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Flexibility Assessment and Risk Management in Supply Chains

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Increased uncertainty in recent years has led the supply chains to incorporate measures to be more flexible in order to perform well in the face of the uncertain events. It has been shown that these measures improve the performance of supply chains by mitigating the risks associated with uncertainties. However, it is also important to assess the uncertainty under which a supply chain network can perform well and manage risk. Flexibility is defined in terms of the bounds of uncertain parameters within which supply chain operation is feasible. A hybrid simulation-based optimization framework that uses two-stage stochastic programming in a rolling horizon framework is proposed. The framework enables taking optimum planning decisions considering demand uncertainty while managing risk. The framework is used to study the trade-offs between flexibility, economic performance, and risk associated with supply chain operation. © 2015 American Institute of Chemical Engineers *AIChE J*, 61: 4166–4178, 2015
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Introduction

Many of the supply chains today are very efficiently designed and operate to maintain consistent low cost, and high customer satisfaction. Over the years, there have been tremendous advances in the field of information technology and with it, supply chains have become much more globalized and complex. Increased globalization leads to increased uncertainty, which has altered the way supply chain management has been considered in the recent past. The need for flexible design and operation has gained attention as an approach to offset the uncertainties in supply chain environment.

In an uncertain environment, the idea that supply chains can be optimized to account for all possible scenarios is not realistic. Companies need to incorporate flexibility in their supply chains in order to adapt to the changing circumstances. Uncertain conditions increase the vulnerability of supply chains to failures. Moreover, companies have been transformed from monolithic supply chains to smaller, distributed, more flexible networks. The more complex, global, and interdependent the supply chain, the more vulnerable it becomes to uncertainties and has a higher exposure to risk. Complex networks make it more difficult to identify all the vulnerabilities in the network and manage the risk due to increased number of suppliers. Outsourcing is used as a cost-effective measure but it can also result in the inclusion of more volatile suppliers. "Just in time" approach followed by lean systems makes the supply chain more efficient but it can expose also weaknesses in the supply network due to decreased inventory and capacity. It is important to assess the impact of uncertainties on the performance of the supply chain network and how the network operates to cope with uncertainties.

Mitigation of risks in the area of supply chains has gained so much attention that it has led to the development of a separate field of study called "Supply Chain Risk Management."[1–3] It attempts to eliminate the vulnerabilities in a supply chain by identifying the failure points and involving the different entities of the supply chain to ensure continuity in supply chain operation. Companies implement different steps like dual sourcing, forward buying, safety stock, postponement, and so forth to introduce flexibility within their supply chains in order to mitigate risk.[4–7]

In this work, we study the operation of a supply chain under demand uncertainty to investigate different aspects such as flexibility assessment, risk management, and economic performance of the supply chain. Multiperiod supply chain planning with uncertain demand leads to a stochastic optimization problem which is formulated as a two-stage stochastic programming problem in a rolling horizon approach. The two-stage optimization problem is solved using a hybrid simulation-based optimization approach that has been shown to effectively find the optimal solution while also retaining a realistic picture of the dynamics of the actual supply chain. The benefits of the hybrid simulation-based optimization approach regarding realistic representation of supply chains and reasonable execution times even for complex nonlinear dynamics have been demonstrated in the recent studies.[8–12] The proposed framework is used to study the trade-off between the economic performance and flexibility of the supply chain network as well as how the behavior differs under risk-neutral and risk-averse conditions. Flexibility is defined in terms of the bounds of uncertain demand within which the supply chain operation is feasible.

Background

The important aspects covered in this work are supply chain flexibility and risk management. The literature review

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presented here tries to cover the majority of the work that appears in the literature in these areas.

Although supply chain flexibility has been studied for quite some time now, it has been looked at from very diverse perspectives. A major portion of work in this area is focused on manufacturing flexibility. However, it has been noticed that it should be studied from a supply chain perspective as the actual competition is among supply chains rather than manufacturing plants. Different definitions have been proposed and the benefits have been assessed. Garavelli[13] proposes a simulation model to study the concept of limited flexibility. Different configurations are selected to decide about the appropriate degree of flexibility of the network. Two types of flexibilities are considered, namely process flexibility and logistics flexibility. Tang and Tomlin[14] investigate how much flexibility is needed to mitigate risks. They show that significant strategic value can be obtained with a relatively low level of flexibility. Grave and Tomlin[15] analyze the benefits of flexibility in multistage supply chains. A flexibility measure is developed to account against the stage-spinning bottlenecks and floating bottlenecks. Kwon et al.[16] propose using agent-based web services to support collaboration within a supply chain under internal and external uncertainties. Flexibility of the system is demonstrated through two collaboration situations and simulation models are used to test the feasibility of the approach. Chan and Chan[17] propose an adaptive make-to-order coordination mechanism and study how the performance of two-level multiproduct make-to-order supply chains can be improved by flexibility and adaptability in delivery quantity and due date. Two different coordination mechanisms are used to account for flexibility and adaptability. The operations of the supply chain are modeled by agent-based simulation models. It is shown that there is a trade-off between choosing flexibility alone and adopting the proposed adaptive mechanism for different capacity utilizations. Laínez et al.[18] propose a flexible formulation approach instead of a rigid predefined network structure to solve the design-planning problem of supply chain networks. Net present value (NPV) is considered as the key performance metric and is optimized in the resulting mixed integer linear programming model. Mansoornejad et al.[19] study sustainable decision-making regarding biorefinery strategies and consider economic, social, and environmental objectives. They state that in order to be robust to market volatility, biorefinery strategies have to be flexible. Performance of the supply chain in a dynamic environment is analyzed using the metrics of flexibility and robustness. The change of robustness and profitability with respect to flexibility is studied. In process engineering, a lot of work is based on the work of Grossmann and coworkers.[20–24] They presented a general framework for analyzing flexibility in chemical process design. They define flexibility as a measure of the size of the parameter space over which feasible steady-state operation of the plant is obtained by proper adjustment of the control variables. Ierapetritou and Pistikopoulos[25] introduced an integrated metric to assess future plan feasibility along with potential economic risk for two-period linear planning models based on the concepts of flexibility and maximum regret. Finally, Stevenson and Spring[26] present a review of the literature on supply chain flexibility.

Various strategies and models have been investigated to mitigate the supply chain disruptions and losses associated with the different types of risks. Talluri et al.[27] consider various risk categories and supply chain configurations and evaluate different risk mitigation strategies for them. They provide insights for deciding the suitable strategy corresponding to the particular context of risk and state that the suitability of the mitigation strategy depends on the internal and external environments. Wu et al.[28] investigate how stockout disruptions impact a consumer goods supply chain. An agent-based simulation is used to study stockouts in terms of consumers, retailers, and manufacturers. They state that an understanding of consumer response in the face of a stockout disruption at both the manufacturer and retailer is required for developing efficient risk mitigation strategies at both the levels. Ahmadi-Javid and Seddighi[29] consider a location-routing problem with production and distribution disruption risks. They solve the problem of choosing, locating, and allocating a set of potential producer-distributers and building routes to meet supply chain demands. The objective is to minimize the total cost of location, routing, and disruption. The problem is solved under moderate, cautious, and pessimistic risk-measurement policies. Giannakis and Louis[30] consider the problem of disruption risk management in manufacturing supply chains. A multiagent-based framework is proposed for the design of a decision support system that enables collaborative risk management. The framework is able to proactively mitigate a series of risks at the operational and tactical levels of supply chain management. Hahn and Kuhn[31] develop an integrated value-based performance and risk management framework to increase shareholder value holistically. The metric "Economic Value Added" is applied to midterm sales, and operations planning and robust optimization methods are used to handle operational risks in supply chain management. Finally, Tang[32] presents a review of the various quantitative models for managing supply chain risks and relates the supply chain risk management strategies in the literature with actual practices.

