

A queuing-location model for in multiproduct supply chain with lead time under uncertainty

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Abstract

Supply chain network design (SCND) problem has recently been gaining attention because an integrated management of the supply chain (SC) can reduce the unexpected/undesirable events and can affect definitely the efficiency of all the chain. A critical component of the planning activities of a manufacturing firm is the efficient design of its SC. Hence, SCND affords a sensitive platform for efficient and effective supply chain management and is an important and strategic decision in one. This paper presents a supply chain network model considering both strategic and tactical decisions. The model determines location of plants and distribution centers regarding single sourcing and capacity of plants and distribution centers (strategic level) while the shipments have to wait in the queue for transporting from plants to distribution centers (tactical level), which lead to the lead time is incorporated in model. Because of high-impact decision of a supply chain network design, we extend the model in an uncertain environment. To deal with uncertainty where the uncertain parameters are described by a finite set of possible scenarios, the two-stage stochastic programming approach is applied. Finally, a numerical example is given to demonstrate the significance of problem.

Keywords: Supply Chain Network Design; queue model; two-stage stochastic programming.

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1. Introduction

A supply chain is a set of supplies, facilities, distribution centers, customers, collection and recovery centers, products and procedures of controlling inventory, purchasing, and distribution. The chain joins suppliers and customers, beginning with the production of raw material by a supplier, and ending with the consumption of the finished product by the customer. In a supply chain, the flow of goods between a supplier and customer moves through several stages, and each stage may comprise many facilities (Sabri & Beamon, 2000). In recent years, the supply chain network (SCN) design problem has been gaining importance due to increasing competitiveness interjected by the market globalization. Firms are compelled to maintain high customer service levels while at the same time they want to reduce cost and maintain profit margins. Marketing, distribution, planning, manufacturing and purchasing organizations

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traditionally along the supply chain have operated independently. These organizations follow their own objectives and they have often conflict of interest. Therefore, it needs a mechanism through which these different purposes can be integrated together. Supply chain management (SCM) is a strategy through which such integration can be achieved (Shapiro, 2004). Illustration of a supply chain network is shown in Figure 1 (Melo et al., 2009).

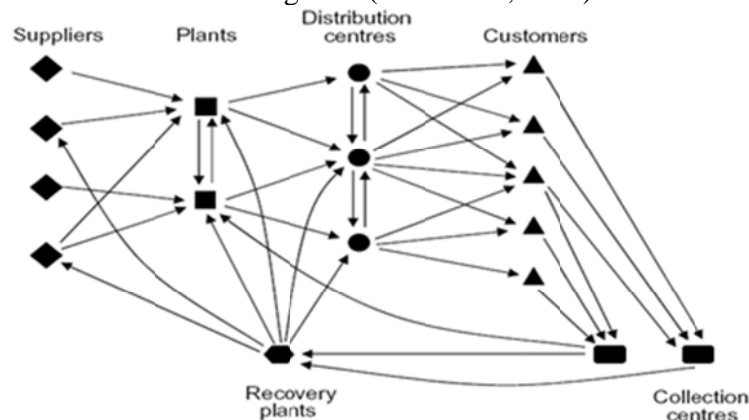


Figure 1: A generic supply chain network.

In SCM, three planning levels are usually distinguished depending on the time horizon: strategic (long term), tactical (medium term) and operational (short term). Simchi-Levi et al. (2003) state that “the strategic level deals with decisions that have along-lasting effect on the firm. These include decisions regarding the number, location and capacities of warehouses and manufacturing plants, or the flow of material through the logistics network”. This statement specifies a clear link between location models and strategic SCM, see also (Santoso, 2005). In practice, strategic decisions are made by top managers, while the tactical and operational decisions are made by bottom level managers. Examples of these tactical/operational aspects are the lead time and inventory control policy, the choice of transportation mode/capacity, warehouse design and management, vehicle routing, among others.

