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An integrated multi-objective supply chain network and competitive facility location model

Canser Bilir [a,*], Sule Onsel Ekici [b], Fusun Ulengin [c]

[a] Istanbul S. Zaim University, Industrial Engineering Department, Halkali Cd. Kucukcekmece, 34303 Istanbul, Turkey
[b] Dogus University, Engineering Faculty, Industrial Engineering Department, Zeamet Sok., No: 21 Kadikoy, 34722 İstanbul, Turkey
[c] Sabanci University, Sabanci School of Management, Orta Mah. Universite Cad. No: 27 Orhanli – Tuzla, 34956 Istanbul, Turkey

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ABSTRACT

In this study, a multi-objective supply chain (SC) network optimization model based on the joint SC network optimization and competitive facility location models is proposed to analyse the results of ignoring the impacts of SC network decisions on customer demand. The objectives utilized in the model are profit maximization, sales maximization and SC risk minimization. The unique unknown variable within the model is the demand. The demand at each customer zone is assumed to be determined by price and the utility function. The utility function is defined as the availability of same-day transportation from the distribution centre (DC) to the customer zone. The application of the proposed model is illustrated through a real-world problem and is solved as single and multi-objective models. The results of single and multi-objective models are subsequently compared. After solving the problem, a sensitivity analysis is also conducted to test the applicability of the model with respect to various parameter coefficients, such as price elasticity, one–day replenishment coverage impact, risk factors (disruption probabilities) and the relative weights of the objectives.

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1. Introduction

The optimization of SC networks plays a key role in determining the competitiveness of the whole SC. Therefore, during the last two decades, an increasing number of studies have focused on the optimization of the overall SC network. However, in most of these optimization studies, the structure of the SC network is considerably simplified (e.g., a single product and a single location layer are usually assumed), and there is still a need for more comprehensive models that simultaneously capture many aspects that are relevant to real-world problems such as demand dynamics on the market.

Facility location decisions—more specifically, decisions on the physical network structure of a SC network—are important factors affecting chain's competitiveness, especially for the SCs serving retail markets. However, SC network optimization models in the current literature ignore the impacts of SC network decisions on customer demand. Nevertheless, competitive facility location problems model only the distribution part of the SC, even though they have certain characteristics of SC networks and analyse the rival chains existing on the market (Bilir, Ekici, & Sweeney, 2015).

In this study, a new model has been proposed in which the concept of SC network optimization modelling is incorporated with competitive facility location factors (e.g., changing demands that are dependent not only on price but also on customer service related functions). The aim of this model is to include the impact of a SC's physical network structure on customer demand.

The remainder of the paper is organized as follows: the next section provides a brief literature review. Section 3 focuses on the proposed model as well as its objectives, variables, and parameters. Section 4 defines a real-world problem to which the proposed model is applied. Section 5 provides the results of the model that is applied to a real-world scenario. The paper ends with final conclusions of the study and provides further research suggestions.

2. Literature review

In order to identify different characteristics of the various models and common trends, we conducted a comprehensive literature of recently developed (from 2009 to 2013) SC network optimization models. In this review, our focus was on identifying studies that included a strategic-level SCN model. Models that considered

* Corresponding author.
E-mail addresses: canser.bilir@izu.edu.tr (C. Bilir), sonsel@dogus.edu.tr (S.O. Ekici), fulengin@sabanciuniv.edu (F. Ulengin).

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the reconfiguration or relocation of the SCN nodes and arcs (0–1 decisions) are considered as strategic-level models.

To generate a list of relevant articles published between 2009 and 2013, "SC network modelling" was entered as a search term in the Science Direct database. This generated an initial list of articles, from which 72 that were published only in the most relevant journals and included strategic level decision variables were selected and analysed.

Supply chains are dynamic networks consisting of multiple transaction points with complex transportation, information transactions and financial transactions between entities. Therefore, SC modelling involves several conflicting objectives, at both the individual entity and SC levels. Our survey on SC network model objectives showed that the majority of SC network optimization models are solely based on cost minimization (e.g., Lundin, 2012; Melo, Nickel, & Saldanha-da-Gama, 2012; Nagurney, Ladimer, & Nagurney, 2012) or profit maximization objectives (e.g., Kabak & Ulengin, 2011; Rezapour & Farahani, 2010; Yamada, Imai, Nakamura, & Taniguchi, 2011), even though the number of multi-objective models is increasing and there appears to have been a major shift from cost minimization to profit maximization objectives (Bilir et al., 2015).

Indeed, 24% of studies in the SC literature from 2009 to 2014 feature multi-objective functions. When compared to 9% of the articles reviewed by Melo, Nickel, and Saldanha-da-Gama (2009), it can be concluded that multi-objective models are becoming increasingly popular. Multi-objective models typically include a cost minimization or profit maximization function, together with customer service, environmental effects or risk mitigation related objectives (e.g., Akgul, Shah, & Papageorgiou, 2012; Olivares-Benitez, Ríos-Mercado, & González-Velarde, 2013; Prakash, Chan, Liao, & Deshmukh, 2012; Shankar, Basavarajappa, Chen, & Kadadevaramath 2013).

The existence of competition within the market (both among firms and via other SCs providing the same or substitutable goods) is an important factor that must be considered when designing a SC network.

The literature survey that we have conducted regarding competition modelling for SCs identified only seven papers (Masoumi, Yu, & Nagurney, 2012; Nagurney, 2010; Nagurney & Yu, 2012; Rezapour & Farahani, 2010; Rezapour, Farahani, Ghodsipou, & Abdollahzadeh, 2011; Yu & Nagurney, 2013; Zamarripa, Aguirre, Méndez, & Espuña, 2012) explicitly modelling competition within the market. Among these papers, the demand is simultaneously modelled as a function of both the retailer's and the competitor's price (oligopolistic competition). These authors developed an equilibrium model to design a centralized SC network operating in markets under deterministic price-dependent demands and with a rival SC present. The competing chains provide products, either identical or highly substitutable, that compete for participating retailer markets. Using this approach, the authors were able to model the joint optimizing behaviour of these chains, derive the equilibrium conditions, and establish and solve the finite-dimensional variational inequality formulation. In six other models (Amaro & Barbosa-Póvoa, 2009; Cruz, 2009; Cruz & Zuzang, 2011; Meng, Huang, & Cheu, 2009; Yamada et al., 2011; Yang, Wang, & Li, 2009), demand is modelled as a function of only the retailer's price. Only one study modelled demand as a function of selected marketing policy (e.g., inventory-based replenishment policy, made-to-order policy or vendor managed inventory policy) (Carle, Martel, & Zufferey, 2012). None of the reviewed papers included customer service related factors—or, more specifically, the location or number of SC network points—in their demand models. However, the physical network structure of a SC clearly influences its performance and is an important factor that affects a chain's competitiveness, especially for retail markets.

SC risk management is also an important part of SC network configuration and optimization. SC risk management involves designing a robust SC network structure and managing the product flow throughout the configured network in a manner that enables the SC to predict and address disruptions (Baghalian, Rezapour, & Farahani, 2013). The uncertainties associated with disruptive events such as heavy rain, excessive wind, accidents, strikes and fires may dramatically interrupt normal operations in SCs. Hendricks and Singhal (2005) quantified the negative effect of SC disruptions on long-term financial performance (e.g., profitability, operating income, sales, assets and inventories).

In the literature survey, nine models (Baghalian et al., 2013; Bassett & Gardner, 2010; Cruz, 2009, Cruz & Zuzang, 2011; Kumar & Tiwari, 2013; Lundin, 2012; Masoumi et al., 2012; Pan & Nagi, 2010; Yu & Nagurney, 2013) explicitly included SC risk modelling (defined as SC robustness or SC risk models). In those models, the robustness of the models is quantified in SC risk equations to identify how it changes through the changes in the SC network.

A careful analysis of the SC network modelling literature finds that almost all SC network models assume that customer demands (either deterministic or stochastic) are not substantially influenced by the configuration of the SC network itself. However, the physical network structure of a SC clearly influences its performance and is one of the most important factors affecting a SC's competitiveness, especially for SCs serving retail markets. This disconnect between models and reality represents a gap in the literature and an opportunity for future research.