Problem Statement

A supply chain consisting of raw material suppliers, production sites, warehouses, and markets is considered in this work. The markets fulfill the demand of different products that can be manufactured from raw materials. The daily demand for the future periods for each product is assumed to be a random variable with a known normal distribution. The bills of material relationships for the manufacture of products at the production sites are known. The warehouses have a limited storage capacity for products while the production sites have limited storage capacities for products and raw materials. There is a limited production capacity for each production site. The various capacities are assumed to be known and fixed. There is no time delay associated with information flow between entities while there is a time delay associated with the material flows. Each market has a primary warehouse to which it sends its orders. Similarly, each warehouse has a primary production site from which it procures products. However in the event of higher demand values, orders can be sent to secondary warehouses and secondary production sites as well. Also, primary warehouses and production sites can increase their transportation capacities for their corresponding markets and warehouses, respectively. The amount of products that warehouses and production can ship is limited by their transportation capacities. Primary and secondary warehouses and production sites can accommodate additional orders by increasing their transportation capacities. There are costs associated with inventory holding, transportation, backorders, production, and transportation capacity increase. Demand is considered to be uncertain. Shipment, inventory, and production information for all the planning periods have to be found out in order to maximize profit while taking risk into consideration. The risk is required to be kept below a certain predefined level.

Solution Methodology

The multiproduct supply chain planning problem under demand uncertainty gives rise to a stochastic optimization problem. A two-stage stochastic linear programming in a rolling horizon approach is proposed to solve the problem where hybrid simulation-based optimization approach is used to solve the first stage of the two-stage problem. The basic concepts related to the proposed methodology are described below.

Rolling horizon

The multiperiod planning problem under uncertainty corresponds to a multistage stochastic programming problem. Decisions have to be made sequentially at each period based on the information available at that period. Such problems extend two-stage programming to a multistage setting. Multistage stochastic programming problems become computationally very expensive as the number of scenarios and stages increase. The rolling horizon decomposes the actual problem into problems with less number of periods and therefore fewer scenarios. The idea is to routinely revise the plan taking into consideration more recent data as they are available. The approach reflects the way decisions related to a firm's business and activities are taken.

Figure 1 illustrates the implementation of the rolling horizon. At the beginning of t2, the second period, demand information up to t2 is revealed while the demand for the future periods is uncertain. The first stage of the two-stage problem is solved to obtain the solution for the first-stage decision variables. The solution is implemented for t2. Then at the beginning of t3, the demand for t3 becomes known. The first stage problem is solved again and the solution is implemented for t3. Similarly, at the beginning of each period, the decisions for the current period are implemented by solving the first stage of the two-stage problem. As the planning horizon at each period remains constant, a rolling horizon is obtained.

Two-stage stochastic programming

Two-stage stochastic programming is based on the idea that decisions should be made on the basis of information that is available at that time rather than information that might be available in the future. The classical two-stage linear stochastic programming formulation can be represented as

$$\min_{x\in X}\{g(x):=c^T xE[Q(x,\xi)]\}$$

where $Q(x,\xi)$ is the optimal value of the second stage problem which is represented as

$$\min_{y} q^T y \text{ subject to } Tx+Wy\leq h$$

where x represents the first-stage decision vector, X is a polyhedral set, defined by a finite number of linear constraints, y is the second stage decision vector, and $\xi=(q,T,W,h)$ is the second stage data.[33] At the first stage, a "here and now" decision is taken based on the first stage information available. The variables of the second stage are considered to be a random vector. The second stage problem is a simple optimization

Figure 1. Rolling horizon approach.

[Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

problem solved after the uncertain data is revealed. The second stage solution is considered as a recourse action that is required to take due to the first stage decision.

In this work, we are only required to solve for the first stage decision variables at each period. At the beginning of each new period, a new two-stage programming problem is formulated and the first stage problem is solved. In the problem considered in this work, the demand values are considered to be a random vector with known probability distribution function. It is assumed that the random vector can be represented by a finite number of possible scenarios. The probability for each scenario is considered to be equal. Monte Carlo sampling technique is used to generate the scenarios. The required number of scenarios for a particular level of accuracy is obtained using statistical methods.[34] Less number of scenarios would not be able to represent the probability distribution of demand. The two-stage optimization problem uses the expected value of all the scenarios. A less than sufficient number of scenarios could affect the quality of the solution obtained as well as the feasibility of the problem.

The formulation gives rise to a large linear programming problem if the objective function and the constraints are linear. The problem considered here involves complex dynamics of the supply chain and thus it is not possible to formulate a mathematical programming problem that is a good representation of the actual dynamics. Hybrid simulation-based optimization has been shown to be an effective approach to solve such problems and is used to solve the two-stage problem in this work.

Hybrid Simulation-Based Optimization

Hybrid simulation-based optimization approaches that aim to take advantages of simulation models as well as mathematical programming approaches have been used to solve supply chain optimization problems.[12] Such approaches give a realistic representation of the supply chain dynamics through the use of a detailed simulation model while a simplified optimization model is used to guide the simulation toward the optimal solution. Different decision-making strategies result in different dynamics in supply chains. The approach, therefore, proves to be an effective way to capture these decision-making strategies and provide the optimal supply chain operation.[35,36]

In this work, the hybrid simulation-based optimization approach is used to solve the two-stage problem at the beginning of each period in the planning horizon. A description of the hybrid simulation-based optimization approach and its components, the simulation model, and the optimization model are presented in the following subsections.

Optimization model

The mathematical programming model includes constraints related to suppliers, production sites, warehouses, and markets. Warehouses (wh $\in$ WH) store products ($s \in$ PR) and transfer them to markets to fulfill the demand during the planning horizon ($t \in T$). Warehouses replenish their inventory with the products they receive from production sites ($p \in$ PS). Production sites procure raw materials ($r \in R$) from raw material suppliers (sup $\in$ SUP) and manufacture products. In the hybrid approach, the role of the optimization model is to guide the simulation toward better results. The optimization model is kept quite simple compared with the simulation model which is more detailed. Therefore, no time delays associated with information or material flows have been considered. The total cost associated with the supply chain consists of inventory holding costs, transportation costs, backorder costs, production costs, and costs due to transportation capacity increase. Inventory holding cost is considered to be proportional to the inventory level. Transportation cost is considered to be proportional to the amount of shipment. Backorder cost is proportional to the amount of unfulfilled demand while production cost is proportional to the amount of product produced. Cost due to increase in transportation capacity is proportional to the increase in capacity. Revenue is obtained by fulfilling the demand at the selling price. The model has been formulated as a mixed integer linear programming problem where the objective is to maximize the total profit. The optimization model is as follows

$$\max \quad \text{Profit1}+\sum_{\text{sc}}\text{Profit2}_{\text{sc}}/n\text{SC}, \qquad \text{sc}\in\text{SC} \tag{1}$$

$$\begin{aligned}\text{Cost1}=&\sum_{\text{wh}}\sum_{s\in\text{PR}}h_s^{\text{wh}}\text{Inv}_s^{\text{wh},1}+\sum_{p}\sum_{s\in\text{PR}}h_s^{p}\text{Inv}_s^{p,1}+\sum_{p}\sum_{r\in R}h_r^{p}\text{Inv}_r^{p,1}\\&+\sum_{m}\sum_{s\in\text{PR}}u_s^{m}U_s^{m,1}+\sum_{p}\sum_{s}v^{p}P_s^{p,1}+\sum_{m}\sum_{\text{wh}}\sum_{s\in\text{PR}}c_s^{\text{wh}}\text{CI}_s^{\text{wh},m}\\&+\sum_{\text{wh}}\sum_{p}\sum_{s\in\text{PR}}c_s^{p}\text{CI}_s^{p,\text{wh}}\ \sum_{m}\sum_{\text{wh}}\sum_{s\in\text{PR}}d_s^{\text{wh},m}\text{dis}^{\text{wh},m}D_s^{\text{wh},m,1}\\&+\sum_{\text{wh}}\sum_{p}\sum_{s\in\text{PR}}d_s^{p,\text{wh}}\text{dis}^{p,\text{wh}}D_s^{p,\text{wh},1}+\sum_{\text{sup}}\sum_{p}\sum_{r\in R}d_r^{\text{sup},p}\text{dis}^{\text{sup},p}D_r^{\text{sup},p,1}\\&s\in\text{PR},r\in R,m\in M,\text{wh}\in\text{WH},p\in P,\text{sup}\in\text{SUP}\end{aligned} \tag{2}$$

