HYBRID SIMULATION BASED OPTIMIZATION FOR SUPPLY CHAIN MANAGEMENT

by

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ABSTRACT OF THE DISSERTATION

Hybrid Simulation based Optimization for Supply Chain Management

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Supply chain management (SCM) has been recognized as one of the key issues in the process industry. The growing size of the distributed supply chain structures, market dynamics and variability involved in the internal operations pose a challenge to efficiently managing the whole network. Globalization of supply chains and advances in information technology have led to a greater need for integrated operations as they have caused a more distributed network with potentially larger number of customers. It is essential that the various bodies constituting the supply chain operate in an integrated manner and their activities are synchronized towards a common goal. Thus, there is a need for efficient integration of information and decision making among the various functions of the supply chains.

The growing need for integrated information and decision-making necessitates the development of a framework which allows the different entities of a supply chain to have access to a common information system as well as provides them with advanced decision-making tools. With the advancements in information technology, it is possible

for supply chain members to share information and several such tools are also commercially available. However there is a need to combine intelligent decision making with information sharing to develop the required framework.

The main objective of this dissertation is the development of novel methodologies that will facilitate intelligent decision-making and their application in the analysis of supply chains for chemical industries. Simulation models are used to depict supply chain dynamics so that they represent the decision-making by various entities. In order to obtain improved decision-making, a hybrid simulation based optimization framework is proposed. The framework considers the decision rules followed by the different entities and guides the simulation model towards improved solutions. The benefits of these methodologies include a more realistic representation of supply chain dynamics and reduced computational times for large-scale problems. The framework is applied to a number of case studies. Uncertainty in supply chain is also considered and the framework is used to determine the flexibility of the supply chain and manage risk under uncertainty. A derivative free optimization method is also proposed which has been applied to optimize the performance of a multi-enterprise supply chain network.

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1 Decision making in the process industry

Decision making in the process industry ranges across different scales, from process control to supply chain management as shown in figure 1.1. The decisions taken at these levels vary in terms of time horizon, complexity and objectives. On one end of the spectrum, strategic decisions determine the configuration of the supply chain network and usually have time horizons of years. On the other end, process control decisions have time horizons of seconds and focus on transition periods when processes are subject to disturbances. Although these levels are interconnected, they are considered in silos traditionally. Separate decision-making at these levels either leads to infeasibility or sub-optimality. Therefore there is a need to integrate these levels and make the decisions simultaneously.

A supply chain (SC) is a complex dynamic system. Unlike the term suggests, it is usually a network of various entities performing different functions instead of linear chains. The operations of an SC usually proceed as local interactions among the entities rather than a central entity coordinating all the operations. These interactions lead to flows of information, material and money which in turn result in subsequent interactions. Therefore the overall operations of an SC develop as a network of feedback loops of interactions and information, material and money flows[1,2]. The term SCM has evolved to encompass operations of supply, manufacturing and distribution as well as integration of information and decision-making among the different entities constituting the supply chain. Typically in the context of supply chains, a lot of emphasis is laid on distribution. However with regard to the chemical industry, manufacturing plays an extremely

significant role. Grossmann uses the term "Enterprise-wide Optimization" and distinguishes it from supply chain optimization by laying more emphasis on optimization of the manufacturing facilities[3].

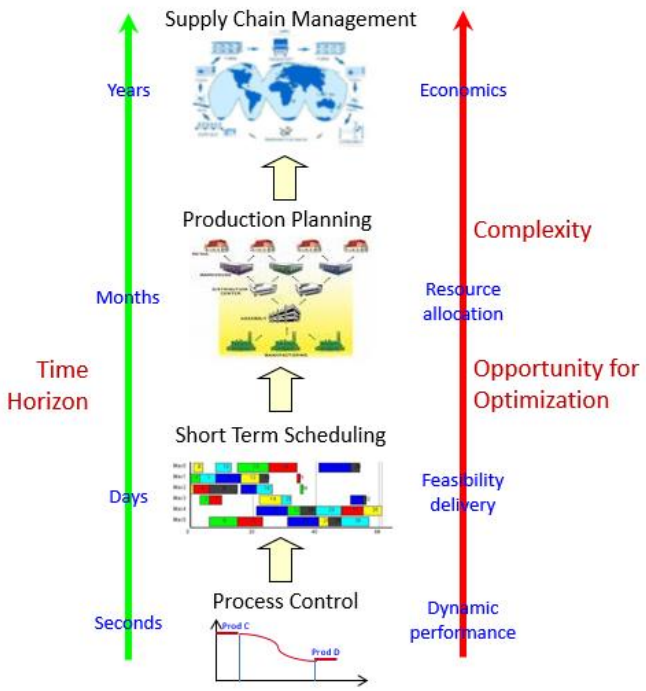

Figure 1.1: Enterprise-wide decision-making

1.1 Motivation

Supply chain management (SCM) has been recognized as one of the key issues in process industry. The growing size of the distributed SC structures, market dynamics and variability involved in the internal operations pose a challenge to efficiently managing the whole network. It is essential that the various bodies constituting the supply chain operate in an integrated manner and their activities are synchronized towards a common goal. Globalization of SC's and advances in information technology they have caused a more distributed network with potentially larger number of customers. That, in turn has led to a

greater need for integrated operations. Thus, there is a need for efficient integration of information and decision making among the various functions of the supply chains[3].

The growing need for integrated information and decision-making necessitates the development of a framework, which allows the different entities of a supply chain to have access to a common information system, as well as provides them with advanced decision-making tools. With the advancements in information technology, it is possible for supply chain members to share information and several such tools are also commercially available. However there is a need to combine intelligent decision making with information sharing to develop the required framework. This proposal *targets the development of novel methodologies that will facilitate intelligent decision-making and analysis in supply chains for chemical industries*.

1.2 Significance in the chemical industry

According to National Academies Workshop report[4] 80,000 chemicals are registered for use in the US and 2,000 more are introduced each year. According to the American Chemistry Council, the business of chemistry [in the United States] is a $460 billion enterprise and although chemical companies invest more in R&D than any other business sector, the effects of many chemicals on human health and the environment are far from benign, and are often largely unknown. Among the grand challenges identified for the chemical industry to move forward, most are related to better utilization of resources. Due to its tremendous significance to the US economy, the increased complexity given the highly diversified nature of the chemical industry, and the rapidly growing degrees of freedom given by globalization, application of such decision-making methodologies to the chemical supply chain can result in great benefits. In practice, managing and

designing chemical supply chains is a complex task. There are a number of very important challenges:

- Most chemical companies use a variety of different tools including complex spreadsheets, enterprise resource planning, and supply chain management applications that in most times do not talk to each other and thus are not appropriate to track and optimize the company's assets throughout the entire enterprise
- Most of the times information is gathered and kept in different places and viewed by different people. Thus different decision makers do not have the information that they need to make the optimal decisions for the entire enterprise since they are missing part of the picture.
- Most of the chemical companies utilize SC simulation to understand their enterprise state using different simulation techniques, however very rarely the decision makers have the capacity to study different scenarios before a decision is due and moreover to understand what are the implications of different parameters in their SC state as well as how far is their decision from the optimum one.
- Designing and operating a supply chain involves decisions that span strategic, tactical, and operations spaces. These decisions have a wide span of time scales and range from global in scope to the very localized. While these decisions are highly interdependent it is a challenge for individual decision makers to consider this interdependence. This results in outcomes that do not meet the expectations.
- Products often serve as basic raw materials far upstream from the final consumers. This can lead to complicated market dynamics that are not easily understood

by decision makers. Thus market signals may be misinterpreted resulting in poor planning decisions.

- Being capital intensive, chemical companies have very long capital planning horizons that must deal with significant uncertainty and financial risk. It is a tremendous challenge for chemical companies to design supply chains that are responsive to market dynamics, changing energy availability, new regulations, and new technology.
- Extended supply chains involving raw material suppliers, manufacturing facilities, distribution centers, and final customers can be global and involve many transportation modes that are vulnerable to disruption. To be sustainable, supply chains need to be flexible and resilient. Quantifying supply chain resiliency so that it can be rigorously considered during design and operations is a difficult challenge.
- For a chemical company, sustainability requires consideration of the potential environmental, social and economic impacts for all the company's activities and to improve not only what is in their direct control, but what they can influence or choose in both upstream and downstream supply chains for their products and activities. Inclusion of additional dimensions greatly increases the complexity of the supply chain management, but chemical companies must take on this challenge if they are to successfully find solutions that have farther-reaching and longer-lasting benefits.

2 Agent based Simulation Models in Supply Chain Management

Performance evaluation in supply chain management can basically be done using analytical methods, physical experimentations or simulations.[5] Analytical methods become too complex to be solved for large scale systems and physical experimentations are impractical due to technical and cost limitations. Simulation models are a practical approach to study such systems and therefore have been widely used.

There are three main types of simulation models that have been used in the field of SCM. System dynamics[6] is a continuous simulation approach where the states vary continuously. Enterprises can be seen as complex systems with flows of various types and inventory or levels that can be determined by integrating flows over time. The approach does not differentiate between different types of entities of the supply chain network. Discrete event simulation modeling is widely used in job shop simulation. As expected, it is also used in SCM. However the size of problems in SCM poses a challenge for this approach. The large problem size results in prohibitively large number of events which makes the approach infeasible for supply chain problems. Agent based modeling and simulation has emerged as a more suitable approach for the supply chain research field compared to the traditional methods. The industrial supply chain networks are otherwise too complex to be adequately modeled. Also traditionally, a lot of assumptions have been used to model such systems. Agent based simulation enable the relaxation of such assumptions and thus facilitate a more realistic representation of the system.

A supply chain is a distributed and decentralized system with autonomous entities. For such a system, it is suitable to model from a bottom-up perspective. Agent based modeling can be a preferred approach to model a supply chain. In this work, agent-based

simulation models of the entire supply chain have been developed to provide a better representation of the dynamic environment of the supply chain. The model has been implemented using the Repast simulation platform and Java programming environment. Java is an object-oriented language which makes it suitable for modeling the individual agents. Each agent has been created as an instance of a class. The individual classes for the agents derive from a parent class that has the common attributes each supply chain agent should have.

2.1 Agents

An agent based model consists of ‘agents’. It has been difficult to have a universal agreement on the precise definition of ‘agents’. However in simple terms, agents are independent small computer programs that may be used to represent the individual entities in the simulated world. These can interact with each other and help reveal or explain phenomena. As shown in figure 2.1, agents can have diverse, heterogeneous and dynamic attributes. While some authors believe any independent component to be an agent, others believe that an agent should be able to learn from the environment and therefore be adaptive. So essentially an agent can be coded as either as simple as a set of if-then rules or as intelligent as possible by Artificial Intelligence[7].

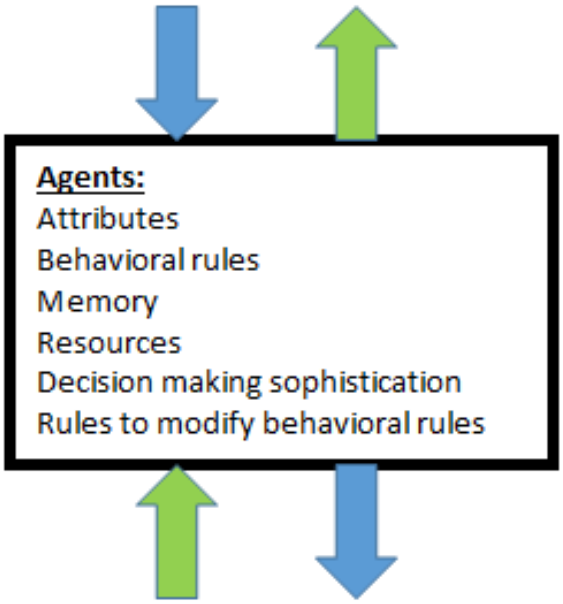

Figure 2.1: A typical agent

For practical modeling purposes, it is considered that agents should have the following basic properties.

- Agents should be autonomous. Given the environment, agents should function independently and interact with other agents on their own. An agent's decisions are a function of the information it receives from the environment.
- Agents should be discrete individuals that have a set of attributes and decision-making ability. Discreteness helps determine whether an element, an attribute belongs to a particular agent or is shared among agents.
- Agent should interact with other agents. In the context of supply chain networks, these interactions can be in the form of flow of information, material or money.

Apart from these basic properties, they may have additional properties based on the system. For example, an agent may have the ability to learn or adapt. It may have specific goals that drive its behavior[7].

In the following chapters, agent based simulations have been used for supply chain networks. All the agents have some common agents. However based on the specific problem being studied, the simulation model may have additional agents or an agent may have additional attributes and actions. Since the simulation models used in each of the studies are different from each other in some aspects, the individual models are described separately in each chapter.

2.2 Supply Chain Agents

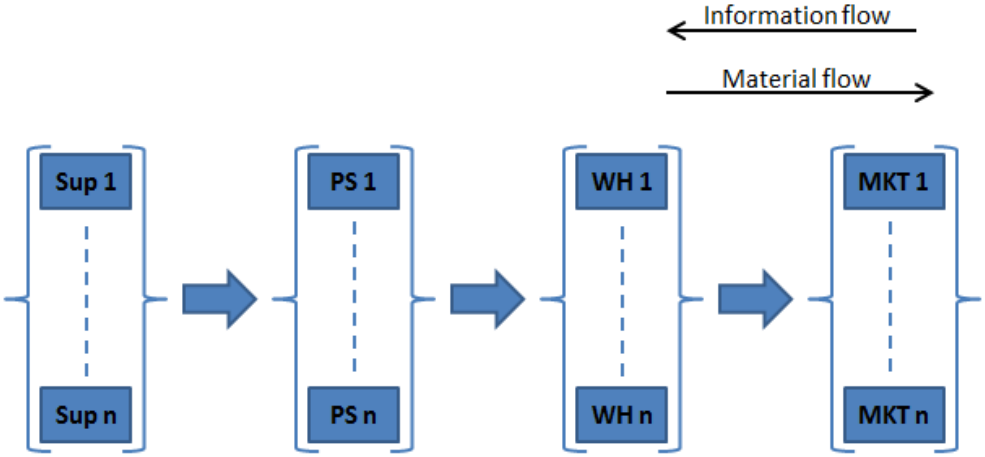

Figure 2.2: Supply chain network

Figure 2.2 shows the overall structure of the supply chain networks used in all the work presented. The actual size of the network is variable since that depends on the specific case study being solved. As we can see in the figure, the network can be modeled as consisting of 4 kinds of agents, namely markets, warehouses, production sites and raw

material suppliers. Additional agents and sub-agents have been included to add some attributes and functionalities but these are the 4 basic agents present.

Each agent has its own characteristic behavior. They are able to interact with each other and adapt their behavior accordingly. Communication among the agents is an important feature of the supply chain. Since the agents can communicate with each other, they are able to schedule actions for other agents after they have performed a particular action. Apart from being connected by information flows, the agents are also connected by material flows. Sharing of information among agents from different stages of the supply chain has been considered in the model. The agents are able to share information regarding their inventory, and time to fulfill orders with the downstream agents. This enables coordination among the agents for demand allocation and order fulfillment.

3 Supply Chain Management using an Optimization Driven Simulation Approach

Supply chain networks are often very complex with a large number of entities and complex interactions among them like inventory policies, modes of transport and stochastic demand. Different solution approaches have been used to model such systems. Traditionally, mathematical optimization techniques have been used to solve such problems. However it is often difficult to model the detailed behavior of each entity and their interactions using these techniques. These models are therefore, simplified versions of the actual system. For large networks, even these simplified models become so computationally expensive that they do not remain solvable. Another approach for solving such problems is building simulation models. Simulation models can incorporate the individual behavior of the supply chain entities. They provide more flexibility and are able to better represent the complex environment of a supply chain. However, they provide a solution, which is often away from the optimal one. This section provides a brief overview of the work that has been done in the area of supply chain optimization problem.

3.1 Optimization approaches

The different optimization models present in the literature can be classified on the basis of mathematical programming approaches used such as linear and nonlinear programming, multi-objective programming, stochastic programming etc. Since our proposed approach is based on the multi-objective optimization we are reviewing the works in this category. Chen et al. [8] develop a multi-objective production and distribution planning model to study fair profit distribution for a multi-enterprise supply

chain network. There are multiple objectives of the model such as profit maximization of each enterprise, customer service level, safe inventory level and fair profit distribution. The proposed method is shown to provide an improved solution for multi-objective problems by using one numerical example. Chen and Lee [9] proposed a multi-product, multi-stage, and multi-period scheduling model for a supply chain network. Uncertainty of market demands and product prices has been considered and the model has multiple goals which are incommensurable. Demand uncertainty has been modeled using different scenarios. Fuzzy sets are used for describing the sellers' and buyers' incompatible preference on product prices. A mixed integer nonlinear programming problem is formulated for the supply chain scheduling model. It has conflicting objectives like fair profit distribution among all participants, safe inventory levels, maximum customer service levels, and robustness of decision to uncertain product demands. A numerical example is used to prove the effectiveness of the proposed method in providing a compromised solution for a supply chain network with uncertainty. Chern and Hsieh [10] solved master planning problems for a supply chain network using a heuristic algorithm. The supply chain has multiple finished products. The different objectives of the algorithm are minimization of delay penalties, minimization of use of outsourcing capacity and minimization of cost. The algorithm was shown to be very efficient in solving master planning problems. The results generated were sometimes the same as those of linear programming model. Guillen-Gosalbez et al. [11] address the design of hydrogen supply chains. A bi-criterion MILP is formulated to determine the optimal design of the production-distribution network. The objectives considered are minimization of cost and environmental impact. Life Cycle Assessment is used to quantify the environmental

impacts. Pareto solutions are obtained for the problem by using a bi-level algorithm. You and Grossman [12] formulated a mixed-integer nonlinear program for finding out the optimal design of process supply chains. The study is concerned with the economic and responsive criteria of the supply chain. Minimization of cost is the economic objective while minimization of maximum guaranteed service time is the responsiveness objective of the model. The model is used to predict the optimal network structure, transportation amounts and inventory levels. These values are obtained under different specifications of responsiveness. For a detailed overview of the mathematical programming models for supply chains, readers are suggested to refer to [13].

3.2 Simulation approaches

Optimization models have been proved useful in the past. However these models are simplifications of the real supply chain and hence do not represent the actual picture. Dynamic process simulation has been successfully used as a tool to understand and improve decision-making processes. Different simulation approaches have been used in the literature including system dynamics[14-17], discrete event simulation [18-23] and agent-based simulation[24-38].

Agent based simulation is a powerful technique that has been used to develop dynamic models for supply chain networks. In an agent based model, each entity of the supply chain can be modeled as a separate agent with its own autonomous behavior. Swaminathan et al. [39] proposed an approach where supply chain models are composed of supply chain agents, their constituent control elements and their interaction protocols. These are represented by different software components. The challenge of time and effort required to develop simulation models for supply chains is overcome by the proposed

modeling framework. The approach enabled the analysis of performance from different organizational perspectives. Julka et al. [40] proposed a framework to model, manage and monitor supply chains. They classified the supply chain elements as entities, flows and relationships. They consider different situations arising in a supply chain and use the framework to analyze different business policies for those situations. They illustrated the application of the framework to a refinery supply chain [41]. Garcia-Flores and Xue Wang [42] described a multi-agent system to support the distributed supply chains over internet. The agents communicated using the common agent communication language, knowledge query message language. Dynamic distributed simulation of chain behavior allowed compromise decisions to be taken rapidly and also evaluated quantitatively. For a detailed overview of the agent based simulation models for supply chains, readers are suggested to refer to [43].

3.3 Hybrid approaches

Advantages of both optimization and simulation approaches have been demonstrated. In order to make use of both the models and their advantages, hybrid approaches which combine the two approaches have been developed[44-55]. Shanthikumar and Sargent [56] have differentiated between hybrid simulation/analytic modeling and hybrid simulation/analytic models defining each of them. They classified both the categories and gave examples of each of them. Lee and Kim [57] developed an integrated multi product, multi period, multi shop production and distribution model. The objective was to meet the retailers' demand while keeping the inventory as low as possible. They proposed a hybrid method combining mathematical programming and simulation model to minimize the total cost which comprised production cost, inventory holding cost, distribution cost

and deficit cost. Gjerdrum et al. [58] constructed a distributed agent system for a supply chain. They used gBSS (gBSS – © Process Systems Enterprise), a numerical optimization program, to solve the scheduling problem at each production site and used the agent system for tactical decision-making and control policies. They used the framework to study different parameters like reorder point, reorder quantity and lead time. Davidsson et al. [59] provided a very good comparative discussion of the strengths and weaknesses of agent-based approaches and classical optimization techniques. They concluded that the two approaches are complementary and thus it was beneficial to use their combination. They presented two case studies studying two different aspects of hybrid systems. They showed that the ability of agents to be reactive and the ability of optimization techniques to find high quality solutions can be helpful in case of such hybrid systems. Mele et al. [60] proposed a framework where they coupled an agent based simulation model accurately representing a supply chain with a genetic algorithm to improve supply chain operation under uncertain scenarios. The proposed approach did not guarantee optimality of the solutions but provided reasonable and practical solutions. Almeder et al. [61] used a combination of discrete event simulation and linear programming to develop a general framework which supported operational decisions for supply chain networks. They estimated cost parameters, production and transportation times for the optimization model based on the initial simulation runs. The optimization model is used to generate decision rules for the simulation model. This was done iteratively until a small difference between subsequent solutions was reached. The proposed approach was applied to test examples and the results showed that it was faster compared to conventional mixed integer models in stochastic environment. In a recent work by

Nikolopoulou and Ierapetritou [62], a hybrid simulation optimization approach is proposed to address the problem of supply chain management. They combined a mathematical model with an agent-based model to minimize the total cost of the supply chain. The performance of the supply chain was measured using only economic criteria whereas the environmental impacts of the supply chain have not been considered. The hybrid approach has been used to solve the optimization problem using profit as a single objective. Compared to their work, the approach proposed in this work reduces the amount of information exchanged between the optimization and the simulation model in order to enable a more flexible solution approach where the optimization is only used as a target setting. Moreover, a multi-objective problem is solved by taking the environmental impact of the supply chain as an additional objective for decision-making.

In this study, a hybrid simulation based optimization approach has been proposed to solve supply chain operation problems. It is assumed that the design for the supply chain has been pre-determined. Decisions such as the location and capacities of the warehouses and production sites, the modes of transportation to be used, products to be manufactured are made during the design phase. So once the design of the supply chain is fixed, the operation takes place within these constraints. A simulation model is used to capture the realistic conditions of a sustainable supply chain by incorporating the characteristic behavior of the entities while an optimization model is used to guide the simulation towards optimality. The proposed framework couples the independent simulation and optimization models iteratively to arrive at the optimal solution. The idea is to combine the advantages of both the models by representing a dynamic SC and providing an optimization method at the same time. The supply chain consists of a network of different

facilities (raw material suppliers, production sites, warehouses, markets) and different transportation modes connecting these facilities. The goal is to reduce the overall cost, which consists of transportation cost, inventory cost, production cost, and backorder cost while keeping the environmental impact within a predefined upper limit. Two rather small-scale supply chain operation problems have been solved using the proposed framework to demonstrate its applicability.

The rest of the chapter is organized as follows. Section 3.2 presents the problem formulation which also describes the independent optimization and simulation models as well as the hybrid simulation-optimization framework. Section 3.3 presents the case studies which have been studied using the hybrid approach which is followed by some concluding remarks in section 3.4.

3.4 Problem formulation

A supply chain consisting of raw material suppliers, production sites, warehouses and markets has been considered. The markets cater to demand of different products which can be manufactured using three raw materials. A bill of material has been used to define the relation between raw material consumption and amount of product manufactured. Demand of products at the markets is known for a given number of planning periods. The warehouses have limited storage capacity for products while the production sites have storage capacities for products and raw materials. The production sites also have a limited production capacity for products. The various capacities have been assumed to be available and fixed. Information flow between the entities has been considered to take place without any time delay while there is a time delay associated with material flows.

There are costs associated with transportation, inventory holding, production and backorders. Shipments can take place through different modes of transport and manufacturing of products can also be done using different technologies. The modes of transport and production differ in cost and carbon emission. Shipment, inventory and production information for all the planning periods have to be found out so as to minimize cost while taking the environmental impacts into consideration. The environmental impacts are required to be kept below a certain predefined level.

3.4.1 Optimization model

The multisite model includes supplier, production site, warehouse and market constraints. The set of products ($s \in PR$) are stored at the warehouses ($wh \in WH$). Warehouses deliver the products to meet the demands at the markets ($m \in M$) over the planning horizon ($t \in T$). Warehouses receive products from various production sites ($p \in PS$) which in turn manufacture these products from the raw materials ($r \in R$) obtained from raw material suppliers ($sup \in SUP$). The planning horizon has been discretized into fixed time length (daily production periods). There are no time delays associated with information and material flows. Shipment and manufacture of products take place through different modes of transport ($mt \in MT$) and production ($mp \in MP$) respectively. These different modes can vary in the cost they incur and the carbon emission they produce. The total cost associated with the supply chain is the summation of transportation costs, inventory holding costs, production costs and backorder costs. Transportation cost has been considered to be proportional to the amount of shipment. Inventory holding cost has been considered proportional to the inventory level. Production cost is proportional to the amount of product produced while backorder cost is proportional to the amount of

unfulfilled demand. Similarly carbon emissions have been considered to be proportional to the amount of shipment and the amount of product manufactured. The model has been formulated as a multi-objective mixed integer linear programming problem. Minimization of total cost and minimization of total carbon emissions are the two objectives. The model has been solved using the ε-constraint method.

The optimization model is as follows.

$\min \sum_{t}\sum_{wh}\sum_{s\in PR} h_s^{wh} Inv_s^{wh,t} + \sum_{t}\sum_{p}\sum_{s\in PR} h_s^{p} Inv_s^{p,t} + \sum_{t}\sum_{p}\sum_{r\in R} h_r^{p} Inv_r^{p,t}$ $+\sum_{t}\sum_{\sup}\sum_{r\in R} h_r^{\sup} Inv_r^{\sup,t} + \sum_{t}\sum_{m}\sum_{s\in PR} u_s^{m} U_s^{m,t} + \sum_{t}\sum_{p}\sum_{mp}\sum_{s}\left(FixCost^{p} w_t^{p} + VarCost^{p} P_s^{p,t}\right)$ $+\sum_{t}\sum_{mt}\sum_{m}\sum_{wh}\sum_{s\in PR} d_s^{wh,m} D_s^{wh,m,t} + \sum_{t}\sum_{mt}\sum_{wh}\sum_{p}\sum_{s\in PR} d_s^{p,wh} D_s^{p,wh,t} + \sum_{t}\sum_{mt}\sum_{\sup}\sum_{p}\sum_{r\in R} d_r^{\sup,p} D_r^{\sup,p,t}$	1
st $U_s^{m,t} = U_s^{m,t-1} + Dem_s^{m,t} - \sum_{wh\in WH} D_s^{wh,m,t}, \quad \forall s\in PR, m\in M, t\in T$	2
$Inv_s^{wh,t} = Inv_s^{wh,t-1} - \sum_{m\in M} D_s^{wh,m,t} + \sum_{p\in PS} D_s^{p,wh,t}, \quad \forall s\in PR, wh\in \mathrm{WH}, t\in T$	3
$Inv_s^{p,t} = Inv_s^{p,t-1} + P_s^{p,t} - \sum_{wh\in WH} D_s^{p,wh,t}, \quad \forall s\in PR, p\in PS, t\in T$	4
$Inv_r^{p,t} = Inv_r^{p,t-1} - C_r^{p,t} + \sum_{\sup\in SUP} D_r^{\sup,p,t}, \quad \forall r\in R, p\in PS, t\in T$	5
$Inv_r^{\sup,t} \le stcap_r^{\sup}, \quad \forall r\in R, \sup\in SUP, t\in T$	6
$Inv_r^{p,t} \le stcap_r^{p}, \quad \forall r\in R, p\in PS, t\in T$	7
$Inv_s^{p,t} \le stcap_s^{p}, \quad \forall s\in PR, p\in PS, t\in T$	8
$Inv_s^{wh,t} \le stcap_s^{wh}, \quad \forall s\in PR, wh\in WH, t\in T$	9
$\mathrm{P}_s^{p,t} \le prcap_s^{p}, \quad \forall s\in PR, p\in PS, t\in T$	10

$E = \sum_{t}\sum_{mt}\sum_{m}\sum_{wh}\sum_{s\in PR} et^{wh,m} D_s^{wh,m,t} + \sum_{t}\sum_{mt}\sum_{wh}\sum_{p}\sum_{s\in PR} et^{p,wh} D_s^{p,wh,t}$ $+\sum_{t}\sum_{mt}\sum_{\sup}\sum_{p}\sum_{r\in R} et^{\sup,p} D_r^{p,\sup,t} + \sum_{t}\sum_{p}\sum_{mp}\sum_{s}\left(ep^{p} P_s^{p,t}\right)$	11
$E \le ecap$	12

The objective function in equation 1 minimizes the total cost which consists of inventory costs, backorder costs, production costs and transportation costs. Equations 2-5 are the inventory balance equations at the different nodes of the supply chain. Equation 2 describes the backorders at the markets. Any unfulfilled demand gets accumulated as backorder. Equation 3 predicts the inventory at warehouses, shipments from warehouses to markets and shipments from production sites to warehouses. Equation 4 predicts the product inventory at production sites, production amounts and shipments from production sites to warehouses during each planning period. Equation 5 predicts the inventory or raw materials at production sites, consumption of raw materials for the manufacture of products and shipments from raw material suppliers to production sites during each planning period. Equations 6-10 are capacity constraints for the different nodes. Equations 6–9 are storage capacity constraints for raw material suppliers, production sites and warehouses respectively while equation 10 is the production capacity constraint for production sites. Equation 11 and 12 are related to the total carbon emission occurring due to transportation and production. Equation 11 describes the total amount of carbon emission that occurs due to transportation and production while 12 defines the upper limit on the emission that is allowed.

