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RESEARCH PAPER

Supply chain network design: an MILP and Monte Carlo simulation approach

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ABSTRACT

Goal: This study aims to minimize the total cost of a supply chain network and determine the optimal product flow under demand uncertainty.

Design / Methodology / Approach: A mathematical model is presented to minimize the total supply chain cost by identifying the optimal facility locations and product flows. The applicability of the proposed model is evaluated through a real-life case study of a multinational sporting goods retailer with sensitivity analysis. Moreover, Monte Carlo simulation is used to capture the demand uncertainty and test the robustness of the model.

Results: The minimized cost is achieved with optimal facility locations and product flows. The optimal result shows a 3% reduction in the total cost, making it the most robust solution under demand uncertainty.

Limitations of the investigation: The proposed model is only applicable to a single-commodity supply chain network. In addition, the cost components of the network are limited to facility costs and transportation costs, disregarding the other cost components.

Practical implications: This research demonstrates a methodology that can be used as a decision support system by managers to make strategic and tactical decisions in a supply chain network when demand is uncertain.

Originality / Value: The MILP and simulation techniques used together to construct a three-tiered supply chain under uncertainty receive little attention in the literature. In addition to developing a novel three-echelon MILP model, this research makes use of a real-world case study to illustrate the methodology's performance in the context of demand uncertainty through simulation.

Keywords: Supply Chain Network; Supply Chain Network Design; Mixed Integer Linear Programming; Monte Carlo Simulation; Demand Uncertainty.

1 INTRODUCTION

Customer demand is increasing in the modern world, and organizations strive to fulfill client satisfaction to the greatest extent possible. Nowadays, in order to supply products more efficiently to customers, many manufacturing organizations are forming a network of close and well-organized communications termed a supply chain in response to changing circumstances and technological advancements (Sabzevari Zadeh et al., 2014). The supply chain can be defined as the transfer of resources, information, and money between two or more companies, known in the supply chain as echelons, with the purpose of meeting customer needs (Chopra & Meindl, 2007). It not only includes all supply, purchase, and logistics management tasks but also involves working with distributors, vendors, intermediary companies, and customers, making the management of a supply chain a difficult task for any company (Frazzon et al., 2019).

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Supply chain management (SCM) is the technique of planning, controlling, and implementing the supply chain's operations efficiently (Melo et al., 2009). Companies try to make their supply chains work better by making the right number of products in the right place and getting the right product to the right customer at the right time and price, as well as in the right place, amount, and condition. SCM brings together important steps that start with the first suppliers and go on until the customers get the products, information, or services (Gumus et al., 2009).

A supply chain network can be constructed to efficiently manage the whole supply chain. It is a complex entity comprised of suppliers, manufacturers, distributors, and retailers, as well as the systems, subsystems, activities, and operations that assist in the development of the supply chain and its relationships (Gumus et al., 2009). There are three types of decisions that need to be made in the SC network. They are strategic, tactical, and operational. SCND is a strategic type of decision for a longer time horizon. Making strategic decisions in SCND frequently requires large investments. These are extremely difficult decisions to alter and have a lasting effect on the operation of the supply chain. The most typical strategic decisions involve determining the optimal placement of facilities, and capacities of those facilities, allocating technology and space for processing and production of products at various sites, including choosing suppliers. SCND, alternatively referred to as strategic supply chain planning, is a stage in the supply chain management planning process that establishes the physical form and architecture of a supply chain. SCND has been deemed a good fit for facility location models for the past two decades. ReVelle et al. (2008) classified facility location models into four broad categories: continuous, network, discrete, and analytic. Despite their numerous variations, all of these models comprise a list of known consumers and a list of facilities whose sites ought to be given. The majority of SCND models fall under the discrete location model category (Melo et al., 2009). The transportation cost among different facilities and costs related to the facility largely depends on the facility's location. These long-term decisions might not be the same when the demand is uncertain. The appropriate location of a facility for a certain demand might change with the change in demand. As a result, SCND, in the presence of uncertainty, has garnered considerable interest in recent years in both academics and practice.

Establishing a supply chain network is a vital concern for every organization. Traditional distribution of products and poor planning of facilities can increase the total cost as well as lower the level of service. In addition, uncertainty in demand makes it difficult for managers to plan the optimal facility location, product distribution, and capacity allocation. The objectives of this research are,

- To minimize the total transportation and facility costs.
- To determine the optimal product flow.
- To verify the robustness of the model using Monte Carlo simulation.

This research is organized into seven segments, each with its own characteristics and purposes. The first segment offers a thorough description of the supply chain network, including the motivations, aims, and overall structure of the study. The second segment discusses prior research on the SCND model and several optimization techniques for dealing with demand uncertainty and also identifies the research gap. The third and fourth segments deal with describing the problem and formulating the model. In the fifth segment, a case study is introduced, and a snapshot of the data used to present the case study is also shown. The sixth segment displays the output of the model with a thorough explanation of scenario analysis, sensitivity analysis, and robustness test. Finally, the significance of the research, as well as its potential future scope, are also discussed.

2. LITERATURE REVIEW

This section presents an overview of previous research on supply chain network design as well as a review of some approaches in optimization used to handle the uncertainty in the supply chain network.