In this paper, the main objective is the integration of competitive facility location factors (e.g., changing demands dependent not only on price but also on customer service related functions) into SC network optimization model. As SC networks are multi-objective in nature, we define our model as multi-objective. Such multiple objectives might include profit maximization, sales maximization and SC risk minimization. Cost minimization and profit maximization are traditional objectives in SC network optimization problems. Sales maximization may also be utilized within the competitive facility location modelling framework as companies aim to increase (or at least maintain) their sales by reconfiguration of their SC network and possibly by adding new SC network point(s) (Plastria, 2001). The third objective proposed in the multi-objective framework is a risk minimization function. As SC risks have significant effects on the long- and short-term operational and financial performance of the SC (Hendricks & Singhal, 2005), strategic-level SC network decisions should be modelled with a risk metric to help understand how network decisions influence SC risks.

The principal contribution of the proposed model is the improved modelling of demands, which are affected by the price and service characteristics of SCs. The price and service, in turn, are substantially influenced by strategic-level SC network model decisions. As a second contribution of the proposed framework, SC risk will be included in modelling strategic-level SC decisions. Among the many published multi-objective SC network optimization models, only a few include SC risks as an objective.

3. Model definition

In this research, the model is built as deterministic Mixed Integer Linear Programming (MILP) with three echelon SC networks, with multiple products and a single period. The objectives of the model are to optimize SC configuration and to analyse how the location and number of DCs will influence SC performance metrics. The demand at each customer zone is assumed to be determined by the price and the utility function defined as DC-one day transportation coverage availability. The SC structure consists of three echelons: (1) Suppliers, (2) Distribution Centres (DC), and (3) Customer Zones. Fig. 1 summarizes our methodology on the definition and the analysis of the proposed model.

In Phase I, three objectives of the model are identified; profit maximization, maximization of total sales (Plastria, 2001) and SC risk minimization (Hendricks & Singhal, 2005). Phase II defines the mathematical model which integrates the concept of the competitive facility location model into SC Network optimization models. The details of the proposed model may be found under "model overview" section. Phase III provides the results of the models defined as single objective separately for profit maximization, sales maximization, and risk minimization. Meanwhile, phase IV involves a multi-objective optimization model which is constructed and solved to compare with the results of single objective models. In that phase, goal programming algorithm is utilized to solve the multi-objectivity. In the last phase, a sensitivity analysis has been conducted to test the applicability of the model with respect to various parameter coefficients; price elasticity, one–day replenishment coverage impact, risk factors (disruption probabilities), relative weights of the objectives.

3.1. Model overview

Model objectives: The proposed model has three objectives. The first objective is the maximization of the total profits. The second objective is the maximization of the total amount of sales, which are dependent on the price and the distance between the DC and the customer zone. Sales volume is not calculated as the sum of the total products distributed to customer zones, as the model may choose not to fill some of the demand when it is not profitable. The third objective of the proposed model is the minimization of SC risks.

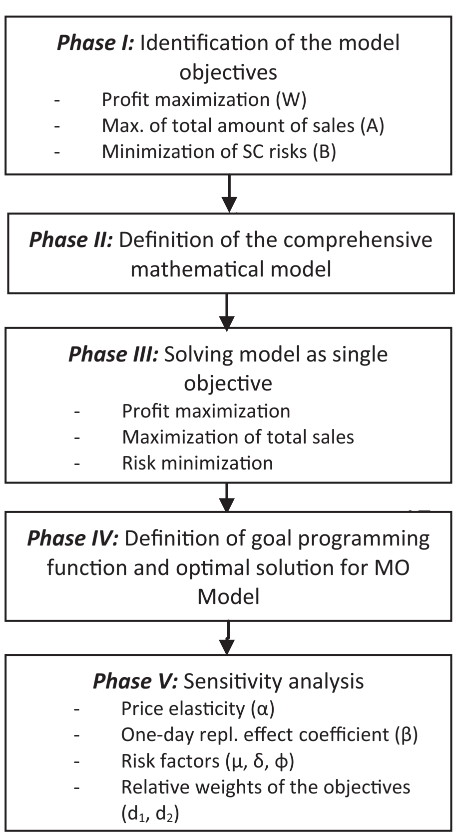

Fig. 1. Methodology on the definition and the analysis of the proposed model.

Decision variables: There are several decision variables that need to be determined:

- Number of DCs and their locations
- Capacity of each DC
- The inbound and outbound traffic network
- DC – customer zone allocation
- Demand fill rate

Demand function: In the SC network modelling literature, demand is generally either defined as deterministic or defined as a product of price. As the main purpose of the present study is to prove that adding a utility (attraction) function, which is also affected by strategic level SC decisions, to the demand model may have substantial influence on SC network optimization decisions, the demand model is built to include both price elasticity and utility function. Demand is defined as the product of both the sales price and the responsiveness of the SC network in terms of the distance between the DC and customer zones. In this study, the demand function includes two independent variables:

- Demand to Price elasticity coefficient (α);
- Availability of the one–day replenishment coverage affect (β); it is assumed that if the distance between the DC and retail outlet is less than a specified distance, the right product will be provided from the DC in one day. Therefore, this availability will have a positive impact on the sales of the products by a predefined coefficient (β).

Risk function: To formulate SC risks, a path-based formulation, as proposed by Baghalian et al. (2013), is utilized. In path-based formulation, possible disruptions in DCs (DC operations), inbound and outbound connecting links (transportation links) are considered and formulated as the probability of disruption occurrence in SC network nodes and links. Path-based formulation helps the analyser to visualize the effects of partial disruption cases.

Predetermined probabilities of disruptions at DCs (DC operations), inbound and outbound connecting links (transportation links) are formulated in risk value calculations. According to path-based supply side risk calculation, the SC risk value of one DC network (current network) is calculated as follows:

$$\text{SC risk value} = (1-\mu)*(1-\delta)*(1-\phi) = 0.995*0.99*0.98 = 0.965 \quad (1)$$

The first term in the formulation (μ) is the probability of transporting the required goods to the DC without any disruptions from suppliers. μ assumed to be 0.5% in the base scenario. The second term in the formulation (δ) is the probability of handling goods at the DC without any disruptions. δ is assumed to be 1% in the base scenario. The third term in the formulation (ϕ) is the probability of transporting the required goods from the current DC to customer zones without any disruptions. ϕ is assumed to be 2% in the base scenario. If more than one DC is utilized within the SC network, the probability of disruption occurrences at each node and link is assumed to be same. However, the disruption occurs at the SC network only if all alternatives at any single node or echelon are disrupted.

Disruption costs: When the SC network does not operate due to disruptions, there will also be a loss of sales. Therefore, shortage costs for each product type are also defined in the model. Shortage costs per product are defined as the net difference between the sales price and the unit cost of the product. Disruption costs are calculated as the total sales times the disruption probability of the whole SC network (total lost sales) multiplied by shortage costs.

3.2. Notations and Formulation for the Model

Indices

i	Products, $i = 1, \ldots, I$
j	Product suppliers, $j = 1, \ldots, J$
k	Distribution centres, $k = 1, \ldots, K$
z	Customer zones, $z = 1, \ldots, Z$
m	Number of DCs, $m = 1, \ldots, M$
n	Alternative cities, $n = 1, \ldots, N$
Inputs	
F_k	Fixed costs for DC k
C_k	Capacity for DC k
TI_{ijk}	Inbound transportation costs for product (i) from supplier (j) to DC (k)
TO_{ikz}	Outbound transportation costs for product (i) from DC (k) to customer zone (z)
IC_{mi}	Inventory costs per item in case of m DC(s)
U_i	Unit purchasing cost of the product (i)
S_i	Shortage cost of the product (i)
SR_{ij}	Supply rate for the product i from supplier j
α	Price elasticity coefficient
β	One-day replenishment coverage area elasticity coefficient
μ	Probability of disruption at the transportation link from suppliers to DC(s).
δ	Probability of disruption at handling goods at DC(s).
ϕ	Probability of disruption at the transportation link from DC(s) to customer zones
P_{0i}	Base (current) price of product (i)
DCK_{kz}	"1" if the distance between DC k and customer zone z is less than 600 km; otherwise, "0"
D_{0iz}	Base demand of product (i) at customer zone (z)
DC_{nk}	"1" if DC k is at city n; otherwise, "0"
Outputs-decision variables	
X_{ikz}	Total amount of product i distributed from DC k to customer zone z
Y_{ijk}	Total amount of product i distributed from supplier j to DC k
D_{iz}	Demand of product i at customer zone z
TIC	Total cost of inventory (changes depending on the total amount of sales and the number of DCs within the SC network)
LS	Total lost sales
LSC	Total lost sales costs
W	Total profit
A	Total amount of sales
B	SC risk value
Binary variables	
DC_k	"1" if DC i is open; otherwise, "0"
DCS_{kz}	"1" if DC k serves customer zone z; otherwise, "0"
O_m	"1" if only m number of DC(s) is / are open; otherwise, "0"