The optimization model results in a mixed integer linear programming problem which has been implemented in GAMS 23.7.3 and solved using CPLEX 12.3.0.0 on Windows 7 operating system with an Intel Pentium D CPU 2.80 GHz microprocessor and 4.00 GB RAM.

3.4.2 Simulation model

As mentioned in Chapter 2, agent based simulation models have been used to represent the supply chain networks in this work. Each agent is an instance of a class and is represented by a collection of attributes and behaviors. The classes also contain implementations of different methods to define the behaviors of the agents. Below is a description of each of the agents.

3.4.2.1 Market agent

Demand for products originates at the market agent. When a market receives a demand, it sends *requests* for the required amounts of products to the warehouses. A *request* is not the actual order for products. A *request* is a way to procure information from the upstream agent regarding how much demand can be fulfilled and at what cost and time. Based on the response from warehouses, the market agent distributes the demand among the warehouses by following its ordering policy. As an ordering policy, the market gives first preference to the warehouse which responds with the lowest cost. It assigns an order of amount either equal to what the warehouse can fulfill or the demand amount, whichever is smaller. If the total demand cannot be fulfilled by the lowest cost warehouse, it assigns an order to the one with the cost next to the lowest cost warehouse. Order amount is decided as either the amount the warehouse can fulfill or the remaining demand, whichever is larger. Similarly, the market keeps assigning orders until the total

demand is assigned or all the warehouses have been considered. In case where more than one warehouse responds with the same cost, the market chooses the one with the maximum amount of demand it can fulfill and the least amount of time. It is desired that the demand is fulfilled during each planning period. However, partial or no fulfillment of demand is also allowed but at a backorder cost. In case of an oversupply from warehouses, the superfluous amount is retained for the future planning periods. The costs associated with this agent are inventory cost and backorder cost. Inventory cost is proportional to the amount of inventory at the agent. Backorder cost is proportional to the amount of backorders. These costs are calculated at the end of each day.

3.4.2.2 Warehouse agent

The warehouse agent maintains an inventory of products. On receiving a *request* from a market, the warehouse sends a *response* in terms of the fraction of demand it would be able to fulfill, the cost and time it would take to ship the products. In order to evaluate the fraction of demand it can fulfill, it considers the demand from all the markets. However, it has a preference level depending on contractual agreements. So it gives preference to the demand from markets with the highest preference level and attempts to fulfill demands from that market before fulfilling demands from markets with lower preference levels. Based on the responses from all the warehouses, the markets send orders for products. If the complete market demand has not been ordered, the markets send *requests* to warehouses again with updated demand. The demand has been updated by reducing the amount which has already been ordered. The process of sending *requests* to warehouses, receiving *response* from warehouses and assigning *orders* to warehouses continues until all the demand has been ordered or the wareshouses cannot fulfill any demand from the markets. In this manner, all the warehouses, together attempt to fulfill

the market demand. Sharing of information between warehouses and markets has been considered. If the demand cannot be fulfilled by a warehouse alone, the other warehouses receive *requests* from markets and they evaluate if they would be able to fulfill the demand. The warehouse agent fulfills the demand from the markets by using its inventory of products. It has a limited storage capacity and regulates its inventory using a reorder level-reorder amount inventory replenishment policy with continuous review. The reorder level and reorder quantity for the agent are pre-defined. When the inventory at the warehouse falls below the reorder level, it orders products from the production sites. In order to distribute its demand among the production sites, the warehouse sends *requests* to the production sites. The distribution is fixed based on the *responses* and ordering policy of the warehouse. As an ordering policy, the warehouse gives first preference to the production site which responds with the lowest cost. It assigns an order of amount either equal to what the production site can fulfill or the demand amount, whichever is smaller. If the total demand cannot be fulfilled by the lowest cost production site, it assigns an order to the one next to the lowest cost. Order amount is decided as either the amount the production site can fulfill or the remaining demand, whichever is smaller. Similarly, the warehouse keeps assigning orders until the total demand is assigned or all the production sites have been considered. In case more than one production site responds with the same cost, the warehouse chooses the one with the maximum amount of demand it can fulfill and the least amount of time. While sending shipments to the markets, the warehouse is able to distribute the total shipment among the different transportation modes available. It tries to minimize the transportation cost while keeping the total

carbon emission below a certain value. The costs associated with this agent are inventory cost and transportation cost.

3.4.2.3 Production Site agent

The production site agent is responsible for the manufacture of products from raw materials. A bill of material (BOM) relationship is defined for the conversion of raw materials to products. It also maintains a small inventory of raw materials and products to meet the demands from the warehouses. It has fixed production capacity and storage capacities. On receiving *request* from a warehouse, the production site sends a *response* in terms of the fraction of demand it would be able to fulfill, cost and time it would take to ship the products. In order to evaluate the fraction of demand it can fulfill, it considers the demand from all the warehouses. However, it has a preference level associated with all the warehouses depending on contractual agreements. So it gives preference to the demand from warehouses with the highest preference level and attempts to fulfill demands from that warehouse before fulfilling demands from a warehouse with a lower preference level. Based on the responses from all the production sites, the warehouses send orders for products. If the complete warehouse demand has not been ordered, the warehouses send *requests* to production sites again with updated demand. The demand has been updated by subtracting the amount which has already been ordered. The process of sending *requests* to production sites by warehouses, receiving *response* from production sites and assigning *orders* to production sites continues until all the demand has been ordered or the production sites cannot fulfill any demand from the warehouses. In this manner, all the production sites, together attempt to fulfill the warehouse demand since sharing of information between production sites and warehouses has been considered. If the demand cannot be fulfilled by a production site alone, the other

production sites evaluate if they would be able to fulfill the demand. The production site agent fulfills the demand from the warehouses by using its inventory of products. It regulates its raw material and product inventories using a reorder level-reorder up-to level inventory replenishment policy with continuous review. The reorder level and reorder up-to level for the agent are pre-defined. When the inventory falls below the reorder level, it orders raw materials from the suppliers. The production site orders raw materials from the raw material supplier with the minimum cost. The bill of material relationship is used to calculate the consumption of raw materials and production of products. While sending shipments to the warehouses, the production site is able to distribute the total shipment among the different transportation modes available. It tries to minimize the transportation cost while keeping the total carbon emission below a certain value. Similarly for the manufacture of products, the production mode can be chosen as to minimize the production cost while keeping the carbon emissions below a certain level. The costs associated with this agent are inventory cost, production cost and transportation cost. Inventory cost and transportation cost are proportional to the amount of inventory stored and amount of products transported, respectively. Production cost consists of the fixed and variable cost components where the variable production cost component is proportional to the amount of products produced.

3.4.2.4 Supplier agent

The supplier agent provides raw materials to the production sites on receiving any demand. The supplier agent has been considered to have an unlimited storage capacity. The costs associated with this agent are transportation cost and inventory cost. While sending shipments to the production sites, the supplier is able to distribute the total

shipment among the different transportation modes available. It tries to minimize the transportation cost while keeping the total carbon emission below a certain value.

3.4.3 Hybrid simulation-optimization approach

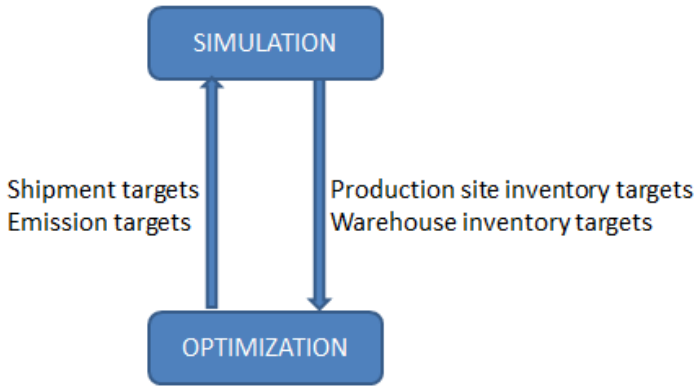

Figure 3.1: Coupling between simulation and optimization

The independent optimization and simulation models are developed independently as discussed in sections 3.1 and 3.2, respectively. In the hybrid approach, the two independent models are coupled together in order to take advantage of the benefits of both models. For this work, the coupling of the optimization model with the simulation model has been done using the following variables as shown in Figure 3.1: i) shipment values obtained from optimization model set as parameters in the simulation model, ii) emission values obtained from optimization model set as parameters in the simulation model, iii) production site and warehouse inventory values from simulation model to optimization model.

By passing the shipment values from optimization model to simulation model, the simulation is provided with shipment targets. Simulation tries to achieve these targets so as to reduce backorder and inventories. The simulation captures a more dynamic environment of the supply chain and whether or not it is able to achieve those shipment targets depends on the behaviors of the agents of the model. The resulting inventory values from the simulation model are fixed as parameters in the optimization model. The optimization model then gives the shipment values for the optimal solution corresponding to those inventory values. The emission values passed from the optimization model to the simulation model act as an additional constraint the model. The simulation model is forced to restrict its total carbon emissions below the level, which is set in the optimization model.

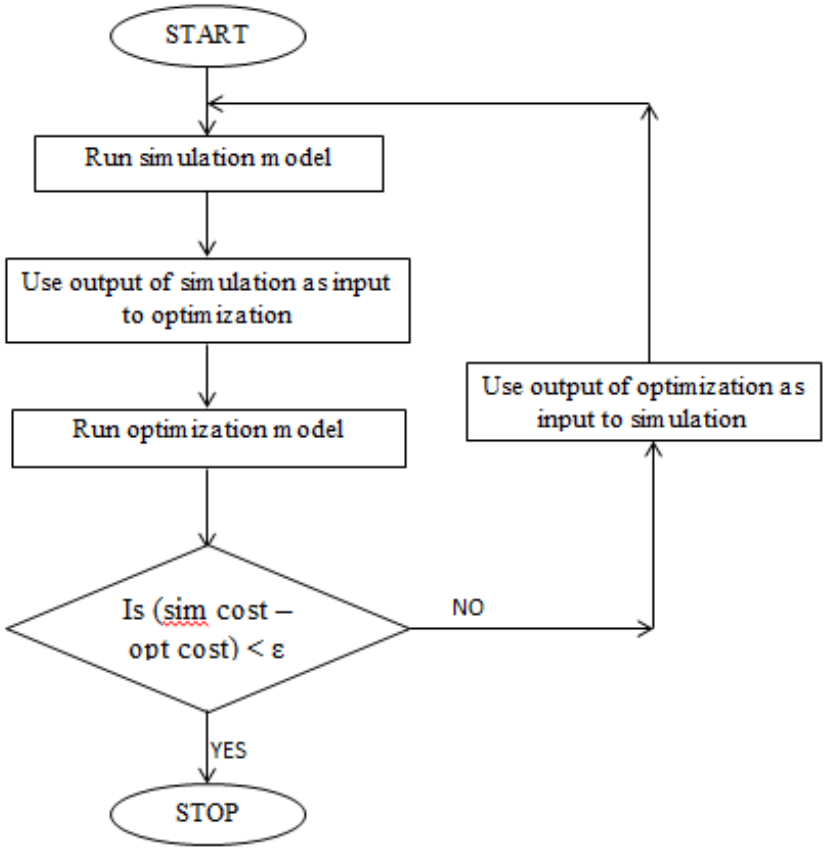

Figure 3.2: Iterative framework for the hybrid simulation–optimization approach

Using the hybrid approach proposed above, a solution methodology has been proposed for the solution of supply chain optimization problems. The framework consists of an iterative procedure as shown above in Figure 3.2, which is initialized by solving the independent simulation model. The variables are then passed to the optimization model, which is solved to obtain values of the decision variables. The two models calculate the total cost for the planning horizon. The costs from both the models are compared. If the difference is below a tolerance level, the procedure is terminated otherwise the values of decision variables are passed back to the simulation model. This process is carried out

iteratively until the difference between the two costs falls below the tolerance level. The above framework uses the simulation model as the master model, which is guided by the optimization model towards the best solution it can achieve.

3.5 Case Studies

In this section, the hybrid simulation-optimization approach has been tested in two rather small-scale supply chain management problems. The values of the parameters are listed in Appendix Chapter 3.

3.5.1 Case study 1

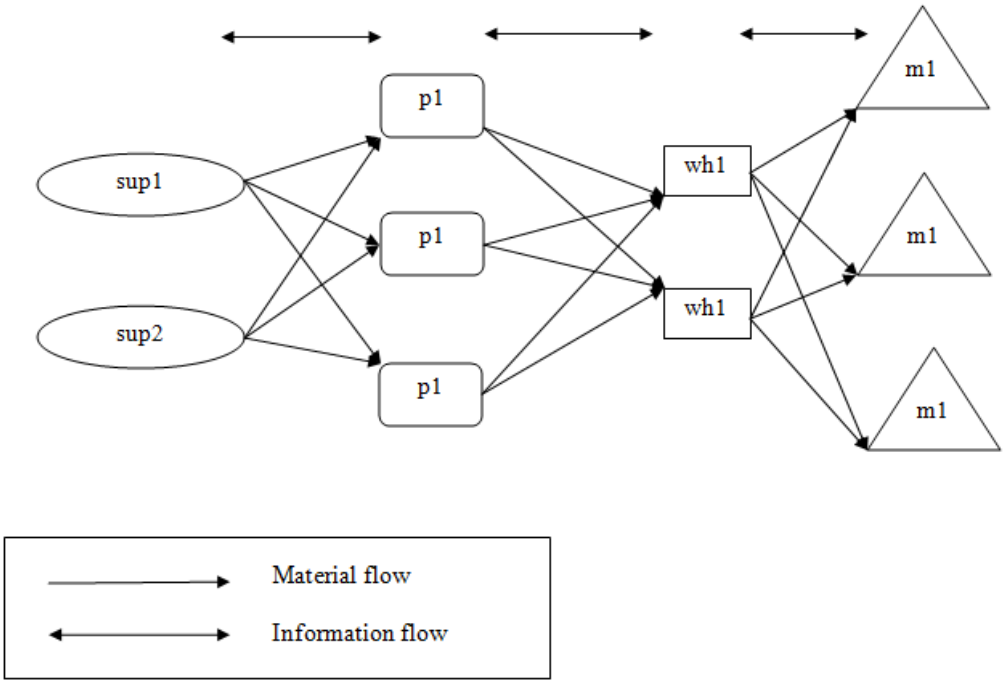

Figure 3.3: Supply chain network for the case study 1

The supply chain consists of 3 markets, 2 warehouses, 3 production sites and 2 raw material suppliers. There are 2 products and 3 raw materials. Transportation can be done

using 2 different modes of transport and production can also be done using 2 different modes. Figure 3.3 above shows the network configuration of the supply chain. The problem is solved for different emission levels. A difference of 1% of cost obtained from simulation model is used as the termination criteria. Deterministic demand data are provided below in Table 3.9. The problem is solved for a planning horizon of 10 planning periods.

The results of the hybrid approach for a specific set of process parameters and maximum emission level are shown in Table 3.2 and Figure 3.4 below. The results illustrate that the framework converges to the optimal solution within 20 iterations. The total computation time was 684 sec on Windows 7 operating system with an Intel Pentium D CPU 2.80 GHz microprocessor and 4.00 GB RAM. The optimization tries to improve the solution given the simulation input iteratively by adjusting the shipment and emission targets. Gradually the gap between the optimal solution and the realistic solution decreases.

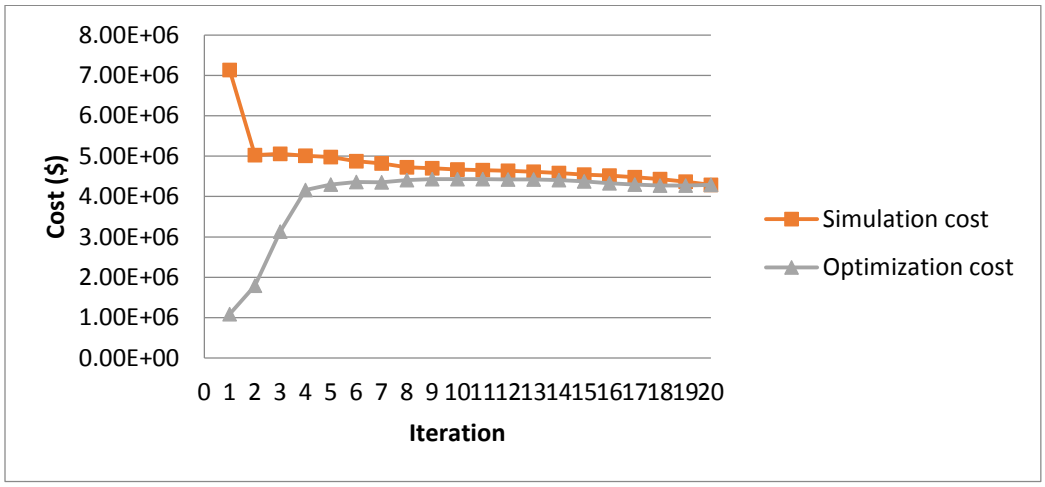

Figure 3.4: Objective values of simulation and optimization models at each iteration for emission equal to 1.4E+06 kgCO2e

Table 3.1: Deterministic demand data for the markets during the planning horizon

Product	Planning period	Demand		
		Market 1	Market 2	Market 3
P1	1	41	58	87
P2	1	57	15	7
P1	2	60	74	65
P2	2	80	106	44
P1	3	75	35	28
P2	3	112	42	17
P1	4	58	16	74
P2	4	38	32	3
P1	5	55	55	16
P2	5	96	45	95
P1	6	58	42	87
P2	6	85	49	43
P1	7	51	91	78
P2	7	110	71	96
P1	8	8	90	7
P2	8	4	73	76
P1	9	72	77	7
P2	9	41	51	1
P1	10	100	15	20
P2	10	76	52	68

Table 3.2: Computational results for the case study in terms of total cost of SC for warehouse capacity=200, production capacity=75, production site storage capacity=100

Iteration	Simulation cost	Optimization cost	% difference
1	7.13E+06	1.08E+06	84.81
2	5.03E+06	1.79E+06	64.33
3	5.06E+06	3.13E+06	38.15
4	5.01E+06	4.16E+06	16.98
5	4.98E+06	4.29E+06	13.71
6	4.88E+06	4.36E+06	10.64
7	4.82E+06	4.35E+06	9.71
8	4.73E+06	4.41E+06	6.74
9	4.70E+06	4.43E+06	5.66
10	4.67E+06	4.43E+06	5.1
11	4.65E+06	4.43E+06	4.87
12	4.63E+06	4.42E+06	4.59
13	4.61E+06	4.42E+06	4.21
14	4.58E+06	4.41E+06	3.85
15	4.54E+06	4.38E+06	3.62
16	4.52E+06	4.33E+06	4.12
17	4.48E+06	4.29E+06	4.06
18	4.43E+06	4.27E+06	3.66
19	4.37E+06	4.27E+06	2.09
20	4.29E+06	4.29E+06	0.11

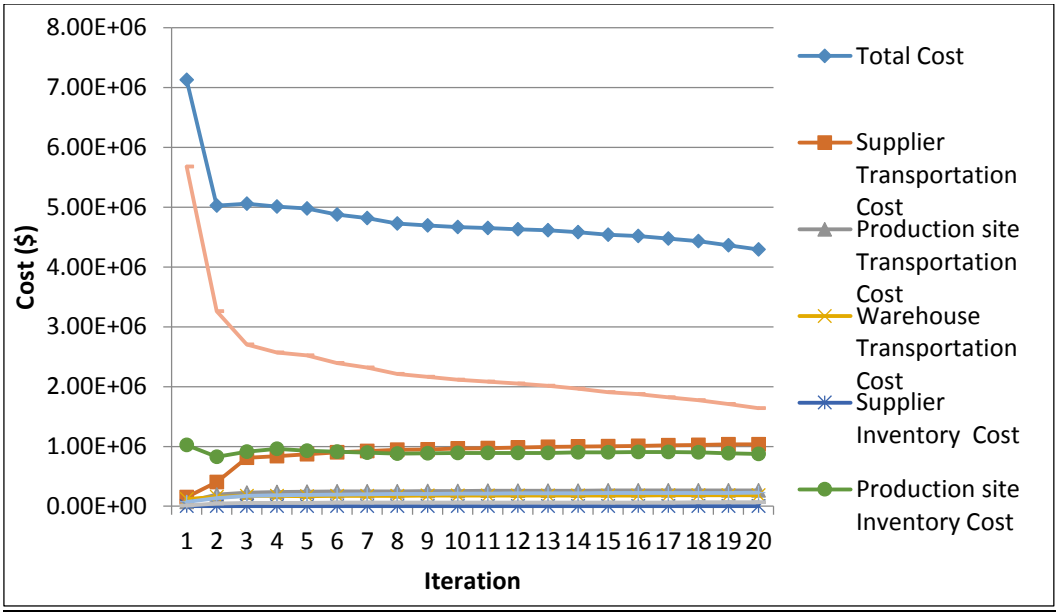

Figure 3.5: Breakdown of different cost components during the algorithm iterations

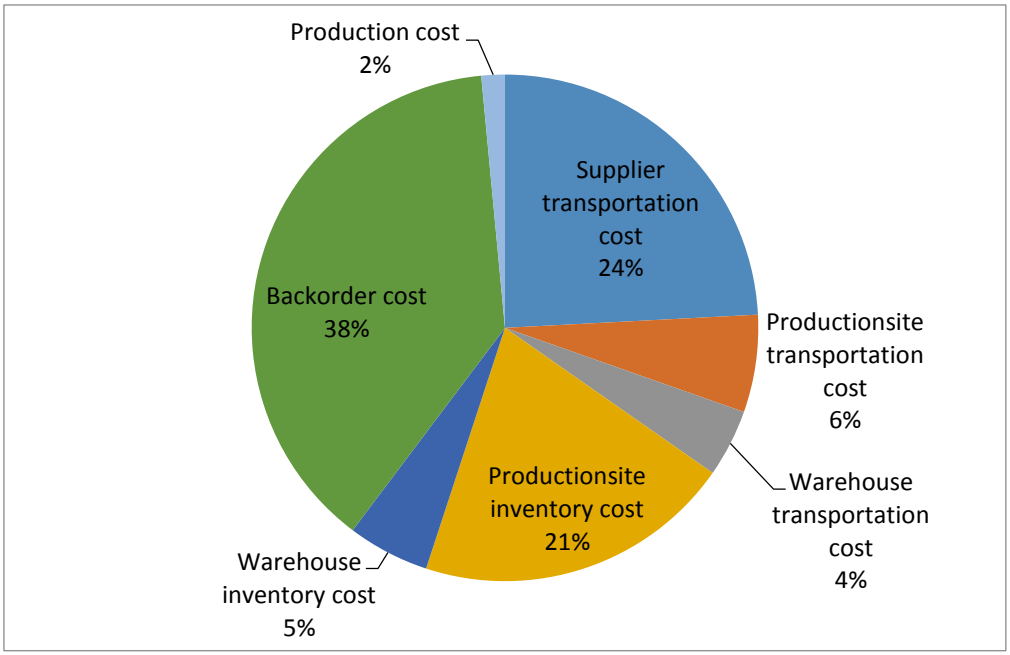

Figure 3.6: Breakdown of different cost components for the final solution

Figure 3.5 above shows the variation in different components of total cost obtained from the simulation model over the iterations while figure 3.6 shown above presents the breakdown for the final solution. It can be seen that backorder costs are the main component of the total cost and the trend of total cost closely resembles that of backorder costs. Supplier transportation cost and production site inventory cost are the other two most important components of the overall cost. The other cost components constitute only small fractions of the total cost. The hybrid approach used sets shipment targets obtained from optimization model with the idea that the optimized shipment targets would guide the simulation towards reduced backorder costs.

The sensitivity of the model and the response of the solution approach for different capacities of warehouses and production site capacities are studied and the results are shown in Figure 3.7 below. Results show that for the range of parameters studied, the framework showed consistent results. Optimization and simulation model results converge as iterations increase. It can be observed that simulation cost and optimization cost are not monotonically decreasing and increasing. The optimization model gives shipment targets to the simulation model. The simulation model is a more realistic representation of the SC and it may or may not be able to achieve those targets. The different ordering policies, shipment policies and production policies impact the results of the simulation model. Therefore the different agents may or may not have sufficient inventory to meet the shipment targets proposed by the optimization model. So there can be a few fluctuations observed in the graphs before the results of the optimization model and simulation model converge.