2.1 Supply Chain Network Design (SCND)

SCND is focused on strategic decisions regarding the amount, location, size, and technology of new facilities, along with modifications to existing facilities and the selection of suppliers. Furthermore, it involves tactical decisions, which include manufacturing and shipping plans and product flows throughout the network (Salem & Haouari, 2017). SCND models are deterministic models and consider no stochastic data as input. The mixed-integer linear programming (MILP) method is one approach to solving SCND problems. Isaloo and Paydar (2020) presented a bi-objective mathematical programming approach for integrating the full chain's flows in order to increase performance in the plastic injection industry's variable conditions and reduce total expenses. Babazadeh et al. (2013) proposed a multi-stage and multi-product MILP framework to reduce the total cost where the objective function is sensitive to fixed opening costs, consumer demand, and outsourcing expenses. León-Olivares et al. (2020) and Chipana-Surquislla et al. (2022) also utilized MILP models to decrease the total costs by selecting the optimal location of facilities. Some research (Salehi-Amiri et al., 2021; Santander et al., 2020; Pourjavad and Mayorga, 2019) used MILP models to reduce the cost of the Closed-Loop Supply Chain (CLSC) network as well as make strategic and tactical decisions. Patidar and Agrawal (2020) formulated two MILP models, where the first model was used to minimize the total distribution cost and the second model was used to decrease post-harvest supply chain losses. Aras and Bilge (2018) performed a case study on a multi-national enterprise where the proposed MILP model was developed to reduce the overall cost and select the best location. Robles et al. (2020) and da Silva et al. (2020) used MILP frameworks to construct hydrogen supply chain (HSC) networks by minimizing various cost components. Duong and Bui (2018) proposed a mathematical model for a multi-item, two-echelon, and multi-period facility location problem. Manufacturing facilities and distribution hubs were chosen to open or not open at preset potential places during each period of horizon planning. The system was designed as an MILP model with the goal of minimizing overall costs, which included transportation costs, inventory holding costs, and fixed expenses for establishing facilities. Gital Durmaz and Bilgen (2020) suggested a multi-objective MILP framework for biomass supply chain design and planning. The model was able to make both strategic such as optimal biogas facility locations and capacity, and tactical decisions such as transportation network flow. To demonstrate the solution technique and viability of the model, a case study was utilized. Mohammadi Bidhandi et al. (2009) suggested an MILP framework and also solution algorithm for multi-commodity, deterministic, and single-period SCND problems. The model made it possible to determine the appropriate sites and allocation of facilities at the same time. It combined the tactical decisions about supplier, factory, warehouse, and allocation of customers with the strategic considerations about facility selection. Sharifzadeh et al. (2015) used mathematical programming to optimize the supply chain for biofuels using fast pyrolysis. Under uncertainty, an MILP model was developed to find the optimal supply chain design and operation. Ochoa Robles et al. (2018) used an MILP formulation to establish the hydrogen supply chain (HSC) network. In the HSC logistic model, a sensitivity analysis showed the most sensitive components and their interactions. Cardoso et al. (2013) devised an MILP framework for planning and designing supply chains involving reverse flows that take into account manufacturing, distribution, and reverse logistics activities all at the same time. The approach was proved to be applicable by applying it to a real case study.

2.2 SCND Under Uncertainty

Uncertainty is a fundamental feature of reality. Different unknown parameters might create significant difficulties for decision-makers when confronted with an SCND problem. They can have an effect on various aspects of a supply chain network problem, including the quantity of supply and demand characteristics. Thus, incorporating various uncertainties into decision-making models can provide decision-makers with a multitude of options to produce more realistic and dependable designs and results. There are several approaches to dealing with uncertainty that are used in practice. This section highlights previous studies utilizing some of the approaches for handling uncertainty.

2.2.1 Stochastic Programming

This is where the uncertainty is defined by a known probability distribution, and the optimization seeks to find the optimal anticipated value of that distribution that is viable for the majority of possible outcomes. Certain approaches employ a loss function to account for this uncertainty. For the perishable goods supply chain, Dutta and Shrivastava (2020) constructed an ideal supply chain network and distribution plan. Stochastic programming was used under demand, supply, and process uncertainty. Fattahi et al. (2020) presented a two-stage stochastic program for SCND that optimized the location, allocation, inventory, and order-size decisions during disruption occurrences. Govindan and Fattahi (2017), Ma and Li (2018), and Yılmaz et al. (2021) also constructed two-stage stochastic programs under highly time-variable and stochastic requirements. The uncertainties in the supply chain network were also quantified using the multistage stochastic optimization problem expressed as the MILP model (Zahiri et al., 2018; Ghelichi et al., 2018; Almansoori and Shah, 2012).

2.2.2 Robust Optimization

Robust optimization is a rapidly expanding field of study that enables the solution of a variety of optimization problems when some of the variables are uncertain. Yahyaei and Bozorgi-Amiri (2019) used robust optimization techniques to protect a relief network design against uncertain conditions. Sangaiah et al. (2020) established a robust MILP model for estimating LNG sales over a specific time frame to reduce vendor costs under uncertainty. To test the model, several exemplary scenarios were solved under varying levels of uncertainty. Bairamzadeh et al. (2018) constructed a robust hybrid optimization model to handle epistemic, random, and deep uncertainties. Using a case study of the biofuel supply chain in Iran, the effectiveness of the proposed model was evaluated. Lotfi et al. (2021), Prakash et al. (2020), Kim et al. (2018), Hasani et al. (2012), and Pishvaee et al. (2011) designed CLSC models using the robust optimization strategy for managing the uncertainties in transportation, supply, and demand. Yavari and Geraeli (2019) and Qiu and Wang (2016) created innovative MILP robust models to reduce costs and pollution under demand and supply uncertainty.