In general, a network design project starts with the determination of potentially interesting sites for new facilities and the required capacities. Usually, large amounts of capital must be allocated to a new facility which it makes this type of investment a long-term project. Accordingly, facilities that are located now are expected to operate for a long-lasting time period. Moreover, changes of various natures during a facility lifetime may turn a good location to day into a bad one in the future. Therefore, the fact that the SC configuration involves the obligation of substantial capital resources over long periods of time makes the SCND problem an extremely important one. Hence, this paper presents a supply chain network model considering both strategic and tactical decisions. The model determines location of plants and DCs regarding single sourcing and capacity of plants and distribution centers (strategic level) while the shipments have to wait in the queue for transporting from plants to DCs (tactical level), which lead to the lead time is incorporated in model. Since problem conditions usually change in practice, then we extend model by defining demands as different scenarios. The two-stage stochastic programming approach is applied to solve it. Finally, a numerical example is given to illustrate the mentioned model.

The rest of the paper is organized as follows. The next section briefly reviews the existing works in context of supply chain network design. Section 3 describes the proposed model and then it is illustrated by a numerical example in section 4. Finally, conclusions are given in section 5.

2. Introduction

Given a set of potential facility locations with capacity limits on the demand that can be served by each location and a set of customers, the objective of the fixed charge capacitated facility location problem (CFLP) is to locate distribution centers (DCs) among candidate locations to satisfy the demand points while minimizing the sum of fixed location and transportation costs. A number of authors (Geoffrion & Graves, 1974; Daskin, 1995; Klose, 1999) present models and solution procedures for the CFLP and its variations. Moreover, distances, times or costs between customers and facilities are measured by a given metric. Possible questions to be answered are: (i) which facilities should be used (opened)? (ii) Which customers should be serviced from which facility (or facilities) so as to minimize the total costs? In addition to this generic setting, a number of constraints arise from the specific application domain. SCND problems include extensive scope of formulations ranged from simple single product type to complex multi-product/multi-period one, from linear deterministic models to complex non-linear stochastic ones and from customary forward networks to reverse closed-loop ones. Many attempts have been made to model and optimize SC design and these studies have been surveyed by (Melo et al., 2009) to support the development of richer SCND models.

Traditionally, the focus of SCND is usually on a deterministic approach and single objective (i.e., minimizing costs or maximizing profit) in a forward logistic. For example, Gen and Syarif (2005) and Amiri (2006) took into account the total cost of forward logistic network as an objective in their works. Also, several studies have been considered about optimization of a multi-objective SCND problem by different researchers. Farahani et al (2010) reviewed the various criteria and objectives used in facility location problem, which plays a critical role in the SCND problem. Chan and Chung (2004) presented a multi-objective SCND in the forward logistic, in which the minimization of costs, total delivery days and the equity of the capacity utilization rate for manufacturers are considered as objectives. They suggested a multi-objective genetic approach for the order distribution problem in a demand driven logistic network. Erol and Ferrell Jr (2004) proposed a multi-objective SC model for minimizing costs and maximizing the customer satisfaction level. Sun et al (2008) presented a bi-level programming model for location of logistic distribution centers by considering benefits of customers and logistics planning departments. Altıparmak et al (2006) presented a SC model with three objectives: namely minimization of the total cost, maximization of the service level and maximization of the capacity utilization balance for distribution centers. They proposed a solution procedure based on a genetic algorithm to obtain the set of Pareto optimal solution for their model.