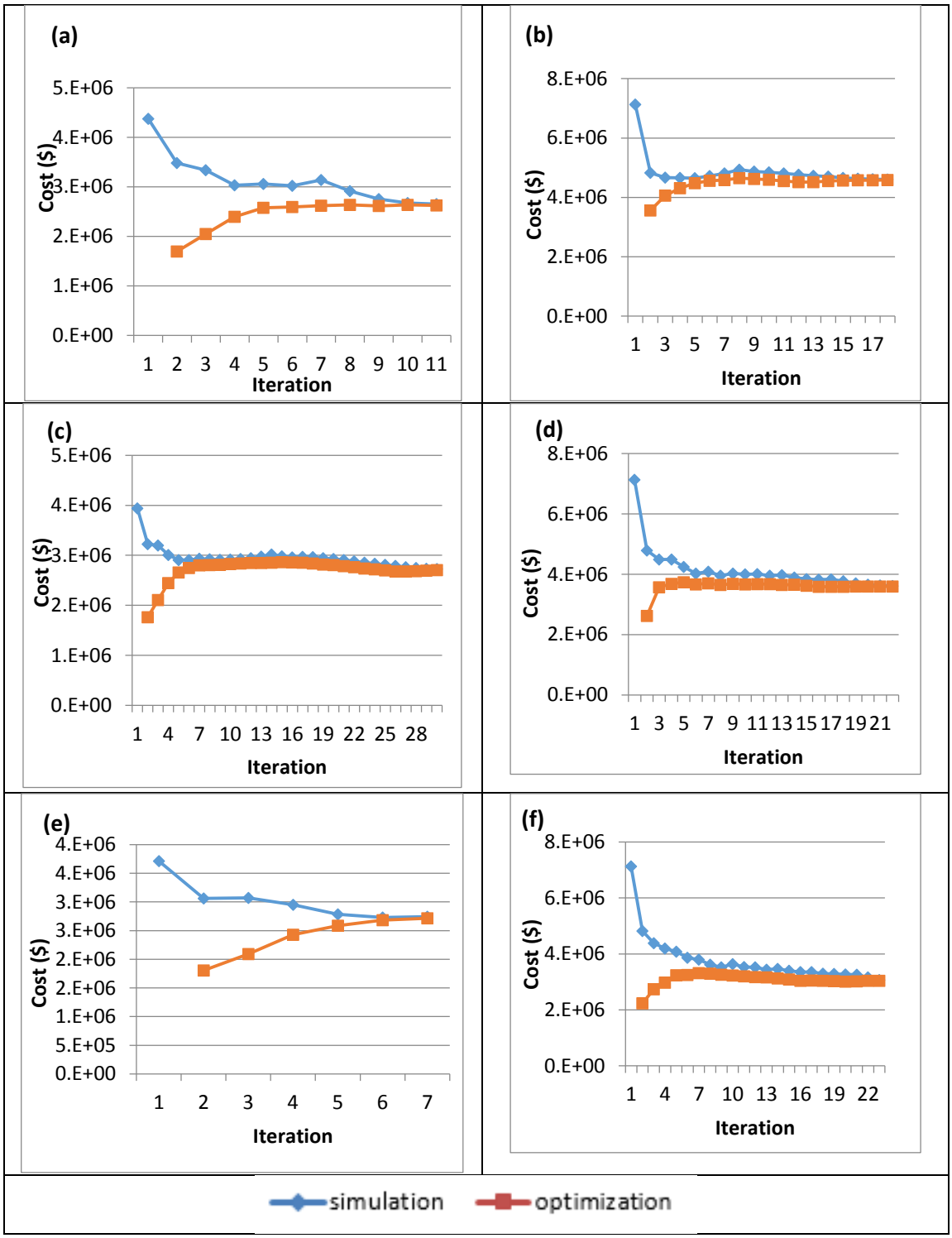

Figure 3.7: Hybrid approach results for different capacities (a) warehouse capacity=375 production site capacity = 75 (b) warehouse capacity=200 production site capacity = 60 (c) warehouse capacity=425 production site capacity = 75 (d) warehouse capaci ty=200 produ ction site capacity = 75 (e) warehouse capacity=450 production site capacity = 75 (f) warehouse capacity=200 production site capacity = 90

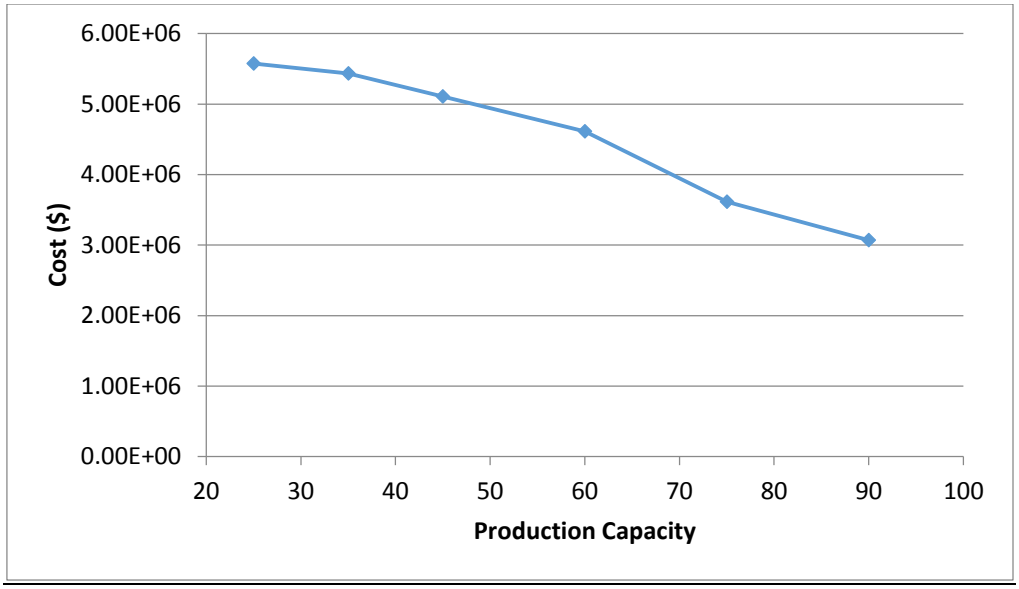

Figure 3.8: Cost for different production capacities

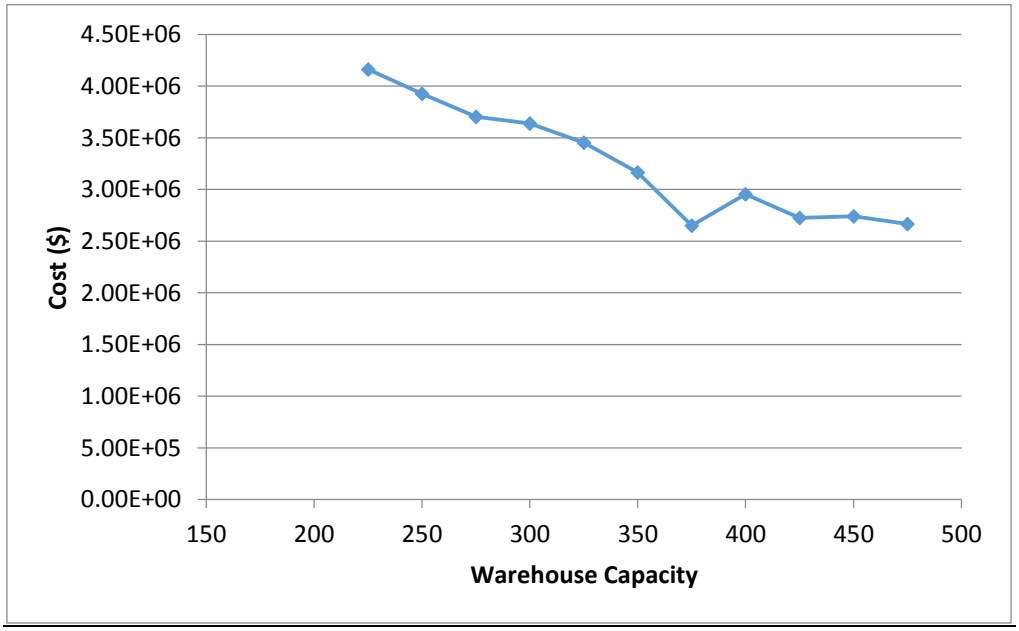

Figure 3.9: Cost for different warehouse capacities

Figure 3.8 and 3.9 above show the trends of cost predicted by the model for varying production and warehouse capacities, respectively. It can be observed that as the production capacity increases, the predicted cost decreases. Backorders which account for the highest fraction of the total cost reduce with increasing production capacities and therefore result in a decrease in the overall cost. It can be observed in Figure 3.9 that the total cost decreases with increasing warehouse capacity with a slight fluctuation in the region of higher capacities. This is expected since as the warehouse capacity increases, more demand is fulfilled which reduces the backorders. For higher capacities however - around 375 - backorders are considerably reduced and backorder costs become comparable to the inventory and transportation costs. Moreover, for increasing capacities, inventory and transportation costs increase. So there can be fluctuations in the total cost for higher capacities because of opposite trends in the relevant cost components.

Transportation and production can take place using two different transportation and production modes, respectively. The two modes differ in cost and carbon emission levels. Cost and carbon emissions have been formulated as two conflicting objectives. The cheaper modes have higher environmental impacts. The hybrid approach has been used to solve the multi-objective optimization problem. The multi-objective problem has been solved using the ε-constraint method. The environmental criterion has been added as a constraint and the economic performance has been optimized. The results are shown in Figure 3.10 below.

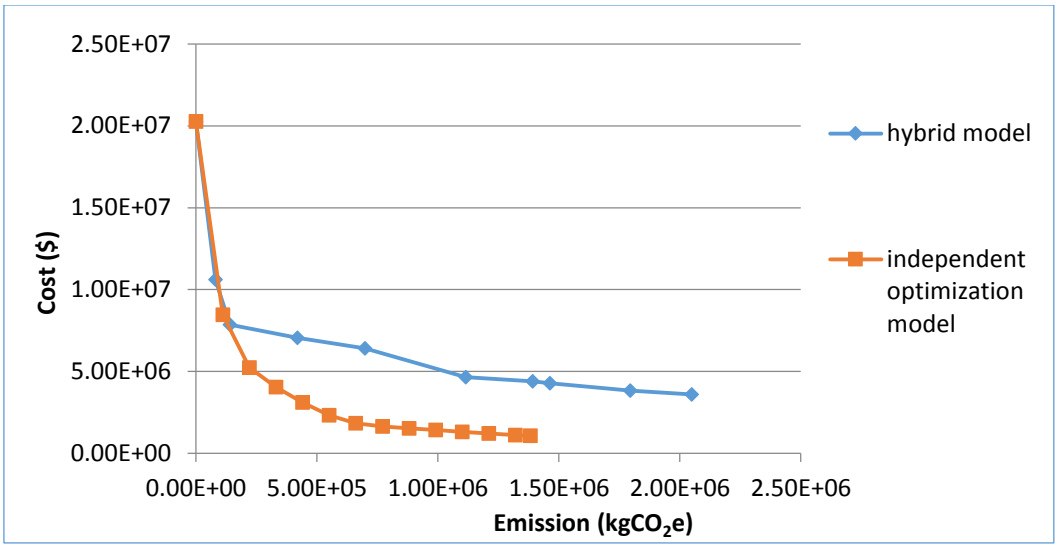

Figure 3.10: Comparison of results from hybrid model and independent optimization model for different values of emission

The two curves in the plot of Figure 3.10 represent the results obtained from the independent optimization model and the hybrid model. Different emission levels were set as constraints in both the cases and the minimum cost was obtained corresponding to the emission constraints. It can be observed that the hybrid model generates a pareto set of solutions like the independent optimization model. The curve with the higher values is the one for hybrid model while the one with lower values is for the independent optimization model. This shows that the hybrid model cannot find a better solution without increasing the carbon emissions. The hybrid model predicts higher costs than the optimization model since it is a better representation of the real supply chain.

It can be seen that the curve for the independent optimization model stops at an emission value below 1.50E+06 $kgCO_2e$ while the one for the hybrid model continues further to higher emission values. The optimization model predicts the minimum cost possible at an

emission value around 1.4E+06. If the emission is allowed to be higher than this value, it does not alter the solution of the optimization model. However, the hybrid model reaches the minimum cost it can predict at a higher emission value of 2.04E+06. This is expected since the simulation model represents the more realistic scenario and thus leads to higher cost and higher emissions.

3.5.2 Case study 2

In this case the supply chain consists of 3 markets, 6 warehouses, 8 production sites and 6 raw material suppliers. There are 2 products and 3 raw materials. Transportation can be done using 2 different modes and production can also be done using 2 different modes. A difference of 1% of cost obtained from simulation and optimization models is used as the termination criterion as well in this case study. Demand is considered deterministic in this case study too for the complete time horizon, which is 30 planning periods in this case study.

The hybrid model is used to solve the problem for different sets of parameters, warehouse storage capacity and production site capacity. Table 3.3 and Figure 3.11 below show the results for a particular set of parameters. The solution converges in less than 40 iterations for all the scenarios considered. The total computation time was less than 2890 sec for all the scenarios on Windows 7 operating system with an Intel Pentium D CPU 2.80 GHz microprocessor and 4.00 GB RAM.

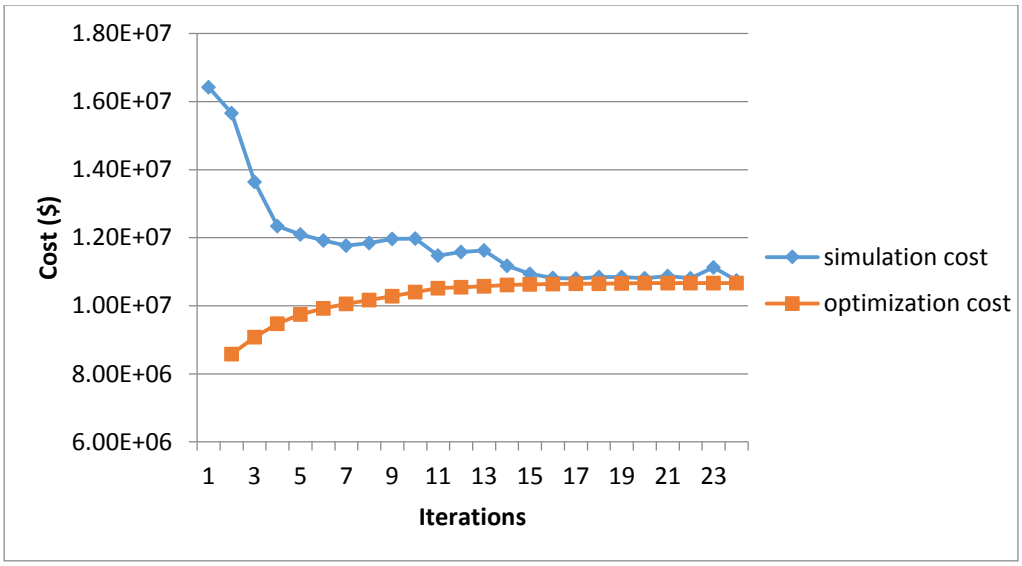

Figure 3.11: Objective values of simulation and optimization models at each iteration for emissions equal to 1.9E+06 kgCO2e

Table 3.3: Computational results for the case study in terms of total cost of SC for warehouse capacity=350, production capacity=100

Simulation cost	Optimization cost	% difference
1.64E+07	8.58E+06	47.77
1.57E+07	9.08E+06	42.05
1.36E+07	9.48E+06	30.54
1.23E+07	9.75E+06	21.01
1.21E+07	9.92E+06	18.00
1.19E+07	1.01E+07	15.66
1.18E+07	1.02E+07	13.58
1.18E+07	1.03E+07	13.12
1.20E+07	1.04E+07	13.02
1.20E+07	1.05E+07	12.19
1.15E+07	1.05E+07	8.16
1.16E+07	1.06E+07	8.69
1.16E+07	1.06E+07	8.72
1.12E+07	1.06E+07	4.92
1.09E+07	1.06E+07	2.71
1.08E+07	1.06E+07	1.59
1.08E+07	1.07E+07	1.38
1.08E+07	1.07E+07	1.73
1.09E+07	1.07E+07	1.72
1.08E+07	1.07E+07	1.33
1.09E+07	1.07E+07	1.89
1.08E+07	1.07E+07	1.28
1.11E+07	1.07E+07	4.09
1.07E+07	1.07E+07	0.68

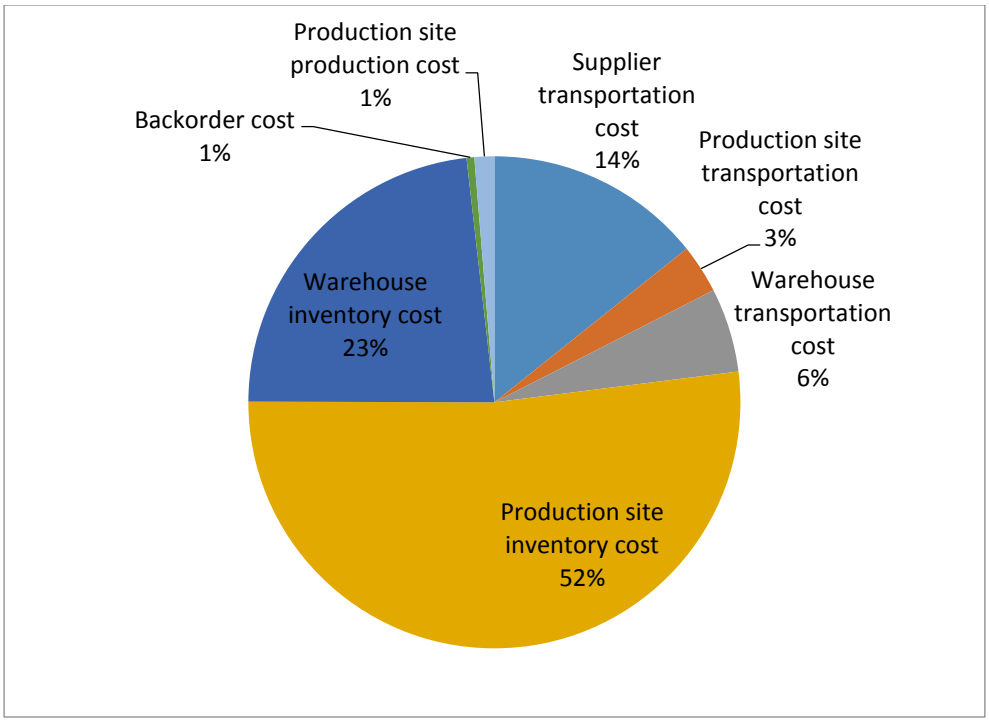

Figure 3.12: Breakdown of different cost components for the final solution

Figure 3.12 shows the breakup of different cost components for the final solution. It can be observed that the main component of the total cost is the production site inventory cost unlike the backorder cost in the previous case. In fact, backorder cost is very low in this case. This is probably because of the larger network of the supply chain available to meet the demand. The number of markets in both cases has remained the same while the numbers of other upstream agents have increased. The larger number of warehouses enables the fulfillment of demand without creating the need for production sites to supply products to the warehouses. So the inventory at the production sites increases and thus the inventory cost increases too.

The sensitivity of the model for this case and the response of the solution approach for different capacities of warehouses and production sites are studied and the results are

shown in Figure 3.13. Results show that for the range of parameters studied, the framework showed consistent results in this case as well. However, as can be observed in Figure 3.13, there are a few fluctuations observed in the graphs before the results of the optimization and simulation model converge. This is similar to what has been also observed for the first case study. The fluctuations are a result of the ordering policies, shipment policies and production policies which have been incorporated in the simulation model. The different agents may or may not have sufficient inventory to meet the shipment targets proposed by the optimization model which results in the fluctuations observed in the plot.

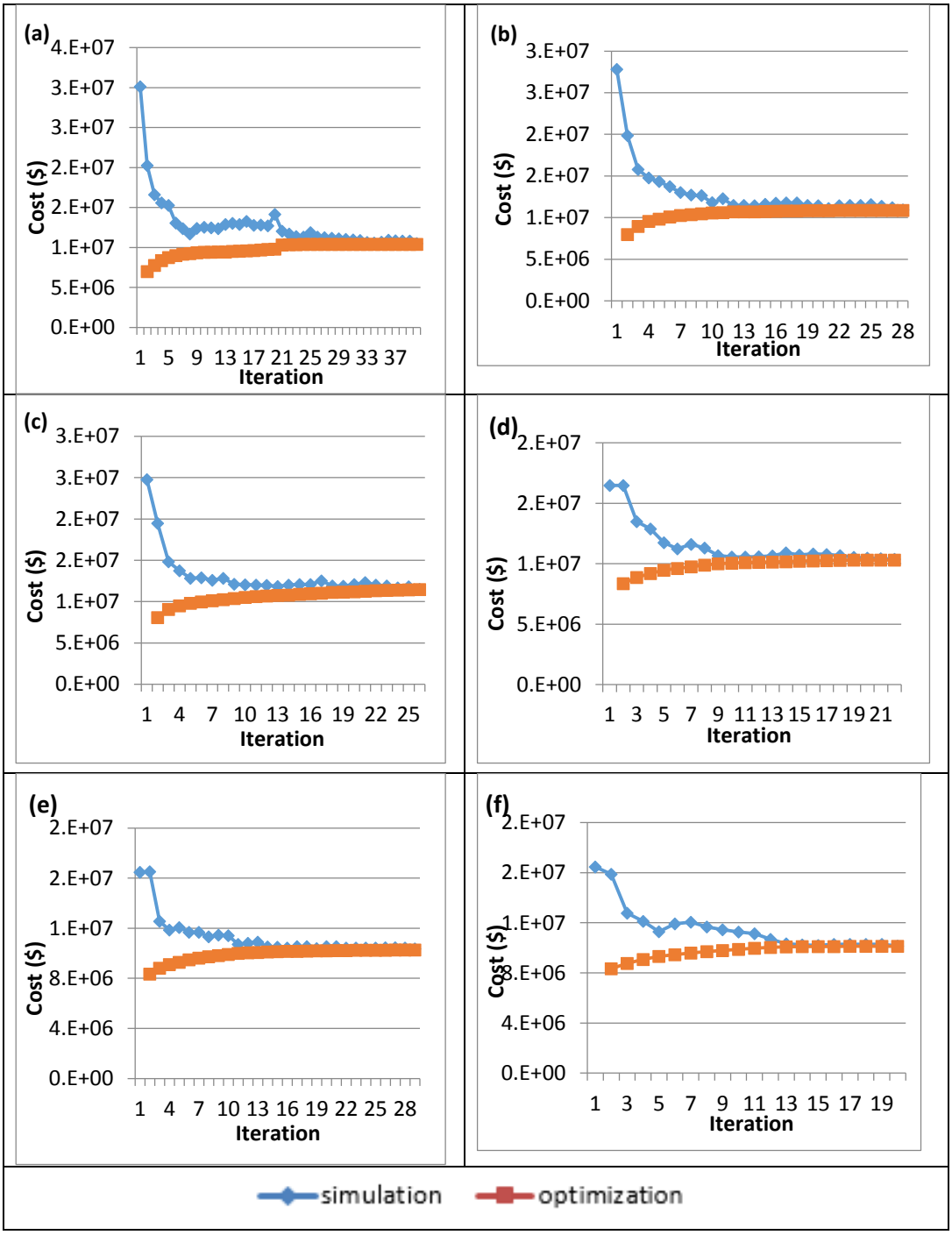

Figure 3.13: Hybrid approach results for different capacities (a) production capacity = 75, warehouse capacity=200 (b) production capacity = 75, warehouse capacity=225 (c) production capacity = 75, warehouse capacity=250 (d) production capacity = 40, w arehouse capacity = 350 (e) production capacity = 50, warehouse capacity =350 (f) production capacity = 60, warehouse capacity = 350

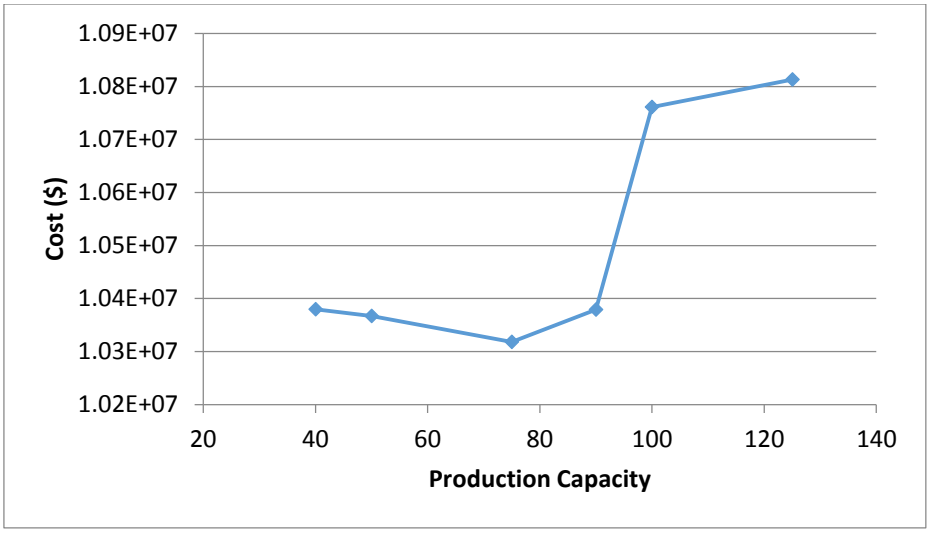

Figure 3.14: Cost for different production capacities

Figure 3.15: Cost for different warehouse capacities

Figure 3.14 and 3.15 show the trend of cost predicted by the model for varying production capacity and warehouse capacity, respectively. In Figure 3.14, it is seen that with increasing production capacity, the predicted cost first decreases but later increases. This is because backorders decrease with increasing production capacities. However for

larger production capacities, the backorders are considerably low due to higher production while more raw materials are transported from suppliers to production sites which dominate over the reduced backorder costs. Therefore there is an overall cost increase for higher production capacities. Similar trend can be seen in Figure 3.15 where the total cost first decreases with increase in warehouse capacity but later increases. Although higher warehouse capacity enables better fulfillment of demand, reduces inventory at production sites, reduces transportation, but also increases the inventory at warehouses which account for a considerable fraction of the total cost. This increase in warehouse inventory raises the total cost predicted by the model.

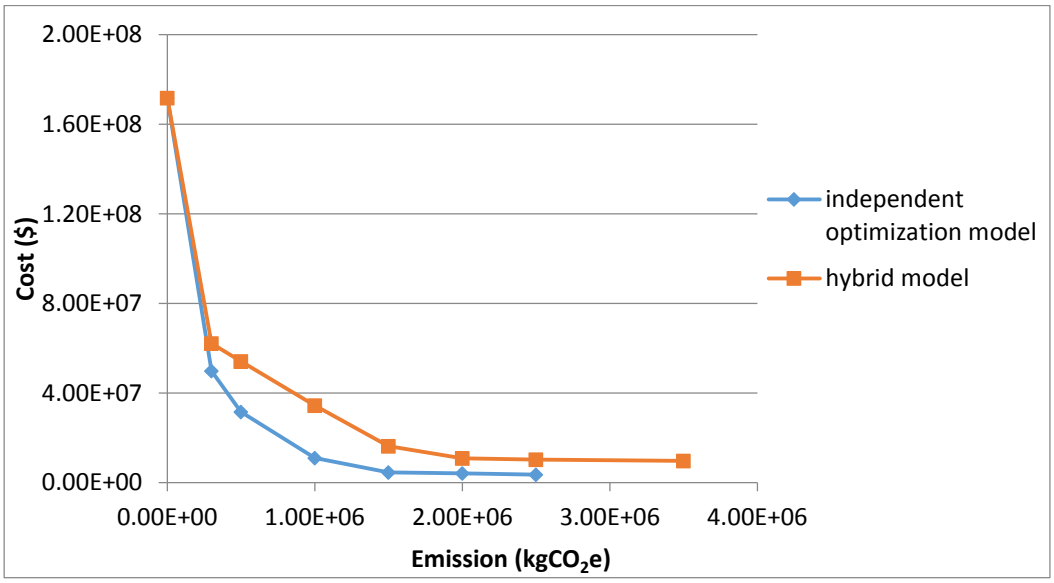

Figure 3.16: Comparison of results from hybrid model and independent optimization model for different values of emission

Like case study 1, ε-constraint method is used to solve the multi-objective optimization problem in order to study the trade-off between environmental impact and economic performance of the supply chain. Environmental impact and economic performance are

formulated as conflicting objectives. The results obtained are shown in Figure 3.16. It can be seen that the hybrid model gives a pareto set of solutions like the independent optimization model. The cost values are greater than those obtained for the independent optimization model.

If we consider a particular emission level, it can be observed that the cost predicted by the hybrid model is greater than that by the independent optimization model. The hybrid model, which is a better representation of the real supply chain, predicts a higher cost than the independent optimization model which represents a simplification of the actual system.

3.6 Conclusions

In this chapter, we presented a hybrid simulation based optimization framework to solve a supply chain operation problem. We developed a rather simple mathematical optimization model and coupled it with a more detailed simulation model. A multi-objective optimization problem was addressed using the hybrid framework. It was shown that the framework can be utilized for multi-objective optimization problems as well. The hybrid model was used to solve two small-scale optimization problems with one problem being slightly larger than the other. The framework has been shown to work well for both cases with the required number of iterations less than 40.

The approach can be used to study different supply chain strategies and get realistic optimal solutions. It can also be used for more holistic sustainable supply chains by using the Life Cycle Assessment technique to assess the environmental impacts. It is envisioned that the proposed approach would prove to be more useful in cases of more complex supply chain networks where the optimization mode will help the decision

makers, emulated using the simulation mode, to perform online optimization taking into consideration the state of the supply chain at the specific time point.

Nomenclature

Indices	
t	planning period
p	production site
sup	supplier
m	distribution market
wh	Warehouse
s	Product state
r	Raw material state
mt	Mode of transportation
mp	Mode of production
Sets	
T	planning periods
PS	production sites
SUP	suppliers
M	distribution markets
WH	Warehouses
PR	Product states
R	Raw material states

MT	Modes of transportation
MP	Modes of production
Parameters	
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*
$h_r^{\sup}$	holding cost of raw material *r* at supplier *sup*
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*
$FixCost^{p}$	fixed production cost of operation of production site *p*
$VarCost^{p}$	unit variable cost of production at site *p*
$Dem_s^{m,t}$	demand of product *s* at market *m* for period *t*
$et^{wh,m}$	Carbon emission due to unit transportation from warehouse *wh* to market *m*
$et^{p,wh}$	Carbon emission due to unit transportation from production site *p* to warehouse *wh*
$et^{\sup,p}$	Carbon emission due to unit transportation from supplier *sup* to

	production site *p*
ep^{p}	Carbon emission due to unit production at production site *p*
$ecap$	Upper limit on the total carbon emission allowed
$stcap_{r}^{\sup}$	Inventory holding capacity of raw material *r a*t supplier *sup*
$stcap_{r}^{p}$	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 or product *s* at production site *p*
Variables	
$D_{s}^{wh,m,t}$	Amount of product *s* transported from warehouse *wh* to market *m* at period *t*
$D_{s}^{p,wh,t}$	Amount of product *s* transported from production site *p* to warehouse *wh* at period *t*
$D_{r}^{\sup,p,t}$	Amount of raw material *r* transported from supplier *sup* to production site *p* at period *t*
$Inv_{s}^{wh,t}$	inventory level of product *s* at the end of the planning period *t* at warehouse *wh*
$Inv_{s}^{p,t}$	inventory level of product *s* at the end of the planning period *t* at production site *p*
$Inv_{r}^{p,t}$	inventory level of raw material *r* at the end of the planning period *t* at production site *p*
$Inv_{r}^{\sup,t}$	inventory level of raw material *r* at the end of the planning period *t*

	at supplier *sup*
$U_s^{m,t}$	Backorder amount of product *s* at the end of planning period t at market *m*
w_t^p	Binary variable to decide whether production site *p* operates during planning period *t* or not
$P_s^{p,t}$	Amount of product s produced at production site *p* during planning period *t*
E	Total emission taking place over the planning horizon

4 Centralized and Decentralized Supply Chains

A supply chain is usually formed by units which belong to different organizations and are parts of more than just one supply chain. In such cases, visibility of the entire network and information sharing among all the entities is not possible. The individual entities in such a network have their own goals and objectives and make their decisions based on their own local goals depending on the information available to them. Supply chains can be distinguished into two main types based on their decision making policies: centralized, where decisions are taken by a central authority by taking into consideration the other entities of the supply chain, and decentralized where the decisions are taken by the individual entities themselves. Centralized supply chains are known to be more economically efficient than decentralized supply chains. However, complete centralization is often not possible and practical in case of complex, distributed enterprises. Often there are different extents of centralization that are followed by the enterprises.