2.2.3 Simulation-Optimization

The primary idea behind this approach is to use numerous replications to simulate various system configurations in order to identify the best solution (Atalan & Dönmez, 2020). Pourhassan and Raissi (2017) proposed a dynamic facility design problem to increase material handling efficiency and reduce expenses. The number of possible transporter interactions was calculated using simulation, and a non-dominated genetic algorithm for sorting was employed to discover the best architecture that met the objective functions. Gholami-Zanjani et al. (2021) constructed a general two-stage MILP model in a study to incorporate essential elements of location-allocation and inventory-replenishment decisions. Then, plausible scenarios were used to incorporate food-specific disruptions. Mavromatidis et al. (2018) and Belvardi (2012) utilized simulation-based optimization as well as sensitivity analysis of the supply chains to deal with modelling errors and the stochastic nature of the processes. The uncertainty analysis was performed using Monte Carlo simulations to quantify the impact of uncertainties. Izadi and Kimiagari (2014) presented a three-echelon supply chain location allocation challenge to transport pharmaceuticals from a warehouse to consumers. This work aimed to solve a real-world model with an uncertain demand function. To account for the demand uncertainty, a set of possible consumer demand scenarios was generated using the Monte Carlo simulation. Zhang et al. (2019) established a multi-simulation MILP model based on Monte Carlo sampling to account for uncertainties in the natural gas purchase price and demand, which was utilized for simulation runs to produce several uncertain parameters.

The literature review demonstrates that the MILP model is an effective method for reducing costs while making strategic and tactical decisions. It offers analytical solutions that can shed light on the internal operations of a supply chain. It can be useful for examining how various parts of the system are connected to one another, which is helpful for better decision-making. As MILP is a deterministic model, several approaches are presented in the review to take into account the uncertainties. In this study, a MILP model is used in conjunction with the Monte Carlo simulation approach, which is extensively utilized in the literature to represent uncertainty, to design a robust three-echelon network in the presence of demand uncertainty.

3. PROBLEM DESCRIPTION

A multi-echelon single-period model is proposed in this study. This model represents a network comprising factories, warehouses, and distribution centers, as illustrated in Figure 1 where decisions are rendered within a specific time interval.

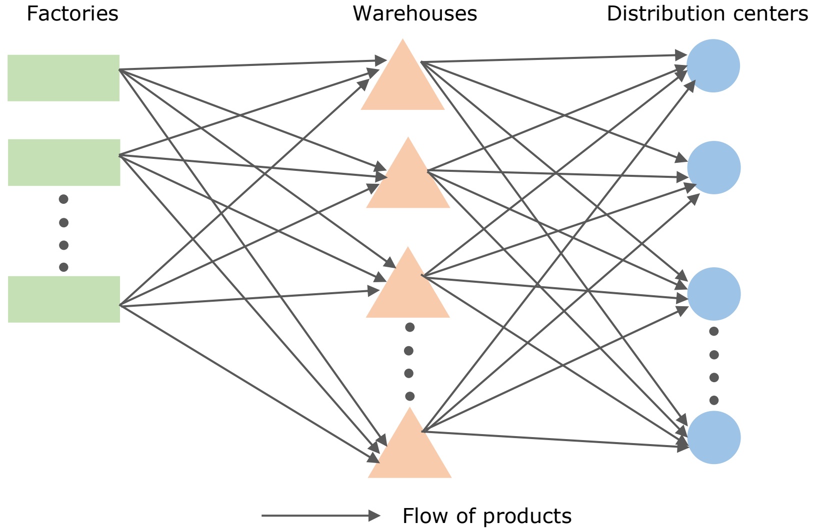

Figure 1 - Supply chain network

The products flow in the network in a forward direction. The distribution centers aggregate the customer demands and place the orders in the warehouses. Factories use raw materials to create final products, which are then delivered to warehouses, from where they are distributed to distribution centers. The products are distributed to retailers or directly to customers by distribution centers. Multiple warehouses can be used to fulfill the demand of a distribution center, and multiple factories can ship products to a warehouse. Assumptions made by the network model include the following:

- The model has three levels, which are the factories, warehouses, and distribution centers.
- The potential locations of factories, warehouses, and distribution centers are known.
- There is a fixed cost associated with the opening of a factory and a fixed cost associated with the opening of a warehouse.
- Each factory has a production cost associated with it, and each warehouse has a handling cost associated with it.
- The transportation costs are deterministic throughout the time period.
- Each factory and warehouse has a maximum production capacity and a maximum handling capacity.
- Factory and warehouse locations must be selected from a list of candidate locations.
- The model specifies a maximum and a minimum number of factories and warehouses that can be opened.
- All parameters have deterministic values.
- The product flow is considered in the forwarding direction between two stages.
- All demands should be satisfied. The model has a single product and a single time period.

4. NETWORK MODEL FORMULATION

4.1 Sets

The following are the sets of desirable facilities used in this study:
S: Set of factories i
W: Set of warehouses j
D: Set of distribution centers k

4.2 Model Parameters

The following notations are used throughout the study to define the model:
C_{ij}: Inbound transportation cost from factory i to warehouse j
C_{jk}: Outbound transportation cost from warehouse j to distribution center k
f_i: Fixed cost per period related to factory i
f_j: Fixed cost per period related to warehouse j
M_i: Manufacturing cost per unit at the factory i

H_j: Handling cost per unit at warehouse j
S_i: Capacity of factory i
W_j: Capacity of warehouse j
FP_{max}: Maximum number of factories allowed to open
FP_{min}: Minimum number of factories allowed to open
WP_{max}: Maximum number of warehouses allowed to open
WP_{min}: Minimum number of warehouses allowed to open
D_k: Demand of distribution center k

4.3 Decision Variables

The following decision variables are used in this research to define the model:
X_{ij}: Total number of products flowing from factory i to warehouse j
X_{jk}: Total number of products flowing from warehouse j to regional warehouse k
Y_i: Binary variable for factory i
Y_j: Binary variable for warehouse j

4.4 Objective Function

The objective function is to minimize transportation costs that include inbound transportation costs from factory i to warehouse j, outbound transportation costs from warehouse j to distribution center k, and fixed costs and variable costs associated with factory i and warehouse j. It is defined as:

$$\text{Min } z = [\textstyle\sum_i\sum_j C_{ij}X_{ij}+\sum_j\sum_k C_{jk}X_{jk}] + [\sum_i f_iY_i+\sum_j f_jY_j] + [\sum_i\sum_j M_iX_{ij}+\sum_j\sum_k H_jX_{jk}] \quad (1)$$

Here, z represents the total transportation costs and facility costs.