$$\begin{aligned}\text{Cost2}_{\text{sc}}=&\sum_{t}\sum_{\text{wh}}\sum_{s\in\text{PR}}h_s^{\text{wh}}\text{Inv}_s^{\text{wh},t,\text{sc}}+\sum_{t}\sum_{p}\sum_{s\in\text{PR}}h_s^{p}\text{Inv}_s^{p,t,\text{sc}}\\&+\sum_{t}\sum_{p}\sum_{r\in R}h_r^{p}\text{Inv}_r^{p,t,\text{sc}}+\sum_{t}\sum_{m}\sum_{s\in\text{PR}}u_s^{m}U_s^{m,t,\text{sc}}\\&+\sum_{t}\sum_{p}\sum_{s}v^{p}P_s^{p,t,\text{sc}}+\sum_{t}\sum_{\text{wh}}\sum_{p}\sum_{s\in\text{PR}}d_s^{p,\text{wh}}\text{dis}^{p,\text{wh}}D_s^{p,\text{wh},t,\text{sc}}\\&+\sum_{t}\sum_{\text{sup}}\sum_{p}\sum_{r\in R}d_r^{\text{sup},p}\text{dis}^{\text{sup},p}D_r^{\text{sup},p,t,\text{sc}}\\&+\sum_{t}\sum_{m}\sum_{\text{wh}}\sum_{s\in\text{PR}}d_s^{\text{wh},m}\text{dis}^{\text{wh},m}D_s^{\text{wh},m,t,\text{sc}}\\&s\in\text{PR},r\in R,m\in M,\text{wh}\in\text{WH},p\in P,\\&\text{sup}\in\text{SUP},\text{sc}\in\text{SC},t\in T\end{aligned} \tag{3}$$

$$U_s^{m,t,\text{sc}}=U_s^{m,t-1,\text{sc}}+\text{Dem}_s^{m,t,\text{sc}}-\sum_{\text{wh}\in\text{WH}}D_s^{\text{wh},m,t}, \quad s\in\text{PR},m\in M,t\in T,\text{sc}\in\text{SC} \tag{4}$$

$$\text{Inv}_s^{\text{wh},t,\text{sc}}=\text{Inv}_s^{\text{wh},t-1,\text{sc}}-\sum_{m\in M}D_s^{\text{wh},m,t,\text{sc}}+\sum_{p\in\text{PS}}D_s^{p,\text{wh},t,\text{sc}} \quad \forall s\in\text{PR},\text{wh}\in\text{WH},t\in T,\text{sc}\in\text{SC} \tag{5}$$

$$\text{Inv}_s^{p,t,\text{sc}}=\text{Inv}_s^{p,t-1,\text{sc}}+P_s^{p,t,\text{sc}}-\sum_{\text{wh}\in\text{WH}}D_s^{p,\text{wh},t,\text{sc}} \quad s\in\text{PR},p\in\text{PS},t\in T,\text{sc}\in\text{SC} \tag{6}$$

$$\text{Inv}_r^{p,t,\text{sc}}=\text{Inv}_s^{p,t-1,\text{sc}}-C_r^{p,t,\text{sc}}\sum_{\text{sup}\in\text{SUP}}D_s^{\text{sup},p,t,\text{sc}}, \quad r\in\text{R},p\in\text{PS},t\in T,\text{sc}\in\text{SC} \tag{7}$$

$$\text{Inv}_{\text{r}}^{p,t,\text{sc}}\le\text{stcap}_r^{p}, \quad \forall r\in\text{R},p\in\text{PS},t\in T,\text{sc}\in\text{SC} \tag{8}$$

$$\text{Inv}_s^{p,t,\text{sc}}\le\text{stcap}_s^{p}, \quad \forall s\in\text{PR},p\in\text{PS},t\in T,\text{sc}\in\text{SC} \tag{9}$$

$$\text{Inv}_{\text{r}}^{\text{wh},t,sc}\le\text{stcap}_s^{\text{wh}}, \quad \forall s\in\text{PR},\text{wh}\in\text{WH},t\in T,\text{sc}\in\text{SC} \tag{10}$$

$$P_s^{p,t,\text{sc}}\le\text{prcap}_s^{p}, \quad \forall s\in\text{PR},p\in\text{PS},t\in T,\text{sc}\in\text{SC} \tag{11}$$

$$D_s^{p,\text{wh},t,\text{sc}}\le\text{trcap}_s^{p}+\text{CI}_s^{p,\text{wh}}, \qquad \forall s\in\text{PR},p\in\text{PS},t\in T,\text{sc}\in\text{SC} \tag{12}$$

$$D_s^{\text{wh},m,t,\text{sc}}\le\text{trcap}_s^{\text{wh}}+\text{CI}_s^{\text{wh},m}, \quad \forall s\in\text{PR},\text{wh}\in\text{WH},m\in M,t\in T,\text{sc}\in\text{SC} \tag{13}$$

$$\text{DRisk}\le R \tag{14}$$

$$\text{DRisk}=\sum_{\text{sc}}P_{\text{sc}}\psi_{\text{sc}}, \quad \text{sc}\in\text{SC} \tag{15}$$

$$\psi_{\text{sc}}\ge\Omega-\text{Profit1}-\text{Profit2}_{\text{sc}}, \ \psi_{\text{sc}}\ge 0, \qquad \forall\text{sc}\in\text{SC} \tag{16}$$

$$\text{Sl}_{m,s,\text{sc}}\ge L, \quad \forall m\in M,s\in\text{PR},\text{sc}\in\text{SC} \tag{17}$$

$$\text{Sl}_{m,s,\text{sc}}=1-\frac{\sum_t U_s^{m,t,\text{sc}}}{\sum_t \text{Dem}_s^{m,t,\text{sc}}}, \quad \forall m\in M,s\in\text{PR},\text{sc}\in\text{SC},t\in T \tag{18}$$

$$\text{Rev2}_{\text{sc}} \ = \ \sum_{t}\sum_{s}\sum_{m}\text{sp}_{s,m}*(\text{Dem}_s^{m,t,\text{sc}}+U_s^{m,t-1,\text{sc}}-U_s^{m,t,\text{sc}}), \quad \forall s\in\text{PR},m\in M,\text{sc}\in\text{SC},t\in T \tag{19}$$

$$\text{Rev1} \ = \ \sum_{s}\sum_{m}\text{sp}_{s,m}*(\text{Dem}_s^{m,1}-U_s^{m,1}), \quad \forall s\in\text{PR},m\in M \tag{20}$$

$$\text{Profit1}=\text{Rev1}-\text{Cost1} \tag{21}$$

$$\text{Profit2}_{\text{sc}}=\max(\text{Rev2}_{\text{sc}}-\text{Cost2}_{\text{sc}}), \quad \text{sc}\in\text{SC} \tag{22}$$

Equation 1 refers to the objective for the first stage of the two-stage problem. The objective function maximizes the profit for the first stage and the expected optimal profit for the second stage considering all the scenarios. Equation 2 defines the cost for the first stage while Eq. 3 gives the cost for the second stage decisions. The cost calculations include backorder cost, inventory cost, production cost, transportation cost, and cost due to increase in transportation capacity. Equation 4 states that any unfulfilled demand during the current period gets accumulated as backorder for the next period. Inventory balance constraints at the warehouses are represented by Eq. 5. It relates warehouse inventory to shipments from warehouses to markets and shipments from production sites to warehouses. Equation 6 represents the product inventory balance constraint at the production sites. It relates product inventory at production sites to shipments from production sites to warehouses, and production amounts during each planning period. Equation 7 represents the raw material inventory balance constraint at production sites. It relates the raw material inventory at production sites to consumption of raw materials for the manufacture of products and shipments from raw material suppliers to production sites. Equations 8–12 represent the capacity constraints for the different nodes. Storage capacity constraints for production sites and warehouses are given by Eqs. 8–10, respectively, while the production capacity constraint for production sites is given by Eq. 11. Equations 12 and 13 state that shipment between a production site and a warehouse, and between a warehouse and a market is less than the respective transportation capacity. The metric, downside risk, is used to measure the risk of having a total profit lower than a target profit. Equation 14 is a constraint on the value of the downside risk. Equations 15 and 16 define the downside risk for the problem. Equation 17 is the service level constraint which restricts the amount of backorders. β-service level is used to calculate the service level. Equation 18 defines the service level in terms of the backorders and demand at markets. Equations 19 and 20 represent the calculation of revenue for the first stage and the second stage by the fulfillment of demand at the markets. Equation 21 represents the calculation of profit for the first stage. Equation 22 represents the optimal profit for the second stage.