Most real SC design problems are characterized by numerous sources of technical and commercial uncertainty, and so the assumption that all model parameters, such as cost coefficients, supplies, demand, etc., are known with certainty is not realistic. A supply chain network is supposed to be in use for a considerable time during which many parameters can change. If a probabilistic behavior is associated with the uncertain parameters (either by using probability distributions or by considering a set of discrete scenarios each of which with some subjective probability of occurrence), then a stochastic model may be the most appropriate for this situation. In this matter, a number of researchers present comprehensive SCND models using a two-stage stochastic approach in a forward logistic. Tsiakis et al (2001) took into account a two-stage stochastic programming model for a SCND problem with uncertain demands. They proposed a large-scale mixed-integer linear programming model for their problem. Goh et al (2007) developed a stochastic multi-stage global SCND model regarding supply, demand, exchange and disruption as uncertain parameters in a forward logistic. In addition, there are different studies focusing on multi-objective SCND problem under an uncertain environment. An integrated multi-objective SCND model under uncertainty of product, delivery and demand is developed by Sabri and Beamon (2000). They consider cost, fill rate, and flexibility as objectives

and use ε -constraint method to solve the problem. Guillén et al (2005) presented a stochastic mixed-integer linear programming model for a multi-objective SCND problem, considering profit, customer satisfaction, and financial risk as objectives in a three echelon supply chain. The problem was solved by the ε -constraint approach and branch-and-bound techniques. Azaron et al (2008) developed a multi-objective stochastic programming approach for a three echelon supply chain design under uncertainty in which the goal attainment technique is used to optimize total cost, total cost variance, and financial risk cost. Franca et al (2010) presented a stochastic multi-objective model for a forward logistic network that uses the Six Sigma measure to evaluate the quality of raw materials acquired by suppliers. The objectives of the problem are to maximize the profit of SC and minimize the total number of defective raw material parts under demand uncertainty. Longinidis and Georgiadis (2011) proposed a model for design of a supply chain network. The paper extends the existing models in the literature by incorporating the financial issues as financial ratios and considering the demand uncertainty as scenario analysis.

Moussawi-Haidar and Jaber (2013) considered the problem of finding the optimal operational (how much to order and when to pay the supplier) and financial decisions (maximum cash level and loan amount) by integrating the cash management and inventory lot sizing problems. They presented the problem as a nonlinear program and proposed a solution procedure for finding the optimal solution. Ramezani et al (2014) presents a financial approach to model a closed-loop supply chain design in which financial aspects are explicitly considered as exogenous variables. The model decides to determine the strategic decisions as well as the tactical decisions. The main contribution of this paper is to incorporate the financial aspects and a set of budgetary constraints representing balances of cash, debt, securities, payment delays, and discounts in the supply chain planning. Ramezani et al (2014) addressed the application of fuzzy sets to design a multi-product, multi-period, closed-loop supply chain network in which three objective functions (i.e., maximization of profit, minimization of delivery time, and maximization of quality) are considered. The authors jointly considered fuzzy/flexible constraints for fuzziness, fuzzy coefficients for lack of knowledge, and fuzzy goal of decision maker(s).

On the other hand, in context of the lead time in SCND problem, Berman and Larson (1985), Owen and Daskin (1998), Jamil et al (1999), and Sourirajan et al (2007); (2009) explicitly consider lead times in network design. Also the lead time at a candidate location is modeled as an explicit function of the volume of flow transport through that location in studies by Wang et al (2002), Wang et al (2004), and Eskigun et al (2005). As summarized above, a few researchers address queue models in a SCND problem. Instead, this paper proposes a stochastic model of multi-product supply chain considering products in queue with respect to the lead time. Furthermore, the properties of the model such as integrating decisions, single sourcing and uncertainty differentiate this paper from others in the literature.

3. Introduction

We consider a supply chain network design problem with production facilities that produce multiple products for which demand occurs at geographically discrete locations (retailer) as possible scenarios. The objective is to locate plants and DCs to serve the retailers such that the sum of fixed cost of operating and opening plants and DCs plus the expected costs of transportation and inventory is minimized.