4.1 Background

This work involves two major aspects: hybrid simulation based optimization for supply chains and centralized versus decentralized supply chains. The approach presented in Chapter 3 proposes a flexible solution approach by reducing the amount of information exchanged between the optimization and the simulation model and using the optimization only as a target setting. Moreover, a multi-objective problem is solved by taking the environmental impact of the supply chain as an additional objective for decision-making.

Researchers have also studied the effects of different supply chain decision-making policies. Saharidis et al. [63] develop analytical models to solve the production planning problem in supply chain involving several enterprises and compare the two types of optimization – centralized and decentralized. They present a case where each enterprise prefers to optimize its production plan without considering the other members of the supply chain. They develop a simple model of decentralized optimization. They compare the optimal profits obtained in both the centralized and decentralized cases. Duan and Warren [64] discuss the optimal replenishment policies of capacitated supply chains under two different control strategies (decentralized vs. centralized). They propose a hybrid meta-heuristic algorithm to solve both the centralized and decentralized capacitated supply chain inventory models. It consists of a differential evolution and harmony search, and one local search method, the Hooke and Jeeves direct search. Palut and Ulengin [65] coordinate the inventory policies in a decentralized supply chain with stochastic demand by means of contracts. They consider a decentralized two-stage supply chain with independent suppliers and a manufacturer with limited production capacities. They model the supply chain as a queuing system and then develop centralized and decentralized models. They compare the solutions to these models and show that the supply chain needs coordination. Jalbar et al. [66] consider a multi-echelon inventory/distribution system with one warehouse and N retailers. They solve the problem of determining the optimal reorder policy which minimizes the overall cost. They study two situations: centralized where the retailers are considered branches of the same firm and decentralized where retailers make decisions independently. They provide two separate solution methods for the two cases.

In this work, hybrid simulation based optimization approaches are proposed to solve supply chain operation problems. Centralized and decentralized decision making policies have been considered for the supply chains and different approaches have been applied to them. The hybrid approach couples an agent based simulation with optimization routines to improve agent actions. In the decentralized case, the individual agents make their own decisions based on limited interaction with the rest of the network. On the other hand, in the centralized case, decision-making is done by an agent that acts as a central decision-making authority and information sharing is enabled across the whole network. The decision making authority inherently performs optimization to decide its action. Hence embedded optimization is used for the agent in the centralized simulation model. The hybrid simulation based optimization framework proposed in chapter 3 is employed for the hybrid approach in each case to guide the simulation models towards better solutions. The different methods used to couple simulation models with optimization models illustrate the flexibility that can be provided to agent behavior. Two rather small scale supply chain problems have been solved using the proposed frameworks to demonstrate their applicability.

4.2 Problem definition

A supply chain consisting of raw material suppliers, production sites, warehouses and markets is considered in this work. The markets cater to demand of different products which can be manufactured using three raw materials. Demand of products at the markets is known for a given number of planning periods. The warehouses have limited storage capacity for products while the production sites have storage capacities for products and

raw materials. The various capacities have been assumed to be available and fixed. Information flow between the entities has been considered to take place without any time delay while there is a time delay associated with material flows. There are costs associated with transportation, inventory holding, production and backorders. Shipment, inventory and production information for all the planning periods have to be found out so as to minimize cost.

The supply chain is assumed to operate under two different decision-making strategies. Decisions related to demand distribution have been considered vary depending on the strategy adopted by the supply chain. In case of centralized decision-making, demand is distributed among the upstream entities by a central planning authority. Information is considered to be shared globally. On the other hand, in the decentralized case, the decisions are taken by the individual entities. So the demand is distributed among the upstream entities by the individual demand producing bodies. Also, information is not shared globally among all the entities of the supply chain. It is shared only locally which means that entities share information with the other entities that are geographically close to them, thus resulting in geographical partitioning of the network.

4.3 Optimization model

The multisite model includes supplier, production site, warehouse and market constraints. The set of products ($s \in PR$) are stored at the warehouses ($wh \in WH$). Warehouses deliver the products to meet the demands at the markets ($m \in M$) over the planning horizon ($t \in T$). Warehouses receive products from various production sites ($p \in PS$) which in turn manufacture these products from the raw materials ($r \in R$) obtained from raw material

suppliers (sup ϵ SUP). The planning horizon has been discretized into fixed time length (daily production periods). In the hybrid approach, the optimization model has been used to guide the simulation towards better results. While the simulation model is more detailed, the optimization model is kept rather simple. Therefore, no time delays have been considered for information or material flows. The total cost associated with the supply chain is the summation of transportation costs, inventory holding costs, production costs and backorder costs. Transportation cost has been considered to be proportional to the amount of shipment. Inventory holding cost has been considered proportional to the inventory level. Production cost is proportional to the amount of product produced while backorder cost is proportional to the amount of unfulfilled demand. The model has been formulated as a linear programming problem and minimization of total cost is the objective function. The optimization model is as follows.

$\min \sum_{t}\sum_{wh}\sum_{s\in PR} h_s^{wh} Inv_s^{wh,t} + \sum_{t}\sum_{p}\sum_{s\in PR} h_s^{p} Inv_s^{p,t} + \sum_{t}\sum_{p}\sum_{r\in R} h_r^{p} Inv_r^{p,t}$ $+\sum_{t}\sum_{\sup}\sum_{r\in R} h_r^{\sup} Inv_r^{\sup,t} + \sum_{t}\sum_{m}\sum_{s\in PR} u_s^{m} U_s^{m,t} + \sum_{t}\sum_{p}\sum_{mp}\sum_{s}\left(FixCost^{p} w_t^{p} + VarCost^{p} P_s^{p,t}\right)$ $+\sum_{t}\sum_{mt}\sum_{m}\sum_{wh}\sum_{s\in PR} d_s^{wh,m} D_s^{wh,m,t} + \sum_{t}\sum_{mt}\sum_{wh}\sum_{p}\sum_{s\in PR} d_s^{p,wh} D_s^{p,wh,t} + \sum_{t}\sum_{mt}\sum_{\sup}\sum_{p}\sum_{r\in R} d_r^{\sup,p} D_r^{\sup,p,t}$	1
st $\quad U_s^{m,t} = U_s^{m,t-1} + Dem_s^{m,t} - \sum_{wh\in WH} D_s^{wh,m,t}, \quad \forall s\in PR, m\in M, t\in T$	2
$Inv_s^{wh,t} = Inv_s^{wh,t-1} - \sum_{m\in M} D_s^{wh,m,t} + \sum_{p\in PS} D_s^{p,wh,t}, \quad \forall s\in PR, wh\in \mathrm{WH}, t\in T$	3
$Inv_s^{p,t} = Inv_s^{p,t-1} + P_s^{p,t} - \sum_{wh\in WH} D_s^{p,wh,t}, \quad \forall s\in PR, p\in PS, t\in T$	4
$Inv_r^{p,t} = Inv_r^{p,t-1} - C_r^{p,t} + \sum_{\sup\in SUP} D_r^{\sup,p,t}, \quad \forall r\in R, p\in PS, t\in T$	5
$Inv_r^{\sup,t} \le stcap_r^{\sup}, \quad \forall r\in R, \sup\in SUP, t\in T$	6
$Inv_r^{p,t} \le stcap_r^{p}, \quad \forall r\in R, p\in PS, t\in T$	7

$Inv_s^{p,t} \le stcap_s^p, \quad \forall s \in PR, p \in PS, t \in T$	8
$Inv_s^{wh,t} \le stcap_s^{wh}, \quad \forall s \in PR, wh \in WH, t \in T$	9

The objective function in equation 1 minimizes the total cost which consists of inventory costs, backorder costs, production costs and transportation costs. Equations 2-5 are the inventory balance equations at the different nodes of the supply chain. Equation 2 describes the backorders at the markets. Any unfulfilled demand gets accumulated as backorder. Equation 3 predicts the inventory at warehouses, shipments from warehouses to markets and shipments from production sites to warehouses. Equation 4 predicts the product inventory at production sites, production amounts and shipments from production sites to warehouses during each planning period. Equation 5 predicts the inventory or raw materials at production sites, consumption of raw materials for the manufacture of products and shipments from raw material suppliers to production sites during each planning period. Equations 6–9 are storage capacity constraints for raw material suppliers, production sites and warehouses respectively.

The optimization model results in a linear programming problem which has been implemented in GAMS 23.7.3 and solved using CPLEX 12.3.0.0 on Windows 7 operating system with an Intel Pentium D CPU 2.80 GHz microprocessor and 4.00 GB RAM.

4.4 Simulation model

As mentioned earlier, agent based simulation is used to represent the supply chain network. The different entities of the supply chain have been modeled as the agents. Two

separate simulation models have been developed for the centralized and decentralized scenarios. Below is a brief description of the different agents in both the models.

Market agent

Demand for products originates at the market agent. The behavior of the agent regarding demand distribution is different for the decentralized and centralized scenarios.

In the decentralized case, the agent itself is responsible for distributing demand among the warehouses. When a market receives a demand, it sends *requests* for the required amounts of products to the warehouses. A *request* is not the actual order for products. A *request* is a way to procure information from the upstream agent regarding how much demand can be fulfilled and at what cost. Based on the response from warehouses, the market agent distributes the demand among the warehouses by following its ordering policy. As an ordering policy, the market gives first preference to the warehouse which responds with the lowest cost. It assigns an order of amount either equal to what the warehouse can fulfill or the demand amount, whichever is smaller. If the total demand cannot be fulfilled by the lowest cost warehouse, it assigns an order to the one with the cost next to the lowest cost warehouse. Order amount is decided as either the amount the warehouse can fulfill or the remaining demand, whichever is larger. Similarly, the market keeps assigning orders until the total demand is assigned or all the warehouses have been considered. In case where more than one warehouse responds with the same cost, the market chooses the one with the maximum amount of demand it can fulfill and the least amount of time. During this process, the market is able to communicate only with the warehouses that are located within a specific distance from itself.

On the other hand, in the centralized case the market sends *request* to a central planner agent responsible for demand distribution among the warehouses. As an individual agent, the market does not decide how to distribute its demand.

It is desired that the demand be fulfilled during each planning period. However, partial or no fulfillment of demand is also allowed but at a backorder cost. In case of an oversupply from warehouses, the superfluous amount is retained for the future planning periods. The costs associated with this agent are inventory cost and backorder cost.

Warehouse agent

The warehouse agent maintains an inventory of products. Its behavior also varies based on whether it is the centralized or the decentralized scenario.

In the decentralized case, it receives a *request* from a market and sends a *response* in terms of the fractional of demand it would be able to fulfill, cost and time it would take to ship the products. In order to evaluate the fraction of demand it can fulfill, it considers the demand from all the markets. Based on the responses from all the warehouses, the markets send orders for products. If the complete market demand has not been ordered, the markets send requests to warehouses again with updated demand. The demand is updated by reducing the amount which has already been ordered. The process of sending requests to warehouses, receiving response from warehouses and assigning orders to warehouses continues until all the demand has been ordered or the warehouses cannot fulfill any demand from the markets. In this manner, all the warehouses, together attempt to fulfill the market demand. Sharing of information between warehouses and markets has been considered. If the demand cannot be fulfilled by a warehouse alone, the other

warehouses receive requests from markets and they evaluate if they would be able to fulfill the demand.

In the centralized case, the warehouse receives *orders* from the Planner agent. Since the Planner agent has access to the inventory information of the warehouses, the warehouse receives orders that it is able to fulfill. Even if the total market demand is not fulfilled, the Planner agent does not try to reallocate the demand among the warehouses as it had information about all the warehouses in the first instance itself.

The warehouse agent fulfills the demand from the markets by using its inventory of products. It has a limited storage capacity and regulates its inventory using a reorder level - order upto level inventory replenishment policy with continuous review. The warehouse is capable of updating its reorder level continuously. On a continuous basis, the agent calculates the average demand it receives per day. Then it calculates the reorder level using the equation below.

Reorder level = Average daily demand per day x lead time in days + safety stock

Since transportation delays have been considered in the model, there is a lead time for the agent. The safety stock and order-upto level for the agent are pre-defined. When the inventory at the warehouse falls below the reorder level, it orders products from the production sites.

The different decision-making strategies affect the way in which warehouse demand is distributed among the production sites. For the decentralized scenario, in order to distribute its demand among the production sites, the warehouse sends *requests* to the production sites. The distribution is fixed based on the *responses* and ordering policy of

the warehouse. As an ordering policy, the warehouse gives first preference to the production site which responds with the lowest cost. It assigns an order of amount either equal to what the production site can fulfill or the demand amount, whichever is smaller. If the total demand cannot be fulfilled by the lowest cost production site, it assigns an order to the one next to the lowest cost. Order amount is decided as either the amount the production site can fulfill or the remaining demand, whichever is smaller. Similarly, the warehouse keeps assigning orders until the total demand is assigned or all the production sites have been considered. In case more than one production site responds with the same cost, the warehouse chooses the one with the maximum amount of demand it can fulfill and the least amount of time. The costs associated with this agent are inventory cost and transportation cost.

On the other hand, in the centralized case the warehouse sends *request* to a central planner agent responsible for demand distribution among the production sites. As an individual agent, the warehouse does not decide how to distribute its demand.

Production Site agent

The production site agent is responsible for the manufacture of products from raw materials. It also maintains a small inventory of raw materials and products to meet the demands from the warehouses. It has fixed production capacity and storage capacities.

In the decentralized case, on receiving *request* from a warehouse, the production site sends a *response* in terms of the fraction of demand it would be able to fulfill, cost and time it would take to ship the products. In order to evaluate the fraction of demand it can fulfill, it considers the demand from all the warehouses. Based on the responses from all the production sites, the warehouses send orders for products. If the complete warehouse

demand has not been ordered, the warehouses send *requests* to production sites again with updated demand. The demand has been updated by subtracting the amount which has already been ordered. The process of sending *requests* to production sites by warehouses, receiving *response* from production sites and assigning *orders* to production sites continues until all the demand has been ordered or the production sites cannot fulfill any demand from the warehouses. In this manner, all the production sites, together attempt to fulfill the warehouse demand since sharing of information between production sites and warehouses has been considered. If the demand cannot be fulfilled by a production site alone, the other production sites evaluate if they would be able to fulfill the demand.

In the centralized case, the production site receives *orders* from the Planner agent. Since the Planner agent has access to the inventory information of the warehouses, the production site receives orders that it is able to fulfill. Even if the total warehouse demand is not fulfilled, the Planner agent does not try to reallocate the demand since it had access to the information about all the production sites in the first place.

The production site agent fulfills the demand from the warehouses by using the products it already has in its inventory. It regulates its inventory using a reorder level order up-to inventory replenishment policy with continuous review. The production site is capable of updating its reorder level continuously. On a continuous basis, the agent calculates the average demand it receives per day. Then is calculates the reorder level using the equation below.

Reorder level = Average daily demand per day x production lead time in days + safety stock

Since production delays have been considered in the model, there is a lead time for the agent. The safety stock for the agent is pre-defined. When the product inventory falls below the reorder level, it schedules the production of another batch. Similarly, the production site has reorder level and order upto level for the raw material inventory which are fixed. When the raw material inventory falls below the reorder level, it orders raw materials from the most preferred supplier. It has the highest preference for the supplier which is located closest. However, the model could easily be adjusted to include a supplier selection process just as there is a selection process for the warehouses, and the production sites. The selection process in that case could be based on transportation cost, raw material cost, shipment time, and raw material availability. The costs associated with this agent are inventory cost, production cost and transportation cost.

Manufacturing at the production sites is a batch production process. The agent uses an embedded optimization program to schedule the manufacturing process. The embedded scheduler minimizes the makespan for the maximum amounts of products produced. The deterministic model for batch process scheduling follows the main idea of continuous time formulation proposed by Ierapetritou and Floudas [67]. The general model involves the following constraints.

$\sum_{i \in I_j} wv_{i,j,n} \leq 1 \; \forall j \in J, \; \forall n \in N$	10
$st_{s,n} = st_{s,n-1} - d_{s,n} + \sum_{i \in I_s} \rho^p_{s,i} \sum_{j \in J_i} b_{i,j,n-1} + \sum_{i \in I_s} \rho^c_{s,i} \sum_{j \in J_i} b_{i,j,n} \quad \forall s \in S, \; \forall n \in N$	11

$st_{s,n} \le st_s^{\max} \quad \forall s \in S,\ \forall n \in N$	12
$v_{i,j}^{\min} wv_{i,j,n} \le b_{i,j,n} \le v_{i,j}^{\max} wv_{i,j,n} \quad \forall i \in I, \forall j \in J, \forall n \in N$	13
$\sum_n d_{s,n} \ge r_s \quad \forall s \in S$	14
$Tf_{i,j,n} = Ts_{i,j,n} + \alpha_{i,j} wv_{i,j,n} + \beta_{i,j} b_{i,j,n} \quad \forall i \in I, \forall j \in J, \forall n \in N$	15
$Ts_{i,j,n+1} \ge Tf_{i,j,n} - U(1 - wv_{i,j,n}) \quad \forall i \in I, \forall j \in J_i, \forall n \in N$	16
$Ts_{i,j,n+1} \ge Tf_{i',j',n} - U(1 - wv_{i',j',n}) \quad \forall i, i' \in I_j, i \ne i', \forall j \in J, \forall n \in N$	17
$Ts_{i,j,n+1} \ge Tf_{i',j,n} - U(1 - wv_{i',j,n}) \quad \forall i, i' \in I_j, \forall j \in J, \forall n \in N$	18
$Ts_{i,j,n+1} \ge Ts_{i,j,n} \quad \forall i \in I, \forall j \in J_i, \forall n \in N$	19
$Tf_{i,j,n+1} \ge Tf_{i,j,n} \quad \forall i \in I, \forall j \in J_i, \forall n \in N$	20
$Ts_{i,j,n} \le \mathrm{H} \quad \forall i \in I, \forall j \in J_i, \forall n \in N$	21
$Tf_{i,j,n} \le \mathrm{H} \quad \forall i \in I, \forall j \in J_i, \forall n \in N$	22

Supplier agent

The supplier agent provides raw materials to the production sites on receiving any demand. The costs associated with this agent are transportation cost and inventory cost. Transportation cost is considered to be parallel to the amount of raw materials transported and inventory cost is considered to be proportional to the amount of raw materials stored.

4.5 Centralized and Decentralized Decision Making

4.5.1 Central Planner agent

For the centralized simulation model, there are additional agents that handle demand distribution among the upstream agents. Market agents send their demand information to a Central Planner agent for it to find a suitable demand distribution among the warehouses. Similarly when the warehouses create demand, they send that information to another Central Planner agent to find a suitable demand distribution among the production sites.

The planner agents are responsible for finding the optimal demand distribution. Since their behavior involves optimization inherently, embedded optimization has been used for this agent. The agent calls this optimizer whenever it has to distribute demand among the upstream agents. As input to the optimizer, the agent passes information regarding the current state of the supply chain, past demand and forecasted demand. The optimizer uses this information to find the optimal shipment levels among the entities for all the future planning periods. The agent fetches the output for the current planning period and uses to set the demand distribution.

This agent is not present in the decentralized model as the demand distribution is done by the individual agents themselves. The structure of the centralized model with the inclusion of the planner agents is shown in figure 4.1 as opposed to the structure of the decentralized model shown in figure 4.2.

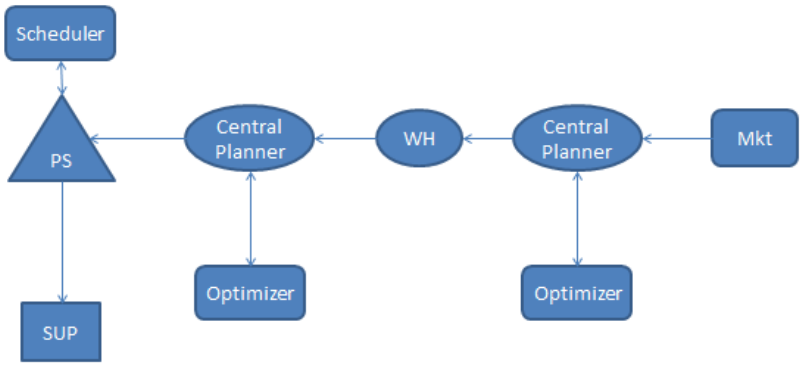

Figure 4.1: Simulation with embedded optimization for centralized scenario

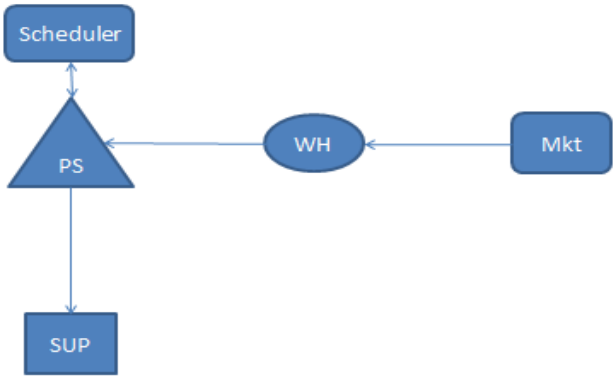

Figure 4.2: Simulation with embedded optimization for decentralized scenario

4.6 Hybrid simulation-optimization approach

The optimization and simulation models are developed independently as discussed in the earlier sections. In the hybrid approach, the two independent models are coupled together in order to take advantage of the benefits of both models. For this work, the coupling of the optimization model with the simulation model has been done using the following variables: i) shipment values obtained from optimization model set as parameters in the

simulation model, ii) production and consumption values from simulation model to optimization model.

By passing the shipment values from optimization model to simulation model, the simulation is provided with shipment targets. Simulation tries to achieve these targets so as to reduce backorder and inventories. The simulation captures a more dynamic environment of the supply chain and whether or not it is able to achieve those shipment targets depends on the behaviors of the agents of the model. Since the optimization model is to be used only for the purpose of setting targets for the simulation model, it has been kept quite simple by not including production scheduling in it. So, the simulation model is used to set production and raw material consumption targets for the optimization model. This provides the optimization model with information about the production behavior. Based on these targets, the optimization model then gives the optimal shipment values.

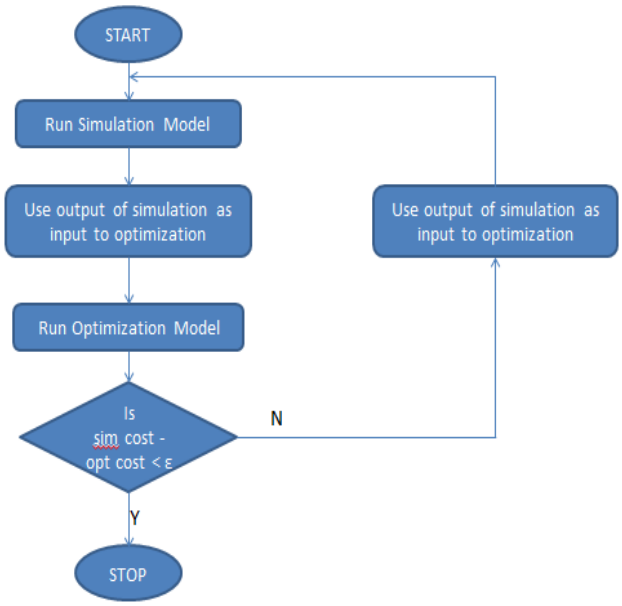

Figure 4.3: Iterative framework for the decentralized hybrid simulation–optimization approach

Using the hybrid approach proposed above, the solution methodology proposed in chapter 3 has been used. The framework consists of an iterative procedure as shown in Figure 4.3, which is initialized by solving the independent simulation model. The variables are then passed to the optimization model, which is solved to obtain values of the decision variables. The two models calculate the total cost for the planning horizon. The costs from both the models are compared. If the difference is below a tolerance level, the procedure is terminated otherwise the values of decision variables are passed back to the simulation model. This process is carried out iteratively until the difference between the two costs falls below the tolerance level. The above framework uses the simulation

model as the master model, which is guided by the optimization model towards the best solution it can achieve.

4.7 Case Studies

In this section, the different hybrid simulation-optimization approaches have been tested for two rather small-scale supply chain management problems.

4.7.1 Case study 1

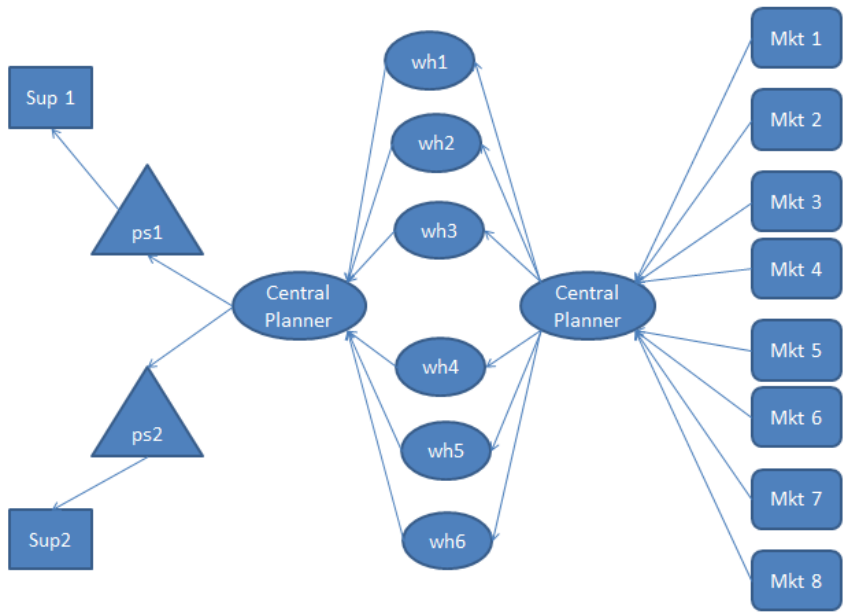

Figure 4.4: Centralized supply chain network for the case study 1

The supply chain consists of 8 markets, 6 warehouses, 2 production sites and 2 raw material suppliers. There are 2 products and 3 raw materials. Figure 4.4 shows the network configuration of the centralized supply chain. As discussed earlier, the network also consists of two Central Planner agents that manage demand distribution. There is a

planner agent that connects the markets with the warehouses and another that connects the warehouses with the production sites.

Manufacture of products is done by a batch production process. The production site agent schedules the production using an embedded scheduler which is an optimization program. Figure 4.5 below shows the state task network for the process.