The optimization model results in a mixed integer linear programming problem which has been solved using the Cplex library embedded in the Java application used for simulation on Windows 7 operating system with an Intel(R) Xeon(R) CPU ES-1620 v2 D CPU 3. 70 GHz microprocessor and 16.00 GB RAM.

Simulation model

Agent-based modeling has been shown to be an effective approach to simulate the supply chain. Using a bottom-up approach, it enables a realistic representation of the actual supply chain dynamics. Repast simulation platform and Java programming environment have been used to implement the model.

The agents in the simulation model represent the different entities of the supply chain. The agents capture the characteristic behavior of the entities. There is interaction among the agents and their behavior is adapted based on these interactions. Each agent performs actions and schedules future actions for itself or other agents. They are connected by information flows as well as material flows. Information about inventory, demand orders, and shipments are shared among the agents which allows them to coordinate demand allocation and order fulfillment.

Each agent is a collection of attributes and behaviors which have been coded using Java, an object oriented programming language. Different classes for different types of agents are developed and are instantiated to create the particular agents. These classes contain properties and methods to represent the attributes and behaviors, respectively. A parent class consists of the common attributes of each supply chain agent and the individual classes for the agents derive from the parent class.

Market agent

Demand for products originates at the market agent. On receiving a demand, the market agent sends *requests* to the warehouses. A *request* is a way to communicate to amount of products required although it is not the actual order. It procures information about how much demand can be fulfilled, how much time it will take, and the cost of fulfilling the demand. The warehouses respond to these requests and then the market agents distribute the demand among the warehouses based on their ordering policies. Each market has a primary warehouse. The market gives first preference to the primary warehouse and then based on which warehouse responds with the lowest cost. While sending an order to any warehouse, the market tries to order as much as possible to the warehouse. So if the remaining demand is lower than the amount, the warehouse can fulfill as per the response, the market orders the remaining demand. Otherwise, the amount that the warehouse can fulfill is ordered. The market stops assigning orders if the total demand amount has been ordered or if the warehouses have no remaining inventory. For warehouses that respond with equal cost, the market uses the higher amount of demand that can be fulfilled and the lower time to fulfill as the deciding factors. Unfulfilled demand during any period is added as backorder to the demand during the next period. Using this ordering policy, the market does not receive any oversupply from warehouses. The markets earn revenue by selling the products. Inventory and backorders have costs associated for this agent. Backorder cost is proportional to the amount of backorders. Inventory cost is proportional to the amount of inventory at the agent. These costs are calculated at the end of each day.

Warehouse agent

The warehouse agent fulfills the market demands by transferring products to the markets. It maintains an inventory of products. When a warehouse receives a *request* from a market, it responds in terms of the cost and time it would take to transfer the products, and the fraction of demand it would be able to fulfill. To determine the fraction of demand it can fulfill, it considers the aggregated demand from all the markets. The warehouses have contractual agreements with markets. Therefore they have different higher preference levels for some markets compared with others. It tries to fulfill demand from the more preferred markets before the less preferred markets. Based on the responses from all the warehouses, the markets send orders for products. If the markets are not able to order the total demand to the warehouses, they update the *requests* and resend them to the warehouses. The *requests* are updated by adjusting the demand amount based on what has already been ordered. Markets keep sending *requests* to warehouses and assigning *orders* to warehouses as long as all the demand has not been ordered and the warehouses can fulfill some demand from the markets. The warehouses attempt to fulfill the demand from the markets collectively. The warehouse agent uses its inventory of products to fulfill the demand from the markets. The storage capacity is limited and a reorder level–reorder amount inventory replenishment policy with continuous review is used to regulate the inventory. The reorder level and reorder quantity for the agent are predefined. As soon as the warehouse inventory drops below the reorder level, it generates a demand for products which is fulfilled by production sites. On generating a demand, the warehouse agent sends *requests* to the production sites. A *request* is a way to communicate the amount of products required although it is not the actual order. It procures information about how much demand can be fulfilled, how much time it will take, and the cost of fulfilling the demand. The production sites respond to these *requests* and then the warehouse agents distribute the demand among the production sites based on their ordering policies. Each warehouse has a primary production site. The warehouse gives first preference to the primary production site and then based on which responds with the lowest cost. While sending an order to any production site, the warehouse tries to order as much as possible to the production site. So if the remaining demand is lower than the amount the production site can fulfill as per the response, the warehouse orders the remaining demand. Otherwise, the amount that the production site can fulfill is ordered. The warehouse stops assigning orders if the total demand amount has been ordered or if the production sites have no remaining inventory. For production sites that respond with equal cost, the warehouse uses the higher amount of demand that can be fulfilled and the lower time to fulfill as the deciding factors. Inventory and transportation have associated costs for this agent. Transportation cost and inventory cost are proportional to the amount of products transported and the amount of inventory stored, respectively.

Production site agent

The production site agent fulfills the demand for products generated at the warehouses. It maintains a small inventory of products by manufacturing them from raw materials. The conversion of raw materials to products is defined by a bill of material relationship. A small inventory of raw material is also maintained. It has fixed production capacity and storage capacities. When a production site receives a *request* from a warehouse, it responds in terms of the cost and time it would take to transfer the products, and the fraction of demand it would be able to fulfill. To determine the fraction of demand it can fulfill, it considers the aggregated demand from all the warehouses. The production sites have contractual agreements with warehouses. Therefore, they have different higher preference levels for some warehouses compared with others. It tries to fulfill demand from the more preferred warehouses before the less preferred warehouses. Based on the responses from all the production sites, the warehouses send orders for products. If the warehouses are not able to order the total demand to the production sites, they update the *requests* and resend them to the production sites. The *requests* are updated by adjusting the demand amount based on what has already been ordered. Warehouses keep sending *requests* to production sites and assigning *orders* to production sites as long as all the demand has not been ordered and the production sites can fulfill some demand from the warehouses. The production sites attempt to fulfill the demand from the warehouses collectively. The production site agent uses its inventory of products to fulfill the demand from the warehouses. The storage capacity is limited and a reorder level–reorder upto level inventory replenishment policy with continuous review is used to regulate the raw material inventory. The reorder level and reorder up to level for the agent are predefined. As soon as the production site raw material inventory drops below the reorder level, it generates a demand for raw materials which is fulfilled by the raw material suppliers. The production site orders raw materials from the raw material supplier with the minimum cost. Inventory, production and transportation have associated costs for this agent. Transportation cost, inventory cost, and production cost are proportional to the amount of products transported, the amount of inventory stored, and the amount of products produced, respectively.

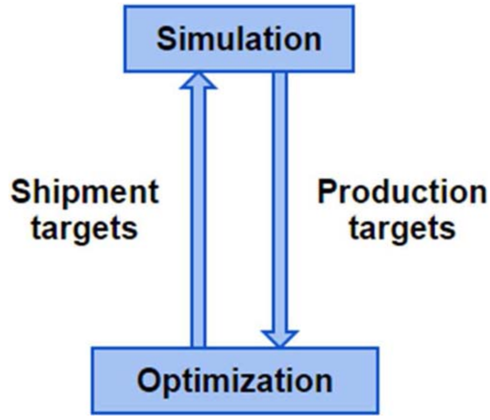

Figure 2. Coupling between simulation and optimization.

