution channels, in which pricing policy and marketing considerations with uncertain demand are incorporated. The model includes simultaneous decisions of location, allocation, inventory policy, order size for each DC and pricing in retail and wholesale channels. However, unlike many previous pricing studies which have considered single channel, the proposed model investigates the dual channel distribution network design. The demand of retailers and wholesalers from the DCs are dependent to the retail and wholesale prices and the population of customers. Wholesalers also have their own retail channel, which may be different from producer's distribution network. These extensions make the model more practical so that a realistic assumption including demand leakage between the retailers and wholesalers is considered. In this dual channel distribution network, according to marketing considerations product's price must be set so that minimum competition occurs between the sales channels.

Objective function is the maximization of supply chain profit, which is the sum of incomes in retail and wholesale channels, minus establishment, ordering and inventory holding costs of DCs, and the network transportation costs.

The problem is formulated as a mixed-integer nonlinear mathematical programming model. The model is solved using a LR method and a GA. Computational results of the algorithms for a set of 35 test problems indicate that both methods perform better than GAMS optimization software. LR algorithm outperforms GA in terms of objective function value and runtime. In addition, the warehouse utilization ratio in the

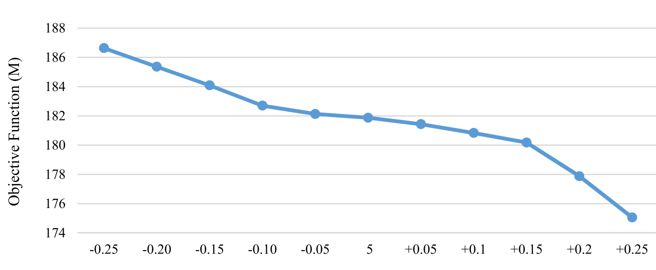

Fig. 8. Sensitivity of objective function to demand leakage ratio.

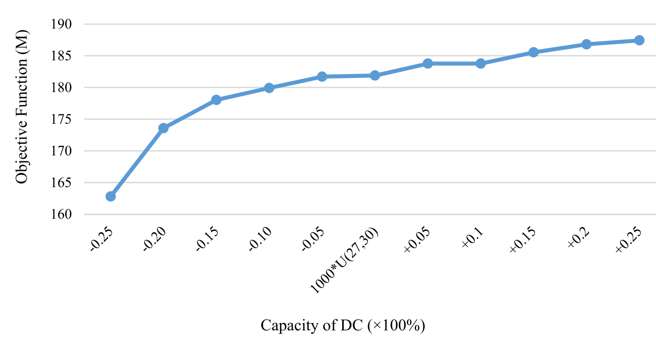

Fig. 9. Sensitivity of objective function to DC capacity.

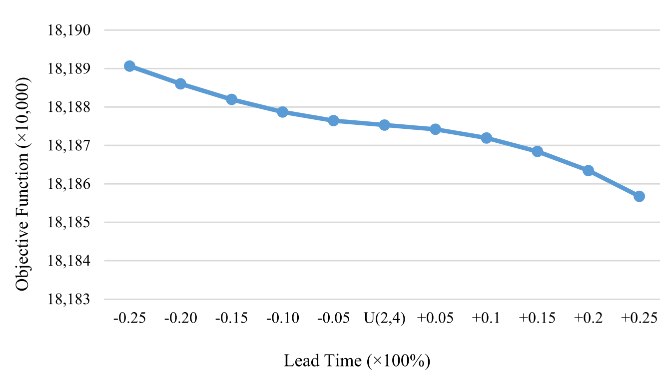

Fig. 10. Sensitivity of objective function to lead time.