4.5 Constraints Related to the Model

The constraints subject to the mixed-integer linear programming model are given below:

$$\textstyle\sum_j X_{ij} \le S_i \qquad \forall i \in S \qquad (2)$$
$$\textstyle\sum_k X_{jk} \le W_j \qquad \forall j \in W \qquad (3)$$
$$\textstyle\sum_i Y_i \le FP_{max} \qquad (4)$$
$$\textstyle\sum_i Y_i \ge FP_{min} \qquad (5)$$
$$\textstyle\sum_j Y_j \le WP_{max} \qquad (6)$$
$$\textstyle\sum_j Y_j \ge WP_{min} \qquad (7)$$
$$\textstyle\sum_i X_{ij}-\sum_k X_{jk}=0 \qquad \forall j \in W \qquad (8)$$
$$\textstyle\sum_j X_{jk} \ge D_k \qquad \forall k \in D \qquad (9)$$
$$X_{ij}-M_{ij}Y_i \le 0 \qquad \forall i \in S, \forall j \in W \qquad (10)$$
$$X_{jk}-M_{jk}Y_j \le 0 \qquad \forall j \in W, \forall k \in D \qquad (11)$$
$$Y_i, Y_j = \{0,1\} \qquad \forall i \in S, \forall j \in W \qquad (12)$$
$$X_{ij}, X_{jk} \ge 0 \qquad \forall i \in S, \forall j \in W, \forall k \in D \qquad (13)$$

Equation (2) represents the capacity constraint of the factory. It implies that the level of product shipped from each factory to warehouses cannot exceed that factory's capacity. This constraint is true for each i in the set S. The constraint in Equation (3) is referred to as the warehouse capacity constraint. It implies that the level of product transferred from each warehouse to the distribution center cannot exceed the capacity of that warehouse. This condition is true for each j in the set W. Equation (4) implies that the total number of open factories cannot be greater than the maximum allowable number of factories that need to be opened. Equation (5) implies that the total number of open factories cannot be less than the minimum allowable number of factories that need to be opened. Equation (6) implies that the total number of open warehouses cannot be greater than the maximum allowable number of warehouses that need to be opened. Equation (7) implies that the total number of open warehouses cannot be less than the minimum allowable number of warehouses that need to be opened. Equation (8) is known as the conservation of flow constraint, which implies that the amount of product distributed from factories to a warehouse is equal to the amount of product distributed from that warehouse to the distribution centers, for all warehouses. Equation (9) is the demand constraint, which implies that the number of products delivered from warehouses to a distribution center cannot be less than the quantity demanded by that distribution center, for all distribution centers. Equation (10) is the linking constraint, which indicates that any product cannot be delivered from a factory unless the factory is open. Equation (11) is the linking constraint that indicates any product cannot be delivered from a warehouse unless the warehouse is open. Equation (12) is the binary constraint, which implies the value of Y_i/Y_j is 1 if the factories/warehouses are open or the value is 0 otherwise. Equation (13) is the non-negativity constraint that indicates that the product quantity delivered from factories to distribution centers cannot be negative.

4.6 Level of Service

Two metrics are used to determine the service level of the supply chain network. The first metric is average distance and the other metric is allowable distance.

$$\sum_{jk}\left(\frac{d_{jk}X_{jk}}{\sum_k D_k}\right) \tag{14}$$

$$\sum_{jk}\left(\frac{a_{jk}X_{jk}}{\sum_k D_k}\right) \tag{15}$$

Equation (14) represents the average distance metric, which is the average weighted distance from the warehouses to distribution centers. Here d_{jk} is the distance to distribution center k from warehouse j in kilometers for all j and k. The allowable distance metric is shown by equation (15), which indicates the percentage of demand that is within 1300 kilometers of a warehouse. Here, the value of a_{jk} is 1 if distribution center k to warehouse j is less than 1300 kilometers or zero otherwise, for all j and k.

5. CASE STUDY

The proposed model is validated in this study using a case study on a multinational sporting goods retailer against multiple scenarios through simulation and utilizing sensitivity analysis. The supply chain network consists of factories that manufacture products and ship them to warehouses known as continental warehouses (CWHs), which distribute them to other distribution centers known as regional warehouses (RWHs). Products are delivered to stores or directly to customers from these regional warehouses. In this study, data on a single product, designated SKU-1, is gathered through interviews with managers and experts for use in the optimization model. The data contains facility data, such as costs and capacity of factories and continental warehouses, transportation data, such as inbound and outbound transportation costs, and demand data. Currently, the product is manufactured at three factories and then supplied through 2 CWHs to twenty-five RWHs. Table A1 in the appendix section shows a snapshot of the locations of the facilities. Due to the increasing demand, the company plans to open a new factory in Chennai, India, and a new CWH in Milan, Italy, to better meet the demand. A detailed study of the company is shown in the following section.

5.1 Facility Data

Facility data comprises basic information about two types of significant facilities: factories and CWHs. Each factory requires a set cost to open that is related to the factory's operating and overhead expenditures. The cost of manufacturing each unit also varies according to the location of the plants. The fixed costs, production costs, and capacity of each factory are listed in Table 1.

Table 1 - Capacity and cost of factories

Factories	Capacity (units/Week)	Fixed Cost/Week (USD)	prod. cost/Unit (USD)
Dhaka, Bangladesh	144900	2905	0.851
Chattogram, Bangladesh	144900	2460	0.864
Dehradun, India	96600	2746	0.895
Chennai, India	132750	3150	0.883

The new CWH, which is to be opened in Milan, has the same capacity with a high fixed cost per week, as the operating cost in Milan is relatively higher. Table 2 2 shows the related capacity, fixed cost, and handling cost of each CWH.