3.1. Modeling lead time at the DCs

We assume that products are shipped from the production facilities to DCs in full truckloads. The products incur a waiting time at the production facilities until material are accumulated adequately to fill a truck. Sending full truckloads is not necessarily optimal in all situations, but it is assumed that the DCs are far enough from the production facilities and that the shipment sizes are high enough (since we group the demands of multiple retailers) to justify it. The shipments dock at an unloading zone when they arrive at the DC and wait in a First-In-First-Out

(FIFO) queue to be unloaded and sent to the retailers. This process is similar to the operation of a cross-docking facility and is shown in Figure 2 (2009). For such a replenishment process, the replenishment lead time at a DC has three components:

1. Load make-up time – The time elapse in the waiting area of the production facilities before the products are transmitted to the DC. As more demand is assigned to a DC, the average load make-up time per unit decreases.
2. Constant DC replenishment time (time/unit) – The replenishment lead time between the production facility and the DC due to the physical locations of facilities. We assume that it also comprises the time spent due to postponements such as material handling, and also general inefficiency and unavoidable processing, such as paperwork.
3. Congestion time – The time elapse in the unloading zone. At high utilization of the resources at the unloading zone, shipments have to wait longer in the queue. This states that congestion time increases as the demand assigned to a location approaches its capacity.

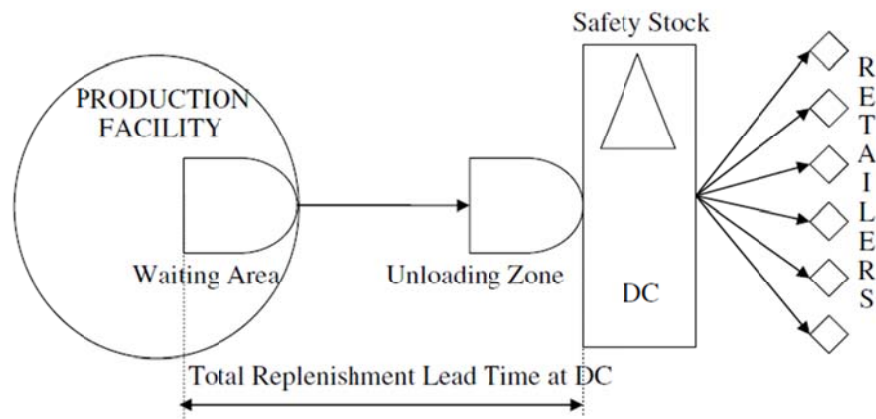


Figure 2: Supply chain structure used for modeling replenishment lead time at DCs.

The total mean demand answered by a DC specifies the expected load make-up time for a shipment to the DC. Whereas all shipments to a DC vie for the same resources at its unloading zone, the expected congestion time is also determined by the total mean demand served by a DC. Given this, we assume the replenishment lead time at a DC to be of the form:

$$LT = \frac{p}{T} + q + \frac{r}{c-T} ;$$

Where Z denotes the total mean demand allocated to the DC and C the throughput at DC. We refer to p as the load make-up time parameter and r as the congestion time parameter. The motivation for this lead time model are deduced from earlier work by Eskigun et al (2005), which used a model of this type derived from an extensive simulation study. Wang et al (2004) also use a similar model for lead times. The first term shows the average load make-up time per unit, q the constant DC replenishment time per unit, and the third term the average congestion time per unit. As the total mean demand at DC increases, load make-up time decreases and congestion time increases.

3.2. Mathematical model

In this section, we provide a mixed integer non-linear programming formulation to the single-source, multi-product, multi-stage SCND problem under uncertain demands along incorporating lead time in model. This problem is to determine the subsets of plants and DCs to be opened and to design the distribution network strategy that will satisfy all capacities and demand requirement for each product while the demands of customers are stochastic. The objective function minimize

sum of investment costs and the expected costs of production, transportation and inventory. The assumptions used in this problem are:

1. The number of potential plants, DCs and their maximum capacities are known.
2. Retailer demands are served from a single DC.
3. The demands are uncertain and are considered as discrete scenarios.