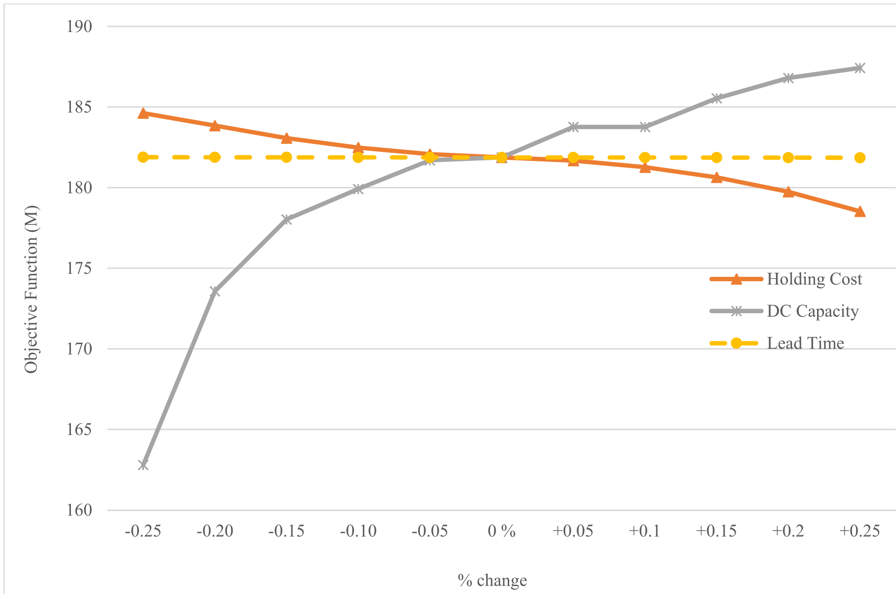

Fig. 11. Sensitivity of objective function to selected parameters.

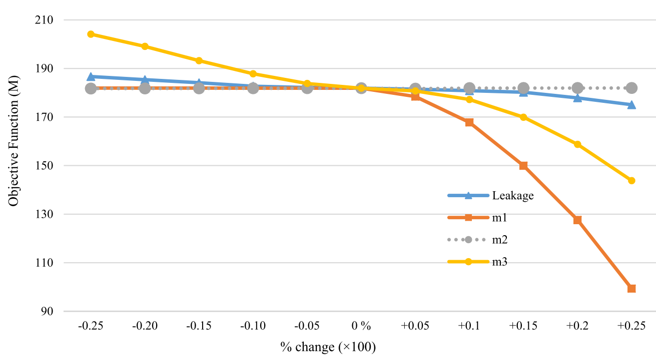

Fig. 12. Sensitivity of objective function to demand parameters.

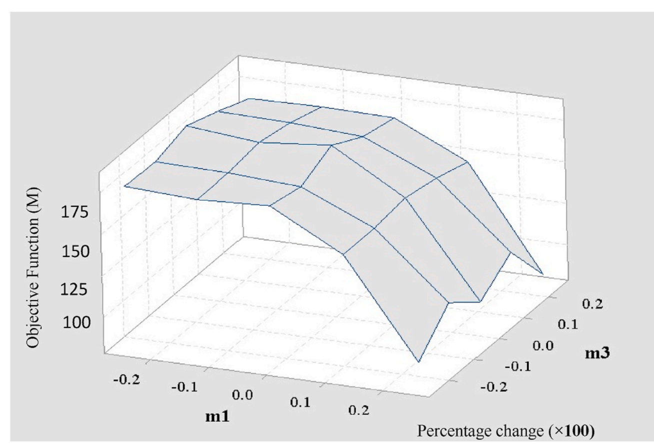

Fig. 13. Sensitivity of objective function vs. m_1&m_3.

solutions obtained by LR algorithm is better than that of the two other algorithms. Furthermore, according to the sensitivity analysis results, objective function is most sensitive to DC capacity levels, and elasticity of retailer's demand to the retail and wholesale channel prices. Moreover, demand leakage between the sales channels is a very important issue that must be controlled according to the marketing policy, competitors' prices, and internal considerations such as unit product cost.