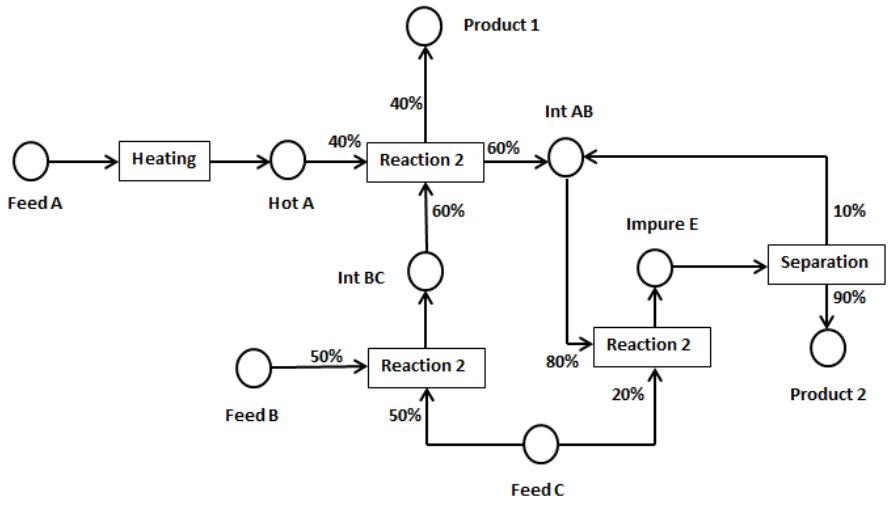

Figure 4.5: State task network for the batch production process

For the decentralized supply chain, the configuration is shown in figure 4.6. Considering figures 4.4 and 4.6, it can be seen how communication among the agents under the two scenarios take place differently. In the centralized case, all the markets communicate with a central planner agent. Similarly all the warehouses communicate with the other central planner agent. On the other hand, in the decentralized case, the warehouses communicate directly with the markets. A central agent is not present in this network. Also, there is limited communication among the agents. For instance, a market does not communicate

with all the warehouses or a warehouse does not communicate with all the production sites.

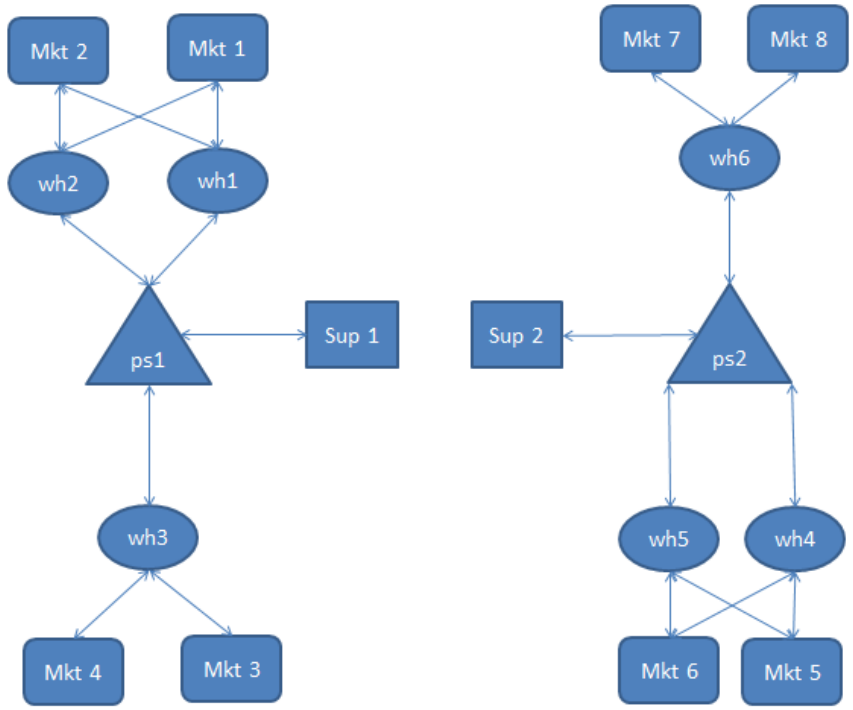

Figure 4.6: Decentralized supply chain network for case study 1

The problem is solved for a planning horizon of 10 planning periods. Figure 4.7 shows the results of the hybrid framework for both the decentralized and centralized approaches. The results illustrate that the framework converges to the optimal solution within 5 iterations. The optimization tries to improve the solution given the simulation input iteratively by adjusting the shipment. Gradually the gap between the optimal solution and the realistic solution decreases. The centralized model gives a total cost of $129,396 that is around 9% lower than the cost of $142,386 predicted by the decentralized model. The computation time for the decentralized scenario is 214 seconds while that for the

centralized scenario is 493 seconds. The centralized model requires longer computational time due to the Planner agent, which distributes demand among all the upstream agents.

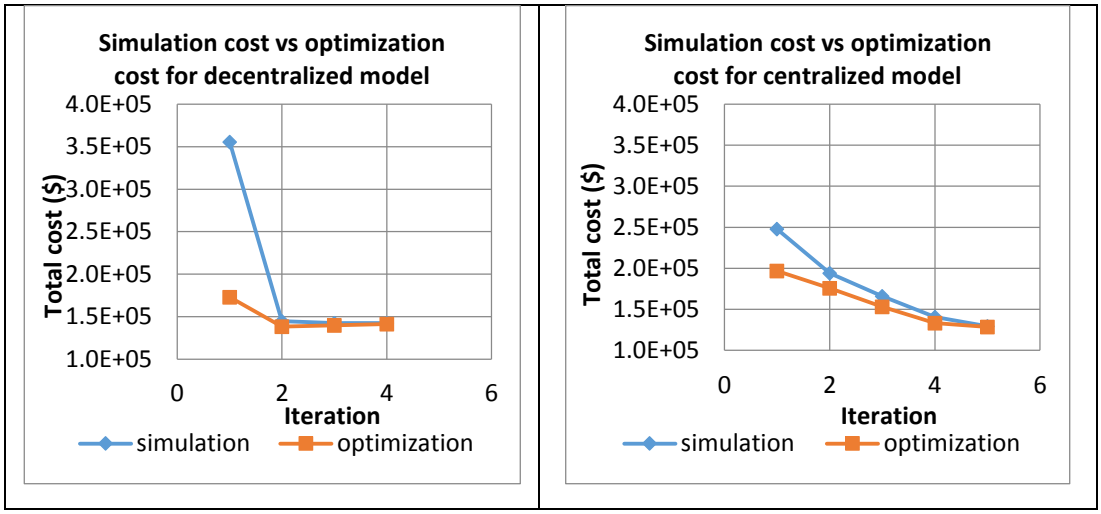

Figure 4.7: Solution of the hybrid framework for the decentralized and centralized scenarios

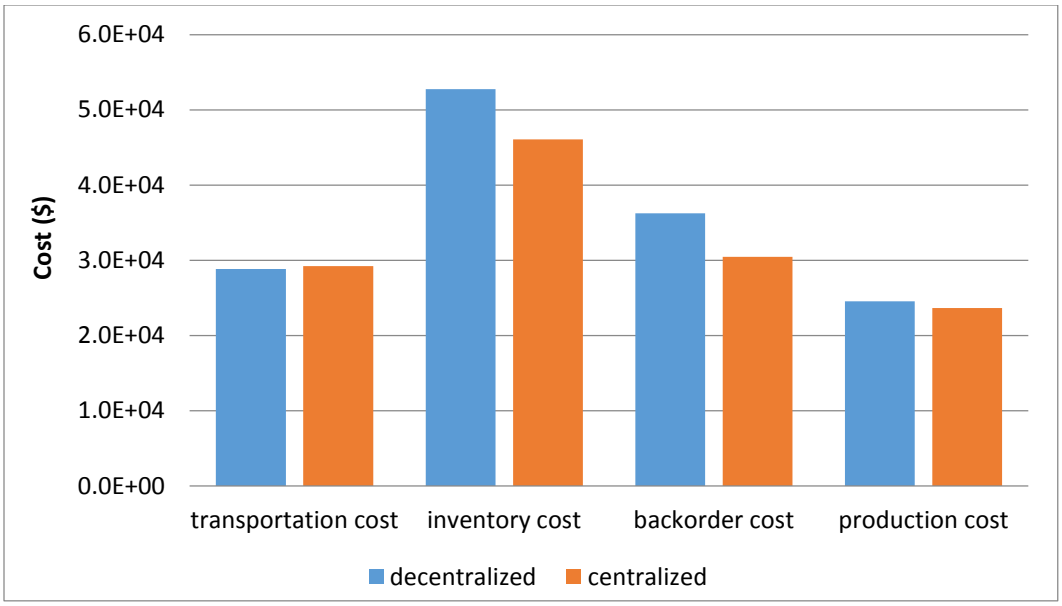

Figure 4.8: Comparison of cost components for the centralized and decentralized scenarios

Figure 4.8 shows a comparison of the different cost components for the centralized and the decentralized scenarios. Inventory cost, production cost and backorder cost are higher in case of decentralized model compared to centralized model. In the centralized model, information is shared across the whole network and also the central planner agents distribute the demand among the upstream agents in a centralized manner. Therefore more demand is able to be fulfilled which reduces the backorder cost. Better information and proper coordination also enable the warehouses and production sites to be able to fulfill demand while maintaining lower inventories. This results in lower inventory costs as well. It can be noticed that in case of centralized model, the transportation cost comes to be higher than in the case of decentralized model. This is quite expected because demand is distributed locally in case of decentralized scenario. Communication within the network is limited which means that demand is fulfilled by agents which are located

close to each other. On the other hand, orders could be sent to agents that are situated very far in order to reduce backorders. As the transportation cost is a function of distance, it becomes higher in case of the centralized scenario.

4.7.2 Case study 2

The proposed frameworks were used to solve another case study with a larger supply chain network. A network with 12 markets, 12 warehouses, 4 production sites and 4 suppliers was considered. The batch manufacturing process was considered to be the same as that in the first case study with 2 products and 3 raw materials.

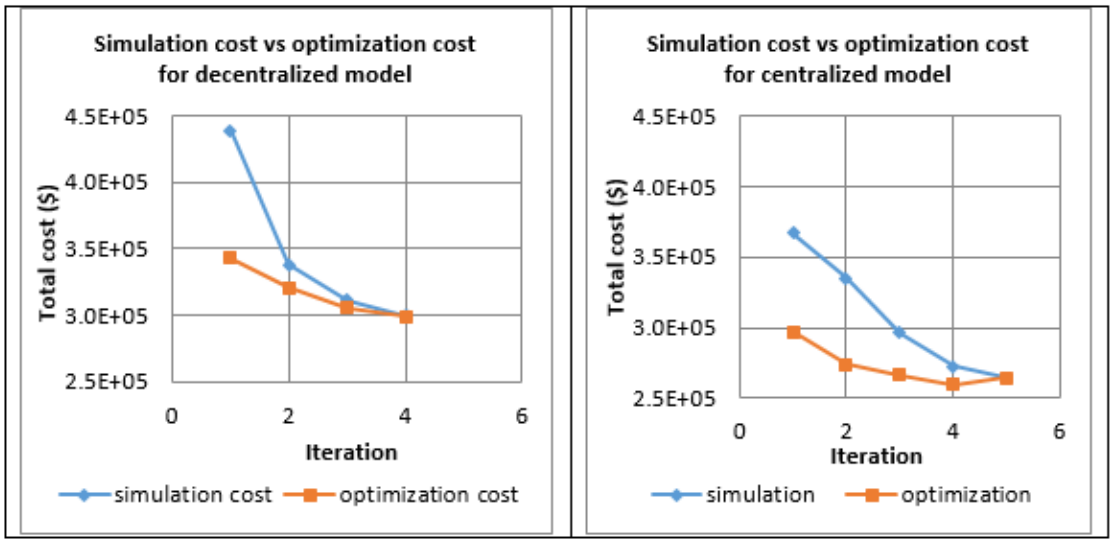

Figure 4.9: Solution of the hybrid framework for the decentralized and centralized scenarios

Figure 4.9 shows the result of the iterative solution hybrid iterative framework for the centralized and decentralized models. Again, convergence is reached in less than 6 iterations. The centralized model gives a total cost of $264,616 that is around 11.5%

lower than the cost of $299,353 predicted by the decentralized model. The computation time for the decentralized scenario is 274 seconds while that for the centralized scenario is 604 seconds.

Figure 4.10 shows a comparison of the cost components for the centralized and decentralized scenarios based on the individual cost coefficients. For this example, a larger supply chain network has been considered which is geographically more dispersed. Therefore, in the centralized case transportation takes place over longer distances. The benefits of centralization are reflected in the lower backorder cost and lower inventory cost. Better coordination leads to less backorders and lower inventory levels. Due to shipments taking place over longer distances, transportation cost is higher in the centralized scenario.

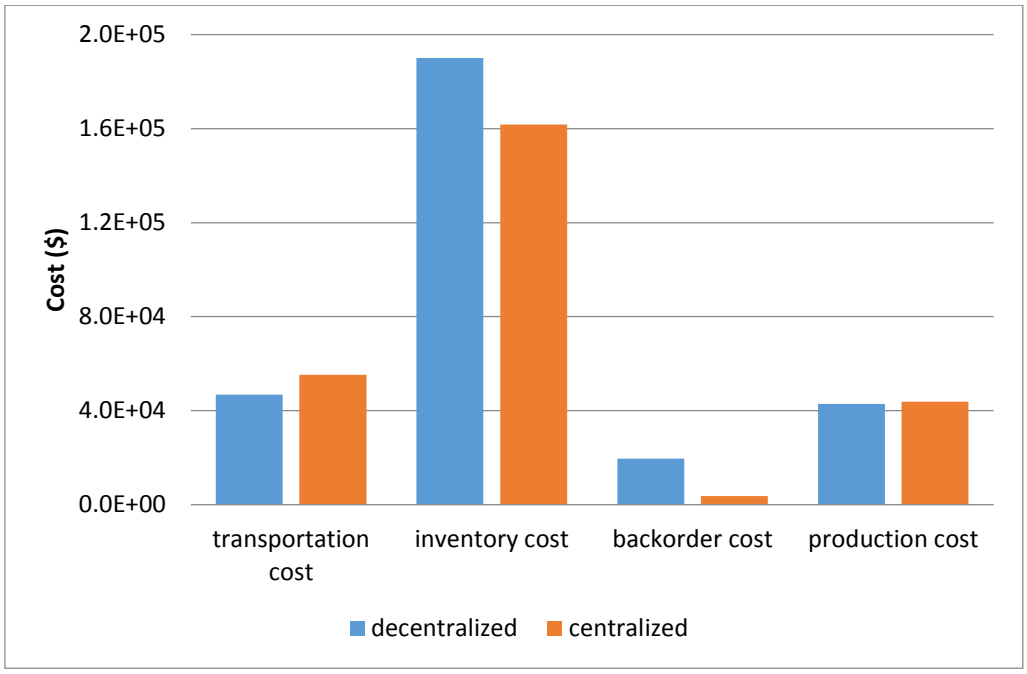

Figure 4.10: Comparison of cost components for the centralized and decentralized models

The sensitivity of the models with respect to the warehouse capacity was studied. Figure 4.11 shows how the total cost predicted by the centralized and decentralized models varies with change in warehouse capacity.

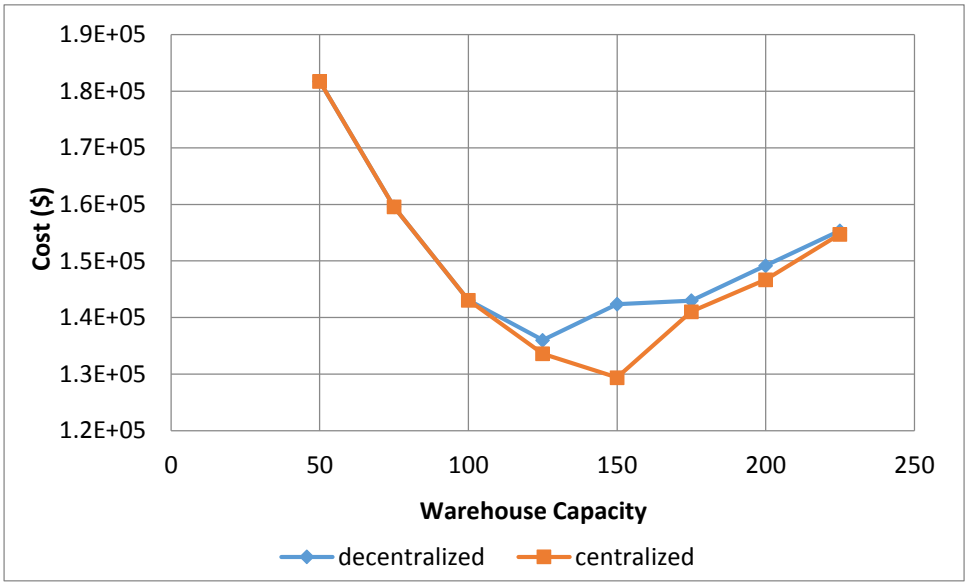

Figure 4.11: Variation of total cost with warehouse capacity

It can be seen that both the models follow the same trend for the variation with warehouse capacity. Total cost first decreases and then increases as the warehouse capacity is increased. At lower warehouse capacities the total cost decreases with the increase in capacity. This is expected as at very low warehouse capacities, the backorders are high. As the capacity gradually increases, more demand can be fulfilled which reduces the backorder cost and hence the overall cost. The trend can be understood by looking at the how the individual cost components vary. It can be seen that while backorder cost decreases, inventory and transportation cost keep increasing with the rise in warehouse capacity. Beyond a certain warehouse capacity, the total cost is dominated

by the increase in inventory and transportation costs rather than the decrease in the backorder cost. As a result, there is an increase in the total cost beyond that warehouse capacity. Figure 4.12, shows the variation in major cost components with warehouse capacity for the decentralized model. Similar trend can be seen for the centralized model as well.

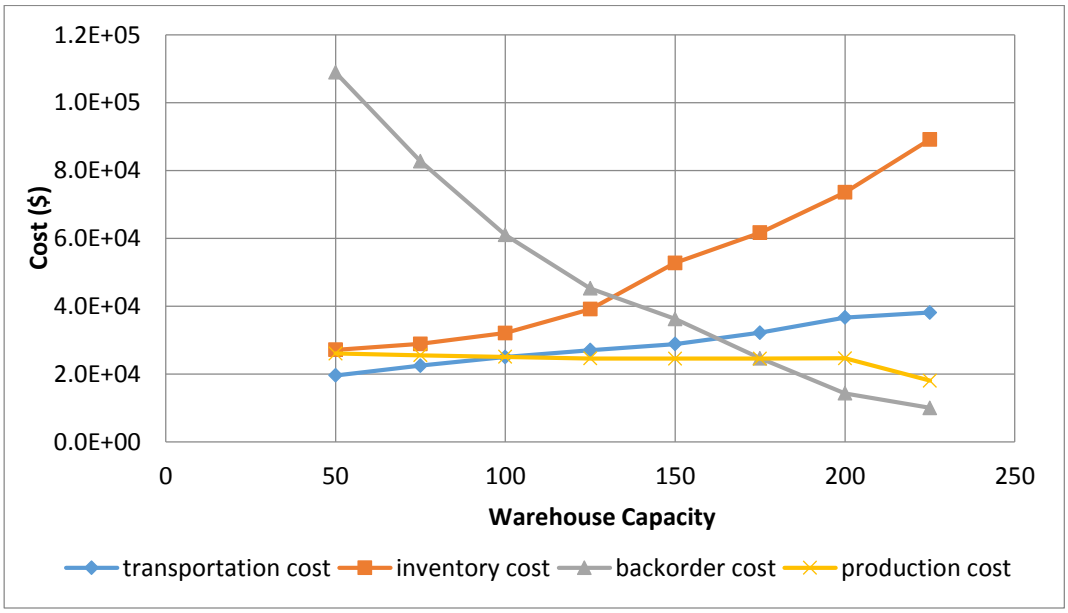

Figure 4.12: Variation of major cost components with warehouse capacity

Figure 4.11 also shows a comparison of the costs obtained from the centralized and decentralized models for the different warehouse capacities. It can be seen that at lower warehouse capacities, results from the two models overlap. As the capacity increases, the gap between the centralized and decentralized models increases. Centralized model predicts a lower cost than the decentralized model. The difference is the maximum at a warehouse capacity of 150 after which it again decreases. Below 125, the capacity is so low that centralization is not able to offer any benefits. The warehouse inventories are

exhausted by the nearby markets. Gradually, with higher capacities, it is advantageous to be able to make centralized decisions and order outside the local region. As we saw earlier that transportation cost and inventory cost start to dominate at higher warehouse capacities, the gap between centralized and decentralized models starts to decrease at higher warehouse capacities.

The effect of different levels of decentralization was also studied. The results are shown in figure 4.13. It can be seen that around the value of 150 for the warehouse capacity where the effects of decentralization are most apparent, the total cost decreases as the level of decentralization decreases from ‘high’ to ‘low’. Level of decentralization here is related to the extent of visibility in the network. A ‘high’ level of decentralization implies that information about fewer warehouses and production sites is visible to the markets and warehouses respectively compared to a ‘low’ level of decentralization where information about more warehouses and production sites is available. In case of ‘high’ decentralization, the markets have been considered to have information about a maximum of 2 warehouses and the particular warehouses depend on the structure of the network. On the other hand, in case of ‘low’ decentralization, the markets have information about all the 6 warehouses. ‘Medium’ decentralization refers to the scenario where the markets have information about an intermediate number of warehouses between 2 and 6 depending on the structure of the network. It is seen that as the visibility increases, the decentralized model approaches a solution closer to the centralized model.

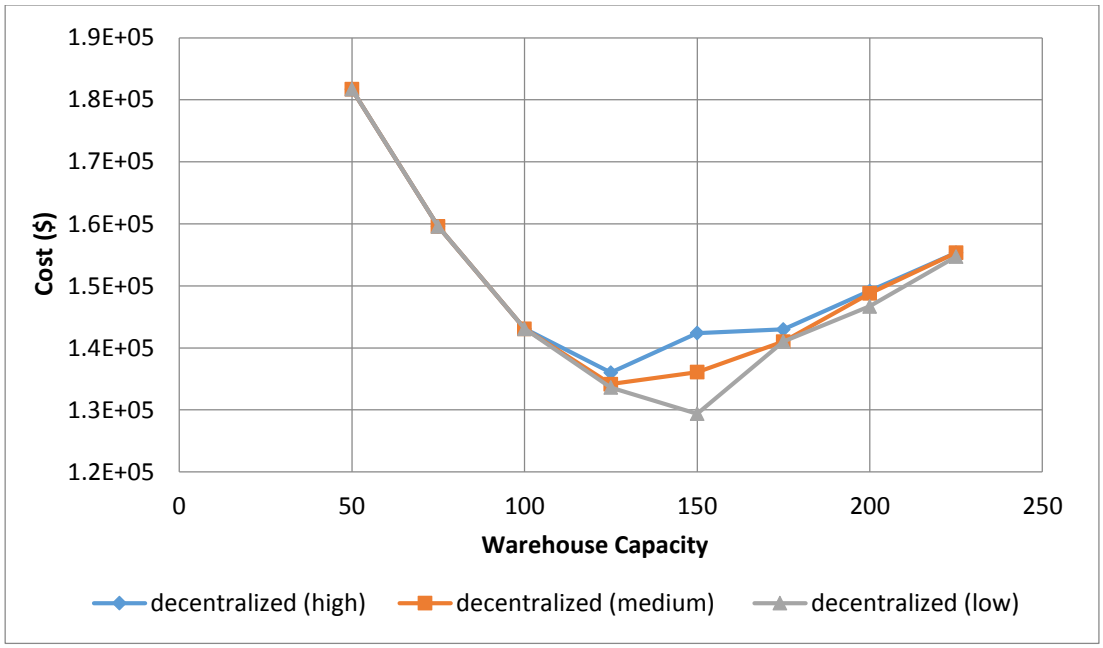

Figure 4.13: Variation of total cost with different levels of decentralization

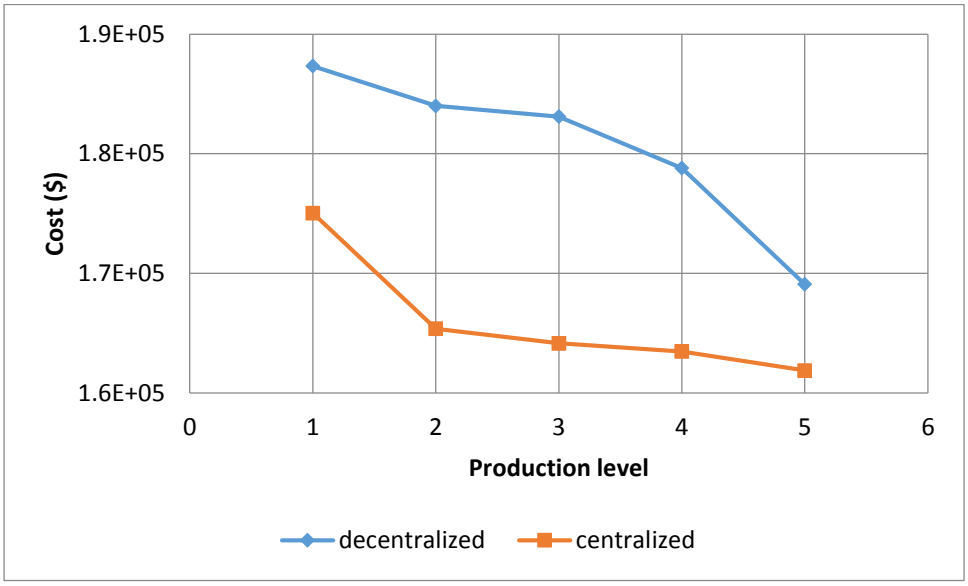

Figure 4.14: Variation of total cost with production capacity

Figure 4.14 shows the variation in the cost predicted by the models for different levels of production capacity. The different levels of production capacity indicate the different capacities for the various units in the production site. The capacities increase with the increasing levels. Production sites have a limited storage capacity which has been considered to be fixed for all the levels production capacities. It can be seen that the total cost decreases with the rise in production capacity for the centralized and decentralized model. The centralized model predicts a lower cost than the decentralized model in all the cases. Figure 4.15 shows the variation in different cost components for the decentralized model with the increase in production capacity. A similar trend for the centralized scenario is also obtained. As the production capacity increases, the production sites are able to manufacture more products in order to meet the demands which results in a decrease in backorder cost and a slight increase in production cost. Since more products are manufactured and more demand is fulfilled, more amounts of shipments are transported among the entities. Therefore, there is an increase in the transportation cost. A similar plot for was obtained for the centralized case as well.

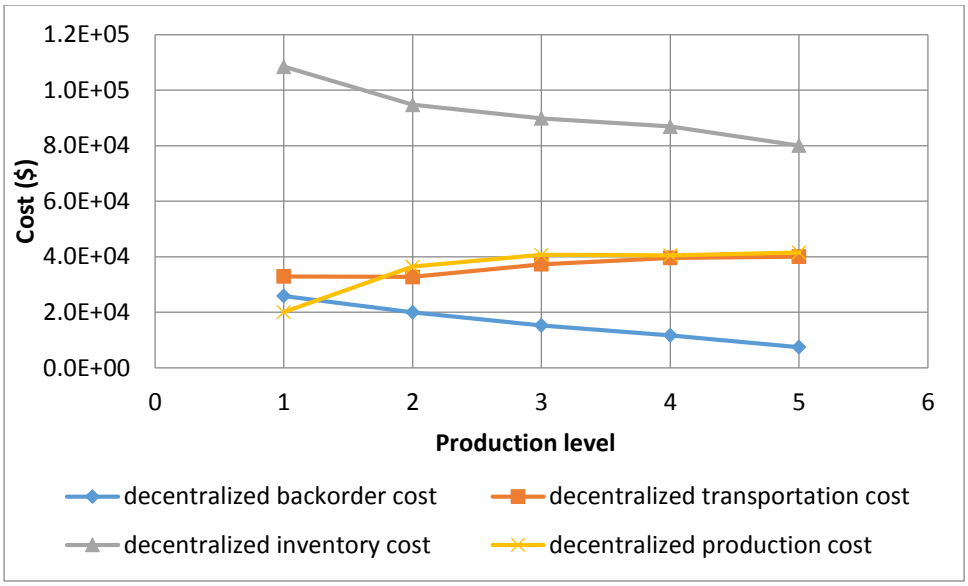

Figure 4.15: Variation of different cost components with production capacity

4.8 Conclusions

In this chapter, we demonstrated different methodologies to develop hybrid simulation based optimization frameworks. The first methodology uses embedded optimization to improve agent behavior while the second one uses optimization to set targets for the simulation model and direct it towards the optimal solution. It illustrates the flexibility with which agent based simulations can be coupled with optimization models to improve the autonomous behavior of agents.

Embedded optimization was used for agents that perform optimization inherently. The other approach where optimization directs the simulation towards optimality is used to improve the performance of the different agents. The proposed hybrid simulation based optimization frameworks offer the capability to incorporate either one or both of these approaches and to improve the behavior of the supply chain entities.