Objective 1: Maximization of total profit

$$W = \left[\left(\sum_i P_i * \sum_{kz}(X_{ikz})\right) - LSC\right] - \left[\sum_i\left(\sum_{kz}(X_{ikz}) * U_i\right)\right] - \left[\sum_{ijk}(Y_{ijk}) * (TI_{ijk})\right] - \left[\sum_{ikz}(X_{ikz}) * (TO_{ikz})\right] - \left[\sum_k (F_k) * (DC_k)\right] - [TIC] \quad (2)$$

Objective 2: Maximization of total amount of sales

$$A = \sum_{ikz}(X_{ikz}) - LS \quad (3)$$

Objective 3: Maximization of SC risk value

$$B = \sum_m (1-\mu^m) * (1-\delta^m) * (1-\varphi^m) * O_m \quad (4)$$

Subject to:

$$D_{iz} = D0_{iz} + \alpha * \left[(P_i - P0_i) * \frac{D0_{iz}}{P0_i}\right] + \beta * \sum_k DCS_{kz} * DCK_{kz} * D0_{iz} \quad \forall i, z \quad (5)$$

$$\sum_j Y_{ijk} \leqslant \sum_z X_{ikz} \quad \forall i, k \quad (6)$$

$$\sum_k X_{ikz} * DCS_{kz} \leqslant D_{iz} \quad \forall i, z \quad (7)$$

$$\sum_k Y_{ijk} = \sum_{kz} X_{ikz} * SR_{ij} \quad \forall i, j \quad (8)$$

$$\sum_{ij} Y_{ijk} \leqslant DC_k * C_k \quad \forall k \quad (9)$$

$$\sum_k DCS_{kz} = 1 \quad \forall z \quad (10)$$

$$X_{ikz} \leqslant DCS_{kz} * 100000000 \quad \forall i, k, z \quad (11)$$

$$\sum_k DC_k = \sum_m O_m * m \quad (12)$$

$$\sum_m O_m = 1 \quad (13)$$

$$\sum_i \left(\sum_{kz} X_{ikz} * IC_{mi}\right) - TIC \leqslant 1000000000 * (1 - O_m) \quad \forall m \quad (14)$$

$$\left[\left(\sum_i S_i \sum_{kz} X_{ikz}\right) * (1-\mu^m) * (1-\delta^m) * (1-\varphi^m)\right] - LSC \leqslant 1000000000 * (1 - O_m) \quad \forall m \quad (15)$$

$$\left[\sum_{ikz} X_{ikz} * (1-\mu^m) * (1-\delta^m) * (1-\varphi^m)\right] - LS \leqslant 1000000000 * (1 - O_m) \quad \forall m \quad (16)$$

$$\sum_k DC_{nk} * DC_k \leqslant 1 \quad \forall n \quad (17)$$

$$X_{ikz}, Y_{ijk}, D_{iz} \geqslant 0 \quad \forall i, j, k, z \quad (18)$$

$$DC_k, DCS_{kz}, O_m = 0 \text{ or } 1 \quad \forall k, z, m \quad (19)$$

The first objective function (W) (Eq. (2)) maximizes total profit and is divided into five components: (1) Total revenue excluding lost sales, (2) Total purchasing costs, (3) Total inbound transportation costs from suppliers to DCs, (4) Total outbound transportation costs from DCs to customer zones, (4) Fixed costs associated with DC operations, and (5) Total inventory costs.

The second objective function (A) (Eq. (3)) maximizes total amount of sales excluding total lost sales due to disruptions. The third objective function (B) (Eq. (4)) maximizes SC risk value, which is a function of disruption probabilities at SC nodes and links.

Eqs. (5)(19) of the model represent the following:

Eq. (5) specifies the demand for each customer zone for each product.
Eq. (6) ensures that any product transferred to a customer zone goes through a DC.
Eq. (7) ensures that the total amount of products sold at each customer zone is equal to or less than the demand at the zone for a specific product.
Eq. (8) matches products sold at customer zones to supplied products.
Eq. (9) ensures that the total amount of products handled at each DC is within DC capacity.
Eq. (10) and (11) ensures that each customer zone is served by only one DC.
Eq. (12) and (13) specify the number of DCs utilized within the model.
Eq. (14) calculates "Total inventory costs" based on the number of DCs utilized within the model. In the calculation, the required Customer Service Level is assumed to be 99%.
Eq. (15) calculates "Lost sales costs" based on disruption probabilities and the number of DCs utilized within the model.
Eq. (16) calculates "Lost sales" based on disruption probabilities and the number of DCs utilized within the model.
Eq. (17) ensures that a maximum of one DC is serving to each customer zone.
Eq. (18) ensures non-negativity for all variables.
Eq. (19) restricts the binary variables.

4. Problem definition for a real–world scenario

XYZ Group Company is one of the leading ready-to-wear clothing companies primarily based in Turkey. The company has approximately 150 retail stores throughout Turkey, including 3 multi-storey mega stores and over 500 sales points. The firm is one of Turkey's first 500 Big Industrial Organizations in terms of sales volume, number of employees, and other factors.

The company currently has only one DC in Istanbul. That DC supports all sales points throughout Turkey. However, the number of sales points and the company's total amount of sales increased sharply in recent years. It is considered that the firm needs to reconfigure its SC network and to decide whether to open additional DC(s) in alternative locations, such as İzmir or Ankara. In the case of opening a new DC, the firm also needs to decide on the capacity of the new DC.

The company's current SC structure is composed of three echelons. Fig. 2 depicts the current SC network of the company:

Customer zones are spread throughout Turkey. The company has 209 retail outlets. The demand for the retail outlets is aggregated to 39 city locations. The company has an enormous number of SKU to provide to the customer zones. To simplify the model, SKUs are aggregated to represent the company's entire product composition. In the current SC network, only some of the stores are delivered the right product in one day. If the distance between the DC and the retail outlet is less than 600 km the right product is assumed to be delivered from the DC in one day.

5. Applications and results

5.1. Results of the model

The proposed model is defined and solved on GAMS (General Algebraic Modelling System) Modeller. GAMS is a standard optimization package used for solving different types of complex and large scale optimization problems in many research fields. In GAMS, Cplex solver is utilized to solve both single objective and multi objective models. The basic statistics for single objective profit maximization problem is provided below;

MODEL STATISTICS			
BLOCKS OF EQUATIONS	35	SINGLE EQUATIONS	4761
BLOCKS OF VARIABLES	24	SINGLE VARIABLES	6446
NON ZERO ELEMENTS	30,283	DISCRETE VARIABLES	282

First, single objective profit maximization, sales maximization, and risk minimization models are run and analysed individually to see the results separately. The models are run on Intel Core i5-5200 CPU Computer with the 2.2 GHz Processor and 6 GB RAM. The models showed no performance problem since running time for different approaches were around several seconds. The computational times and the required number of iterations on each single objective model are listed in Table 1.

Then, a multi-objective optimization model is constructed and solved to compare results of single objective models and multi objective model. The models are run on the same system. The multi objective models showed no performance problem as well. The performance notes on each multi objective model scenario are listed in Table 2.