Given the challenges of decisions integration, it is necessary to mention a few managerial implications for decision making in real world situations. Incorporating strategic cost including DCs establishment in the objective function may reduce the number of opened DCs. Basically, the behavior of this cost is inconsistent with the transportation cost. However, considering inventory costs in the facility location problems is effective in reducing total costs but also risk pooling effect maybe occurred. Therefore, tradeoff between DCs centralization, logistics costs, and availability of products for higher customer satisfaction plays very important role in supply chain management. Therefore, improving distribution planning is highly recommended to reduce stock-out conditions in supply network.

Finally, a number of suggestions can be proposed for the future studies. One suggestion is to consider the location-inventory-pricing problem for closed-loop supply chains. Other possible extensions to make the problem more realistic include considering transshipment between DCs, diverse supply policies, and segmenting the market. Moreover, social responsibility can be captured in pricing strategies by embedding environmental and social consideration in pricing policy. Finally, another interesting topic is to consider engineering economic factors such as interest and inflation rates in payment terms and examining its effect on product price.

Appendix1

Table A1
Main parameters used in test problems

$TC2_{ji} = U(50, 350)$	$\overline{TC2}_{jw} = U(50, 350)$	$m_1 = 0.75$	$m_2 = 0.002$	$m_3 = 0.85$	$PH = 1000$
$z_\alpha = 1.96$	$l_j = U(2, 4)$	$HC_j = U(90, 110)$	$OC_j = 10^4 \times U(3, 5)$	$\sigma_{it}^2 = U(15, 25)$, $U(50, 70)$	$\overline{\sigma}_{wt}^2 = U(19, 31)$, $U(80, 95)$
$Pr_t^{LB} = \{1500, 1550\}$	$Pr_t^{UB} = \{1800, 1850\}$	$Pw_t^{LB} = \{1450, 1500\}$	$Pw_t^{UB} = \{1750, 1800\}$	$\varepsilon_1 = \{0.03, 0.02\}$	$\varepsilon_2 = \{0.1, 0.08\}$
$cap_{j3} = U(4000, 4500)$	$F_{j3} = 10^8 \times U(5, 6)$	H = 5	$cap_{j1} = 0.5\ cap_{j3}$	$cap_{j2} = 0.75\ cap_{j3}$	$cap_{j4} = 1.25\ cap_{j3}$
$cap_{j5} = 1.5\ cap_{j3}$					

Table A2
Attributes of designed test problems

Problem No.	Number of Retailers (I)	Number of Wholesalers (W)	Number of DCs (J)	Number of Decision Variables	Number of 1–0 Variables	Number of Constraints
1	4	1	1	34	10	25
2	5	1	2	66	22	44
3	6	1	3	104	36	67
4	7	1	4	148	52	94
5	8	1	5	198	70	125
6	12	2	6	330	114	212
7	18	2	7	514	175	334
8	24	2	8	734	248	480
9	30	2	9	990	333	650
10	35	3	10	1,282	430	844
11	40	3	11	1,576	528	1,039
12	45	4	12	1,937	648	1,279
13	50	5	13	2,334	780	1,543
14	55	6	14	2,767	924	1,831
15	60	7	15	3,236	1,080	2,143
16	65	8	16	3,741	1,248	2,479
17	70	9	17	4,282	1,428	2,839
18	75	10	18	4,859	1,620	3,223
19	80	11	19	5,472	1,824	3,631
20	85	11	20	6,060	2,020	4,022
21	90	12	21	6,742	2,447	4,476
22	95	12	22	7,393	2,464	4,909
23	100	13	23	8,144	2,714	5,409
24	105	14	24	8,931	2,976	5,933
25	110	15	25	9,754	3,250	6,481
26	115	16	26	10,613	3,536	7,053
27	120	17	27	11,508	3,834	7,649
28	125	18	28	12,439	4,144	8,269
29	130	19	29	13,406	4,466	8,913
30	130	20	30	13,954	4,650	9,276
31	135	25	35	17,314	5,775	11,506
32	140	30	35	18,374	7,000	12,216
33	150	30	40	22,184	7,400	14,746
34	200	35	40	28,839	9,600	19,201
35	200	40	40	29,444	9,800	19,606