The hybrid frameworks were used to study different supply chain decision-making policies. The effects of centralized decision making where the decision maker acts as a central authority with access to all the information are observed. It is observed that centralization enables better fulfillment of customer demands due to better coordination among the agents. The extent of benefit that centralization provides depends on the design of the supply chain. However, the centralized model gives better or equal results in all the cases considered.

This study illustrates that the agent based simulation model can be conveniently used to capture supply chain dynamics under different scenarios. Also, the proposed hybrid simulation based optimization framework can be effectively used to improve the behavior of the agents. Apart from the two decision making policies considered in this work, similar approach may be used to capture varied supply chain management scenarios. 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.

Nomenclature

Indices	
t	planning period
p	production site
sup	supplier
m	distribution market

wh	Warehouse
s	Product state
r	Raw material state
mt	Mode of transportation
mp	Mode of production
Sets	
T	planning periods
PS	production sites
SUP	suppliers
M	distribution markets
WH	Warehouses
PR	Product states
R	Raw material states
MT	Modes of transportation
MP	Modes of production
Parameters	
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*
$h_r^{\sup}$	holding cost of raw material *r* at supplier *sup*
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*
$FixCost^p$	fixed production cost of operation of production site *p*
$VarCost^p$	unit variable cost of production at site *p*
$Dem_s^{m,t}$	demand of product *s* at market *m* for period *t*
$stcap_r^{\sup}$	Inventory holding capacity of raw material *r a*t supplier *sup*
$stcap_r^p$	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 or product *s* at production site *p*
Variables	
$D_s^{wh,m,t}$	Amount of product *s* transported from warehouse *wh* to market *m* at period *t*
$D_s^{p,wh,t}$	Amount of product *s* transported from production site *p* to warehouse *wh* at period *t*
$D_r^{\sup,p,t}$	Amount of raw material *r* transported from supplier *sup* to production site *p* at period *t*
$Inv_s^{wh,t}$	inventory level of product *s* at the end of the planning period *t* at warehouse

	wh
$Inv_s^{p,t}$	inventory level of product *s* at the end of the planning period *t* at production site *p*
$Inv_r^{p,t}$	inventory level of raw material *r* at the end of the planning period *t* at production site *p*
$Inv_r^{\sup,t}$	inventory level of raw material *r* at the end of the planning period *t* at supplier *sup*
$U_s^{m,t}$	Backorder amount of product *s* at the end of planning period t at market *m*
w_t^p	Binary variable to decide whether production site *p* operates during planning period *t* or not
$P_s^{p,t}$	Amount of product s produced at production site *p* during planning period *t*
$C_r^{p,t}$	Amount of raw materials r consumed at production site *p* during planning period *t*
$wv_{i,j,n}$	Binary whether or not task *i* in unit *j* starts at event point n
$st_{s,n}$	continuous, amount of state *s* at event point *n*
$d_{s,n}$	amount of state *s* delivered at event point *n*
$\rho_{s,i}^p$ $\rho_{s,i}^c$	proportion of state *s* produced, consumed by task *i*, respectively
$b_{i,j,n}$	continuous, batch size of task *i* in unit *j* at event point *n*
$st_s^{\max}$	available maximum storage capacity for state *s*
$v_{i,j}^{\min}$ $v_{i,j}^{\max}$	minimum amount, maximum capacity of unit *j* when processing task *i*
r_s	requirement for state *s* at the end of the time horizon

$Tf_{i,j,n}$	time that task *i* finishes in unit *j* while it starts at event point *n*
$Ts_{i,j,n}$	time that task *i* starts in unit *j* at event point *n*
$\alpha_{i,j}$	constant term of processing time of task *i* at unit *j*
$\beta_{i,j}$	variable term of processing time of task *i* at unit *j* expressing the time required by the unit to process one unit of material performing task *i*
H	Time horizon

5 Synchronous and Asynchronous Decision Making Strategies in Supply Chains

The individual entities in such a network have their own goals and objectives. A supply chain network may comprise entities belonging to the same or different organizations. Due to the way the different business processes operate and update information, there is often a disconnection between the physical actions of the entities and information. The different business processes have their own individual goals and objectives and operate on the basis of their own time-scales. Therefore, in an actual supply chain, it is not practical to synchronize the operations of all the processes. The overall operation of the supply chain, therefore, is a mix of synchronous and asynchronous processes.

In the case of real-world supply chains, it is impractical for a single decision maker to have access to all the relevant information and make decisions for the whole network. There are usually multiple decision makers who have access to their own sets of information and make their own independent decisions. These decisions are not synchronized and therefore the operations also take place at their own individual rates and times. Due to this asynchronous nature of operations, the individual decision makers make decisions based on the information available at those specific times.

Simulation models have been widely used to depict supply chain networks. The main idea behind using detailed simulation models is to be able to capture the true dynamics of the network. In a practical scenario, no supply chain operates completely synchronously or asynchronously. It is therefore essential for the simulation models to include the synchronicities and asynchronicities present in the network in order to capture the true dynamics. The way these models are coded is important to get the right set of results.

Here is a brief description of some of the important works available in the literature related to modeling of synchronous and asynchronous processes.

5.1 Background

In a practical scenario, asynchronous decision making within a supply chain is quite common. There are quite a number of works which cover the distributed and asynchronous nature of decision making[68-75]. We discuss some of those works related to modeling of synchronous and asynchronous processes, particularly related to supply chains. Carle et al.[76] propose an agent-based metaheuristic to solve large-scale multi-period supply chain network design problems. Using the concept of asynchronous agent teams (A-teams), they propose an efficient hybrid metaheuristic called Collaborative Agent Team (CAT). The generic model integrates design and modeling concepts and can be used to reengineer real-world supply chain networks. They compare the results for large-scale networks with those obtained with CPLEX. Tolone[77] focuses on agility and time-based manufacturing as critical factors for manufacturing enterprises in today's world. He considers a multi-company supply chain planning and execution environment and emphasizes the importance of real-time and asynchronous collaboration technology in allowing manufacturers to increase their supply chain agility. They propose Virtual Situation Room technology to find and engage quickly the relevant members of a problem solving team. The members are supported by highly interactive access to information and control. They are enabled by business processes, security policies and technologies, intelligence and integration tools. Zheng et al.[78] present a multi-agent architecture for SCM systems in which asynchronous teams (A-Team) of agents exchange results and cooperate to give non-dominated solutions that show the tradeoffs

between objectives. They consider the complex processes, objectives and constraints in today's supply chains and state that agent-based architectures for supply chain management are difficult to implement and maintain. Luh et al.[79] focus on the issue of coordination of activities across a network of suppliers to quickly respond to market conditions. They combine mathematical optimization and the contract net protocol for make-to-order supply network coordination. The overall problem is decomposed into organizational sub-problems. Scheduling of activities by the individual organizations is based on their internal situations and inter-organization prices. Coordination is carried out in a distributed and asynchronous manner. Bond[80] states that most work is organized, that is it is carried out by many people cooperatively solving a set of shared problems. He outlined his research in two areas, (i) cooperation in a vertical structure of an organizational hierarchy and (ii) horizontal cooperation among a team of agents which have different specializations and are solving a common problem. Akiyoshi and Komoda[81] study distributed organizations which can be categorized into demand and supply sites. They state that in order to reach mutual agreement, negotiation based commitment is needed. The negotiation process under asynchronous negotiation is a complicated procedure. In their work, they investigate such a negotiation process. Sohlenkamp and Chwelos[82] present a novel environment called DIVA for group work. The prototype virtual office environment supports communication, cooperation and awareness in both synchronous and asynchronous modes. It is modeled after the standard office and abstracts elements of physical offices required for collaborative work like people, rooms, desks and documents.

In this work we use agent based simulation models for supply chain systems. Therefore we present here a brief description of some work related to asynchronous and synchronous agent based models, not particularly related to supply chains. Some of the works focus on the specific modeling methodology followed in developing the models with regards to update scheme for the different agents in the agent based models. Volf et al.[83] present a simulation framework designed to simulate entities to high details requiring extended computation resources. They present the concept the dynamic partitioning of the multi-agent simulations. Spatial partitioning and dynamic load balancing are used. The simulation combined synchronous and asynchronous parts. They verify the simulation framework by using it for the entire civilian air traffic touching the national airspace of United States. Lormier et al.[84] discuss that the success of individual based models depends on its design and assumptions made during its construction. In particular, they consider synchronous and asynchronous scheduling as two methods for updating object characteristics during interaction. They show that the two methods produce different results for a simple individual based model, particularly for high population densities and increased interaction complexity. Cornforth et al.[85] use 1-dimensional cellular automata as a case study to compare synchronous, random asynchronous and ordered asynchronous updating schemes in multi-agent systems. They show that the type of updating scheme has an impact on the dynamic characteristics of the system. They conclude that ordered asynchronous processes with local temporal coupling play a role in self-organization within many multi-agent systems. Guo and Tay[86] focus on the heterogeneity in update frequencies of the individual agents due to multi-timescales in immunological phenomena. They apply an event-scheduling update scheme

which allows arbitrarily smaller timescales and avoids unnecessary execution and delays. They use the scheme to model the B cell life cycle and compare its simulation performance with the widely adopted uniform time-step update scheme. Boer et al.[87] investigate how the market dynamics for continuous, asynchronous simulation are different from discrete time simulation. They show that the continuous, asynchronous simulation reveals more information and the market prices are different between the two cases. Lawson and Park[88] study the behavior of the artificial society and demonstrate that very different behavior can be observed if agent events occur asynchronously instead of synchronous time evolution which is used in most artificial society discrete event simulations. Results show that by using an appropriate event list implementation, acceptable computational performance can be achieved. Androulakis and Reklaitis[89] developed a methodology for decentralized decision making for problems consisting of interacting sub-systems where each is described by local properties and dynamics. The methodology is based on the solution of a series of sub-problems where each minimizes each local objective while maximizing a common Lagrangean function.

In this work, we investigate how the asynchronous operations of the different members of the supply chain can affect its overall behavior. We consider that the different entities of the network operate based on their timescales. Based on their own operating cycles, they update the relevant information which impacts the information set available to others at any particular point in time. In order to illustrate this, we use rather simple case studies. We use agent based simulation models to capture the dynamics of these simple networks. To include production scheduling for the manufacturing plants, we use embedded optimization with the agent based simulation models. We also develop models for the

synchronous operation and compare the results for the scenarios. Both synchronous and asynchronous decision-making are optimized using the hybrid simulation based optimization approach proposed in chapter 3. The hybrid simulation based optimization approach has been shown to be effective in predicting the optimal operation of the supply chain while capturing the behavior of the individual agents[90]. We use this approach to predict the optimal operation of the supply chain under the two decision making strategies.

5.2 Problem Statement

A supply chain network consisting of different decision – making entities has been considered. The entities specifically included in this study are market, warehouse and production sites. Each entity has its own role in the network and performs its functions based on its individual policies. The actions of the entities are dependent on the information available to them and the state of the network which evolves as the entities perform their functions. Information is exchanged among the decision – making entities as they interact with each other. The market receives demand for products at specific time intervals and assigns orders to the upstream entities based on its ordering policy. The warehouses store products and transport them to fulfill market demand. They regulate their inventory by following their own inventory replenishment policy. Similarly, production sites also transport products to fulfill market demand. They manufacture products to regulate their product inventory by following a production policy. They maintain their raw material inventory by following an inventory replenishment policy.

Interaction among the entities can occur either synchronously or asynchronously. Unlike synchronous interactions where information is exchanged among the entities simultaneously, the exchange of information depends on individual operation cycles of the entities in case of asynchronous interactions. The market ordering policy, inventory replenishment policies and the production site production policy involve making decisions based on the information available to the entities. For example, the market orders products from the upstream entities based on the available information regarding their inventory. Similarly the production site manufactures products based on the available demand information. Consequently, availability of information plays an important role in the dynamics of the network. It becomes significant whether the interactions among the entities occur synchronously or asynchronously.

5.3 Asynchronous and Synchronous Decision Making Scenarios

In this section, we describe how synchronous and asynchronous interactions within the supply chain network have been implemented in this study. As mentioned earlier, for the synchronous scenario, information is shared with the different entities of the supply chain simultaneously. In this way the operation of a particular entity is dependent on those of the other entities as the demand site, considered as the market in the examples studied, waits for responses from all the warehouses regarding fulfillment of demand. However for the asynchronous decision making strategy, the operations of the different entities of the supply chain do not necessarily depend on those of the other entities. Each entity has its own independent operation cycle and the times at which they update their databases and obtain the latest information are not synchronized.

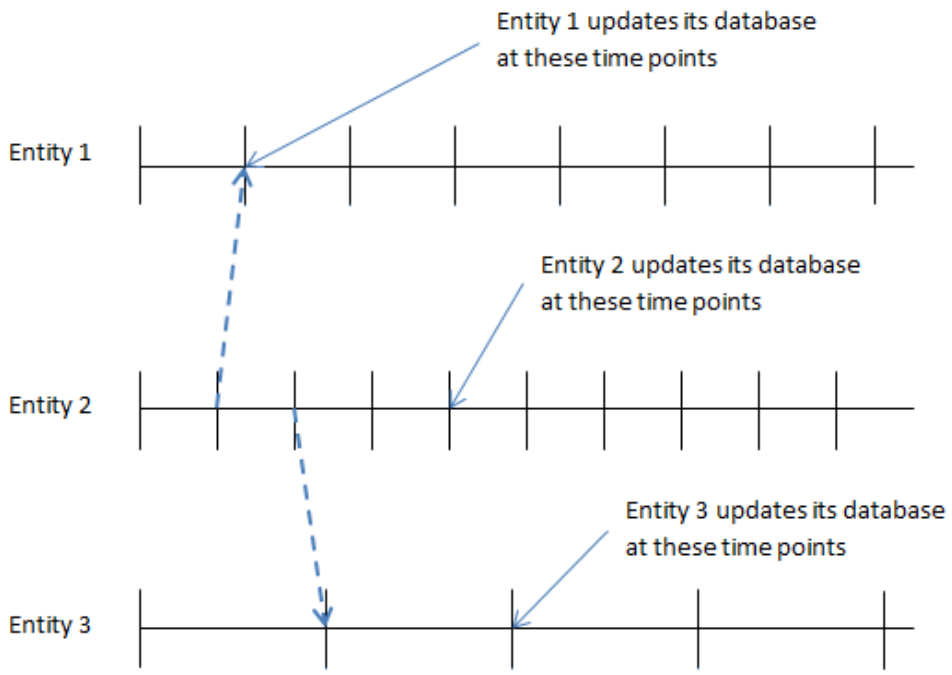

Figure 5.1: Asynchronous implementation for supply chain agents in the study

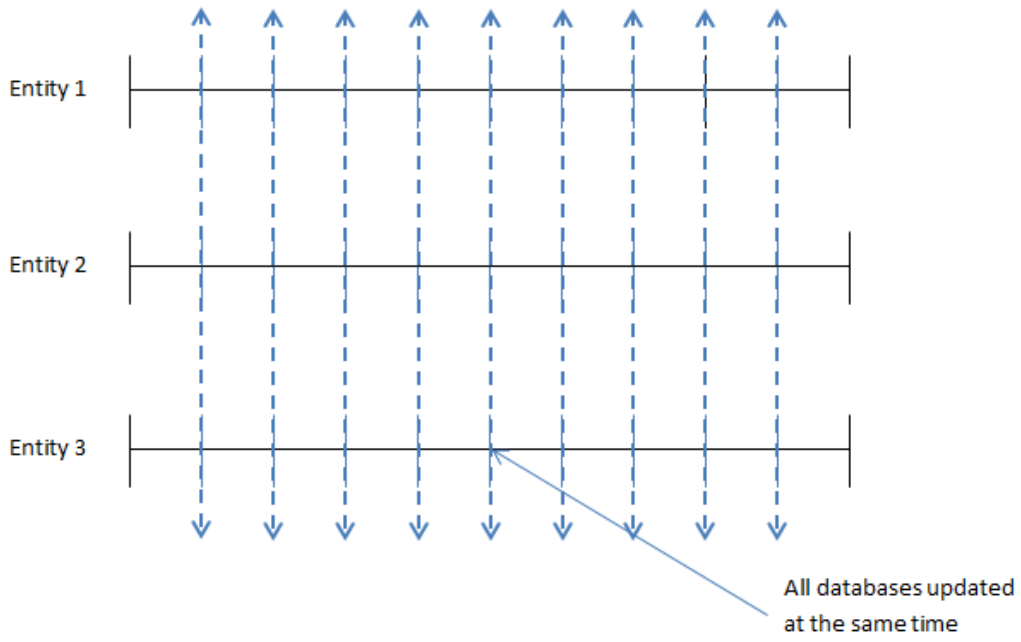

Figure 5.2: Synchronous Implementation for supply chain agents in the study

Figures 5.1 and 5.2 depict an example of the implementation of the asynchronous and synchronous decision-making in the supply chain where three entities are involved. In the figures, the horizontal line depicts the time horizon for which the simulation is run. Information is being shared by entity 2 with entity 1 and entity 3. The vertical lines intersecting the horizontal line are the time points at which the entity performs a particular operation. For example if entity 2 is a market, the line represents the time at which the demand arrives at the market and it updates its database. If entity 1 is a warehouse, it represents the time at which the warehouse obtains the demand from the market and updates its database. The dashed lines connecting the entities represent the exchange of information between the two. As we can see in figure 5.2, the update times for the entities are synchronized and they have access to the same information simultaneously. Figure 5.1 shows the asynchronous implementation where the time points when entities 1 and 3 obtain information and when entity 2 updates information are not synchronized. Hence entity 1 is able to receive the information updated by entity 2 during the 1st period while entity 3 obtains the information from entity 2 during the 2nd period. Based on their individual operating cycles, either of the entities may be able to obtain the latest information.

These scenarios depict how the operations within a supply chain network can occur differently. Even within a single-company supply chain network, entities can operate both synchronously and asynchronously. The different implementations that are adopted here for the two different scenarios represent small portions of the overall dynamics of an actual supply chain and are meant to give an idea of the effects that a combination of the two scenarios would cause in the overall supply chain dynamics.

5.4 Simulation model

A supply chain is a distributed and decentralized system with autonomous entities. For such a system, it is suitable to model using a bottom-up approach. Agent based modeling has been used in the literature to model such systems. It has been shown that an agent based model can be used to better represent the dynamics of a supply chain [62,91]. In this work, agent based simulation model has been implemented using Repast simulation platform and Java programming environment. In order to model the synchronous and asynchronous operations of the supply chain, two different simulations have been developed. Here is a description of the agents in both the models.

5.4.1 Demand agent

Demand for products originates at the demand agent. The behavior of the agent regarding demand distribution is different for the synchronous and asynchronous operations.

In the synchronous case, the agent distributes demand among the supply agents. When a demand site receives a demand, it sends *requests* for the required amounts of products to the supply sites. A *request* is not the actual order for products. A *request* is a way to procure information from the upstream agent regarding how much demand can be fulfilled and at what cost. Based on the response from supply sites, the demand agent distributes the demand among the supply sites by following its ordering policy. As an ordering policy, the demand agent gives first preference to the supply site which responds with the lowest cost. It assigns an order of amount either equal to what the supply site can fulfill or the demand amount, whichever is smaller. If the total demand cannot be fulfilled

by the lowest cost supply site, it assigns an order to the one with the cost next to the lowest cost. Order amount is decided as either the amount the supply site can fulfill or the remaining demand, whichever is larger. Similarly, the demand agent keeps assigning orders until the total demand is assigned or all the supply sites have been considered. In case where more than one supply site responds with the same cost, the demand agent chooses the one with the maximum amount of demand it can fulfill and the least amount of time. In such a scenario, it is ensured that all the supply sites have the same demand updated information available to them at a particular time.

In the asynchronous case, the demand agent updates the demand information at regular intervals. These intervals need not match with the specific time points at which it actually receives the demand. The intervals at which the agent updates the demand information in order to be available for the other entities is referred to as the 'update cycle' of the market. The agent does not coordinate with all the supply sites for demand distribution. The supply sites are allowed to run their own processes independently rather than in a coordinated manner. When one or more supply site communicates with the demand agent regarding demand fulfillment, the demand agent decides to receive product shipment from the supply sites. In such a scenario, the supply sites do not operate in a coordinated manner and need not have access to the same demand information at the same time.

5.4.2 Warehouse agent

The warehouse agent stores products and regulates its inventory using a fixed reorder level and reorder quantity with continuous review. There is a fixed lead time for inventory replenishment. There is a transportation delay between the warehouse and the

demand sites. In the asynchronous scenario, the warehouses obtain the updated demand information at regular intervals that are not coordinated with the update cycles of the demand sites. These regular intervals at which the warehouse obtains the latest demand information from the demand sites is referred to as the 'update cycle' of the warehouse. Based on which warehouse obtains the latest demand information first, the fulfillment of demand by a particular warehouse is done.

On the other hand, in case of synchronous operations, the demand sites share the latest demand information with the warehouses immediately. Therefore, in this case all the warehouses get access to the demand information at the same time. When a warehouse receives a *request* from a demand site, it sends a *response* which includes the cost, the amount it can fulfill and the time it would take to fulfill the demand. Based on the *responses* received from the warehouses, the demand sites send orders to the warehouses which are fulfilled with the available inventory.

5.4.3 Production Site

The Production Site agent stores products and also regulates its inventory by manufacturing products from raw materials. It sends products to the demand sites to fulfill demand. There is a transportation delay between the production site and the demand sites. The production site obtains demand information from the market. At a particular planning period, the production site can obtain information about the future demand for a fixed number of periods. The intervals at which the production site obtains demand information from the demand sites is referred to as the 'update cycle' of the production site. When the information available to a production site gets updated, it is

able to generate a production schedule so as to meet the future demand. The scheduling horizon for the scheduler is the number of time periods for which the demand is known to the production site. There is a production delay between the generation of a schedule and actual change in inventory by manufacturing.

In the asynchronous case, a production site operates based on its own update cycle. It may not obtain the latest demand information immediately. Therefore it may not be able to generate an updated production schedule as soon as a new demand appears at the demand site. An updated production schedule is generated only when the demand information available to the production site gets updated.

On the other hand, in case of synchronous interactions, the demand sites share the latest demand information with the production sites immediately. Therefore, in this case all the production sites get access to the demand information at the same time. When a production site receives a *request* from a demand site, it sends a *response* which includes the cost, the amount it can fulfill and the time it would take to fulfill the demand. Based on the *responses* received, the demand sites send orders to the production sites which are fulfilled with the available inventory.

Manufacturing at the production sites is a batch production process. The agent uses an embedded optimization program to schedule the manufacturing process. The embedded scheduler minimizes the total cost involved for the scheduling horizon. The deterministic model for batch process scheduling follows the main idea of continuous time formulation proposed by Ierapetritou and Floudas [67]. The general model involves the following constraints.

$\sum_{i \in I_j} wv_{i,j,n} \leq 1 \ \forall j \in J, \ \forall n \in N$	1
$st_{s,n} = st_{s,n-1} - d_{s,n} + \sum_{i \in I_s} \rho^p_{s,i} \sum_{j \in J_i} b_{i,j,n-1} + \sum_{i \in I_s} \rho^c_{s,i} \sum_{j \in J_i} b_{i,j,n} \quad \forall s \in S, \ \forall n \in N$	2
$st_{s,n} \leq st_s^{\max} \quad \forall s \in S, \ \forall n \in N$	3
$v_{i,j}^{\min} wv_{i,j,n} \leq b_{i,j,n} \leq v_{i,j}^{\max} wv_{i,j,n} \quad \forall i \in I, \forall j \in J, \forall n \in N$	4
$\sum_n d_{s,n} \geq r_s \quad \forall s \in S$	5
$Tf_{i,j,n} = Ts_{i,j,n} + \alpha_{i,j} wv_{i,j,n} + \beta_{i,j} b_{i,j,n} \quad \forall i \in I, \forall j \in J, \forall n \in N$	6
$Ts_{i,j,n+1} \geq Tf_{i,j,n} - U(1 - wv_{i,j,n}) \quad \forall i \in I, \forall j \in J_i, \forall n \in N$	7
$Ts_{i,j,n+1} \geq Tf_{i',j',n} - U(1 - wv_{i',j',n}) \quad \forall i, i' \in I_j, i \neq i', \forall j \in J, \forall n \in N$	8
$Ts_{i,j,n+1} \geq Tf_{i',j,n} - U(1 - wv_{i',j,n}) \quad \forall i, i' \in I_j, \forall j \in J, \forall n \in N$	9
$Ts_{i,j,n+1} \geq Ts_{i,j,n} \quad \forall i \in I, \forall j \in J_i, \forall n \in N$	10
$Tf_{i,j,n+1} \geq Tf_{i,j,n} \quad \forall i \in I, \forall j \in J_i, \forall n \in N$	11
$Ts_{i,j,n} \leq \mathrm{H} \ \ \forall i \in I, \forall j \in J_i, \forall n \in N$	12
$Tf_{i,j,n} \leq \mathrm{H} \ \ \forall i \in I, \forall j \in J_i, \forall n \in N$	13

5.4.4 Supplier

The supplier agent provides raw materials to the production sites on receiving any demand. The costs associated with this agent are transportation cost and inventory cost. Transportation cost is considered to be proportional to the amount of raw materials transported, and inventory cost is considered to be proportional to the amount of raw materials stored.

The agents discussed above are those that have been specifically used in this study. However, the agent based simulation model provides the flexibility to add similar behavior related to asynchronous and synchronous interactions for other decision-making entities very easily. Moreover different scheduling models and operating policies can be considered by changing the scheduling agent.

5.5 Optimization model

The hybrid simulation based optimization approach uses an optimization model which is coupled with the simulation model. This section provides the details regarding the optimization model used in this work.

The multisite model includes supplier, production site, warehouse and market constraints. The set of products ($s \in PR$) are stored at the warehouses ($wh \in WH$). Warehouses deliver the products to meet the demands at the markets ($m \in M$) over the planning horizon ($t \in T$). Warehouses receive products from various production sites ($p \in PS$) which in turn manufacture these products from the raw materials ($r \in R$) obtained from raw material suppliers ($sup \in SUP$). The planning horizon has been discretized into fixed time length (daily production periods). In the hybrid approach, the optimization model has been used to guide the simulation towards better results. While the simulation model is more

detailed, the optimization model is kept rather simple. Therefore, no time delays have been considered for information or material flows. The total cost associated with the supply chain is the summation of transportation costs, inventory holding costs, production costs and backorder costs. Transportation cost has been considered to be proportional to the amount of shipment. Inventory holding cost has been considered proportional to the inventory level. Production cost is proportional to the amount of product produced while backorder cost is proportional to the amount of unfulfilled demand. The model has been formulated as a linear programming problem and minimization of total cost is the objective function. The optimization model is as follows.

$\min \sum_t \sum_{wh} \sum_{pr \in PR} h_{pr}^{wh} Inv_{pr}^{wh,t} + \sum_t \sum_p \sum_{pr \in PR} h_{pr}^{p} Inv_{pr}^{p,t} + \sum_t \sum_p \sum_{r \in R} h_r^p Inv_r^{p,t}$ $+ \sum_t \sum_{\sup} \sum_{r \in R} h_r^{\sup} Inv_r^{\sup,t} + \sum_t \sum_m \sum_{pr \in PR} u_{pr}^m U_{pr}^{m,t} + \sum_t \sum_p \sum_{pr} VarCost^p P_{pr}^{p,t}$ $+ \sum_t \sum_m \sum_{wh} \sum_{pr \in PR} d_{pr}^{wh,m} D_{pr}^{wh,m,t} + \sum_t \sum_{wh} \sum_p \sum_{pr \in PR} d_{pr}^{p,wh} D_{pr}^{p,wh,t} + \sum_t \sum_{\sup} \sum_p \sum_{r \in R} d_r^{\sup,p} D_r^{\sup,p,t}$	14
st $U_{pr}^{m,t} = U_{pr}^{m,t-1} + Dem_{pr}^{m,t} - \sum_{wh \in WH} D_{pr}^{wh,m,t}, \quad \forall pr \in PR, m \in M, t \in T$	15
$Inv_{pr}^{wh,t} = Inv_{pr}^{wh,t-1} - \sum_{m \in M} D_{pr}^{wh,m,t} + \sum_{p \in PS} D_{pr}^{p,wh,t}, \quad \forall pr \in PR, \mathrm{wh} \in \mathrm{WH}, t \in T$	16
$Inv_{pr}^{p,t} = Inv_{pr}^{p,t-1} - \sum_{wh \in WH} D_{pr}^{p,wh,t} + P_{pr}^{p,t}, \quad \forall pr \in PR, p \in PS, t \in T$	17
$Inv_r^{p,t} = Inv_r^{p,t-1} - C_r^{p,t} + \sum_{\sup \in SUP} D_r^{\sup,p,t}, \quad \forall r \in R, p \in PS, t \in T$	18
$Inv_r^{\sup,t} \le stcap_r^{\sup}, \quad \forall r \in R, \sup \in SUP, t \in T$	19
$Inv_r^{p,t} \le stcap_r^{p}, \quad \forall r \in R, p \in PS, t \in T$	20
$Inv_{pr}^{p,t} \le stcap_{pr}^{p}, \quad \forall pr \in PR, p \in PS, t \in T$	21
$Inv_{pr}^{\mathrm{wh},t} \le stcap_{pr}^{wh}, \quad \forall pr \in PR, wh \in WH, t \in T$	22

The objective function in equation 14 minimizes the total cost which consists of inventory costs, backorder costs, production costs and transportation costs. Equations 15-18 are the inventory balance equations at the different nodes of the supply chain. Equation 15 describes the backorders at the markets. Any unfulfilled demand gets accumulated as backorder. Equation 16 predicts the inventory at warehouses, shipments from warehouses to markets and shipments from production sites to warehouses. Equation 17 predicts the product inventory at production sites, production amounts and shipments from production sites to warehouses during each planning period. Equation 18 predicts the inventory of raw materials at production sites, consumption of raw materials for the manufacture of products and shipments from raw material suppliers to production sites during each planning period. Equations 19–22 are storage capacity constraints for raw material suppliers, production sites and warehouses respectively.