Table 2 - Capacity and cost of CWHs

Continental Warehouses (CWHs)	Capacity (units/Week)	Fixed Cost/Week (USD)	Handling cost/Unit (USD)
Paris, France	300000	4859	0.0910
Madrid, Spain	300000	4760	0.1168
Milan, Italy	300000	5353	0.0890

5.2 Demand Data

The demand data set comprises information on the quantity demanded of RWHs in various locations throughout Europe. The RWHs are located in twenty-five cities and eleven countries. Each RWH depicts the weekly demand of that region. The demand data for each RWH is calculated by averaging the previous twelve months' demand data for that RWH. Table A2 in the appendix provides an overview of demand data for RWHs located in various European regions.

5.3 Transportation Data

Inbound transportation costs are the costs associated with transporting a unit from the factory to CWHs. Inbound costs include the cost of carrying a unit from the plant to the production country's port, the cost of shipping by ocean, and the cost of transporting the unit from the destination port to CWHs. The cost of transporting a unit product from each of the four plants to the CWHs is displayed in Table 3.

Table 3 - Inbound transportation costs from factories to CWHs

Inbound Transportation costs($/unit)	Paris, France	Madrid, Spain	Milan, Italy
Dhaka, Bangladesh	0.2251	0.2248	0.2249
Chattogram, Bangladesh	0.2246	0.2244	0.2245
Dehradun, India	0.2185	0.2182	0.2184
Chennai, India	0.2144	0.2142	0.2143

The outbound transportation costs consist of the cost of transporting the products from each CWH to RWHs. The cost per unit per kilometer in Europe and the distances between each CWH and RWH are collected from reliable sources. The outbound costs from three CWHs to twenty-five RWHs are depicted in Table A3 in the appendix.

The Excel OpenSolver is used to run the proposed optimization model. First, all the decision variables, the objective function, and constraints are used as inputs to develop the proposed model. The model is then solved using the CBC solver engine, which determines the minimized total cost.

6. RESULT AND DISCUSSION

6.1 Scenario analysis

Two different scenarios are developed. The baseline scenario represents the current condition of the retailer company, which has three factories in Dhaka, Chattogram, and Dehradun, as well as two continental warehouses in Paris and Madrid, to satisfy the demand. In the optimal scenario, the MILP model selected the appropriate number and locations of facilities from all the available locations to minimize the total cost of the supply chain network. According to Table 4, the total supply chain cost for the baseline scenario is $515,249, which includes the opening of three factories in Dhaka, Chattogram, and Dehradun, as well as two CWHs in Paris and Madrid to meet total demand. In the optimal scenario, the model uses factories from Dhaka, Chattogram, and Chennai and all the CWHs located in Paris, Madrid, and Milan to serve the total demand by minimizing the total cost to $499,758. That means the total cost in the optimal scenario is reduced by 3.0 percent from the baseline scenario. The average distance in the optimal scenario is decreased by 22.9 percent, and the percent weighted demand in 1300 kilometers is increased by 11.0 percent, showing a significant improvement in the level of service.

Table 4 - Total optimized cost of the supply chain network

	Baseline scenario	Optimal scenario
Total Cost	$515,249	$499,758
No. of factories to open	3	3
No. of CWHs to open	2	3
LOS - Avg. Distance (km)	881.25	679.43
LOS - PctIn1300kms	78.60%	87.27%
Demand	346005	346005
Cost/unit	$1.489	$1.444

In the baseline scenario, factories in Dhaka and Chattogram are operating at their full capacity, whereas the factory at Dehradun is running only at 58 percent of its total potential. The CWH in Paris is supplied from all three factories, Dhaka, Chattogram, and Dehradun, and serves 73.7 percent of the total demand, but the CWH in Madrid is only supplied from Dhaka and serves 26.3 percent of the total demand, which includes markets in Portugal and Spain. The model picked three factories, Dhaka, Chattogram, and Chennai, from the four possible locations in the optimal scenario. Both factories in Dhaka and Chattogram are running at their full capacity, whereas the factory in Chennai only utilizes 42 percent of its total capacity. The model chose all of the CWHs in the optimal scenario. The factory in Chattogram is supplying all CWHs, while the factory in Dhaka is supplying only the CWH in Milan, and the factory in Chennai is supplying only the CWH In Paris. The CWH in Paris is serving 31.6 percent of the total demand, which includes the market in France, Germany, and the United Kingdom, the CWH in Madrid is serving the market in Portugal, Spain, and a portion in France which covers 26.3 percent of the total demand and the CWH in Milan is serving the highest portion which is nearly 42.2 percent of total demand and includes the market in Switzerland, Poland, Italy, Romania, Austria, Ukraine and a portion in Germany. Table 5 and

Table 6Table 6 successively list the quantity produced at each factory and the number of demands served by each CWH.

Table 5 - No. of units produced at each factory

	Baseline scenario	Optimal scenario
Dhaka, Bangladesh	144900	144900
Chattogram, Bangladesh	144900	144900
Dehradun, India	56205	0
Chennai, India	0	56205
% of total demand		
Dhaka, Bangladesh	41.9%	41.9%
Chattogram, Bangladesh	41.9%	41.9%
Dehradun, India	16.2%	0.0%
Chennai, India	0.0%	16.2%

Table 6 - Quantity demand served by each CWH

	Baseline scenario	Optimal scenario
Paris, France	255110	109232
Madrid, Spain	90895	90895
Milan, Italy	0	145878
% of total demand served		
Paris, France	73.7%	31.6%
Madrid, Spain	26.3%	26.3%
Milan, Italy	0.0%	42.2%

6.2 Cost drivers of the model

The total cost is broken down into individual cost drivers. The cost drivers consist of fixed costs associated with factories and CWHs, production costs, handling costs, as well as inbound and outbound transportation costs. Table 7 represents various cost drivers for both scenarios.