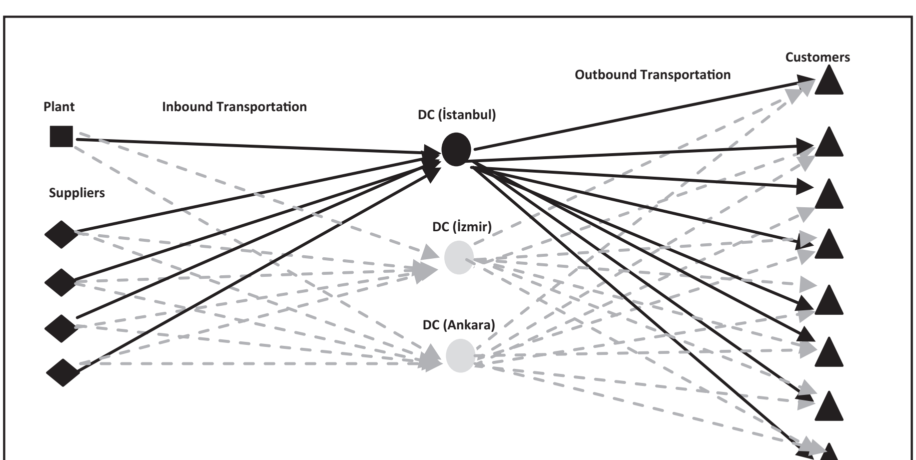

Fig. 2. Current SC Network of XYZ Company.

Table 1
Running times and required number of iterations for Single objective Models.

Model definition	Running time (s)	Number of iteration
Single Objective – Profit Maximization	1.09	137
Single Objective – Sales Maximization	2.50	59
Single Objective – Risk Minimization with Profit maximization as secondary objective	Between 0.97 and 1.88	Between 120 and 166
Single Objective – Risk Minimization with Sales maximization as secondary objective	Between 0.94 and 2.22	Between 19 and 61

Table 2
Running times and required number of iterations for Multi Objective Models.

Model definition	Running time (s)	Number of iteration
Scenarios with 1 DC	Between 0.93 and 1.81	Between 26 and 42
Scenarios with 2 DCs	Between 1.58 and 4.58	Between 155 and 211

5.1.1. Single objective models

First, the problem is solved as a *single objective profit maximization problem*. Because the firm operates in the ready-made retail clothing industry, the price elasticity coefficient is assumed to be as high as 2.5. All of the coefficients utilized in the model are summarized in Table 3.

Fig. 3 shows how the total profit and total amount of sales change according to changes in the price level. The figure shows that when the price increases, the profit also starts to increase mainly due to increasing profit margin. When the price increases, total costs decrease more than revenue decreases. Therefore, the total profit increases by up to 11%.

In the optimal solution, only one DC (the current DC) is opened. In the profit maximization problem, in any case, the model chooses not to open any additional DCs because the fixed cost of opening a DC is more than the additional profit generated by opening a second DC even though total amount of sales increases. Moreover, even though profit is maximized, total amount of sales decreases by 26%. Because of competition within the market, a 26% sales decrease is not acceptable by any firm, as firms aim to maintain their market share in order to keep their long term profitability sustainable. In addition to sales decreases, a SC risk value of 0.965 is also high in an optimal solution. Therefore, it may be concluded that modelling the problem as profit maximization does not generate the required results.

In the second phase of this step, the problem is solved as a sales maximization problem with the same coefficients. *As a last phase, the risk value maximization problem is analysed*. Within the model, the SC risk value is influenced only by the number of DCs opened. Therefore, there are only three alternative values for SC risk value. To optimize the model, a secondary objective—either profit maximization or sales maximization—is utilized.

An optimal solution summary for separate single objective problems is summarized in Fig. 4. As summarized in the figure, in the single objective model, the model generates different solutions depending on the chosen objective. For example, when profit is maximized, total amount of sales decreases by 25.8%. However, when total amount of sales is maximized at the lowest price level (a 15% price decrease), the total profit decreases to – TL 492,823, which is not acceptable because it is non-profitable. Nevertheless, when "risk value" is increased by opening new DCs, total profit decreases and the total amount of sales slightly increases.

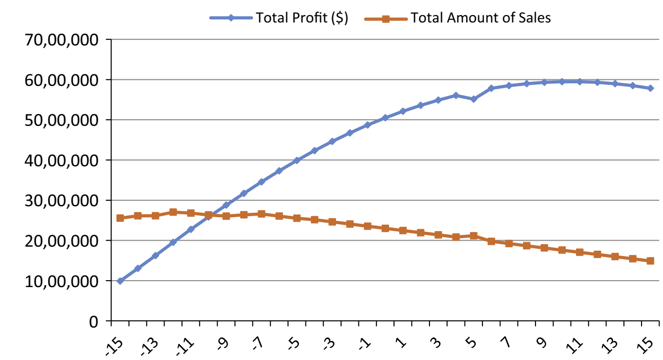

Fig. 3. Total profit and total amount of sales changes in profit maximization problem.

The figure also shows that "total amount of sales" and "total profit" change adversely; that is, when total amount of sales increases, total profit decreases. The balance between those two objectives is wholly dependent on the difference between marginal revenue generated by increasing sales and additional costs (especially the cost of opening an additional DC).

Table 4 depicts how the model objectives are influenced by the decision variables utilized within the model. According to the table, only two major decision variables have major impacts on the value of model objectives regardless of the chosen objective. On the below table, the change is called major when the change is substantial enough to have a potential to change the configuration of the SC network. On the other hand, the change is called minor when it has a potential to change only the value of the objective function.

Ultimately, as discussed after the literature review section, it can be concluded that a SC network configuration decision only based on a single objective does not provide efficient results. A method that incorporates all three objectives—profit maximization, sales maximization, and risk minimization—needs to be applied to find the most suitable SC network configuration.

5.1.2. Multi-objective model

In the literature, several different approaches are used to handle multi-objective SC network optimization models. Multi-objective solution approaches such as weighted objectives or goal programming are generally criticized for being dependent on the subjective importance of each objective. In some cases, instead of providing one single mathematically optimal solution, the modellers try to shorten the list of alternative Pareto - optimal solutions using scenario analysis in which the alternative number of scenarios is limited (Chaabane, Ramudhin, & Paquet, 2012; Costantino, Dotoli, Falagario, Fanti, & Mangini, 2012; Zamarripa et al., 2012).

Table 3
Model base scenario parameters.

α: (Price Elasticity)	β: (Coverage Elasticity)	μ: (Inbound Transportation Disruption Probability)	δ: (DC Disruption Probability)	Φ: (Outbound Transportation Disruption Probability)
−2.5	0.10	0.50%	1.00%	2.00%

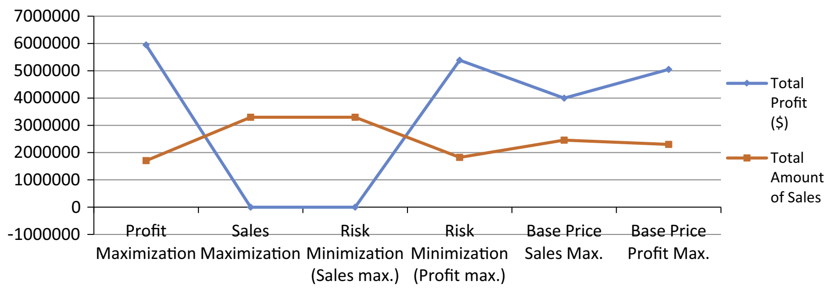

Fig. 4. Optimal solution summary for various single objective models.

Table 4
Impacts of Decision Variables on Model Objectives.

Decision variables	Model objectives		
	Total profit	Total amount of sales	SC risk value
Number and location of DCs	Major	Major	Major
Sales price	Major	Major	×
Capacity of DCs	Minor	×	×
Network traffic	Minor	×	×
DC-customer zone allocation	Minor	×	×
Demand fill rate	Minor	Minor	×

In the proposed model, the performance measures are substantially influenced by only strategic level SC decisions, such as the number and location of the DCs and the price change level. In addition to strategic level decisions, tactical level decisions, that is, SC network traffic decisions and demand fill rate decisions, have no influence on SC risk value and only a minor influence on SC profit and total amount of sales.