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Supplier agent

On receiving demand orders from production sites, the supplier agent sends raw materials to them. The supplier agent is considered to have an unlimited storage capacity. Transportation has associated costs for this agent.

Hybrid simulation-based optimization methodology

As discussed in Optimization model and Simulation model sections, the optimization and simulation models are developed. In the hybrid approach, the two independent models are coupled together by exchange of information between them, thus allowing taking advantage of the benefits of both models. As shown in Figure 2, the following variables are used to couple the optimization model with the simulation model in this work: (1) production and consumption values from simulation model to optimization model and (2) shipment values obtained from optimization model to simulation model.

By communicating the shipment values from the optimization to the simulation model, shipment targets are obtained by the simulation and it tries to achieve these targets, thereby reducing backorders and inventories. The simulation represents a more realistic dynamic environment of the supply chain and the behavior of the agents of the model determines if it is able to achieve the shipment targets or not. Production and consumption values obtained from the simulation model are set as parameters in the optimization model. The optimization model then provides the shipment values for the optimal solution corresponding to those production and consumption targets.

Using the hybrid approach proposed above, the solution methodology proposed by Sahay and Ierapetritou[12] has been used. As shown in Figure 3, an iterative procedure is used where the framework is initialized by solving the simulation model for each scenario. The variables associated with each scenario are then passed to the optimization model, which is solved to obtain values of the decision variables. The total profit for the planning horizon is calculated by the two models for each scenario. If the difference for each scenario is below a tolerance level, the procedure is terminated otherwise the values of decision variables for each scenario are passed back to the corresponding simulation model. This process is repeated until the difference between the profits falls below the tolerance level for each scenario. The above framework

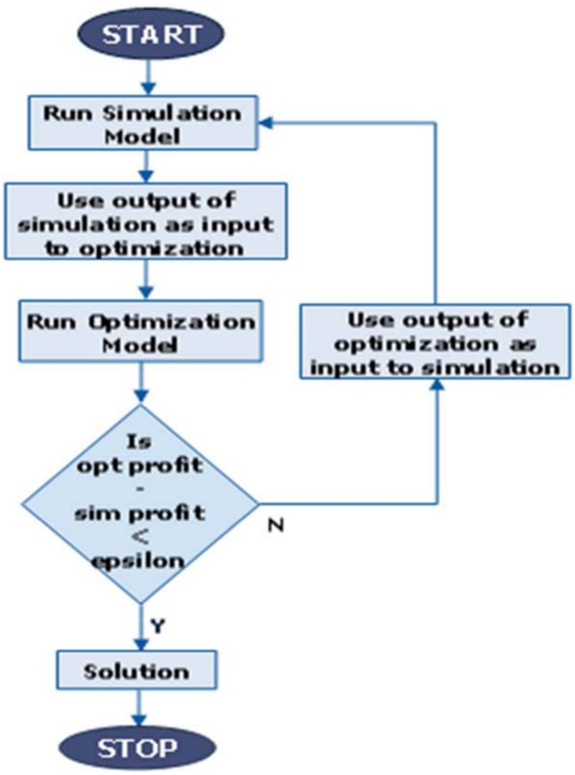

Figure 3. Iterative framework for the hybrid simulation-optimization approach.

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uses the optimization model to guide the simulation model, used as the master model, toward the best solution that can be achieved. The proposed algorithm considers a fixed supply chain design and starts by solving the simulation model for that design. The algorithm always gives the same result for a particular demand scenario and supply chain design. It uses the simulation model and the optimization model to set values of some of the decision variables for each other. These values are used as targets for each other. The framework is initiated by solving the simulation model for each demand scenario. The optimization model is linear. It leads to the optimal and the simulation moves to those targets if feasible.

The approach described above is implemented to solve the two-stage problem at the beginning of each period. It is to be noted that a separate simulation model is executed for each scenario and the outputs from all the simulations are used as inputs to the optimization model. The optimization model gives the optimal values of the decision variables for each scenario which are used as input to each simulation model.

Overall Framework

The overall solution framework consists of the hybrid simulation-based optimization model incorporated in the rolling horizon. Figure 4 shows the different steps of the framework.

The iterative framework starts at the first period. So, the period is initialized to 1. At this point, the planning horizon and the number of scenarios are fixed. At the beginning of each period, the first step is to generate demand scenarios for all the future periods using the Monte Carlo sampling technique. It is assumed that the current demand values are known. Once all the scenarios are determined, the hybrid simulation-based optimization model is used to solve the first stage problem. The solution for the first stage is implemented for the current period. The framework moves to the next period until the last period of the planning horizon is reached. The framework allows taking the optimal decisions based on the information available at the current period. The initial input parameters for the hybrid model are updated during each period as they depend on the decisions taken during the earlier periods. The initial backorder at the beginning of the first period is 0 for the first period while it may be greater for subsequent periods. Similarly, initial inventory values also need to be updated. Also, information about any shipments scheduled to arrive in a future period need to be incorporated as input parameters in the hybrid model.

Risk Management

For the problem considered here, a key objective of decision-makers is not only to find the optimal solution with the maximum profit but also to avoid the risk of lower profits due to demand variability. Different risk metrics have been proposed in the literature.[37–39] You et al.[34] concluded that the downside risk model performs best to reduce the risk of high cost without being computationally demanding. They showed that variance and variability index are good at reducing the variance but shift the solution toward higher expected cost. In this work, the downside risk model is used to manage risk. The model can be expressed for profit as follows

$$\min \mathrm{DRisk}(x, \Omega) = \sum_s P_s \psi \tag{23}$$

$$\psi_{sc} \geq \Omega - \mathrm{Profit1} - \mathrm{Profit2}_{sc}, \quad \psi_{sc} \geq 0, \qquad \forall sc \in SC \tag{24}$$

To solve the multiobjective problem, the ε-constraint method is used.

Case Studies

The proposed solution framework is used for two case studies. The first case study involves a smaller network while the second is for a bigger more realistic network.

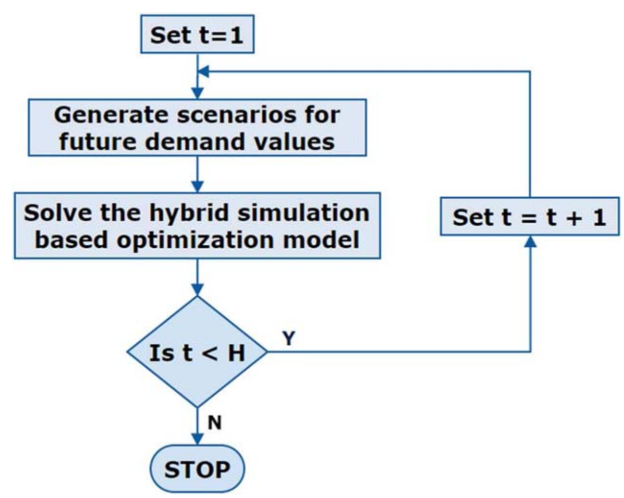

Figure 4. Solution framework.

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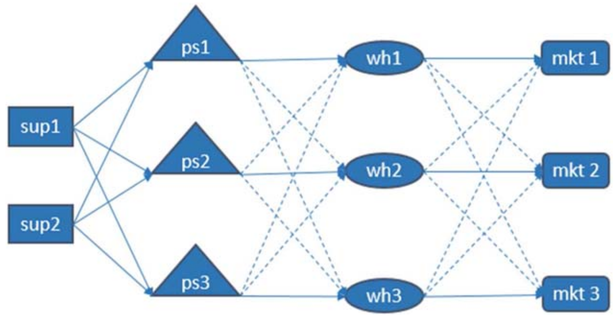

Figure 5. Supply chain network for Case study 1.

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Case study 1

The supply chain network considered in the first study consists of three markets, three warehouses, three production sites, and two suppliers, as shown in Figure 5. There are two products and three raw materials. For the hybrid simulation-based optimization model, a difference of 1% of profit obtained from simulation model is used as the termination criterion. The planning horizon for the problem is 10 planning periods. The mean demand was considered to be 80 for each product at each market during each period. The total number of demand scenarios generated for the second stage was 500. The values of the distances of warehouses from production sites and markets are provided in Table 1. Distances of production sites from raw material suppliers are provided in Table 2.