Table 7 - Cost drivers of the model

	Baseline scenario	Optimal scenario
Total Cost	$515,249	$499,758
Factory fixed cost	$8,111	$8,515
Production cost	$298,807	$298,133
Inbound transportation cost	$77,415	$77,165
Outbound transportation cost	$87,465	$67,435
CWH fixed cost	$9,619	$14,972
CWH handling cost	$33,832	$33,540

Production costs, inbound transportation costs, and outbound transportation costs are the three major cost drivers. The production cost is the largest contributor to the total cost, accounting for about 58 percent in the baseline scenario and 60 percent in the optimal scenario. The cost of inbound transportation is 15.02 percent in the baseline scenario and 15.44 percent in the optimal scenario. Outbound transportation costs accounted for about 17 percent in the baseline scenario and 13.50 percent in the optimal scenario. The Pareto analysis for various cost drivers contributing to the total cost of the supply chain network is shown in Figure 2 and Figure 3.

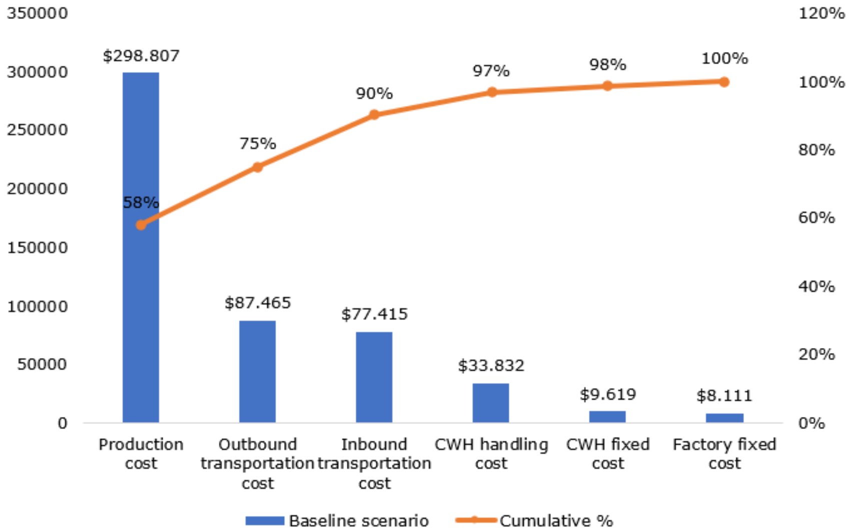

Figure 2 - Pareto analysis for the baseline scenario

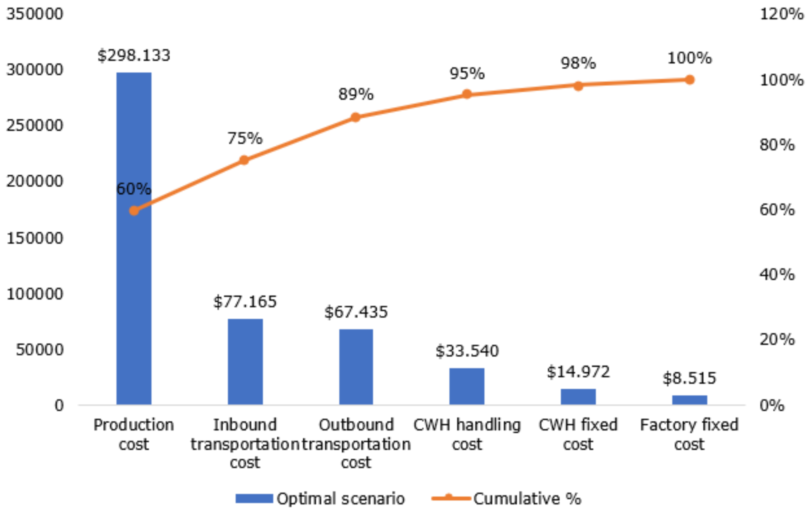

Figure 3 - Pareto analysis for optimal scenario

6.3 Sensitivity Analysis

Demand is increased by 25% for each RWH in both the baseline and optimal scenarios to assess the effect of demand on the cost functions. Here, the demands in RWHs are represented from D1 to D25. The change in D22, which represents demand in Bucharest, Romania, increased the total cost most in the baseline or current scenario, which can be seen in Figure 4. The total cost increased by 1.8 percent more than the total cost in the baseline scenario, and the outbound cost increased by nearly 4 percent compared to the outbound cost in the baseline scenario. In the optimal scenario, the total cost increased by 1.7 percent from the optimal cost with the increase of D22, which is depicted in Figure 5. The outbound cost is 3.7 percent higher than the optimal outbound cost, which impacts most on the total cost. In both scenarios, D22 shows a major impact on total cost, making it the most sensitive to changes in demand. The high volume of demand and the long distance from CWHs are the most likely causes of D22's sensitivity.