The model is optimized for each alternative scenario (price change and number of DCs combination) and provides solutions to decision makers for alternative scenarios. To convert profit maximization and sales maximization objectives into one single objective for each scenario, goal programming methodology is utilized. As the multi-objective approach utilized in this study combines scenario analysis and the goal programming method, it may be called a hybrid methodology.

In the goal programming method, the goals are defined as a 10% increase from the current level of the objectives (in the base scenario), and then the objectives are rescaled. Next, distance functions from each objective (d_1 and d_2) are defined. The goal function is set to minimize the total distance from both goals. The goals are as follows:

Target Profit:	TL 5.550.000
Target Amount of Sales:	2.530.000 items

Distance Functions:

Profit Distance (d_1):	Total Profit – Target Profit
Sales Distance (d_2):	Total Amount of Sales – Target Amount of Sales

Objective Function:

$$\text{Maximization of Total Distance} = d_1 + 2 * d_2$$

As the distance functions are defined as the targeted profit and targeted sales subtracted from the values of total profit and total sales, the results are negative values. Therefore, maximization of the value of distance function indeed means the minimization of the total distance from the targeted values. In the Distance Function Formula, total amount of sales is multiplied by two in order to rescale objectives to be at the same level, as the profits are approximately two times higher than the total amount of sales in the base scenario. In addition to rescaling, the relative weights of the two separate objectives are assumed to be the same.

The results show that the multi-objective model results differ from the single objective model results. In the multi-objective model, the distance function is maximized when the price is increased by 4% and two DCs (the current DC and a new DC in Ankara) are utilized concurrently (Table 5). The model proposes that the Ankara DC be opened with the least possible capacity. Compared to the current situation with one DC, opening a second DC in Ankara helps the SC network increase its sales by approximately 5% mainly due to the one-day replenishment coverage effect. However, the profit is decreased by approximately 3.1%. In the optimal point, only 7 of 39 customer locations are replenished by the new DC.

Compared to the optimal point of profit maximization problem (1 DC, 11% price increase), the profit is decreased by only approximately 8.5%, however; the total amount of sales is increased by approximately 28%. Nevertheless, unlike the optimal point of sales maximization problem, the profit is increased by 6 Million TL; however, the total amount of sales is decreased by 33.8%.

In contrast to the single objective models, when the multi-objective model tries to only maximize the distance function regardless of the price and number of DC scenarios, the result generated by the model seems quite balanced in terms of total amount of sales, total profit and SC risk value. In the optimal point, even though the distance function is maximized, the company's total amount of sales decreases due to the increasing sales price.

Comparison among the single objective and multi objective comparison results illustrated that single objective models may not generate acceptable results and may be biased in terms of performance objectives. Therefore, it may be concluded that, due to the multi - objective nature of SCs, SC network optimization models need to be defined as multi-objective.

In most cases, the firms (DMs) may need to see the results of all alternative scenarios and review how the SC performance metrics change within these scenarios before reaching a final decision. Therefore, it has been decided to provide all optimum solutions for various scenarios to DMs.

As mentioned above, instead of building a model to generate a mathematically optimal solution that is subjectively weighted by a decision maker, the optimal solution for each alternative scenario (price – number of DCs combinations) is provided in Figs. 5–7. These figures depict how total profit, total amount of sales, and distance function change according to different price and the number of DC combinations. By analysing the results and the figure, conclusions may be drawn to both narrow the alternative solutions and comprehensively understand them.

Table 5
Results for Multi-objective model (Maximizing Distance Function).

Price change (%)	# of DC (s)	SC risk value	Total revenue (000 TL)	Total costs (000 TL)	Total profit (000 TL)	Total amount of sales (000)	Distance function (000)
−11	1	0.965	38,477	36,300	2177	2892	−2648
−11	2	0.999	39,110	37,055	2054	3009	−2537
−10	1	0.965	38,189	35,669	2520	2838	−2414
−10	2	0.999	38,826	36,434	2392	2954	−2309
−9	1	0.965	37,884	35,038	2846	2784	−2195
−9	2	0.999	38,556	35,848	2708	2902	−2099
−8	1	0.965	37,563	34,407	3156	2730	−1993
−8	2	0.999	38,233	35,215	3018	2846	−1900
−7	1	0.965	37,226	33,777	3450	2676	−1807
−7	2	0.999	37,890	34,581	3310	2790	−1720
−6	1	0.965	36,873	33,146	3727	2623	−1638
−6	2	0.999	37,539	33,957	3582	2735	−1558
−5	1	0.965	36,503	32,515	3988	2569	−1485
−5	2	0.999	37,175	33,330	3845	2679	−1407
−4	1	0.965	36,117	31,884	4233	2515	−1348
−4	2	0.999	36,789	32,701	4088	2624	−1274
−3	1	0.965	35,714	31,253	4461	2461	−1227
−3	2	0.999	36,382	32,067	4314	2568	−1159
−2	1	0.965	35,296	30,622	4673	2407	−1123
−2	2	0.999	35,958	31,435	4523	2513	−1062
−1	1	0.965	34,861	29,992	4869	2353	−1035
−1	2	0.999	35,518	30,802	4715	2457	−981
Base	1	0.965	34,409	29,361	5048	2299	−964
Base	2	0.999	35,087	30,195	4892	2403	−913
1	1	0.965	33,942	28,730	5212	2245	−908
1	2	0.999	34,615	29,563	5052	2347	−864
2	1	0.965	33,458	28,099	5358	2191	−869
2	2	0.999	34,143	28,946	5198	2292	−828
3	1	0.965	32,957	27,468	5489	2137	−847
3	2	0.999	33,647	28,318	5329	2237	−807
4	1	0.965	32,441	26,838	5603	2083	−840
4	2	0.999	33,136	27,694	5442	2182	−805
5	1	0.965	31,908	26,207	5701	2029	−850
5	2	0.999	32,605	27,065	5540	2126	−817
6	1	0.965	31,359	25,576	5783	1975	−877
6	2	0.999	32,064	26,442	5622	2070	−848
7	1	0.965	30,793	24,945	5848	1921	−919
7	2	0.999	31,505	25,818	5687	2015	−892
8	1	0.965	30,211	24,314	5897	1867	−978
8	2	0.999	30,931	25,196	5736	1961	−952
9	1	0.965	29,613	23,683	5930	1814	−1053
9	2	0.999	30,340	24,571	5770	1906	−1028
10	1	0.965	28,999	23,053	5946	1760	−1145
10	2	0.999	29,736	23,949	5788	1851	−1121
11	1	0.965	28,368	22,422	5946	1706	−1252
11	2	0.999	29,114	23,325	5788	1796	−1229

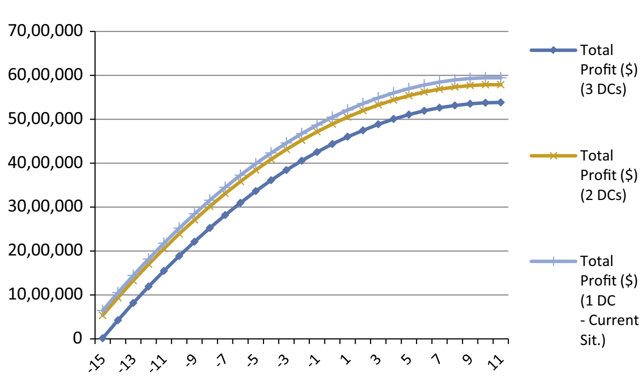

Fig. 5. Multi-objective solution results within scenarios (Total Profit).

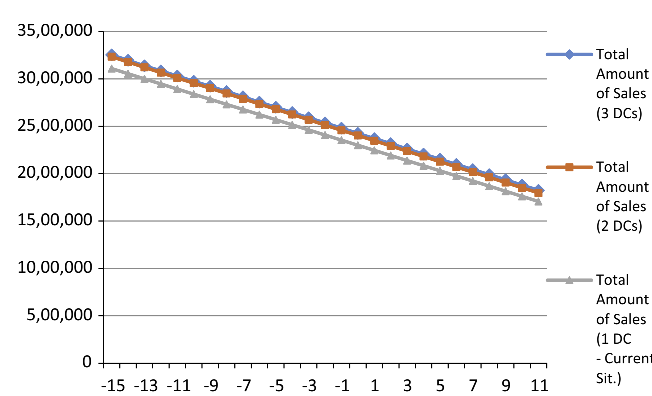

Fig. 6. Multi-objective solution results within scenarios (Total Amount of Sales).

