



Design of a Supply Chain-Based Production and Distribution System Based on Multi-Stage Stochastic Programming

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Abstract. Supply chains are one of the key tools in optimizing production and distribution simultaneously. However, information uncertainty is always a challenge in production and distribution management. The main purpose of this paper is to design a two-echelon supply chain in a multi-cycle state and in conditions of demand uncertainty. The task includes determining the number and location of distribution centers, planning capacity for active distribution centers, and determining the amount of shipments between different levels so that the total costs of the chain are minimized. Uncertainty is applied through discrete

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scenarios in the model and the problem is formulated by multi-stage stochastic programming method in the form of a mixed integer linear model. The results acquired using two indicators called VMS and VSS demonstrated that modeling the supply chain design problem with the multi-stage stochastic approach can result in significant costs reduction. Plus, utilizing mathematical expectation can generate misleading results, therefore resulting in the development of supply chain designs incapable of satisfying demand due to its overlooked limitations.

Keywords: demand uncertainty, location, capacity planning, multi-stage stochastic programming, production and distribution.

1. Introduction

Given the fierce competitiveness of today's business world, it is now extremely important for businesses to design their supply chains according to the needs of consumer markets [1-4]. One of the most important decisions in the field of supply chain management is facility location, as it tends to have long-term impacts on the performance of businesses [5-8]. Since demand may change over time and it could be very costly to relocate or resize existing facilities, a great deal of interest has also been shown in the subject of dynamic facility location [9-12].

In a study by Ambrosino and Scutella [3], they have reviewed and examined several types of distribution network design problems, including location, warehousing, transportation, and inventory decisions with deterministic parameters. Researchers developed a method for designing production-distribution networks through the location of distribution centers and production-distribution centers in multi-period multi-product mode [13-16]. In this method, each facility can have different design, capacity, and technology options. In the inventory location problem formulated by Hinojosa et al. [9], the location of limited-capacity facilities and the closure of existing facilities are planned at two levels of plants and warehouses, while the inventory holding decisions are also planned in warehouses. Albareda-Sambola et al. [1] formulated a model for multi-period facility location with single-source allocation. In a study by Paksoy and Chang [15], they examined the problem of selecting the best locations for popup retailers from among a set of candidate locations so that transportation costs, the cost of establishing stores, inventory holding costs, and late orders are minimized. El-Sayed et al. [5] developed a model for designing multi-level multi-stage forward-reverse logistics networks. Sha and Huang [17] developed a multi-period location-allocation model for emergency blood supply systems and used a heuristic method based on Lagrangian relaxation to solve it. In a study by Alumur et al. [2], they formulated a model for reverse logistics network design with the profit maximization objective. They developed a multi-period, multi-commodity formulation for decision-making about establishing and expanding the capacity of inspection and remanufacturing centers in the deterministic state. The model of these researchers consists of a set of capacity modules, of which only one is selected in each period and a fixed cost is imposed accordingly. Melo et al. [12] provided a general structure for facility location and capacity planning.

Mahar et al. [11] examined the problem of online sales in a multi-level supply chain in the multi-period mode. In this model, demand is uncertain and has a mean and variance. Gebennini et al. [7] developed a model for the dynamic location-inventory problem. In

addition to determining the number and location of local warehouses and allocating customers to them, this model facilitates making tactical decisions including inventory control, production rate, and service level under uncertain conditions.

In a study by Nickel et al. [13], they investigated the problem of supply chain design in multi-period multi-commodity mode. They defined the problem as determining the location of facilities and the flow of goods and making financial decisions under uncertainty. The problem was formulated as a multi-stage stochastic program in the form of a mixed-integer linear model. Cardoso et al. [4] introduced the notion of demand uncertainty to the supply chain design problem with reverse logistics using a tree scenario. They used this model to determine the location and capacity of facilities under the defined conditions. Pimentel et al. [16] used a multi-stage stochastic programming approach to model the network design and capacity planning problem. In this model, they defined a set of capacity levels from which the initial capacity of each facility had to be selected. They also defined a discrete set of capacities for capacity expansion [18-20].