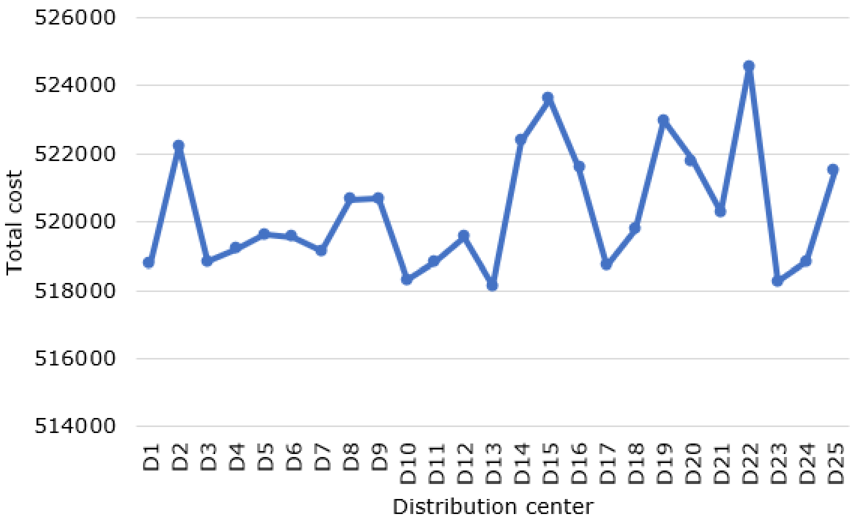

Figure 4 - Total costs in baseline scenario for changing demands

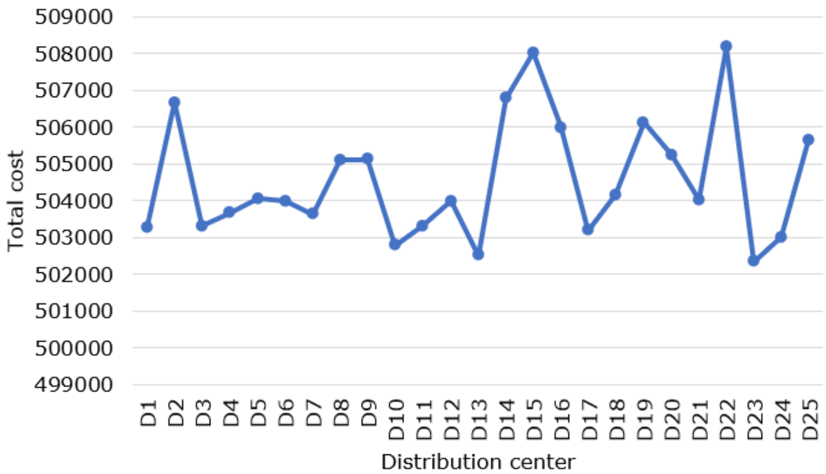

Figure 5 - Total costs in the optimal scenario for changing demands

6.4 Robustness Test

Assessing the robustness of the model is accomplished by the use of Monte Carlo simulation. Demand is considered to be uniformly distributed. 140 scenarios are established, with each scenario allowing for a 50 percent variation from the overall demand. The demand data for each scenario is used as the input to run the model. The constraints from equations 4 to 7 are set to flexible while running the model. Total demand ranged from 266124 to 423556 in 140 simulated demand runs, with a median of 344236. All simulated demand scenarios result in the opening of the factories in Dhaka and Chattogram, suggesting that selecting these two factories as part of the network is a robust decision. The Chennai factory was operational 96.4 percent of the time and closed only when total demand decreased by more than 17 percent. The factory in Dehradun only opened 1.4 percent of the time and only when total demand in Dhaka, Chattogram, and Chennai exceeded total capacity. The high production cost of the Dehradun factory increases the total cost of the network and makes it unsuitable for the model. The CWHs in Paris, Madrid, and Milan are open for all simulated demand runs in the same manner as these three CWHs serve three distinct regions of Europe. As a result, the addition of a CWH in Milan is expected to make the network more robust. Figure 6 depicts the percentage of facilities opening during the simulated demand runs.

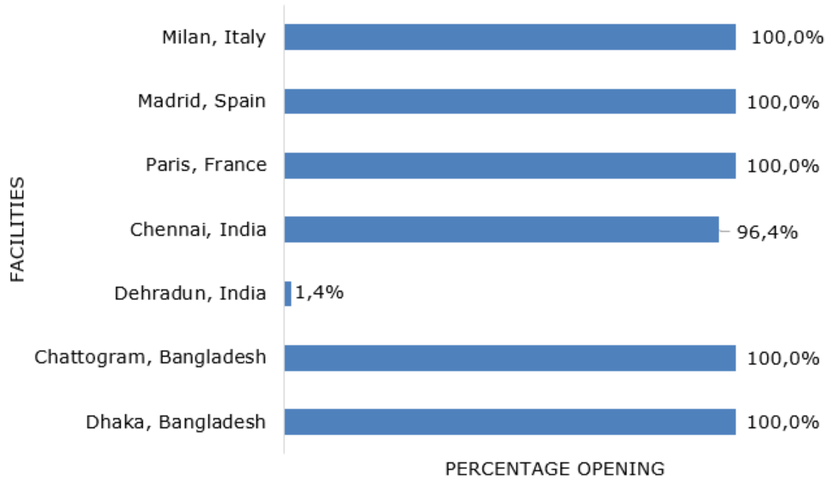

Figure 6 - Percentage opening of facilities from simulated demand runs

The 140 scenarios had total costs ranging from $385,281 to $613,814, with an average total cost of $497,282, which is within 0.5% of the optimal total cost. The unit cost fluctuates between $1.469 and $1.422, remaining within a 2% margin of the optimal unit cost. Furthermore, it is also observed that as demand increases in any given region, the unit cost decreases. The increase in demand in Portugal, Spain, France, Germany, Italy, the United Kingdom, and Switzerland lowers unit costs more than the increase in demand in Romania, Poland, Austria, and Ukraine. When demand in Romania, Austria, and Ukraine was lower, the level of service increased.