Number of DCs: One of the most important conclusions that may be drawn from the results provided in this section concerns the number of DCs. At any price level, when the number of DCs is increased from 2 to 3, very little impact occurs regarding SC risk value (from 0.999 to 1) and total amount of sales (increased by approximately 1%). However, total profit and, eventually, total distance value substantially decrease. Therefore, it may be concluded that alternatives with 3 DCs may be dropped from the alternative

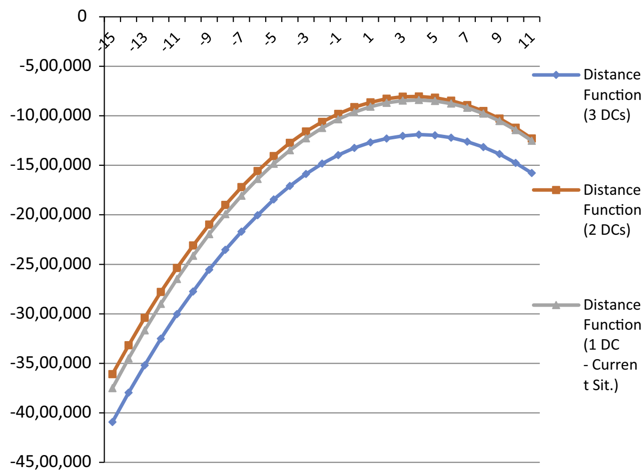

Fig. 7. Multi-objective solution results within scenarios (Distance Function).

solutions, as these scenarios have a substantial negative effect on total profit and the total distance function.

However, when the model proposes to open an additional DC (from one DC to two DCs), the model generally generates less profit due to increasing fixed DC costs, slightly increasing inventory holding costs, and slightly increasing transportation costs. Nevertheless, in the solutions with two DCs, the model generates approximately 5% more sales amount due to the one-day replenishment coverage effect and decreasing lost sales. The increased sales amount also generates more revenue; however, the revenue increase is not sufficient to cover cost increases. Therefore, in profit maximization problems, the current situation with one DC options are chosen. In the model capturing both sales amount and profit, alternatives with two DCs are proposed to be opened, as the sales amount increase is more than the profit decrease.

Price Decreases: Price decreases have a substantial positive impact on total amount of sales due to price elasticity level. However, beyond an 11% price decrease, price decreases have a negative effect on profit. The negative effect on profit increases as the price continues to decrease. After a 12% price decrease, the model may generate even negative profits, depending on the objective. After that point, the model may choose not to fill the demand at some locations because of the shrinking profit margin. Therefore, we may conclude that a price decrease level beyond a certain point, for example, 11% may not be reasonable and may be dropped from our final result table, including all solutions for price and number of DCs combinations.

The results also helped us to understand the conflicting nature of the objectives: total profit and total sales. Fig. 8 provides the Pareto - optimal solutions set for those objectives through different

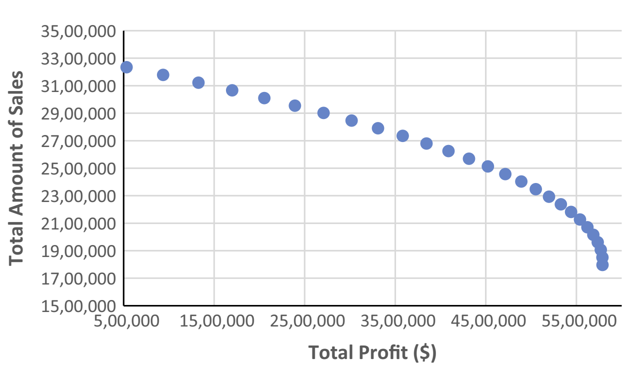

Fig. 8. Pareto – optimal solution set.

scenarios with 2 DCs. Similar Pareto optimal set may be generated for options for the scenarios with 1 DC and 3 DCs.

In conclusion, the proposed model is able to specify how the total amount of sales and total profit of the model company change as the strategic level network configuration decisions change. The model is also capable of capturing how the SC network traffic needs to be modelled to maximize profit or sales amount or both SC objectives, depending on the chosen model objectives.

The model is also utilized to model SC disruption risks. However, due to the multi-objective nature of the SC network, the model firm wants to maximize its profit, sales amount and SC risk value. To support decision making, the model is solved as a goal programming function. The distance maximization function of the model provides suggestions regarding the best solution for the firm's problem. However, the objectives in the distance function are rescaled and weighted by subjective weights. We provide a list of optimal solutions for each scenario that will help DMs (Table 5).

After providing the optimal solution list for separate scenarios, we analyse the sensitivity of the model to test whether the model generates similar results when some of the assumptions and coefficients within the model are changed.

5.2. Sensitivity analysis

After solving the problem, a sensitivity analysis is conducted to test the applicability of the model with respect to different parameter coefficients. These coefficients are:

- Price elasticity
- One–day replenishment coverage impact
- Risk factors (disruption probabilities)
- Relative weights of the objectives.

In addition to the changes in those coefficients, the sensitivity of the model outputs to the changes of the scale of the model is also analysed.

5.2.1. Price elasticity coefficient (α)

In the model, the price elasticity coefficient is assumed to be 2.5, as the firm operates in the ready-made retail clothing industry. However, the value of the coefficient does not depend on a detailed market analysis or a historical sales analysis. Therefore, it would be required to analyse how the model reacts according to the changes in the value of the price elasticity coefficient. Table 6 shows the sensitivity of the distance function with respect to the price elasticity coefficients.

The table shows that regardless of the price change and the price elasticity coefficient, the best and highest distance value is acquired when two DCs are opened concurrently. Opening an additional DC has a positive impact on sales volume even though it has a negative impact on profitability. As the impact on sales volume is more than the influence on profitability, the distance function increases when two DCs are opened concurrently.

The results also show that the developed model is capable of representing the changes in the SC performance objectives (SC risk value, profitability, and total amount of sales) as the price elasticity coefficient changes. In addition, strategic level SC network decisions, such as the number and location of DCs, are not influenced by the value of the coefficient even though the optimum price level needs to be deliberately analysed on the market to determine the distance value maximizing point.

Another important managerial implication of the model is that the firm may apply brand loyalty programs to decrease price elasticity coefficients in order to maximize its profits without substantially harming its total amount of sales.

Table 6
Distance function results with respect to the price elasticity coefficient.

Price elasticity coefficient	−1	−2	−2.5	−3	−4
Price increase to maximize distance function	Above +11%	9%	4%	2%	5%
# of DCs to maximize distance function	2 DCs	2 DCs	2 DCs	2 DCs	2 DCs

Table 7
Summary of optimum results for different values of coverage area effect coefficient (β).

Scenario	Number of DCs	Optimum price (%)	Distance function value
β: 0.05	1	+3	−1.268.410
β: 0.1	2	+3	−807.211
β: 0.2	2	+6	226.873

5.2.2. One–day replenishment coverage area effect coefficient (β)

In the model, it is assumed that a distance between the DC and the retail outlet of less than 600 km will have a positive impact on the demand with a predefined coefficient (β). That coefficient is assumed to be 0.1. However, that predetermined coefficient value only depends on estimates of company experts. Therefore, it would be required to analyse the sensitivity of the model results with respect to different values of the one-day replenishment coverage area effect coefficient.

The best results for each objective and for different values of one-day replenishment coverage area effect coefficient are summarized in Table 7.

The results show that performance metrics such as profitability and total amount of sales are quite sensitive to the values of the coverage effect coefficient. However, the developed model is capable of representing the changes in performance objectives as the coverage coefficient value changes. The results also show the potential of a program that aims to increase the value of coefficient (β) for the chain's profitability and the company's sales volume. Therefore, the firm may try to increase the value of the coefficient through awareness programs, promotions, advertisements, or other methods.