This study is unique because it is the first time that it has been proposed a two-echelon supply chain in a multi-cycle state and in conditions of uncertainty in demand. In order to achieve this goal, it is necessary to define the number and location of distribution centers, plan capacity for active distribution centers, and calculate the number of shipments between different levels, in order to significantly reduce the total costs of the chain.

2. Materials and Methods

2.1. Problem definition

The problem of interest in this paper is how to design a supply chain with limited demand information. It is assumed that the supply chain has two levels consisting of a number of potential distribution centers and a number of retailers. The problem is modeled in multi-period single-commodity mode. It is also assumed retailers are dissimilar and have uncertain demand.

The considered supply chain design problem involves location decisions, capacity planning decisions, and delivery decisions. In Table (1), the past studies in the field are classified based on their approach to demand modeling and the decisions involved in supply chain design (location or location-capacity planning).

Table 1. Classification of multi-period supply chain design models in terms of approach to demand modeling

Stochastic		Deterministic	Demand
Based on discrete scenarios	Based on mean and variance		
[13,20]	[11,21]	[1, 3] [5,8,15, 17]	Location
[4, 16]	[7,23]	[2,9,12,14]	Location and capacity planning

The planning horizon is divided into a number of time periods. At the beginning of each period, the suitable locations for establishing distribution centers (if needed) are selected from among a set of potential sites and the need for capacity expansion in active distribution centers is also investigated. Since customer demand tends to grow over time, the demand is assumed to have an increasing trend. Therefore, in this model, capacity planning is only done in the form of capacity expansion to meet the demand growth. At the end of each period, the amount of product that must be delivered from the distribution center to retailers is determined. The demand of each retailer can be met by more than one distribution center.

As mentioned, one of the main characteristics of this problem is uncertainty in the demand of retailers. This uncertainty is applied to the model through discrete scenarios and the scenario tree (shown in Figure 1). In the model, it is assumed that the stochastic demand depends on certain events, according to which the size of demand can be determined. Each period has a set of such events, each leading to a specific demand at the end of that period. Since there is no repetition in the pattern of events and consequently in the pattern of stochastic demands, it is decided to use multi-stage stochastic programming to reach a more realistic model.

At the beginning of each period, location and capacity expansion decisions are made before the events take place. Then, specific demands appear depending on the occurred events and the delivery decisions are made accordingly at the end of the period.

Before presenting the mathematical model, it is necessary to introduce the model notations and their definitions.

- Sets of indices
- $D(d \in D, d = 1,2, \dots, D)$: Set of potential distribution centers
- $R(r \in R, r = 1,2, \dots, R)$: Set of retailers
- $T(t \in T, t = 1,2, \dots, T)$: Set of time periods
- $S(s \in S, s = 1,2, \dots, S)$: Set of scenarios

2.2. Parameters

- Demand of retailer r in period t under scenario s :
- Initial capacity of distribution center d that will be established:
- Minimum increase in the capacity of distribution center d :
- Maximum increase in the capacity of distribution center d :
- $D_{r \ s}^t$
- $c_{\ . \ d}$
- l_d
- u_d

Maximum number of times distribution center d can undergo capacity expansion:	n_d
Probability of scenario s :	p_s
Interest rate in period $t \in T$:	roi
Cost of delivering one unit of product from distribution center d to retailer r :	v_{dr}
External funding available at the beginning of period t :	e^t
Fixed cost of establishing distribution center d at the beginning of period t :	f_d^t
Fixed cost of the operation of distribution center d in period t :	$f_o_d^t$
Cost of each unit of increase in the capacity of distribution center d at the beginning of period t :	vc_d^t
Fixed cost of expanding the capacity of distribution center d at the beginning of period t :	fc_d^t
Minimum service level of retailer r :	β_r
Information available up to time t :	ξ_t
History of decision-making up to time t :	$\xi_{[t]}$ $= (\xi_1, \dots, \xi_t)$
History of scenario s up to time t :	$\xi_{[t]}^s$
Current situation:	$\xi_{[0]}^s$

2.3. Variables

Amount of product delivered from distribution center d to retailer r in period t under scenario s :	X_{drs}^t
Capacity of distribution center d in period t under scenario s :	C_{ds}^t
Capacity expansion of distribution center d in period t under scenario s :	CE_{ds}^t
=1 if distribution center d is established in period t under scenario $s=0$ otherwise:	U_{ds}^t
=1 if distribution center d undergoes capacity expansion in period t under scenario $s=0$ otherwise:	Y_{ds}^t