7. CONCLUSION

Supply chain network design and development is one of the most complicated and specialized areas of industrial engineering, requiring consideration of both long- and short-term decisions on facility location, capacity allocation, transportation, production, product handling, and routing. To make things as simple as possible, these choices are typically made under predetermined conditions. In addition, networks are typically designed using general models, regardless of industry. Most mathematical programming models are deterministic and vulnerable to changing demands. An MILP model for a three-echelon supply chain (factories, warehouses, and distribution centers) is proposed in this research that minimizes the total cost of the network, which includes fixed and variable costs associated with the facilities as well as transportation costs. To validate the model, a case study of a multinational retail company is presented, where the sensitivity analysis shows the total cost remained within a 2% range of the optimal total cost, showing the effectiveness of the model with changing demand. The reliability and robustness of the suggested model are evaluated by utilizing the Monte Carlo simulation side by side with the optimization model to make it applicable over the long term when demand is variable. The average total cost derived from the output of the simulation shows approximately 0.5% deviation from the optimal total cost, indicating a mathematically robust model. The study also

shows that the choice of facilities and product flows among the facilities for the manufacture of the products is mostly influenced by the variable costs of facilities. Depending on the types of products and the locations of the facilities, different cost drivers may have varying effects on the overall cost. Most of the time, demand surges compromise the outcome by raising the total cost, and taking uncertainty into consideration decreases the risk of unsatisfied demand by increasing the resiliency of the network. Prior to making crucial investment decisions, the management team can face a number of challenges, and this study proposes a methodological approach that can guide the decision-makers to solve these issues. The proposed model intends to aid managers in building a supply chain network with a corresponding structure and help them make better decisions where the level of service metrics enable the supply chain network to be monitored for service levels while satisfying demand. Additionally, sensitivity analysis assists managers in determining how to serve each demand region most effectively. Furthermore, using the simulation approach in conjunction with the optimization model makes the model more realistic and suited for designing a resilient supply chain network that simultaneously optimizes operations and withstands real-world fluctuations and challenges. Future scholars will be able to use the concept as a road map for tackling increasingly intricate supply chain design issues. The suggested MILP model can be altered by researchers by including new constraints—such as time, inventory, or sustainability constraints—or by taking into consideration new variables. The following are possible prospective directions that future scholars can implement in their research:

- Multiple commodities may be considered in the design of a supply chain network, enabling the model to address more storage issues in the warehouse and thereby making it more sophisticated.
- Future researchers can construct a model with multiple objective functions to improve the model's quality.
- Scholars may benefit from the use of stochastic programming, robust optimization, or metaheuristic approaches to solve the proposed supply chain network model, allowing for improved results with less computation time.

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APPENDIX:

Table A1 - List of the locations of the facilities

	Factories	CWHs	RWHs
1	Dhaka, Bangladesh	Paris, France	Lisbon, Portugal
2	Chattogram, Bangladesh	Madrid, Spain	Porto, Portugal
3	Dehradun, India		Puente Genil, Spain
4			Murcia, Spain
5			Madrid, Spain
6			Valladolid, Spain
7			Pau, France
8			Toulouse, France
9			Paris, France
10			Lille, France
11			Frankfurt, Germany
12			Dortmund, Germany
13			Avry, Switzerland
14			London, United Kingdom
15			Newcastle upon Tyne, United Kingdom
16			Berlin, Germany
17			Poznań, Poland
18			Łódź, Poland
19			Milan, Italy
20			Bologna, Italy
21			Naples, Italy
22			Bucharest, Romania
23			Klagenfurt, Austria
24			Vienna, Austria
25			Kyiv, Ukraine

Table A2 - Quantity demanded per week in units

SL. No.	Regional Warehouses (RWHs)	Demand
1	Lisbon, Portugal	10162
2	Porto, Portugal	19956
3	Puente Genil, Spain	10560
4	Murcia, Spain	11734
5	Madrid, Spain	14125
6	Valladolid, Spain	13270
7	Pau, France	11088
8	Toulouse, France	15605
9	Paris, France	17840
10	Lille, France	9636
11	Frankfurt, Germany	10465
12	Dortmund, Germany	12436
13	Avry, Switzerland	8500
14	London, United Kingdom	20550
15	Newcastle upon Tyne, United Kingdom	22700
16	Berlin, Germany	16796
17	Poznań, Poland	8810
18	Łódź, Poland	11016
19	Milan, Italy	21400
20	Bologna, Italy	17410
21	Naples, Italy	12141
22	Bucharest, Romania	19800
23	Klagenfurt, Austria	7720
24	Vienna, Austria	9060
25	Kyiv, Ukraine	13225

Table A3 - Outbound transportation cost per unit

Outbound Transportation cost($/pair)	1	2	3	4	5	6	7	8
	Lisbon, Portugal	Porto, Portugal	Puente Genil, Spain	Murcia, Spain	Madrid, Spain	Valladolid, Spain	Pau, France	Toulouse, France
Paris, France	0.5011	0.4483	0.4879	0.4590	0.3588	0.3267	0.2206	0.1824
Madrid, Spain	0.1698	0.1695	0.1274	0.1147	0.0095	0.0645	0.1781	0.2378
Milan, Italy	0.6311	0.5823	0.5536	0.4592	0.4710	0.4567	0.3224	0.2719

9	10	11	12	13	14	15	16
Paris, France	Lille, France	Frankfurt, Germany	Dortmund, Germany	Avry, Switzerland	London, United Kingdom	Newcastle upon Tyne, United Kingdom	Berlin, Germany
0.0126	0.0654	0.1753	0.1730	0.1474	0.1784	0.2682	0.3109
0.3700	0.4237	0.5381	0.5312	0.4346	0.5310	0.6210	0.6692
0.2516	0.3084	0.1999	0.2593	0.1064	0.4197	0.4968	0.3041

17	18	19	20	21	22	23	24	25
Poznań, Poland	Łódź, Poland	Milan, Italy	Bologna, Italy	Naples, Italy	Bucharest, Romania	Klagenfurt, Austria	Vienna, Austria	Kyiv, Ukraine
0.3758	0.4435	0.2432	0.3058	0.4529	0.6752	0.3523	0.3784	0.6836
0.7340	0.8063	0.4690	0.5060	0.6147	0.9658	0.6187	0.7013	1.0418
0.3677	0.4088	0.0046	0.0737	0.2212	0.5100	0.1520	0.2484	0.5961