It may also be concluded that with higher coefficient values, opening an additional DC becomes more profitable for the company. In our base scenario, opening an additional DC has a negative impact on profitability; however, an additional DC has a positive influence on total amount of sales. With a 0.2 value of the (β) coefficient, profitability is not negatively influenced by opening a second DC. These results support the idea that adding a utility function to the demand model may change the optimal solution the model generates and, eventually, strategic level SC network decisions.

5.2.3. Risk factors (μ, δ, ϕ)

In the base scenario, disruption probabilities are utilized as follows:

μ (disruption probability at transporting goods from suppliers to DC): 0.5%.
δ (disruption probability at handling goods at any DC): 1%.
ϕ (disruption probability at transporting goods from DC to customer zones): 2%.

Two additional scenarios are created to analyse the sensitivity of the model objectives. Table 8 presents those two new scenarios. Table 9 summarizes the optimal solution for each scenario and depicts how SC risk value, total profit, total amount of sales and distance function value change through different scenarios.

Both the total amount of sales and profitability of the SC are influenced by disruption probabilities due to lost sales volume and the costs of lost sales. Although both profitability and total amount of sales values are influenced by the disruption probabilities, the results essentially follow the same pattern through the various scenarios defined in Table 9.

The results also show that when the probabilities are higher, as in Scenario II, opening an additional DC becomes more profitable. Unlike Scenario II, the profit difference between the current situation and two DC options is so high that the distance function results are also lower in the two DC option in Scenario I.

In conclusion, the proposed model reflects the changes in the objectives through different disruption probability scenarios. As the results change, the decisions do not necessarily change, as the results follow the same patterns through different scenarios. The results also show that controlling and lowering disruption probabilities as much as possible through the network is crucial for the success of the SC, as they have a substantial negative impact on all of the objectives. To serve customers without interruption, lowering the disruption probabilities is also highly important.

5.2.4. Relative weights of the objectives (d_1, d_2)

In addition to the base scenario, two other scenarios are created to analyse how the value of distance function changes with respect to the changes in the relative importance of the objectives. Table 10 defines those scenarios (see Table 11).

Optimal solutions for each scenario are depicted in the table below. The table also shows how optimal price level, total profit,

Table 8
Risk factor probabilities – sensitivity analysis scenarios.

Scenario	μ (%)	δ (%)	Φ (%)
Base Scenario	0.5	1	2
Scenario I	0.25	0.5	1
Scenario II	1	2	3

Table 10
Relative weights of the objectives.

Scenario	d_1 (Multiplied by)	d_2 (Multiplied by)
Base scenario	2	1
Scenario I	1	1
Scenario II	4	1

Table 9
Summary of optimum results for different values of disruption probabilities.

Scenario	Number of DCs	Optimum price (%)	SC risk value	Total profit (TL)	Total amount of sales	Distance function value
Scenario I	1	+4	0.983	5.762.828	2.120.418	−606.333
Base	2	+4	0.999	5.441.562	2.181.503	−805.430
Scenario II	2	+4	0.999	5.432.656	2.179.833	−817.677

Table 11
Summary of optimum results for different relative weights of objectives.

Scenario	Number of DCs	Optimum price (%)	SC risk value	Total profit (TL)	Total amount of sales	Distance function value
Scenario I	1	+7	0.965	5.848.034	1.921.423	−310.541
Base	2	+4	0.999	5.441.562	2.181.503	−805.430
Scenario II	2	− 3	0.999	4.312.729	2.568.492	−1.083.300

Table 12
Different scales of the model.

Scenario	# of products	# of alternate DCs (with different Capacity Options)	# of customer locations
Small Scale	5	2 DCs with (4 with capacity options)	20
Medium Scale (Real Life Scenario)	10	3 DCs (with 7 capacity options)	39
Large Scale	15	5 DCs (with 10 capacity options)	50

Table 13
Summary of optimum results for various scale of the models.

Scenario	Running time (s)	Required # of iterations	Number of DCs	Optimum price	SC risk value	Total profit (TL)	Total amount of sales	Distance function value
Small Scale	0.82	21	1	No Change	0.965	−1.539.350	316.086	−977.180
Medium Scale	1.58	155	2	+4%	0.999	5.441.562	2.181.503	−805.430
Large Scale	7.57	100	2	+4%	0.999	6.189.995	2.486.895	11.043.784

total amount of sales, and distance function value change through each scenario.

The model results show that the distance values in scenarios I and II change due to changing distance function formulation; however, the total amount of sales and total profit do not substantially change. Even for the current situation with one DC option, the model finds the exact same solution. For the two DC option, the model sometimes finds the same solution or very close solutions. Therefore, it may be concluded that the model finds almost the same solution with different values of relative weights of the objectives.

Even though the best solution for each price change and number of DC options does not change substantially, the price that maximizes the distance value changes according to the relative weights of the objectives. When the relative weight of the total amount of sales increases, the mathematically optimal price level is decreased.

In conclusion, the analysis of the three different scenarios with different relative weights of the objectives showed that the proposed model reflects the changes in the objectives through different scenarios. As the results change, SC-based decisions—such as the number, location, and capacity of the DCs, demand fill rate, and network traffic—do not necessarily change, as the results follow the same patterns through various scenarios.

5.2.5. Different scales of the model

As mentioned before, the problem solved by the model is a real life problem. However, how the model responds to the changes in the size of the model is also observed to understand if the model generates similar or different results with the different scale of the models. Table 12 defines basic features of different scales of the models (see Table 13).

Optimal solutions for each scenario are depicted in the table below. Along with run time values, the table also shows how optimal price level, total profit, total amount of sales, and distance function value change through scenarios.

The model results show that the distance values in small and medium scale of models change due to changes in the distance function formulation, in the number of products and amount of sales through scenarios. However, the solutions found in medium scale and large scale problem are identical. The value of distance function follows pretty much the same pattern in different scales of the problems. Compared to the medium and small scale problems, the running time seems to be much longer, however, the model did not face any problem to find the optimal solution. Another major observation gathered in this analysis is that, in large scale problem, the model chose the DC location which provides the highest sales increase due to defined utility function.

Table 14
Summary of optimum results for different values of coverage area effect coefficient (β) for Large Scale Model.

Scenario	Number of DCs	Optimum price (%)	Distance function value
β: 0.05	2	+3	10.511.793
β: 0.1	2	+4	11.043.784
β: 0.2	2	+6	12.206.614

In order to evaluate the impact of adding utility function to SC network optimization model to the large scale problem, the latter is solved with different values of the one-day replenishment coverage area effect coefficient. The best results for each objective and for different values of one-day replenishment coverage area effect coefficient are summarized in Table 14.

The results show that the model follows the same patterns through different values of the one-day replenishment coverage area effect as the scale of the model gets larger. However, detailed analysis of the results with the larger scale model also led us to believe that impact of adding a utility function to the demand model becomes more important as the scale of the model gets larger. That is, with the larger scale of the model, adding utility function to the model has higher chances to change the optimal solution and, eventually, strategic level SC network decisions.

6. Conclusions and further research suggestions

This study aims to analyse and explore how strategic level SC network decisions, such as number, location, and capacity of SC nodes affect sales volume and, ultimately, strategic level SC network decisions. The developed model is the first SC network optimization model to incorporate the changes in demand, which is defined as being subject to both the price change and distance from the end-customers and which is substantially influenced by strategic level SC network optimization model decisions. The results prove that including a utility function (based on the number and the location of DCs) in demand substantially changes the value of all three performance objectives of the model. Impact of including utility function on the SC network optimization decisions becomes even more important when the scale of the network gets larger. When the model proposes opening an additional DC, it generates approximately 5% more sales volume due to the defined utility function. However, the model generates less profit due to the fixed DC costs, slightly increased inventory holding costs, and slightly increased transportation costs.

The model also proves that single objective models may not generate acceptable results and that SC network optimization models need to be defined as multi-objective, as SCs are multi-objective in nature.

The model results also show that the model's performance objectives are substantially influenced by strategic level SC network decisions such as the number and location of DCs, price change level, and other factors, which have a substantial influence on all performance objectives. However, decisions such as SC network traffic decisions, DC – customer zone allocation, and demand fill rate have either minor or no influence on performance of the SC.