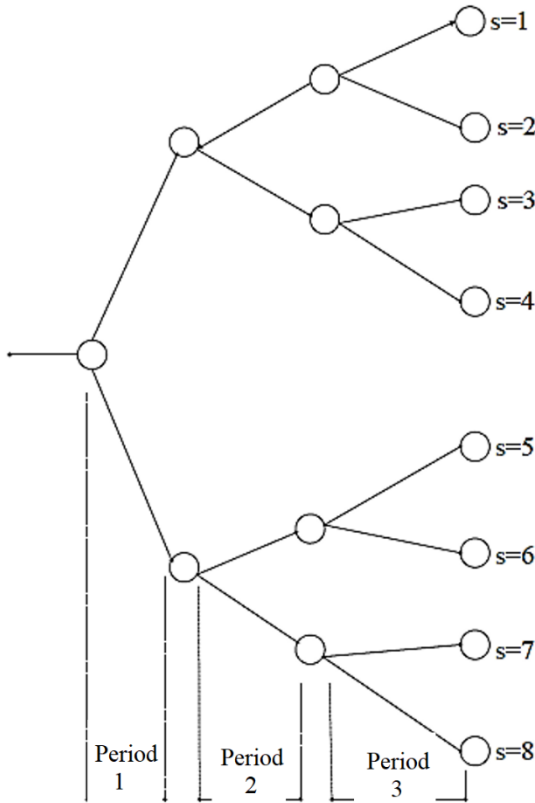


Figure 1. Scenario tree for 3 periods and 8 scenarios

The constraints considered in the problem formulation are as follows.

2.4. Facility establishment and capacity expansion constraints

The process of establishing distribution centers and expanding their capacity is financed through external funding. In fact, this is one of the reasons for considering the design to be multi-period. The maximum external funding available for investment in each period is known and given.

As mentioned, capacity expansion only applies to distribution centers that have already been established and are currently active. Therefore, according to Equation (1), in the first period, external funding can only be spent on establishing distribution centers:

$$e^t - \sum_d [f_d^t \cdot U_{ds}^t + fo_d^t \cdot U_{ds}^t] \geq 0$$

$$t = 1, \forall S \tag{1}$$

Equation (2) shows that what remains of external funding in each period is carried over to the next period, albeit after applying the interest rate:

$$(1 + roi)^{t-1} \left(e^1 - \sum_d [f_d^1(U_{ds}^1) + fo_d^1 U_{ds}^1] \right) \quad t > 1, \forall S \quad (2)$$

$$+ \sum_{t''=2}^t (1 - roi)^{t-t''} \left(e^{t''} - \sum_d [f_d^{t''}(U_{ds}^{t''} - U_{ds}^{t''-1}) + fo_d^{t''} U_{ds}^{t''} + vc_d^{t''} CE_d^{t''} + fc_d^{t''} Y_{ds}^{t''}] \right) \geq 0$$

According to Equation (3), any distribution center that is established in any period must remain active until the end of the planning horizon:

$$U_{ds}^{t-1} \leq U_{ds}^t \quad t > 1, \forall d, \forall S \quad (3)$$

Constraint (4) indicates the minimum and maximum allowable capacity change each time a distribution center undergoes capacity expansion. According to Constraint (5), the number of times the capacity of a distribution center is increased must not exceed the maximum allowed number:

$$l_d \cdot Y_{ds}^t \leq CE_{ds}^t \leq u_d \cdot Y_{ds}^t \quad t > 1, \forall d, \forall S \quad (4)$$

$$\sum_t Y_{ds}^t \leq n_d \quad \forall d, \forall S \quad (5)$$

Equations (6)-(8) indicate that capacity expansion can only be done in distribution centers that have been established in previous periods and are still active:

$$Y_{ds}^t \leq 1 - (U_{ds}^t - U_{ds}^{t-1}) \quad t > 1, \forall d, \forall S \quad (6)$$

$$Y_{ds}^t \leq U_{ds}^t \quad t > 1, \forall d, \forall S \quad (7)$$

$$Y_{ds}^t = 0 \quad t = 1, \forall d, \forall S \quad (8)$$

The total capacity of each distribution center in each period is determined by Equations (9) and (10) based on the considered initial capacity and capacity expansion levels:

$$C_{ds}^t = c_{.d} U_{ds}^t \quad t = 1, \forall d, \forall S \quad (9)$$

$$C_{ds}^t = c_{.d} (U_{ds}^t - U_{ds}^{t-1}) + CE_{ds}^t + C_{ds}^{t-1} \quad t > 1, \forall d, \forall S \quad (10)$$