The following notations are used to define the mathematical model:

Indices

I	Set of customers
J	Set of warehouses
K	Set of plants
L	Set of products
S	Set of scenarios

Parameters

p_{jl}	load make-up time parameter of lead time for product l at DC j
q_{jl}	constant lead time component per unit for product l at DC j
r_{jl}	congestion parameter of lead time for product l at DC j
D_k	Capacity of plant k
W_j	throughput at DC j
d_{ij}^s	Demand for product l at customer i under scenario s
M	Maximum number of DCs
N	Maximum number of plants
o_j	Annual fixed cost for operating a DC j
g_k	annual fixed cost for operating a plant k
v_{lk}	Unit production cost for product l at plant k
h_{jl}	unit inventory cost for product l at DC j
c_{ijl}	Unit transportation cost for product l from DC j to customer i
a_{jkl}	Unit transportation cost for product l from plant k to DC j
n_l	Space requirement rate of product l on a DC
m_l	Capacity utilization rate per unit of product l
p_s	Occurrence probability of scenario s

Variables

z_j	1 if DC j is opened, 0 otherwise.
p_k	1 if plant k is opened, 0 otherwise
y_{ij}^s	1 if DC j serves customer i , 0 otherwise.
x_{lk}^s	Quantity of product l produced at plant k under scenario s
q_{ijl}^s	Quantity of product l shipped from DC j to customer i under scenario s
f_{jkl}^s	Quantity of product l shipped from plant k to DC j under scenario s

Using the lead time expression from Section 3.1, the expected lead time LT_{jl} at the DC at location j when the mean demand flow of product l through that DC is T_{jl} units is given by

$$LT_{jl} = \frac{P_{jl}}{T_{jl}} + q_{jl} + \frac{r_{jl}}{W_{jl} - T_{jl}} ;$$

Where

$$T_{jl} = \sum_i d_{il}^s y_{il}^s \quad \forall s ;$$

By Little's Law, the inventory between the production facility and the DC at location j is given by

$$I_{jl} = LT_{jl}T_{jl} ;$$

The expected inventory cost between the production facility and DC at location j can be obtained as:

$$\text{Inventory Cost}_{jl} = h_{jl}I_{jl} ;$$

Accordingly, the problem can be formulated as follows:

$$\begin{aligned} \text{Min} \quad Z = & \sum_j o_j z_j + \sum_k g_k p_k + \sum_s p_s \left(\sum_l \sum_k v_{lk} x_{lk}^s + \sum_i \sum_j \sum_l c_{ijl} q_{ijl}^s + \sum_j \sum_k \sum_l a_{jkl} f_{jkl}^s \right. \\ & \left. + \sum_j \sum_l h_{jl} \left(p_{jl} + q_{jl} \sum_i d_{il}^s y_{il}^s + \frac{r_{jl} \sum_i d_{il}^s y_{il}^s}{W_j - \sum_i d_{il}^s y_{il}^s} \right) \right) \end{aligned}$$

$$\text{S.t.} \quad \sum_j y_{ij}^s = 1 \quad \forall i, \forall s \tag{1}$$

$$\sum_i \sum_l n_l d_{il}^s y_{ij}^s \leq W_j z_j \quad \forall j, \forall s \tag{2}$$