The results from the proposed solution framework for the case study are presented here. The solution of a hybrid simulation-based optimization model for one scenario in the first stage problem is shown in Figure 6. It can be seen that the profit values obtained from the simulation model and the optimization for the particular scenario converge in eight iterations. It should be noticed that similar plots can be obtained for all the 500 scenarios at each period. However for each scenario, the number of iterations required for convergence changes at every period due to changing input parameters (i.e., initial inventory, and demand values due to backorders from previous period). As the input parameters are different at every period, the progress of the hybrid simulation-based optimization approach varies in every period, the number of iterations required to converge could vary at each time period.

The different entities can increase their transportation capacity to accommodate a rise in demand. However, there is an associated cost with the increase in capacity, which is referred as transportation capacity cost. Figure 7 shows a comparison of the transportation capacity cost with demand variability. The *y* axis represents the cost due to increasing the transportation capacity to accommodate the uncertainty in demand. The *x* axis represents the coefficient of variation for the uncertain demand. Coefficient of variation is a standardized measure of dispersion of the demand probability distribution and is defined as the ratio of the standard deviation to the mean. As variability in demand is considered to be higher for a future period that is far from the current period compared with one which is closer, the comparison is made between the cost and coefficient of variation for the last period of the planning horizon. It can be seen that increased transportation capacity is required as demand variability increases. Beyond a certain level of demand variability, the value of transportation capacity cost does not increase further. The increase in transportation capacity reached is not the highest value possible.

Table 1. Distance of Warehouses from Markets and Production Sites

	mkt1	mkt2	mkt3	ps1	ps2	ps3
wh1	10	20	15	10	15	20
wh2	15	10	20	20	10	15
wh3	20	15	10	15	20	10

Table 2. Distance of Production Sites from Raw Material Suppliers

	sup1	sup2
ps1	10	15
ps2	20	10
ps3	15	10

As mentioned earlier, the markets sell products which bring revenue. It is important to study whether the supply chain operation is profitable and how the profit varies with the demand variability. Figure 8 shows how the profit of the supply chain operation varies as demand variability changes. It can be seen that for lower levels of variability, the profit increases with variability. However, after a certain level of variability, the profit starts to decrease. This is because the cost increases with increasing variability but the revenue does not increase beyond a certain level as the amount of products available to sell is limited by the capacity constraints. For lower levels of variability, although the total cost increases with increasing variability, as a minimum service level is maintained, the revenue also increases. It is to be noted that the trend obtained in Figure 8 can vary depending on the values of the parameters associated with the problem. The trend shown is valid for the particular supply chain design considered. As shown in Figure 7, increased variability in demand results in an increase in transportation capacity. Transportation capacities between secondary warehouses and production sites are increased. The amount of transportation for demand fulfillment involving secondary warehouses and production sites also increases with demand variability. Figure 9 shows the variation in secondary shipment as demand variability changes. It can be seen that the percentage of demand fulfilled through secondary shipment increases with demand variability.

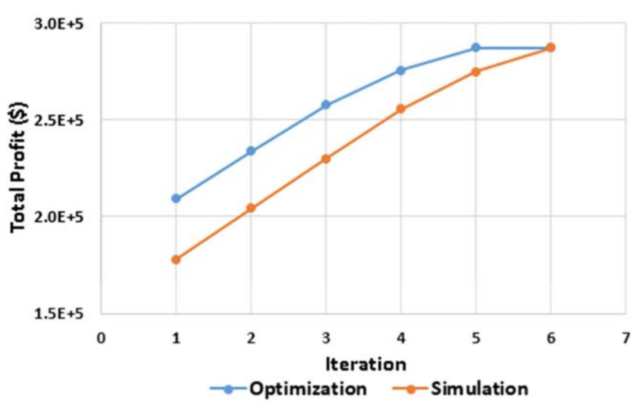

Figure 6. Solution of the hybrid simulation-based optimization model.

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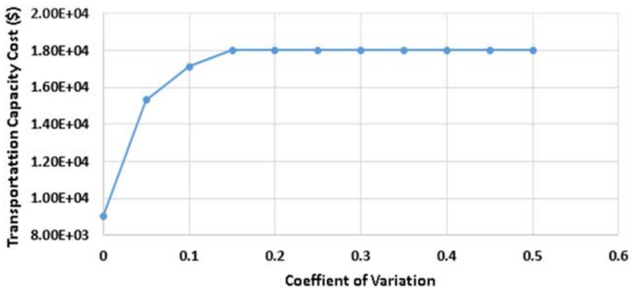

Figure 7. Comparison of transportation capacity cost with variability on demand.

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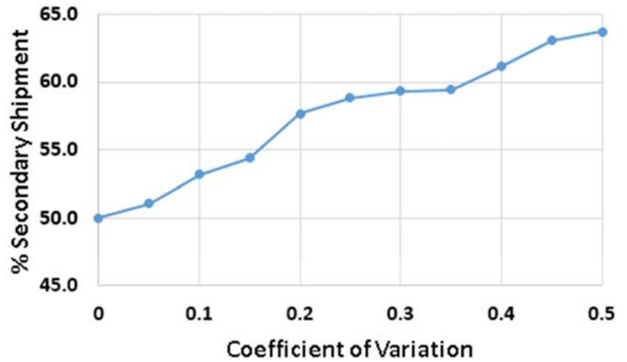

Figure 9. Variation of secondary shipment with demand variability.

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In this work, flexibility is defined as the upper bound on the coefficient of variation within which supply chain operation is feasible. The model incorporates a lower bound on the service level constraint which causes infeasibility beyond a certain level of variability. To study the change in flexibility with downside risk, different values of downside risk are used in the risk constraint and the value of flexibility is found out for them. To find the value of flexibility, the demand variance is increased from a low value and the value at which the problem becomes infeasible is found out. Figure 10 shows the change in flexibility with risk. It can be seen that as the value of downside risk is increased, flexibility increases which means that the supply chain can operate for higher values of demand variance if a higher value of risk is allowed. However, it is seen that beyond a certain level of risk, flexibility does not increase. This is because at higher values of risk, the service level constraint becomes active before the risk constraint. Therefore, although a high probability of profit lower than the target profit is allowed, the supply chain is not able to operate at very high values of demand variance. A β-service level constraint is included in the model. It is to be noted that the target profit for the calculation of risk is lower than the actual profit obtained from the solution. This is because the backorders increase along the planning horizon which reduces the profit. Therefore, the profit obtained from the solution toward the end of the planning horizon is lower. A higher target profit toward the end of the planning horizon would result in infeasibility.

The computational time required to solve the case study at a particular risk level and demand variance is 13,893 s. This solution time is obtained for demand with a coefficient of variation of 0.30 and no risk constraint. The high computational time is due to the number of scenarios considered. The hybrid simulation-based optimization model is required to converge for each scenario during each period.

The effect of the length of rolling horizon on the solution time is investigated. Figure 11 shows the change in computational time with the rolling horizon length. It is observed that the solution time increases as the length of the rolling horizon is increased. However, it is also observed that the profits obtained from solving with lower rolling horizon lengths are

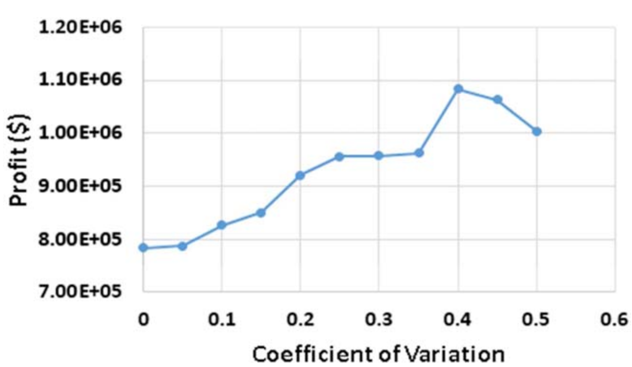

Figure 8. Variation of profit with demand variability.