2.5. Delivery constraints

Equation (11) ensures that the total amount of product delivered from each distribution center is at most equal to the capacity of that distribution center:

$$\sum_d X_{d r s}^t \leq C_{d s}^t \quad \forall r, \forall S \quad (11)$$

The service level of each retailer is determined as the ratio of the total demand satisfied in that retailer to the total demand during the planning period. According to Equations (12) and (13), the total delivery to each retailer must be such that the minimum expected service level is reached without exceeding the demand size at that retailer:

$$\sum_t \sum_d X_{d r s}^t \geq \beta_c \cdot \sum_t D_{r s}^t \quad \forall r, \forall S \quad (12)$$

$$\sum_d X_{d r s}^t \leq D_{r s}^t \quad \forall t, \forall r, \forall S \quad (13)$$

2.6. Consistency and sign constraints

Since the decisions made at the beginning of the period $t = 1, \dots, T$ cannot have distinct values for scenarios with the same history $\xi_{[t-1]}$, the consistency constraint (14) is added to the model:

$$\begin{aligned} U_{d s}^t &= U_{d s'}^t, & C_{d s}^t &= C_{d s'}^t, & Y_{d s}^t &= Y_{d s'}^t, & CE_{d s}^t &= CE_{d s'}^t, & \forall s, s' \text{ for which } \xi_{[t-1]}^s &= \xi_{[t-1]}^{s'}, \forall t, \forall d \end{aligned} \quad (14)$$

Also, the decision to make deliveries from distribution centers to retailers, which are made at the end of each period, cannot differ in scenarios with the same history $\xi_{[t]}$. Therefore, another consistency constraint is added to the model:

$$X_{d r s}^t = X_{d r s'}^t \quad \forall s, s' \text{ for which } \xi_{[t]}^s = \xi_{[t]}^{s'}, t = 1, \dots, T, \forall d, \forall r \quad (15)$$

The sign constraints of the model are as follows:

$$X_{d r s}^t \geq 0, \quad C_{d s}^t \geq 0, \quad CE_{d s}^t \geq 0, \quad U_{d s}^t = \{0; 1\}, \quad Y_{d s}^t = \{0; 1\}, \quad (16)$$

2.7. Objective function

The objective function of the problem is to minimize the total cost, which comprises the delivery cost, the cost of establishing distribution centers, the operating cost of established distribution centers, and the cost of capacity expansion of distribution centers, which are all calculated with the interest rate taken into consideration.

$$\begin{aligned}
\min \sum_t \sum_s p_s \times (1 + roi)^{T-t} \times \sum_d \sum_r V_{dr} \cdot X_{drs}^t & \quad (17) \\
& + \sum_s p_s \times (1 + roi)^T \times \sum_d [f_d^1 \cdot U_{ds}^1 + fo_d^1 \cdot U_{ds}^1] \\
& + \sum_{t>1} \sum_s p_s \times (1 + roi)^{T-t+1} \\
& \times \sum_d [f_d^t (U_{ds}^t - U_{ds}^{t-1}) + fo_d^t \cdot U_{ds}^t + VC_d^t \cdot CE_{ds}^t + fc_d^t \cdot Y_{ds}^t]
\end{aligned}$$

2.8. Value of the solution of the multi-stage stochastic model

Before deciding to use stochastic programming to solve optimization problems that involve uncertainty, it is highly important to examine the value of using this method over simplified methods [13]. In fact, multi-stage stochastic programming is more complex and time-consuming and requires more complete data than many other solution approaches. For this purpose, the problem can be formulated as a two-stage stochastic model and a deterministic model, and the results can be compared with the outcomes of a multi-stage stochastic model.