$$\sum_j z_j \leq W \tag{3}$$

$$q_{ijl}^s = d_{il}^s y_{ij}^s \quad \forall i, j, l, \forall s \tag{4}$$

$$\sum_k f_{jkl}^s = \sum_i q_{ijl}^s \quad \forall j, l, \forall s \tag{5}$$

$$\sum_l m_l x_{lk}^s \leq D_k p_k \quad \forall k, \forall s \tag{6}$$

$$\sum_j f_{jkl}^s \leq x_{lk}^s \quad \forall k, l, \forall s \tag{7}$$

$$\sum_k p_k \leq P \tag{8}$$

$$z_j = \{0,1\} \quad \forall j \tag{9}$$

$$p_k = \{0,1\} \quad \forall k \tag{10}$$

$$y_{ij}^s = \{0,1\} \quad \forall i, j, \forall s \tag{11}$$

$$x_{lk}^s \geq 0 \quad \forall l, k, \forall s \tag{12}$$

$$q_{ijl}^s \geq 0 \quad \forall i, j, l, \forall s \tag{13}$$

$$f_{jkl}^s \geq 0 \quad \forall j, k, l, \forall s \tag{14}$$

The objective function minimizes the total cost of the supply chain. It consists of the fixed cost of operating and opening plants and DCs and the expected costs of production, inventory, transportation of the products from plants to DCs and from DCs to customers. Constraint (1) represents the unique assignment of a DC to a customer in each scenario, constraint (2) is the capacity constraint for DCs, constraint (3) limits the number of DCs that can be opened, constraints (4) and (5) give the satisfaction of customers and DCs demand for all products in each scenario, constraint (6) is the plant capacity constraint, constraint (7) limits the total quantity of product shipped from a manufacturing plant to customers through DCs that cannot exceed the amount of that product produced in that plant in each scenario, constraint (8) limits

the number of plants that are opened, constraints (9)–(11) imposes the integrality restriction on the decision variables Z_j, P_k, y_{ij}^s , constraints (12)–(14) impose the non-negativity restriction on decision variables $x_{lk}^s, q_{ij}^s, f_{jkl}^s$. Since the customers are supplied products from a single DC, the considered problem is a single-source, multi-product, multi-stage SCN design problem.

In order to deal with the effects of uncertainty in demands, the two-stage stochastic programming approach is applied in this paper. Decision variables, which characterize the network configuration, namely those binary variables that represent the existence and the location of plants and warehouses of the SC, are considered as first-stage variables. It is assumed that they have to be taken at the design stage before the realization of the uncertainty. On the other hand, decision variables related to the amount of products to be produced and stored in the nodes of the SC and the flows of materials transported among the entities of the network are considered as second-stage variables, corresponding to decisions taken after the uncertain parameter has been revealed.

4. Numerical Example

Consider a supply chain design network consists of plants, distribution centers and demand points. Suppose a company is willing to design its SC. This company produces two products for three customer located in three different cities A, B and C. There are four possible locations D, E, F, and G to establish the distribution centers as well as four possible locations H, I, J and K to establish the plants. The products produced await in area of the production facilities before the products are transmitted to the DCs. Also products sent to DCs have to wait in the unloading zone. For simplicity, without considering other market behaviors (e.g. novel promotion, marketing strategies of competitors and market-share effect in different markets), each market demand merely depends on the local economic conditions. Transportation costs between nodes on each stage of SCN are acquired as coefficient of their Euclidean distances. The congestion time parameter is equalized to capacity of the DC. The space requirement rate of products on a DC, and capacity utilization rate of products in plants are drawn according to U[2,5]. While the fixed cost of DCs are generated from U[10000,30000], the fixed cost of plants are generated from U[50000,150000]. After calculating the total capacity of DCs as $1.5 \sum_{i \in I} \sum_{l \in L} n_l d_{il}$, the capacity of DCs are determined randomly by sharing the total capacity into DCs. In a similar way, the capacities of plants are determined. The total capacity of plants is calculated as $1.5 \sum_{i \in I} \sum_{l \in L} m_l d_{il}$. The parameters relevant to costs and lead time are shown in Tables 1-4, and finally the demand for each type product is assumed as discrete scenarios with corresponding probabilities shown in Table 5.

Table 1: The unit production cost of products at plants.

	Plants			
	H	I	J	K
p1	6	7	6	9
P2	5	5	7	6

Table 2: The unit inventory cost of product at warehouses.

	Distribution centers			
	D	E	F	G
p1	3	2	4	4
P2	3	4	2	3

Table 3: The load make-up time at warehouses.

	Distribution centers			
	D	E	F	G
p1	142	136	130	148
P2	151	142	137	146

Table 4: The replenishment lead time at warehouses.