The model is also utilized to model SC disruption risks. The risk factor sensitivity analysis shows that controlling and lowering disruption probabilities as much as possible through SC nodes and links is crucial for the company's success, as lower disruption probabilities may lead to lower risks, higher sales volume, and higher profitability, all of which are very important to serving customers without interruption.

To enhance the developed model, other utility (attraction) functions that are also influenced by SC network configuration decisions—such as customer service level, availability of the stores at the demand point, distance between the store and the customers—may be defined to explore how demand and, ultimately, network configurations are influenced by those decisions.

A major limitation of the study concerns the lack of research on several major parameters of the model, such as the price elasticity coefficient and the DC – customer zone one-day replenishment coverage effect coefficient. After a more deliberate study of price elasticity in the market and after implementing the one-day replenishment program, the study may be rerun with the real data gathered from the market on those coefficients.

Another limitation of the developed model concerns the time period analysed in the model. The model is defined as a single term model. Therefore, the model may be enhanced by including more than one term data in the analysis or by including possible future projections of the model company.

To explore the usefulness of the model, it may also be applied to real-world scenarios from other highly competitive sectors such as food products, electronic products. The SC network of the model firm only consisted of three echelons. Defining a more complex SC network with more than three echelons and possibly including recycling centres, globalization issues, and other factors may also enhance the usefulness of the model.

In the proposed model, a simple, linear demand model that includes price elasticity and utility function is defined for the sake of simplicity. A more complex demand model may be defined to analyse how SC network optimization decisions and model objectives change. Again, to simplify the model, only supply side path-based risk formulation is utilized. The model may be defined with a more comprehensive SC risk modelling. To avoid non-linearity in revenue function, different price change values are defined as alternative scenarios, and each scenario is solved separately instead of defining sales price as a decision variable. In a future study, a non-linear model that defines sales price as a decision variable may be defined and solved by non-linear solution algorithms.

References

Akgul, O., Shah, N., & Papageorgiou, L. G. (2012). An optimization framework for a hybrid first/second generation bioethanol supply chain. *Computers & Chemical Engineering, 42*(11), 101–114.

Amaro, A. C. S., & Barbosa-Póvoa, A. P. F. D. (2009). The effect of uncertainty on the optimal closed-loop supply chain planning under different partnerships structure. *Computers & Chemical Engineering, 33*(12), 2144–2158.

Baghalian, A., Rezapour, S., & Farahani, R. Z. (2013). Robust supply chain network design with service level against disruptions and demand uncertainties: A real-life case. *European Journal of Operational Research, 227*(1), 199–215.

Bassett, M., & Gardner, L. (2010). Optimizing the design of global supply chains at Dow AgroSciences. *Computers & Chemical Engineering, 34*(2), 254–265.

Bilir, C., Ekici, S. O., & Sweeney, D. C. (2015). From a literature review to a research direction: İntegrative supply chain network optimization models. In *Computer & industrial engineering, 2015 45th international conference proceedings*. .

Carle, M., Martel, A., & Zufferey, N. (2012). The CAT metaheuristic for the solution of multi-period activity-based supply chain network design problems. *International Journal of Production Economics, 139*(2), 664–677.

Chaabane, A., Ramudhin, A., & Paquet, M. (2012). Design of sustainable supply chains under the emission trading scheme. *International Journal of Production Economics, 135*(1), 37–49.

Costantino, N., Dotoli, M., Falagario, M., Fanti, M. P., & Mangini, A. M. (2012). A model for supply management of agile manufacturing supply chains. *International Journal of Production Economics, 135*(1), 451–457.

Cruz, J. M. (2009). The impact of corporate social responsibility in supply chain management: Multicriteria decision-making approach. *Decision Support Systems, 48*(1), 224–236.

Cruz, J. M., & Zuzang, L. (2011). Modeling and analysis of the multiperiod effects of social relationship on supply chain networks. *European Journal of Operational Research, 214*(1), 39–52.

Hendricks, K. B., & Singhal, V. R. (2005). Effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production and Operations Management Society, 14*(1), 35–52.

Kabak, O., & Ulengin, F. (2011). Possibilistic linear-programming approach for supply chain networking decisions. *European Journal of Operational Research, 209*(2011), 253–264.

Kumar, S. K., & Tiwari, M. K. (2013). Supply chain system design integrated with risk pooling. *Computers & Industrial Engineering, 64*(2), 580–588.

Lundin, J. F. (2012). Redesigning a closed-loop supply chain exposed to risks. *International Journal of Production Economics, 140*(2), 596–603.

Masoumi, A. H., Yu, M., & Nagurney, A. (2012). A supply chain generalized network oligopoly model for pharmaceuticals under brand differentiation and perishability. *Transportation Research Part E: Logistics and Transportation Review, 48*(4), 762–780.

Melo, M. T., Nickel, S., & Saldanha-da-Gama, F. (2009). Facility Location and supply chain management – A review. *European Journal of Operational Research, 196*, 401–412.

Melo, M. T., Nickel, S., & Saldanha-da-Gama, F. (2012). A tabu search heuristic for redesigning a multi-echelon supply chain network over a planning horizon. *International Journal of Production Economics, 136*(1), 218–230.

Meng, Q., Huang, Y., & Cheu, R. L. (2009). Competitive facility location on decentralized supply chains. *European Journal of Operational Research, 196*(2), 487–499.

Nagurney, A. (2010). Supply chain network design under profit maximization and oligopolistic competition. *Transportation Research Part E: Logistics and Transportation Review, 46*(3), 281–294.

Nagurney, A., Ladimer, S., & Nagurney, S. (2012). Medical nuclear supply chain design: A tractable network model and computational approach. *International Journal of Production Economics, 140*(2), 865–874.

Nagurney, A., & Yu, M. (2012). Sustainable fashion supply chain management under oligopolistic competition and brand differentiation. *International Journal of Production Economics, 135*(2), 532–540. Chemical Engineering, Volume 47, 20 December 2012, Pages 183–193.

Olivares-Benitez, E., Ríos-Mercado, R. Z., & González-Velarde, J. L. (2013). A metaheuristic algorithm to solve the selection of transportation channels in supply chain design. *International Journal of Production Economics, 145*, 161–172.

Pan, F., & Nagi, R. (2010). Robust supply chain design under uncertain demand in agile manufacturing. *Computers & Operations Research, 37*(4), 668–683.

Plastria, F. (2001). Static competitive facility location: An overview of optimisation approaches. *European Journal of Operational Research, 129*, 461–470.

Prakash, A., Chan, F. T. S., Liao, H., & Deshmukh, S. G. (2012). Network optimization in supply chain: A KBGA approach. *Decision Support Systems, 52*(2), 528–538.

Rezapour, S., & Farahani, R. Z. (2010). Strategic design of competing centralized supply chain networks for markets with deterministic demands. *Advances in Engineering Software, 41*(2010), 810–822.

Rezapour, S., Farahani, R. Z., Ghodsipou, S. H., & Abdollahzadeh, S. (2011). Strategic design of competing supply chain networks with foresight. *Advances in Engineering Software, 42*(2011), 130–141.

Shankar, B. L., Basavarajappa, S., Chen, J. C. H., & Kadadevaramath, R. S. (2013). Location and allocation decisions for multi-echelon supply chain network – A multi-objective evolutionary approach. *Expert Systems with Applications, 40*(2), 551–562.

Yamada, T., Imai, K., Nakamura, T., & Taniguchi, E. (2011). A supply chain-transport supernetwork equilibrium model with the behaviour of freight carriers. *Transportation Research Part E: Logistics and Transportation Review, 47*(6), 887–907.

Yang, G., Wang, Z., & Li, X. (2009). The optimization of the closed-loop supply chain network. *Transportation Research Part E: Logistics and Transportation Review, 45*(1), 16–28.

Yu, M., & Nagurney, A. (2013). Competitive food supply chain networks with application to fresh produce. *European Journal of Operational Research, 224*(2), 273–282.

Zamarripa, M. A., Aguirre, A. M., Méndez, C. A., & Espuña, A. (2012). Improving supply chain planning in a competitive environment. *Computers & Chemical Engineering, 42*(11), 178–188.