2.9. Two-stage stochastic model

To formulate a multi-period problem in the form of a two-stage stochastic model, one can make the first-stage decisions for all periods without attention to possible events and scenarios, and then make the second-stage decisions according to the values of first-stage variables and the occurred events. In this approach, the first-stage variables including location and capacity expansion of distribution centers and inventory control policy parameters will not have a scenario index, which means these decisions are made without considering the value of stochastic parameters in different scenarios. These variables have only a time index and take different values at different times regardless of events. The second-stage variables, which include those related to orders, deliveries, and inventories, will have a scenario index as well as a time index [10].

Here, V^{MS} and V^{TS} are the optimal objective function values in multi-stage and two-stage stochastic programming, respectively. The difference between these two values (Equation 18) represents the value of the solution of multistage stochastic programming (VMS):

$$VMS = V^{TS} - V^{MS} \quad (18)$$

2.10. Deterministic model

The two-stage stochastic issue can be modeled with the deterministic format. In this format, the expected value of demand must be used to create a deterministic optimization problem. The solution obtained for the first-stage variables must then be substituted into the two-stage stochastic model and this model must be solved accordingly. The variation among the result of the previous two-stage stochastic model and the result of the two-stage stochastic model whose first-stage variables are acquired through resolving the deterministic model (denoted by EEV) represents the value of the solution of the two-stage stochastic problem (VSS). In fact, the difference between the solution of this deterministic model and the two-stage

stochastic model on the one hand and the variation among the solution of the two-stage stochastic model and the multi-stage stochastic model on the other hand can indicate the significance of expressing the mentioned issue as a multi-stage stochastic pattern.

$$VSS = V^{TS} - EEV$$

(19)

3. Results and Discussion

The problem instances used for examining the model are demonstrated in Table (2).

Table 2. Considered problem instances

External funding			Num ber of scenario s	Num ber of periods	Num ber of retailers	Num ber of distributi on centers	Probl em No.
= 3 t	= 2 t	= 1 t					
15.0 00	25.0 00	30.0 00	64	3	15	5	1
15.0 00	25.0 00	35.0 00	125	3	25	8	2
-	25.0 00	30.0 00	144	2	15	5	3

In all of these problems, retailers and potential distribution centers are randomly distributed in a geographic area of size 100×100m² with the supplier positioned at point (0,0). The cost of transportation between each two points is proportional to the distance between them. The cost of hauling each unit of product is (0.01, 0.05) per unit distance traveled, which is uniform across the chain.

Also, in all of the problem instances, the service level is 90%, the interest rate is 20% and the maximum number of capacity expansions is the number of periods minus one. The value of the demand parameter is determined using the autoregression method (according to Equation 20) according to the scenario tree. The values of other parameters are determined using Equations (21)-(25):

$$D_{rs}^t = D_{rs}^{t-1} + \varepsilon \qquad \forall t > 1, \quad D_{rs}^t \sim LN(7, 0.5) \text{ and } \varepsilon \sim LN(7, 0.5) - 0.9 \cdot E[D_{rs}^1]$$

(20)

$$c_{.d} = ceil(uniform(10000, 20000)), \quad l_d = ceil(c_{.d}/4), \quad u_d = ceil(c_{.d}/2)$$

(21)

$$f_d^t = ceil(uniform(0.90)) + ceil(uniform(100, 110)) \times sqrt(c_{.d})$$

(22)

$$fo_d^t = ceil(uniform(0.40)) + ceil(uniform(20, 40)) \times sqrt(c_{.d})$$

(23)

$$fc_d^t = ceil(uniform(0.10)) + ceil(uniform(5, 10)) \times sqrt(c_{.d})$$

(24)

$$vc_d^t = ceil(uniform(0.2))$$

(25)

The results obtained by solving the multi-stage stochastic model for the problem instances are presented in Table (3).

Table 3. Best value of the objective function of the multi-stage stochastic model for the problem instances

Problem instance 3	Problem instance 2	Problem instance 1	Problem
6.6557×10^4	1.7059×10^5	1.1217×10^5	Best objective function value

To demonstrate the importance of modeling the problem through multi-stage stochastic programming, these problem instances were also solved with the alternative approach explained in Section 3 (two-stage stochastic programming and deterministic modeling). In Table (4), the results obtained from these approaches are compared with each other.