The optimization model results in a linear programming problem which has been implemented in GAMS 23.7.3 and solved using CPLEX 12.3.0.0 on Windows 7 operating system with an Intel Pentium D CPU 2.80 GHz microprocessor and 4.00 GB RAM.

5.6 Hybrid Simulation based Optimization

In order to optimize the behavior of the agents, a hybrid simulation based optimization approach has been used. The approach can effectively lead to the optimal solution while capturing the individual behavior of the agents. The hybrid approach couples the agent-based simulation model with the optimization model to improve agent actions. An

independent optimization model is developed which is coupled with the simulation model. The approach allows both the models to take advantage of the benefits of each other. For this work, the coupling of the optimization model with the simulation model has been done using the following variables: i) shipment values obtained from optimization model set as parameters in the simulation model, ii) production and consumption values from simulation model to optimization model.

The optimization model provides the simulation with shipment targets by passing shipment values to the simulation model. The simulation captures a more dynamic environment of the supply chain and whether or not it is able to achieve those shipment targets depends on the behavior of the agents of the model. Since the optimization model is to be used only for the purpose of target setting, production scheduling has not been included and it has been kept quite simple. So, the simulation model is used to set production and raw material consumption targets for the optimization model. This provides the optimization model with information about the production behavior. Based on these targets, the optimization model then gives the optimal shipment values.

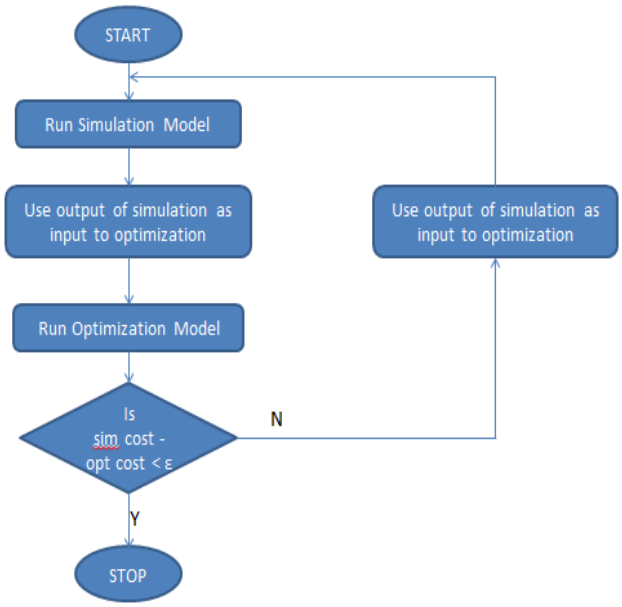

Figure 5.3: Iterative framework for the decentralized hybrid simulation–optimization approach

Using the hybrid approach proposed above, the solution methodology proposed in chapter 3 has been used. The framework consists of an iterative procedure as shown in Figure 5.3, which is initialized by solving the independent simulation model. The variables are then passed to the optimization model, which is solved to obtain values of the decision variables. The two models calculate the total cost for the planning horizon. The costs from both the models are compared. If the difference is below a tolerance level, the procedure is terminated otherwise the values of decision variables are passed back to the simulation model. This process is carried out iteratively until the difference between the two costs falls below the tolerance level. The above framework uses the simulation model as the master model, which is guided by the optimization model towards the best solution it can achieve.

5.7 Case Studies

In this section, three case studies have been presented. In the first two, the simulation models have been used to study two rather small-scale case studies to illustrate the effect of applying different decision making strategies in supply chain management. The idea behind considering these case studies is to be able to illustrate at a small scale, the asynchronicities in supply chain operations that can occur in the industry and what are their effects in SC decision making. In a large scale supply chain network, synchronized interactions among entities is not always easy. For example, a production team may not obtain information about the sales commitment decisions in a synchronized manner, which could lead to incomplete fulfillment of the committed product orders. Due to asynchronous operation of the production team and the sales team, there might be insufficient time for the production of the required amount of products based on the due dates of the committed sales. In the third case study, a larger problem with synchronous and asynchronous decision making strategies is considered. The hybrid simulation based optimization approach is used to study the optimal supply chain operation for both the scenarios. The third case study aims at investigating how optimizing the supply chain operation under asynchronous decision making strategy can improve its performance and make it closer to or even better than operating under synchronous decision making strategy but not optimized. Although at a small scale, these case studies illustrate the impact such asynchronicities can have on the overall behavior of the supply chain and its economics.

5.7.1 Case Study 1: Investigating different decision making strategies between warehouse and sales

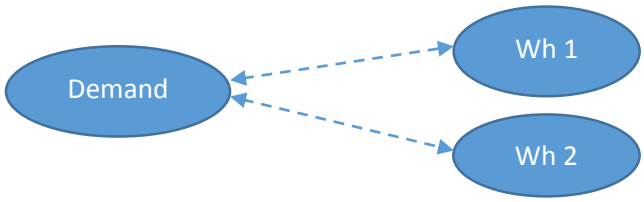

Figure 5.4: Small – scale two stage supply chain network

Figure 5.4 above shows a two stage supply chain with 1 demand site and 2 supply sites. The supply sites in this case study are warehouses. Demand arrives at the demand site during each planning period. Both the warehouses have limited storage capacities and regulate their inventory following a (Q, r) policy with continuous review. The reorder level and reorder quantity for the warehouses are assumed to be half their holding capacity values. However they can very easily be changed to other values. Warehouse 1 is located closer to the demand site and also has a larger capacity than warehouse 2. Therefore warehouse 1 is the primary warehouse for the demand site while warehouse 2 is the secondary warehouse. All the warehouses and the demand site belong to the same company. There are constant lead times for inventory replenishment and delivery. There is a single product being considered. There are costs associated with warehouse inventory, transportation and backorders. Backorder cost is $30/lb/day.

Simulation models representing synchronous and asynchronous scenarios were used for this case study. The simulation was run for particular demand data and different sets of

update frequencies for the two warehouses in the asynchronous scenario. It was observed that the behavior of the entire supply chain varies as the update frequencies varied.

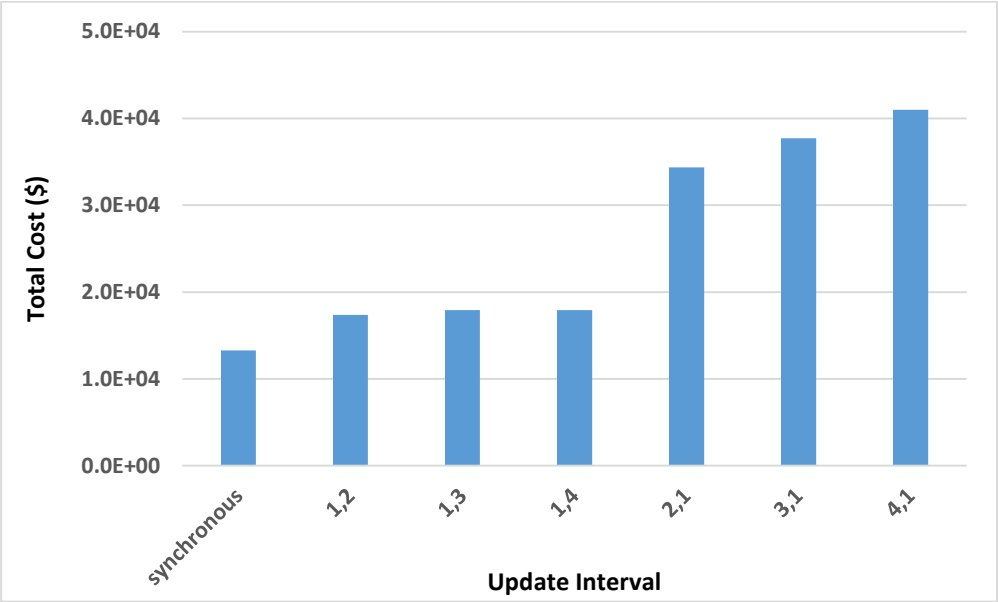

Figure 5.5: Total cost for synchronous and asynchronous operations

Figure 5.5 shows the total cost values obtained for the different scenarios. In the figure, the x-axis value (1, 2) represents the asynchronous scenario where warehouse 1 (wh1) has an update interval of 1 period while warehouse 2 (wh2) has an interval of 2 periods. This means that wh1 obtains the latest demand information from the market during every period while wh2 does that every two periods. It is considered that demand arrives at the market during every period. It can be observed that the lowest cost obtained is in the synchronous case where there is coordination among the demand site and the warehouses. The total cost value increases with increase in update interval. However, an increase in the update interval for wh1 causes a higher increase in total cost as compared to the same increase in update intervals for wh2. This is because wh1 has a larger

capacity than wh2 and is therefore able to fulfill more demand when both have the same update intervals. However when the update intervals for wh1 increase, there is less fulfillment of demand as compared to when the update intervals for wh2 increase. This is evident in figure 5.6 where higher values of backorder cost can be seen for higher update intervals of wh1. As wh1 is located closer to the demand site compared to wh2, less frequent updates for wh1 result in more transportation from wh2 to the demand site, which in turn increases the transportation cost. The computation time for the simulation runs was observed to be around 4 sec.

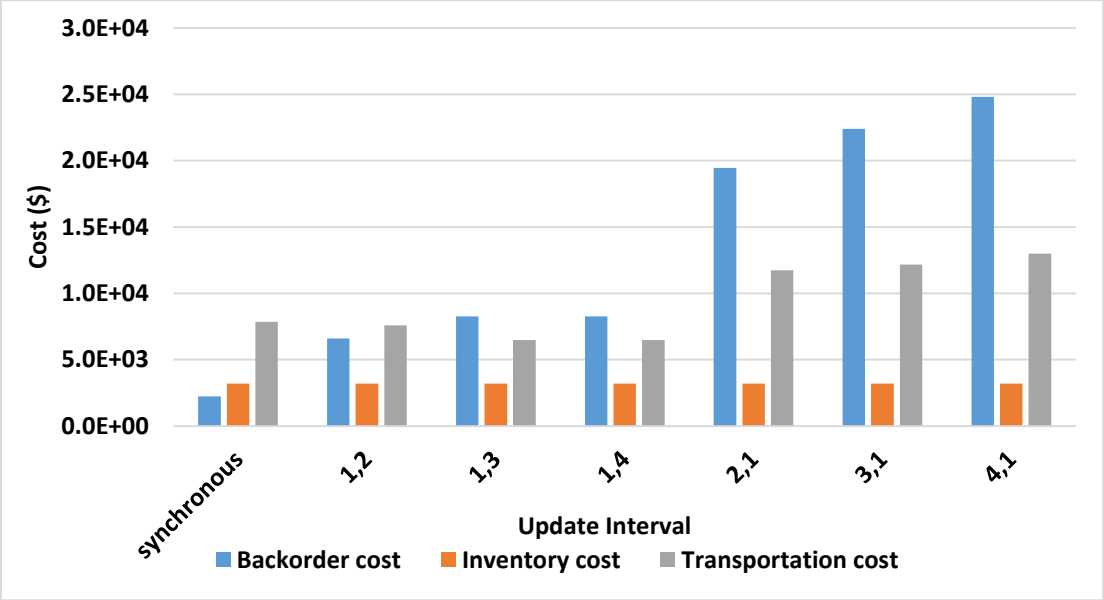

Figure 5.6: Cost components for synchronous and asynchronous operations

It is important to look into how the variation in costs is caused with the variation in update intervals. As mentioned earlier, depending on which warehouse updates the information and at what time, a particular warehouse picks up the demand. Since the warehouses have different capacities and are located at different locations with one of

them being closer to the demand site than the other, which specific warehouse picks up the demand results in either higher or lower cost.

Figure 5.7 shows the amount of products shipped from warehouses to the demand site during each period. Both the warehouses have been considered to have different storage capacities and different inventory replenishment policies. It can be seen that although the process happens synchronously, the demand site prefers wh1 which is closer over wh2. Therefore it always attempts to fulfill the demand from wh1 first. During some of the periods, since the demand is low, no shipment takes place from wh2. During other periods, the total demand which includes the backorders is so high that wh1 sends a shipment equal to its maximum capacity which has been considered as 100 in this example. During asynchronous operations, the mechanism will be different since a warehouse may not pick up the demand information immediately.

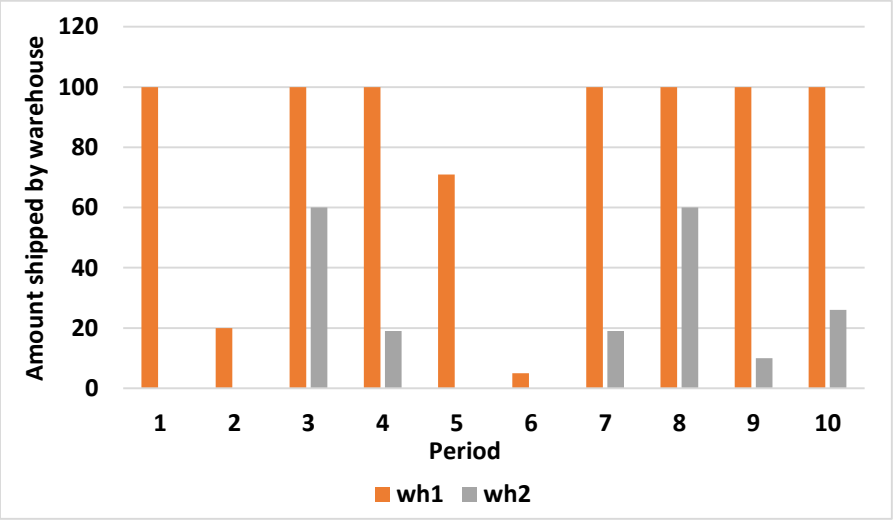

Figure 5.7: Amount of product shipped by warehouses under synchronous operation

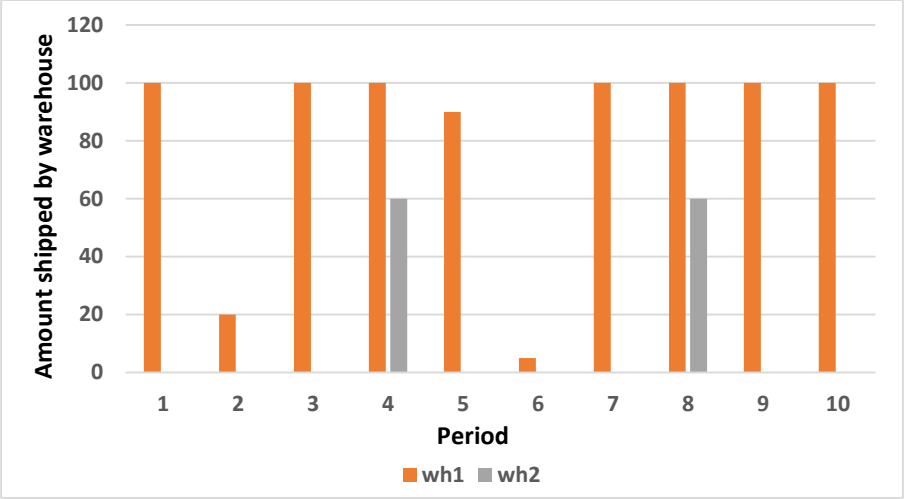

Figure 5.8: Amount shipped by warehouses under asynchronous operation (1, 4)

Figure 5.8 shows the asynchronous scenario (1,4). It can be seen that wh2 receives demand information only during periods 4 and 8 and therefore sends shipments at those times. During other periods, only wh1 sends products to the demand site. Similar plots for asynchronous operations with other update cycles are shown in Figure 5.9. When the demand values including backorders are more than the warehouse storage capacities, the warehouses send shipments equal to their maximum capacity to the demand site.

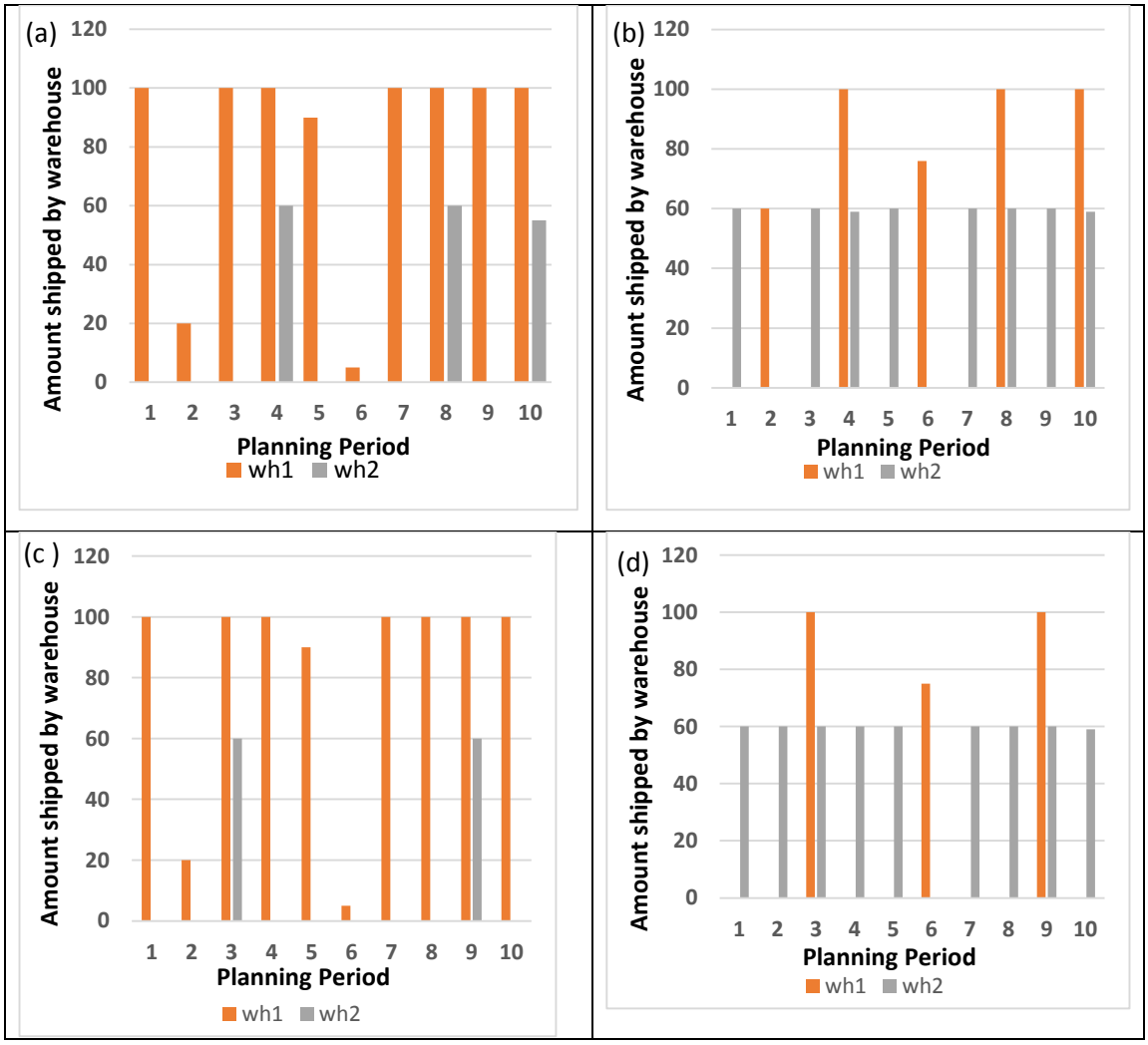

Figure 5.9: Amount shipped by warehouses under (a) asynchronous operation 1,2 (b) asynchronous operation 2,1 (c) asynchronous operations 1,3 and (d) asynchronous operations 3,1

5.7.2 Case Study 2: Exploring different decision making strategies between sales and production sites

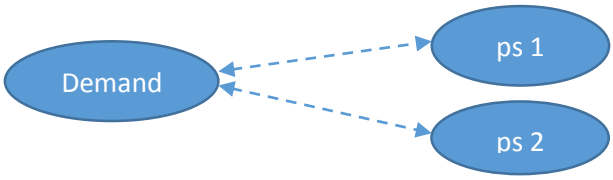

Figure 5.10: Small-scale two stage supply chain

Figure 5.10 above shows a two stage supply chain with 1 demand site and 2 supply sites. The supply sites in this case study are production sites. Demand arrives at the demand site during each planning period. Any arriving demand has a specific due date which has been considered as 2 periods in this example. Both the production sites have limited storage capacities and regulate their product inventory by manufacturing using raw materials. They obtain raw materials from suppliers that have a limited capacity. The raw material reorder level and reorder quantity for the production sites are assumed to be half their raw material holding capacity values. However they can very easily be adjusted to other values. Production site 1 (ps1) has a higher production capacity and is located closer to the demand site than production site 2 (ps2). Therefore ps1 is the primary production site for the demand site while ps2 is the secondary production site. All the production sites and the demand site belong to the same company. The example considers 2 products and 3 raw materials. There are costs associated with production site inventory, transportation, production and backorders. The production sites update their information based on their update cycles. Therefore they need not have the updated demand information at all times.

Manufacture of products is done in batch operation mode. The production site schedules the production using an embedded scheduler which relies on the solution of the scheduling optimization problem. The state task network for the process is shown in Figure 5.11. When the production site updates the demand information, the scheduler gets to know the demand requirements for a certain number of planning periods in the future. The scheduler generates a production schedule to minimize cost. The scheduling horizon is the period for which the demand information is available to the scheduler.

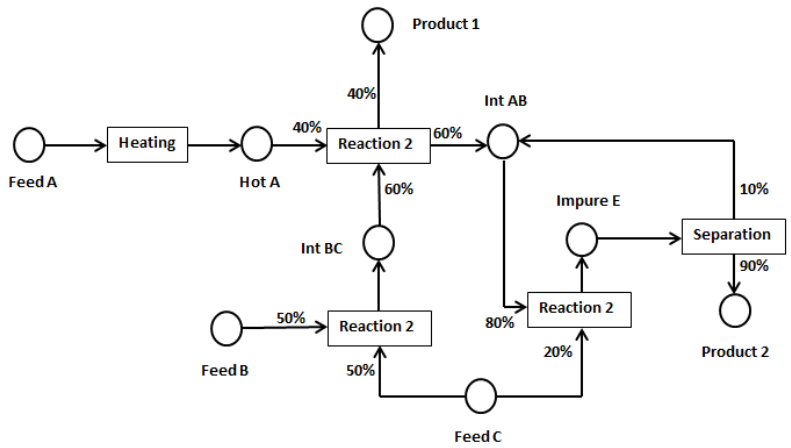

Figure 5.11: State task network for the batch production process

Simulation models considering synchronous and asynchronous scenarios were used again for the specific case study. The simulation was run for particular demand data and different sets of update frequencies for the two production sites in the asynchronous scenario. It was observed that the behavior of the supply chain as a whole varies as the update frequencies varied. The computation time for the update intervals (1,3) was observed to be 74 sec. The computation time is observed to be higher than it is in case

study 1 because of the additional execution time of the embedded scheduler used by the production site agent.

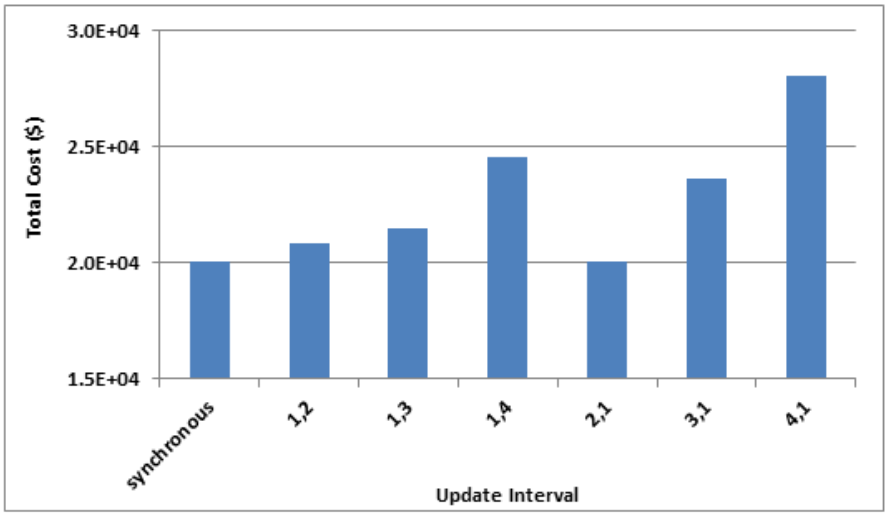

Figure 5.12: Total cost for synchronous and asynchronous operations

It can be observed in Figure 5.12 that the synchronous operation of the market and the production sites results in the lowest cost. As we introduce asynchronicity between their operations, the cost increases. Similar to the previous case study, the x-axis in the plot shows the update intervals of the two production sites where 1,4 represents an update interval of 1 period for production site 1 (ps1) and 4 periods for production site 2 (ps2). It can be observed that a greater update interval results in a higher cost. A higher value of update interval means that the production site takes longer to receive the updated demand information. This can either result in the production site missing the due date or give the production site insufficient time to manufacture products and maintain its inventory. The figure also shows a higher increase in cost when the update of ps1 is less frequent as compared to when ps2 updates less frequently. The production site ps1 has a higher

capacity than ps2. Therefore when ps1 updates less frequently, the market has to order from ps2, which is not able to manufacture as much products as ps1. Therefore the backorders in this case are higher compared to when ps2 does not update frequently.

Figure 5.13 shows the variation of the different cost components with the update intervals. It can be seen that backorder cost is the most dominating component. As the update interval increases, the backorders keep increasing. At high update intervals, the backorder cost becomes very high compared to the rest of the cost components. It can also be seen that the other components decrease with the increase in update intervals. This is because at less frequent updates, the production sites have less frequent access to demand information and therefore manufacture fewer products. This results in a decrease for the other cost components as the interval increases.