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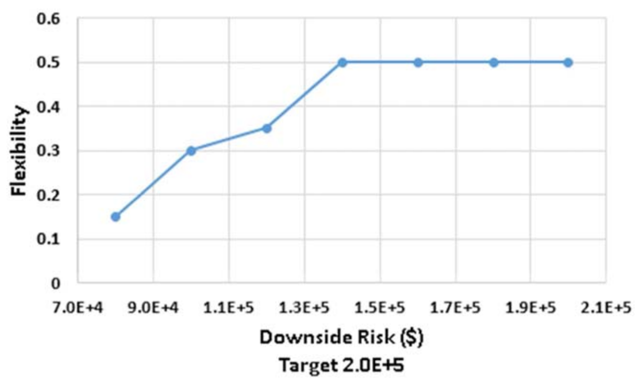

Figure 10. Variation of flexibility with risk.

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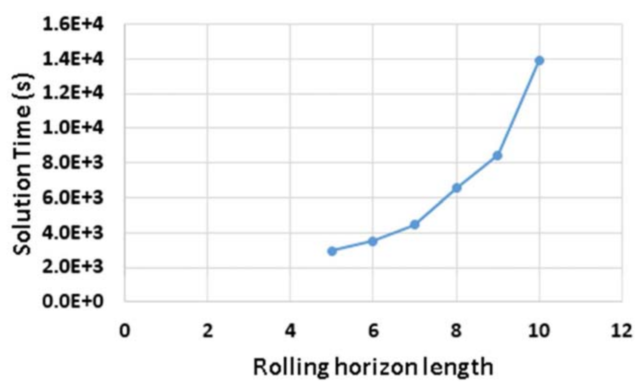

Figure 11. Variation of solution time with rolling horizon length.

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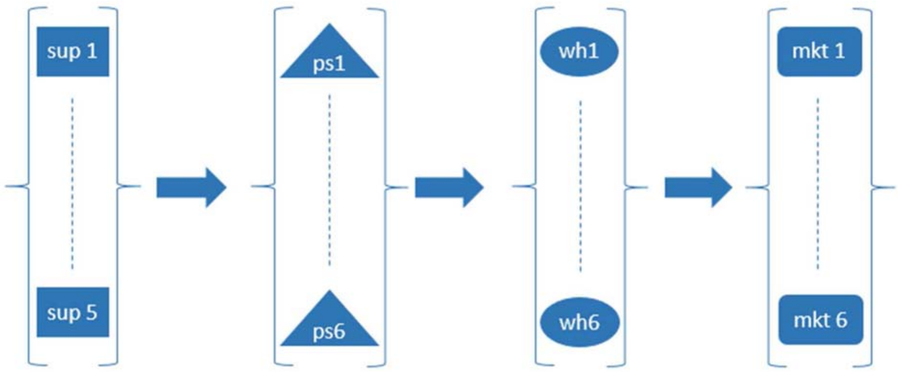

Figure 12. Supply chain network for Case study 2.

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less than the value obtained for a rolling horizon length equal to the planning horizon. For rolling horizon lengths of 3 and 4, the problem was found to be infeasible. This means that if decisions during the initial periods are taken based on shorter planning horizons, the service level constraint is not met later during the planning horizon.

Case study 2

A second case study was used to test the solution framework for a larger supply chain network. The supply chain network considered in this case study consists of six markets, six warehouses, six production sites, and five suppliers, as shown in Figure 12. There are two products and three raw materials. For the hybrid simulation-based optimization model, a difference of 1% of profit obtained from simulation model is used as the termination criteria. The planning horizon for the problem is 10 planning periods. The mean demand was considered to be 80 for each product at each market during each period. The total number of demand scenarios generated for the second stage was 500. Tables 3–5 contain the values of distances between the different entities of the supply chain network.

Figure 13 below shows how the operating profit of the network varies as the variability in demand increases. The risk constraint is relaxed and the demand variability is increased. It can be seen that the profit increases with demand variability. As the variability increases, the total cost starts to increase. However, as the desired service level is maintained, the revenue also increases. Unlike the first case study, the profit does not decreasing at higher levels of demand variability. Beyond a coefficient of variability of value 0.30, the problem becomes infeasible as the service level constraint cannot be satisfied. Therefore, we know that there is an upper bound of 0.3 on the flexibility of the network.

Figure 14 shows a comparison of the transportation capacity cost with demand variability. Similar to Case study 1, it can be seen that increased transportation capacity is required as demand variability increases. However, the highest value of transportation capacity cost reached is observed to be still lower than the maximum value possible. Unlike the first case study, the transportation capacity cost does not reach a constant value beyond which it does not increase. This is because of the presence of other constraints that make the problem infeasible for coefficient of variation higher than 0.3. Figure 15 shows the variation in secondary shipment with demand variability. It can be seen that increased secondary shipment is

Table 3. Distance of Warehouses from Markets

	mkt1	mkt2	mkt3	mkt4	mkt5	mkt6
wh1	10	35	30	25	20	15
wh2	15	10	35	30	25	20
wh3	20	15	10	35	30	25
wh4	25	20	15	10	35	30
wh5	30	25	20	15	10	35
wh6	35	30	25	20	15	10

Table 4. Distance of Warehouses from Production Sites

	ps1	ps2	ps3	ps4	ps5	ps6
wh1	10	15	20	25	30	35
wh2	35	10	15	20	25	30
wh3	30	35	10	15	20	25
wh4	25	30	35	10	15	20
wh5	20	25	30	35	10	15
wh6	15	20	25	30	35	10

Table 5. Distance of Production Sites from Raw Material Suppliers

	sup1	sup2	sup3	sup4	sup5
ps1	10	15	20	25	30
ps2	20	10	15	20	25
ps3	25	30	10	15	20
ps4	20	25	30	10	15
ps5	15	20	25	30	10
ps6	15	20	25	30	10

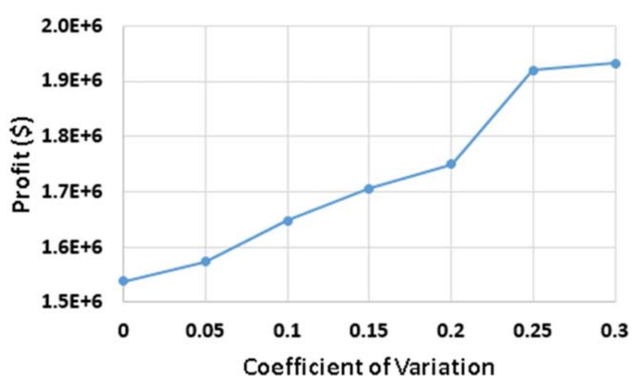

Figure 13. Variation of profit with demand variability.

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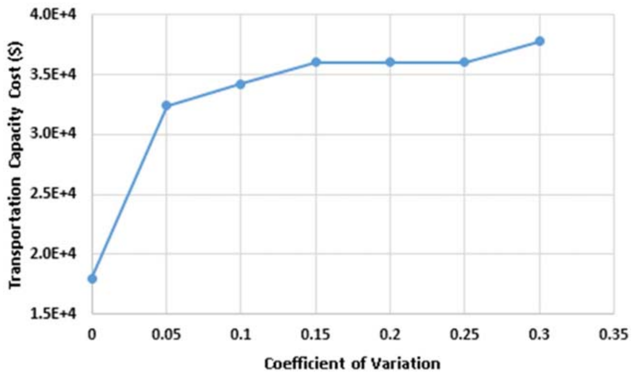

Figure 14. Comparison of transportation capacity cost with variability.

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required to meet the required service level in case of increased demand variability.

The value of flexibility is obtained for different levels of risk. It is seen that just as in the case of the first case study, the value of flexibility increases as the value of downside risk is increased. However, it reaches a constant value beyond a certain level of risk. The target cost was considered to be \$3E+05. It can be seen in Figure 16 that for a completely risk-averse condition where the downside risk is \$0, the value of flexibility is 0.0. However, for a downside risk of \$1.6E+05, the value of flexibility increases to 0.3. Beyond that level of risk, the flexibility does not change. This is because the service level constraint becomes active in that region. For downside risk of less than \$1.6E+05, the downside risk constraint is active. Therefore, the value of flexibility keeps increasing as the downside risk is increased in that region.