	Distribution centers			
	D	E	F	G
p1	2	3	2	4
P2	3	2	4	2

Table 5: Product demands.

Customers	Product 1						Product 2					
	Scenarios			Probabilities			Scenarios			Probabilities		
A	110	160	210	0.4	0.4	0.2	130	195		0.35	0.65	
B	125	180		0.3	0.7		115	180	245	0.3	0.4	0.3
C	170	295	380	0.15	0.35	0.5	120	210		0.22	0.78	

This problem attempts to minimize the fixed investment costs and expected cost arising from different scenarios while making the following determinations:

1. Which of the plants and warehouses to build (first-stage variables)?
2. Amount of product to be produce in each plant, amount of product to be transport from plants to distribution centers and finally amount of product to be transport from distribution centers to customer centers (second-stage variables)?

To solve the stochastic model, the deterministic equivalent approach is employed by GAMS, in which the status of all solution is optima by solver BARON and set option optcr=0. Since the product demands are defined as discrete distribution in Table 1, total number scenarios are obtained by multiplying possible situation of each uncertain demand is equal to $3 \times 2 \times 3 \times 2 \times 3 \times 2 = 216$. In fact the problem can be treated as a deterministic problem with $|I||S|$ customers instead of $|I|$. Table 6 shows configurations (1 means the plant/warehouse is built and 0 otherwise) and the values of the expected total cost of supply chain.

A usual question in the stochastic programming is whether this approach can be nearly optimal or whether they are inaccurate. The theoretical answer to this issue is provided by two concepts: the expected value of perfect information (EVPI) and the value of stochastic solution (VSS). The EVPI is difference between the WS approach and the stochastic programming (or RP approach). In the WS approach, each scenario separately is solved and the mean of objective functions is considered as wait-and-see solution (WS). To compute the VSS, first the mean value of each stochastic parameter is taken and the model is solved by mean of each parameter, known in the literature as Expected Value (EV) approach. Then the optimal variables of EV approach are considered as an input for two-stage model and it is allowed that second-stage decisions to be chosen optimality as functions of EV solution and stochastic parameters, known in the literature as EEV approach. The difference between the objective functions of EEV approach and stochastic program would be VSS. To learn more about these issues, we refer the reader to (2011).

Table 6: The results of numerical example.

Approach	Plants				warehouses				Total expected cost
	H	I	J	K	D	E	F	G	
EV	1	0	1	0	1	0	1	0	358281.241
WS	1	0	1	0	1	1	1	0	362164.817
RP	1	0	1	1	1	1	1	0	363358.958
EEV	-	-	-	-	-	-	-	-	-

Tables 6 show the solutions of RP, WS, and EV approaches and EVPI measure is equal to 1194.141. EVPI defines the maximum value a decision maker would be ready to pay in return for complete information about the future. The results show the values of stochastic program is more than WS problem as expected. In addition, the computation shows that the solution of EEV approach is infeasible. This issue points that solution of EV approach in terms of two-stage stochastic program (RP problem) don't cover the solution of RP problem. These reports confirm the accurateness of two-stage stochastic program and give the consistent results for the presented model.

5. Conclusions

In supply chain design, strategic decisions and tactical/operational decisions have been tackled in isolation from one another. Also determining the optimal SC configuration is a difficult problem since a lot of factors and conditions practically are changed in long period of time which may turn a good location to day into a bad one in the future. Hence, the proposed model in this paper presented a supply chain network model considering both strategic and tactical decisions. The model determines location of plants and DCs regarding single sourcing and capacity of plants and distribution centers (strategic level) while the shipments have to wait in the queue for transporting from plants to DCs (tactical level), which lead to the lead time is incorporated in model. To afford the condition change in practice, then we extended model by defining demands as different scenarios. The two-stage stochastic programming approach was applied to solve it. We illustrated the proposed model by a numerical example. Finally, the resulting solutions were also compared with other approaches by two measures of EVPI and VSS. The results reported the consistent outputs for the presented problem.

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