Appendix2. Calculation of inventory holding cost in DCs

In order to calculate the inventory holding cost in DCs, it is assumed that they follow the continuous review policy. In this policy, when inventory level falls below r_j, an order size Q_j is released, which will be received with lead time l_j. Since demands by retailers and wholesalers are probabilistic, when an order is released for DC j, its inventory level must satisfy the demands with probability of $1-\alpha$, during the lead time. Service level constraint is expressed as below:

$$P\left(D_{l_j} \leq D_{\max(j)}\right) = 1-\alpha \quad \text{(A1)}$$

Where, D_{l_j} is the probabilistic demand allocated to DC j during lead time l_j, and $D_{max(j)}$ is the maximum demand during lead time which is obtained by the following formula:

$$D_{max(j)} = \overline{D_{l_j}} + ss_j \quad \text{(A2)}$$

Here, $\overline{D}_{l_j}$ is the mean of demand allocated to DC *j* during lead time, and ss_j is it safety stock level. Supposing that demand during lead time follows the Normal distribution, the required level of safety stock in DC *j*, can be obtained using relations (A3)- (A5).

$$ss_j = z_{1-\alpha} \cdot \sqrt{Var(D_{l_j})} \tag{A3}$$

$$Var(D_{l_j}) = \sqrt{l_j V_j} \tag{A4}$$

$$ss_j = z_{1-\alpha} \cdot \sqrt{l_j V_j} \tag{A5}$$

Considering the above relations, following formula is obtained for computing the reorder point in DC *j*.

$$r_j = l_j D_j + Z_{1-\alpha} \cdot \sqrt{l_j V_j} \tag{A6}$$

Mean of holding and ordering costs for DC *j* (per time unit), can be obtained by combining the above formulas as follows:

$$\frac{OC_j D_j}{Q_j} + \frac{HC_j Q_j}{2} + HC_j Z_{1-\alpha} \cdot \sqrt{l_j V_j} \tag{A7}$$

The first part denotes ordering cost. The second part is the holding cost of maintainingQ_j, which is the inventory used for satisfying demands between each two consecutive orders. The last part is the mean cost of holding safety stock in DC *j*.

There is no restriction for order quantity, and thus by taking the derivative of expression (A7) with respect to Q_j for each DC and setting it equal to zero, equation (A8) is obtained:

$$\frac{HC_j}{2} - \frac{OC_j}{Q_j^2} D_j = 0 \tag{A8}$$

Simplifying equation (A8), gives the formula of optimum order size for DC *j* as follows:

$$Q_j^* = \sqrt{\frac{2OC_j D_j}{HC_j}} \quad \forall j \in \{1, \dots, J\} \tag{A9}$$

By substituting equation (A9) in equation (A7), total holding cost is obtained as follows:

$$Total\ Holding\ Cost(THC) = \sum_{j \in J} PH \cdot \sqrt{2OC_j \cdot D_j \cdot HC_j} + \sum_{j \in J} PH \cdot HC_j \cdot Z_{1-\alpha} \cdot \sqrt{l_j V_j} \tag{A10}$$

For the sake of simplicity, equation (A11)- (A13) are used to represent the total holding cost:

$$CH_j = PH \sqrt{2OC_j \cdot HC_j} \tag{A11}$$

$$CS_j = PH \cdot HC_j \cdot Z_{1-\alpha} \cdot \sqrt{l_j} \tag{A12}$$

$$THC = \sum_{j \in J} CH_j \cdot \sqrt{D_j} + \sum_{j \in J} CS_j \cdot \sqrt{V_j} \tag{A13}$$

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