The computational time required to solve the case study at a particular risk level and demand variance is 30,581 s. This is higher than the time required to solve Case study 1 due to the larger size of the supply chain network considered in this case study. Compared with Case study 1, the total number of agents has increased from 11 to 23 while the computational time has increased by around 120%. As the number of agents in the model increases, the size of the optimization problem solved during each iteration of the hybrid simulation-based optimization approach grows larger. Reducing the solution time for the optimization problem will be investigated in our future work.

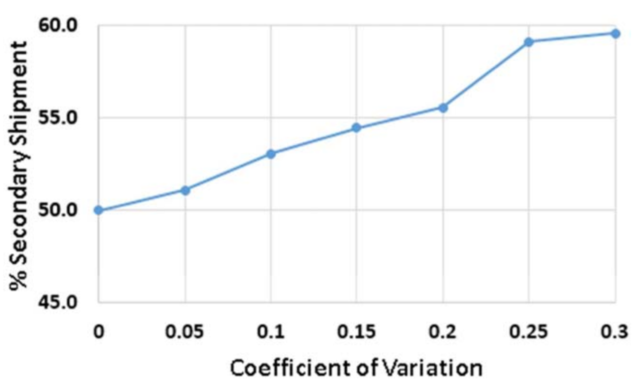

Figure 15. Variation of secondary shipment with demand variability.

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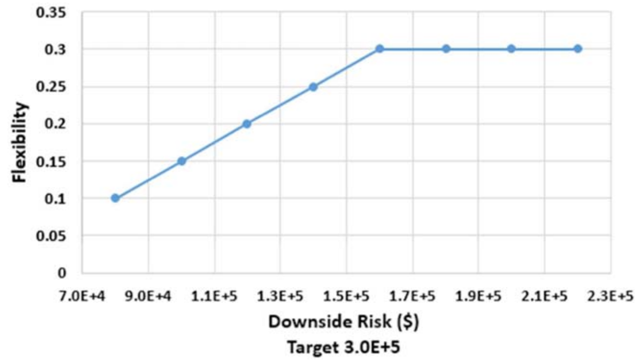

Figure 16. Variation of flexibility with risk.

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Conclusions

In this work, a hybrid simulation-based optimization framework is presented for assessment of flexibility of supply chain operations and risk management. Uncertainty in demand is considered and it is considered that planning decisions for the current period are taken after the demand for that period have realized. Decisions are taken based on the information available at that time. The framework enables the evaluation of flexibility of the network and can provide risk-neutral as well as risk-averse solutions. The framework determines the optimal decisions for the supply chain network at each period considering the uncertainty in the future periods.

The hybrid simulation-based optimization approach used in the study enables a detailed representation of the supply chain dynamics. The agent-based simulation approach provides a convenient way to model the behavior of the different entities and can be improved to depict the actual dynamics more realistically. Although the proposed framework was used for rather small scale supply chain problems, it can conveniently be used for larger problems with more number of agents and also where agents behave differently and follow different decision making policies.

In this study, only demand uncertainty is incorporated in the model as the source of uncertainty. Other sources of uncertainty can also be included. The flexibility metric in that case would depend on the variability in other input parameters. Also, other measures of making the supply chain more flexible should be included to have a systems approach. To make the overall supply chain more flexible, different aspects of the supply chain need to introduce flexibility. Different sources of uncertainty and flexibility will be considered in our future work.

Acknowledgment

Financial support from NSF under NSF CBET 0966861 is gracefully acknowledged.

Notation

Indices

t = planning period
p = production site
sup = supplier
m = distribution market
wh = warehouse
s = product state
r = raw material state
sc = scenario

Sets

T = planning periods
PS = production sites
SUP = suppliers
M = distribution markets
WH = warehouses
PR = product states
R = raw material states
SC = scenarios

Parameters

nSC = total number of scenarios
h_s^{wh} = holding cost of product s at warehouse wh
h_s^p = holding cost of product s at production site p
h_r^p = holding cost of raw material r at production site p
u_s^m = backorder cost of product s at distribution market m
$d_s^{wh,m}$ = unit transportation cost of product s from warehouse wh to market m
$d_s^{p,wh}$ = unit transportation cost of product s from production site p to warehouse wh
$d_r^{sup,p}$ = unit transportation cost of raw material r from supplier sup to production site p
$\mathrm{dis}^{wh,m}$ = distance between warehouse wh and market m
$\mathrm{dis}^{p,wh}$ = distance between production site p and warehouse wh
v^p = unit production cost at site p
c_s^{wh} = unit transportation increase cost at warehouse wh for product s
c_s^p = unit transportation increase cost at production site p for product s
$\mathrm{Dem}_s^{m,t,sc}$ = demand of product s at market m for period t for scenario sc
stcap_r^p = inventory holding capacity of raw material r at production site p
stcap_s^p = inventory holding capacity of product s at production site p
stcap_s^{wh} = inventory holding capacity of product s at warehouse wh
prcap_s^p = production capacity of product s at production site p
R = upper bound on downside risk
L = lower bound on service level

Variables

Cost1 = cost of the first stage
$\mathrm{Cost2}_{sc}$ = cost of the second stage for scenario sc
$D_s^{wh,m,t,sc}$ = amount of product s transported from warehouse wh to market m at period t for scenario sc
$D_s^{p,wh,t,sc}$ = amount of product s transported from production site p to warehouse wh at period t for scenario sc
$D_r^{sup,p,t,sc}$ = amount of raw material r transported from supplier sup to production site p at period t for scenario sc
$\mathrm{Inv}_s^{wh,t,sc}$ = inventory level of product s at the end of the planning period t at warehouse wh for scenario sc
$\mathrm{Inv}_s^{p,t,sc}$ = inventory level of product s at the end of the planning period t at production site p for scenario sc
$\mathrm{Inv}_r^{p,t,sc}$ = inventory level of raw material r at the end of the planning period t at production site p for scenario sc
$\mathrm{Inv}_r^{sup,t,sc}$ = inventory level of raw material r at the end of the planning period t at supplier *sup* for scenario sc
$U_s^{m,t,sc}$ = backorder amount of product s at the end of planning period t at market m for scenario sc
$P_s^{p,t,sc}$ = amount of product s produced at production site p during planning period t for scenario sc
$C_r^{p,t,sc}$ = amount of raw material r consumed at production site p during planning period t for scenario sc
$\mathrm{CI}_s^{wh,t,sc}$ = increase in transportation capacity at warehouse wh for product s at planning period t for scenario sc
$\mathrm{CI}_s^{p,t,sc}$ = increase in transportation capacity at production site p for product s at planning period t for scenario sc
DRisk = value of downside risk
$\mathrm{Sl}_{m,s,sc}$ = service level for product s at market m for scenario sc
$\mathrm{sp}_{s,m}$ = selling price of product s at market m
Rev_{sc} = revenue for scenario sc

List of parameter values

$n\mathrm{SC} = 500$
$h_s^{wh} = 1.0$
$h_s^p = 1.0$
$h_r^p = 1.0$
$u_s^m = 10.0$
$d_s^{wh,m} = 1.0$
$d_s^{p,wh} = 1.0$
$d_r^{sup,p} = 1.0$
$v^p = 1.0$
$c_s^{wh} = 300.0$
$c_s^p = 300.0$
$\mathrm{stcap}_r^p = 800.0$
$\mathrm{stcap}_s^p = 800.0$
$\mathrm{stcap}_s^{wh} = 800.0$
$\mathrm{prcap}_p^s = 75.0$
$\mathrm{trcap}_s^p = 20.0$
$\mathrm{trcap}_s^{wh} = 20.0$
$\mathrm{CI}_s^{p,wh} = 20.0$
$\mathrm{CI}_s^{wh,m} = 20.0$

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