Table 4. Difference between the solutions of the multi-stage stochastic model and the alternative methods

VSS	EEV	VMS	V^{TS}	V^{MS}	Problem No.
6.9215×10^5	8.1253×10^5	8.21×10^3	1.2038×10^5	1.1217×10^5	1
1.6339×10^6	1.8211×10^6	1.661×10^4	1.8720×10^5	1.7059×10^5	2
2.0578×10^5	2.7921×10^5	6.877×10^3	7.3434×10^4	6.6557×10^4	3

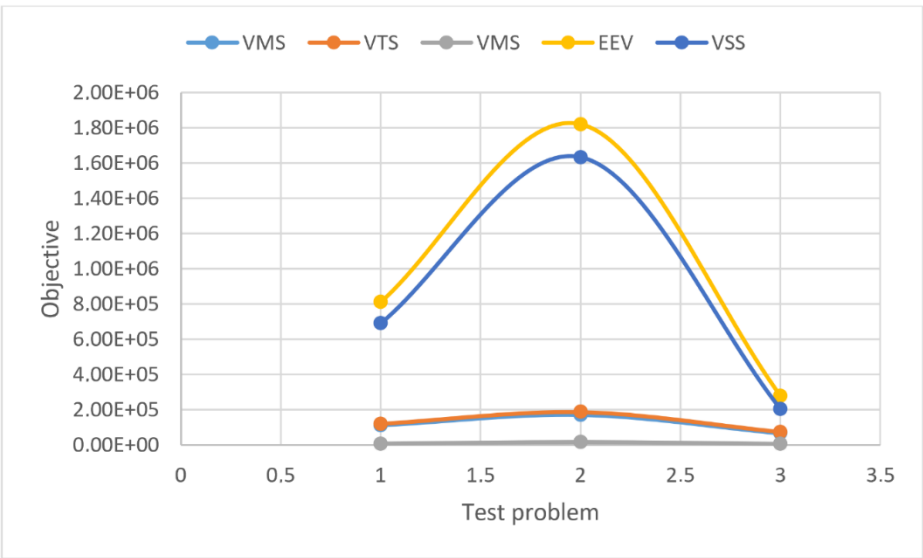


Figure 2. Comparison of the results of different methods in terms of the best objective function value

As depicted in Figure 2, the outcomes of VSS and EEV are substantially different from those of other methods. To put it another, these two methods do more desirable in dealing with uncertainty in the supply chain. High VSS values are a clear indication of the importance of considering demand uncertainty through discrete scenarios in the model. Furthermore, significant VMS values indicate that the use of discrete scenarios in the multi-stage stochastic model can result in substantial costs reduction in comparison to the two-stage model.

4. Conclusion

The main purpose of this paper was to develop a model for supply chain design under demand uncertainty. The main issues considered in this model include how to determine the number of distribution centers, how to determine the best location for these centers from among a set of candidate locations, how to perform capacity planning for active distribution centers, and how to determine the size of deliveries from active distribution centers to retailers. It is common for multi-period supply chain design models to assume that demand is known and given (deterministic). In addition, in most models in which demand is stochastic, the mean and variance are used to model the demand. We modeled demand uncertainty using a multistage stochastic programming approach using discrete scenarios.

In the section titled numerical results, the formulated model was used to solve a number of problem instances. To illustrate the importance of solving the problem with the multi-stage stochastic model, the same problem instances were also solved with two-stage stochastic programming and deterministic programming. Comparison of the obtained results using two indicators called VMS and VSS showed that modeling the supply chain design problem with the multi-stage stochastic approach can lead to substantial costs reduction. This highlights the importance of considering demand uncertainties through discrete scenarios in the supply chain design process. In fact, using mathematical expectation can produce misleading results, thereby leading to the development of supply chain designs that will be incapable of satisfying demand because of overlooked limitations.

Further progress in this field can be achieved by developing multi-stage stochastic models for multi-commodity supply chains with uncertainty and for supply chains with inventory control policies at different levels.

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