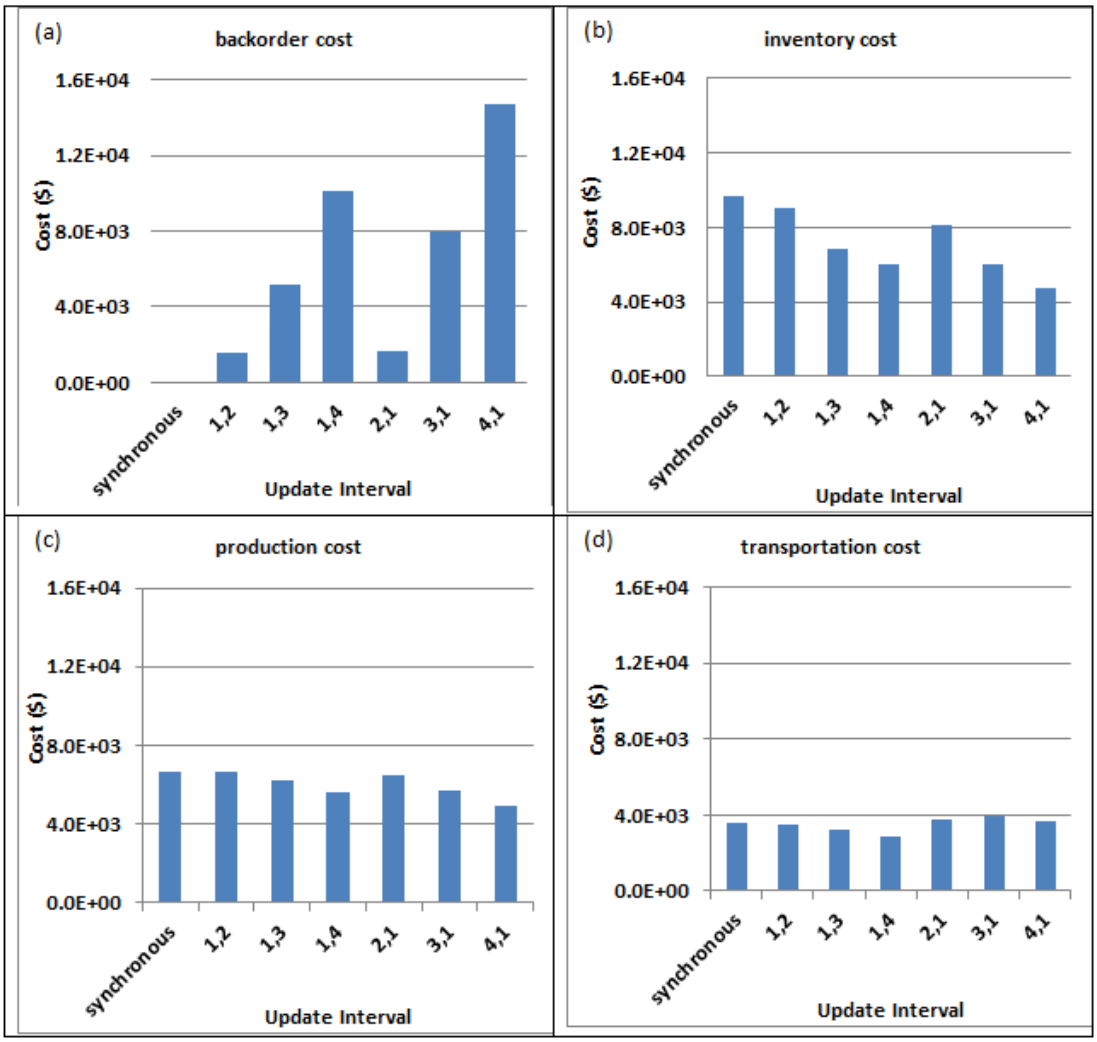

Figure 5.13: Cost components for synchronous and asynchronous operations (a) backorder cost, (b) inventory cost, (c) production cost, (d) transportation cost

A better idea of how the two production sites behave can be obtained by looking at the plots showing the shipment values from the production sites to the market during each period. Figure 5.14 shows the amounts of products shipped by the production sites to the market during each planning period for synchronous operation. As the due date for the demand which arrives in the first period is the 3rd period, the first shipment takes place during the 3rd period. Also as ps1 is closer to the market, it is selected over ps2 to receive

the orders. Production site ps1 has a higher capacity compared to ps2. Therefore during the remaining periods, it can be seen that ps1 sends a larger shipment compared to ps2. The asynchronous decision making scenario is shown in Figure 5.15. It can be seen that based on the update intervals of the production site ps2, shipment from ps2 to the market happens only intermittently rather than during every planning period.

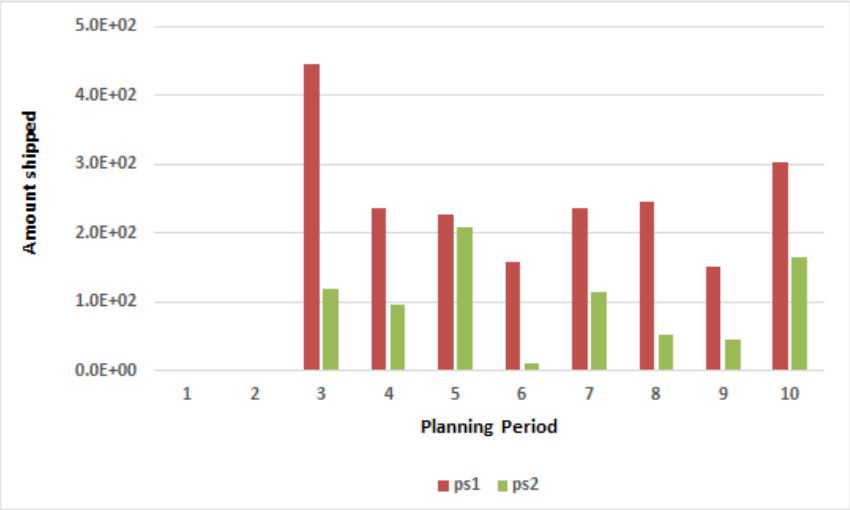

Figure 5.14: Amount of products shipped by production sites under synchronous operation

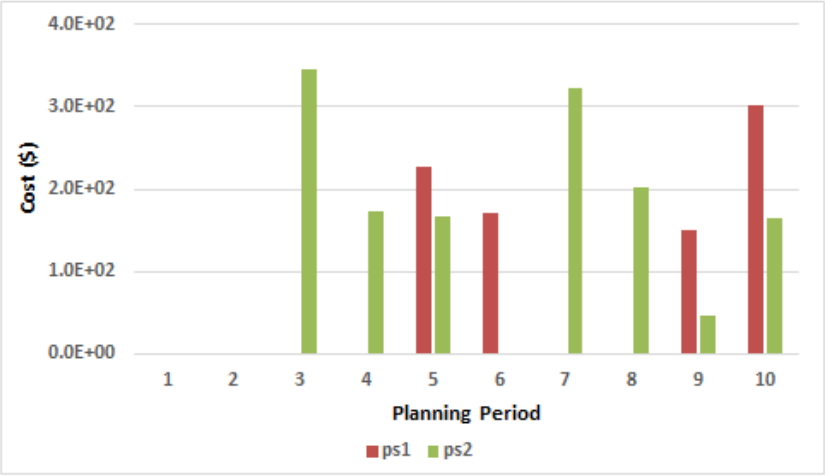

Figure 5.15: Amount of products shipped by production sites under asynchronous operation (4,1)

Similar plots for asynchronous scenarios with various update intervals can be seen in Figure 5.16. It can be observed that when one of the production sites obtains the demand information less frequently, the other one has to operate at a higher production capacity. This is because due to less frequent updates regarding the demand orders there is an increase in backorders.

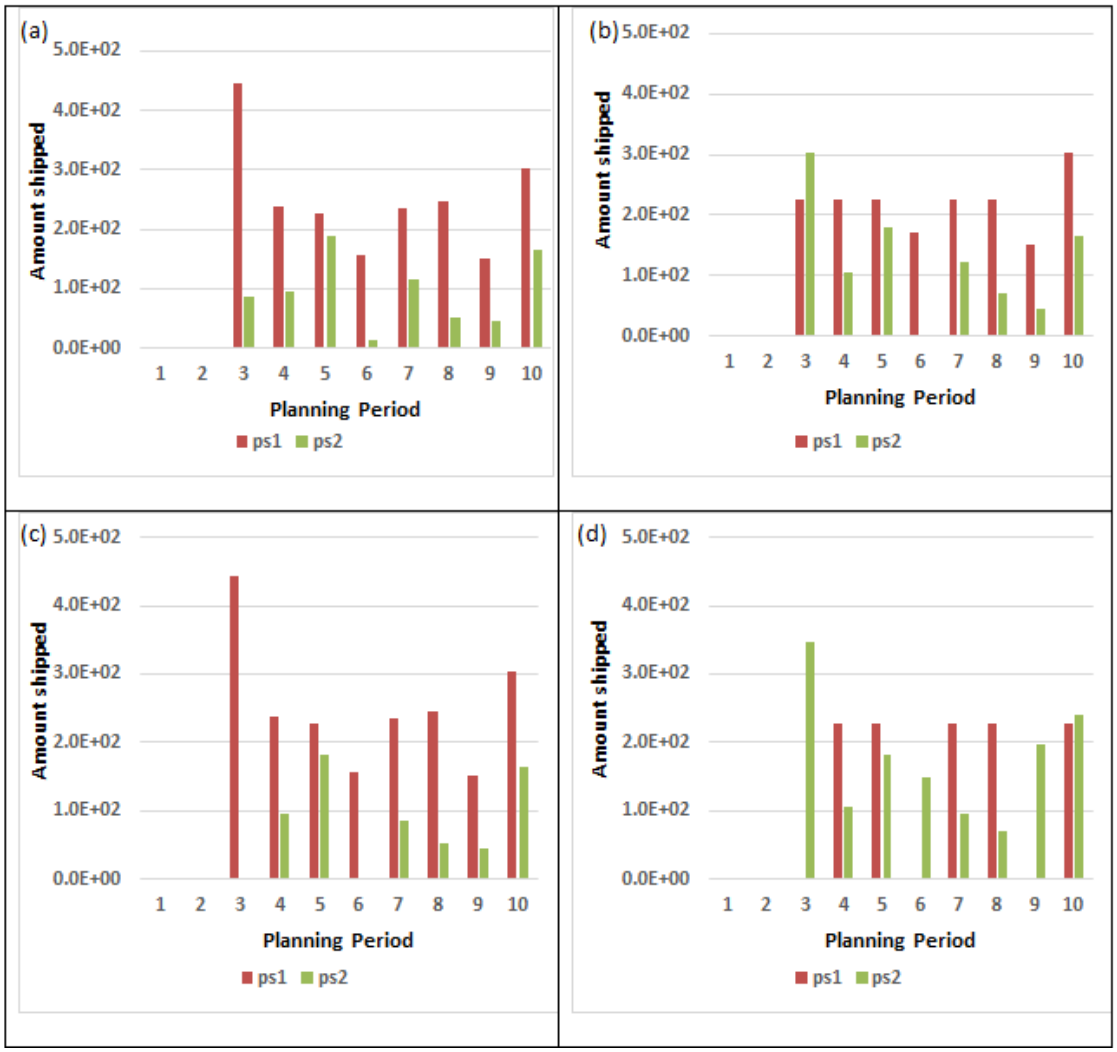

Figure 5.16: Amount shipped by production sites under (a) asynchronous operation 1,2 (b) asynchronous operation 2,1 (c) asynchronous operations 1,3 and (d) asynchronous operations 3,1

5.7.3 Case Study 3: Exploring different decision making strategies for a larger supply chain

Similar synchronous and asynchronous decision making strategies were implemented for a larger supply chain network. A supply chain consisting of 4 markets, 4 warehouses, 4 production sites and 2 suppliers as shown in figure 5.17 was considered. Manufacture of

products is done in batch operation mode. The production site schedules the production using an embedded scheduler which relies on the solution of the scheduling optimization problem. The state task network for the process is the same as that in case study 2 and is shown in figure 5.11. Backorder cost is $80/lb. Demand is considered to be a constant value at 100 lb during every period.

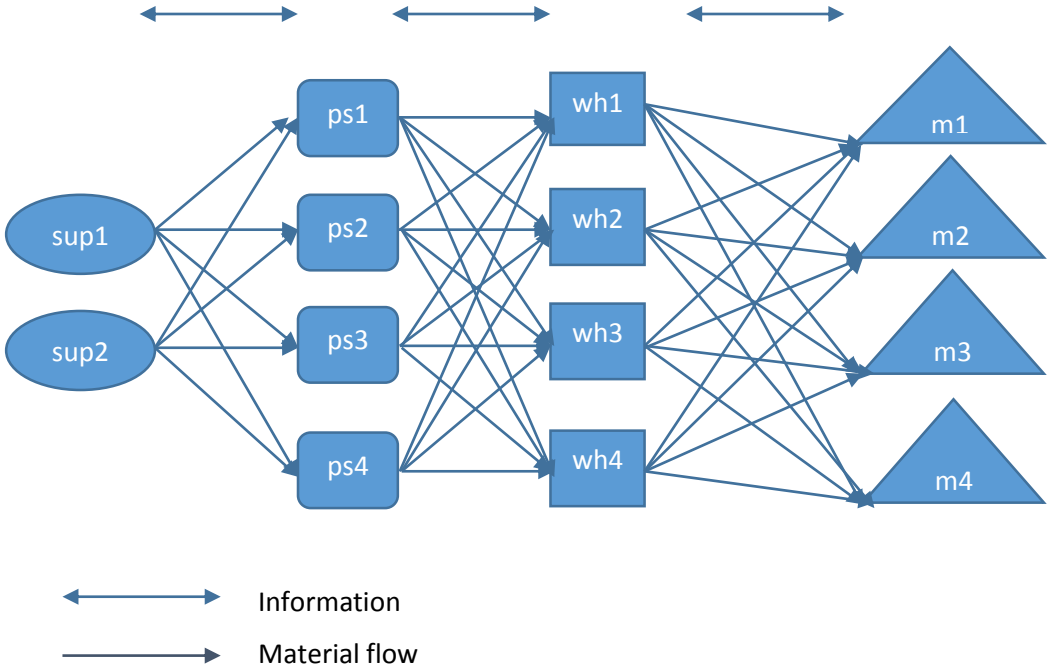

Figure 5.17: Supply chain network for case study 3

Two decision making strategies have been considered. In the first one, all the entities operate synchronously while in the other, a mix of synchronous and asynchronous operations are considered. For the asynchronous case, a specific scenario is considered. Raw material suppliers are considered to operate synchronously with the production sites while markets, warehouses and production sites make decisions asynchronously. The

update intervals for the four warehouses are (2, 3, 1, 5) while those for the production sites are (1, 2, 5, 3). The agent based simulation models were run for these two specific scenarios. However, as shown in the previous case studies, the model can be used for different sets of update intervals as well. For synchronous decision-making strategy, the total cost obtained was $1,70,378 while that for the asynchronous decision-making strategy was $2,71,739 which was around 60% higher.

The hybrid simulation based optimization approach was used to optimize the supply chain operation under the two decision making strategies. The results of the hybrid approach for the two specific cases are shown in figures 5.18 and 5.19. The hybrid simulation based optimization framework converges in both the cases. The computation time for the asynchronous scenario was observed to be 1360 sec while that for the synchronous scenario was observed to be 3794 sec.

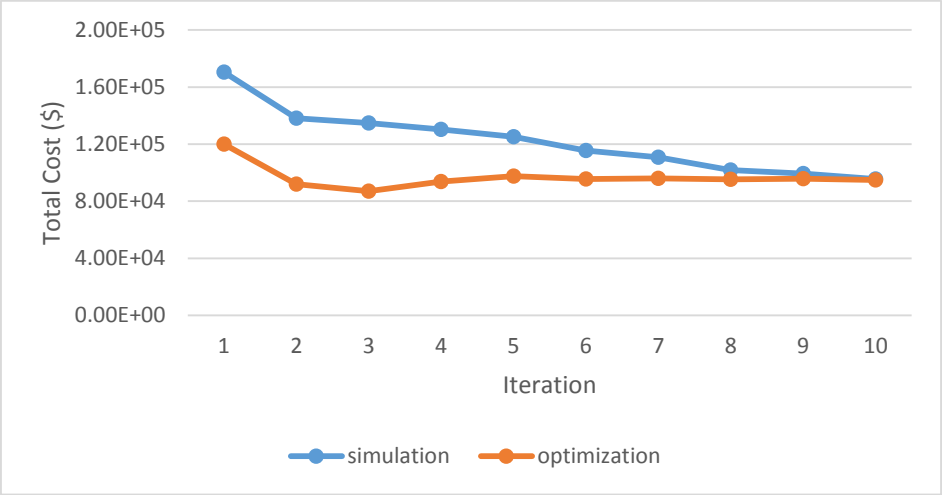

Figure 5.18: Objective values of simulation and optimization models at each iteration under synchronous decision making strategy

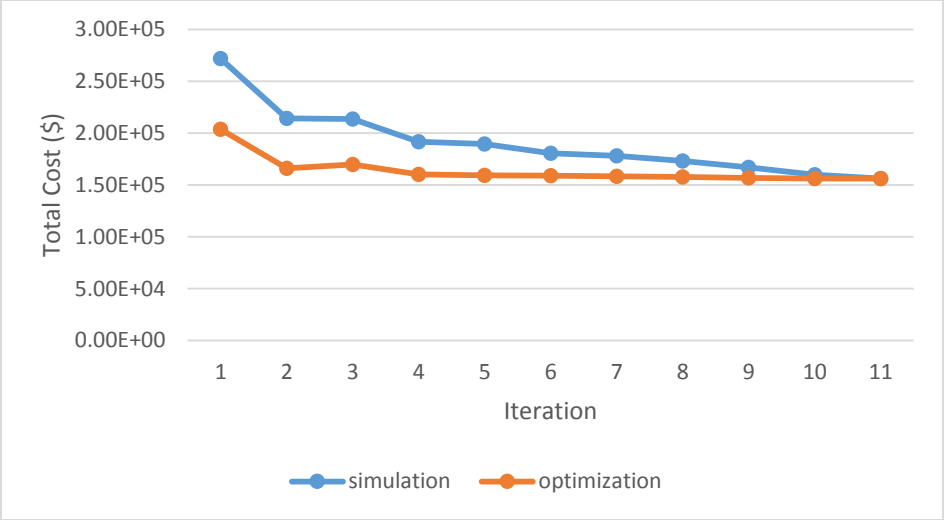

Figure 5.19: Objective values of simulation and optimization models at each iteration under asynchronous decision making strategy

Table 5.1: Comparison of total cost values for different scenarios

	Total Cost ($)	% difference with (1)
Synchronous without optimization	$170,378	
Asynchronous without optimization	$271,739	59.49
Synchronous with optimization	$95,524	-43.93
Asynchronous without optimization	$156,110	-8.37

A comparison of the total cost values obtained for the synchronous and asynchronous scenarios with and without optimization are presented in table 5.1. The optimal solution for the synchronous case gives a total cost of $95,524 while that for the asynchronous case gives a total cost of $1,56,110. It can be seen that optimization results in a reduction in total cost of around 44% and 43% for the synchronous and asynchronous scenarios respectively. It can also be observed that the optimal solution for the asynchronous case

gives a cost around 8.4% lower than the cost for the synchronous case without optimization. Since implementing synchronous operations for large scale supply chains is not easy, optimized asynchronous operations can provide an alternative to synchronous operations. However, optimized synchronous operation is still better than optimized asynchronous operation.

5.8 Conclusion

The decision-making strategies of the different entities in a supply chain affect its operation and performance. This chapter illustrates the effects of the different strategies using agent based models. In particular, two different interaction schemes among the decision-making entities of the network were considered, namely synchronous and asynchronous.

Separate agent based simulation models were developed to capture the dynamics of the two interaction schemes. In order to illustrate the impact of the interaction scheme alone, two rather small scale case studies were used. The two schemes were compared on the basis of the operating cost of the supply chain as well as the resulting dynamics. It was shown that the interaction scheme and the information available to decision – making entities can have a significant impact on cost and dynamics. It is observed that synchronous interactions result in the lower cost compared to asynchronous interactions. However, optimized asynchronous interactions can perform better than synchronous interactions without optimization.

Since synchronous interactions are not always easy to implement, the model for the asynchronous scenarios provides useful results regarding the operation of the supply

chain and its structure. The decision – making entities in the case studies involved markets, warehouses, production sites and raw material suppliers. However agent based simulation provides the flexibility to conveniently adapt the model for other decision – making entities with different behaviors or to increase the size of the model with larger number of decision – making entities. Similar concepts can be used for larger supply chains where the overall operation is a complex combination of the both synchronous and asynchronous operations. The case studies used in this study considered the entities belonging to a single organization. A similar approach can be used to study a multi-company supply chain network and gain insight into how cooperative behavior would serve the objectives of the different companies under the different scenarios. For this case different formulas can be used to assign cost to different companies and this will be the subject of our future work.

Nomenclature

Indices	
t	planning period
s	state
i	task
j	unit
n	event point
wh	warehouse
m	market
P	production site

sup	supplier
r	raw material
pr	product
Sets	
T	planning periods
S	states
I	tasks
J	units
WH	warehouses
M	markets
PS	production sites
SUP	suppliers
R	raw materials
PR	Products
Variables	
$wv_{i,j,n}$	Binary whether or not task *i* in unit *j* starts at event point n
$st_{s,n}$	continuous, amount of state *s* at event point *n*
$d_{s,n}$	amount of state *s* delivered at event point *n*
$b_{i,j,n}$	continuous, batch size of task *i* in unit *j* at event point *n*
r_s	requirement for state *s* at the end of the time horizon
$Tf_{i,j,n}$	time that task *i* finishes in unit *j* while it starts at event point *n*
$Ts_{i,j,n}$	time that task *i* starts in unit *j* at event point *n*
$C_r^{p,t}$	Amount of raw material r consumed at production site p during time t

$D_{pr}^{wh,m,t}$	Amount of product pr transported from warehouse wh to market m during time t
$D_{pr}^{p,wh,t}$	Amount of product pr transported from production site p to warehouse wh during time t
$D_{r}^{\sup,p,t}$	Amount of raw material r transported from supplier sup to production site p during time t
$P_{pr}^{p,t}$	Amount of product pr produced at production site p during time t
$U_{pr}^{m,t}$	Backorder of product pr at market m at time t
$Inv_{r}^{\sup,t}$	Inventory of raw material r at supplier sup at time t
$Inv_{pr}^{wh,t}$	Inventory of product pr at warehouse wh at time t
$Inv_{pr}^{p,t}$	Inventory of product pr at production site p at time t
$Inv_{r}^{p,t}$	Inventory of raw material r at production site p at time t
Parameters	
h_{pr}^{wh}	Inventory holding cost for product pr at warehouse wh
h_{pr}^{p}	Inventory holding cost for product pr at production site p
h_{r}^{p}	Inventory holding cost for raw material r at production site p
$h_{r}^{\sup}$	Inventory holding cost for raw material r at supplier sup
u_{pr}^{m}	Backorder cost for product pr at market m
$VarCost^{p}$	Production cost at production site p
$d_{pr}^{wh,m}$	Transportation cost per unit product pr between warehouse wh and market m
$d_{pr}^{p,wh}$	Transportation cost per unit product pr between production site p and warehouse wh

$d_r^{\sup,p}$	Transportation cost per unit raw material r between production site p and supplier sup
$stcap_r^{\sup}$	Inventory holding capacity for raw material r at supplier sup
$stcap_{pr}^{wh}$	Inventory holding capacity for product pr at warehouse wh
$stcap_{pr}^{p}$	Inventory holding capacity for product pr at production site p
H	Time horizon
$\beta_{i,j}$	variable term of processing time of task *i* at unit *j* expressing the time required by the unit to process one unit of material performing task *i*
$\alpha_{i,j}$	constant term of processing time of task *i* at unit *j*
$v_{i,j}^{\min}$ $v_{i,j}^{\max}$	minimum amount, maximum capacity of unit *j* when processing task *i*
$\rho_{s,i}^{p}$ $\rho_{s,i}^{c}$	proportion of state *s* produced, consumed by task *i*, respectively
$st_s^{\max}$	available maximum storage capacity for state *s*

6 Flexibility Assessment and Risk Management in Supply Chains

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 in order 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" [92-94]. 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, etc. to introduce flexibility within their supply chains in order to mitigate risk [95-98].

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. Multi-period 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 non-linear dynamics have been demonstrated in the recent studies [62,91,99-101]. 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.

6.1 Background

The important aspects covered in this chapter are supply chain flexibility and risk management. The literature review presented here tries to cover the majority of the work that appear 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 since the actual competition is among supply chains rather than manufacturing plants. Different definitions have been proposed and the benefits have been assessed. Garaveli [102] 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 [103] 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 [104] analyze the benefits of flexibility in multi-stage supply chains. A flexibility measure is developed to account against the stage-spinning bottlenecks and floating bottlenecks. Kwon et al. [105] 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 [106] propose an adaptive make-to-order coordination mechanism and study how the performance of two-level multi-product make-to-order

supply chains can be improved by flexibility and the proposed adaptability in delivery the correct deliveries at the exact due dates. 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. Lainez et al. [107] propose a flexible formulation approach instead of a rigid predefined network structure to solve the design-planning problem of supply chain networks. NPV is considered as the key performance metric and is optimized in the resulting mixed integer linear programming model. Mansoornejad et al. [108] 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 co-workers [109-113]. 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 [114] 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 [115] 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. [116] 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. [117] 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. Javid and Seddighi [118] 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 [119] consider the problem of disruption risk management in manufacturing supply chains. A multi-agent 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 [120] develop an integrated value-based performance and risk management framework to increase shareholder value holistically. The metric ‘Economic Value Added’ is applied to mid-term sales and operations planning and robust optimization methods are used to

handle operational risks in supply chain management. Finally Tang [121] 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.

6.2 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.

6.3 Solution Methodology

The multi-product 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.

6.3.1 Rolling horizon

The multi-period planning problem under uncertainty corresponds to a multi-stage 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 multi-stage setting. Multi-stage 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.

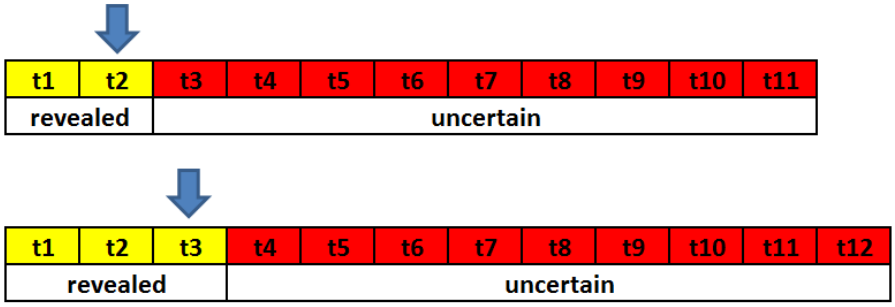

Figure 6.1: Rolling horizon approach

Figure 6.1 illustrates the implementation of the rolling horizon. At the beginning of t2, the 2nd period, demand information up to t2 is revealed while the demand for the future periods are 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.

6.3.2 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

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

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

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

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 [122]. 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 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[123]. 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.

6.3.3 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 [91]. 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 towards 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 [90,124].

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.

6.3.3.1 Optimization model

The mathematical programming model includes constraints related to suppliers, production sites, warehouses and markets. Warehouses (wh ϵ WH) store products (s ϵ PR) and transfer them to markets in order to fulfill the demand during the planning horizon (t ϵ T). Warehouses replenish their inventory with the products they receive from production sites (p ϵ PS). Production sites procure raw materials (r ϵ R) from raw material suppliers (sup ϵ SUP) and manufacture products. In the hybrid approach, the role of the optimization model is to guide the simulation towards better results. The optimization model is kept quite simple compared to 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.

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

$\text{Cost1} = \sum_{wh}\sum_{s\in PR} h_s^{wh} Inv_s^{wh,1} + \sum_{p}\sum_{s\in PR} h_s^{p} Inv_s^{p,1} + \sum_{p}\sum_{r\in R} h_r^{p} Inv_r^{p,1} + \sum_{m}\sum_{s\in PR} u_s^{m} U_s^{m,1} + \sum_{p}\sum_{s} v^{p} P_s^{p,1} + \sum_{m}\sum_{wh}\sum_{s\in PR} c_s^{wh} CI_s^{wh,m} + \sum_{wh}\sum_{p}\sum_{s\in PR} c_s^{p} CI_s^{p,wh} \sum_{m}\sum_{wh}\sum_{s\in PR} d_s^{wh,m} dis^{wh,m} D_s^{wh,m,1} + \sum_{wh}\sum_{p}\sum_{s\in PR} d_s^{p,wh} dis^{p,wh} D_s^{p,wh,1} + \sum_{\sup}\sum_{p}\sum_{r\in R} d_r^{sup,p} dis^{\sup,p} D_r^{sup,p,1},$ $s\in PR, r\in R, m\in M, wh\in WH, p\in P, \sup\in SUP$	2
$\text{Cost2}_{sc} = \sum_{t}\sum_{wh}\sum_{s\in PR} h_s^{wh} Inv_s^{wh,t,sc} + \sum_{t}\sum_{p}\sum_{s\in PR} h_s^{p} Inv_s^{p,t,sc} + \sum_{t}\sum_{p}\sum_{r\in R} h_r^{p} Inv_r^{p,t,sc} + \sum_{t}\sum_{m}\sum_{s\in PR} u_s^{m} U_s^{m,t,sc} + \sum_{t}\sum_{p}\sum_{s} v^{p} P_s^{p,t,sc} + \sum_{t}\sum_{wh}\sum_{p}\sum_{s\in PR} d_s^{p,wh} dis^{p,wh} D_s^{p,wh,t,sc} + \sum_{t}\sum_{\sup}\sum_{p}\sum_{r\in R} d_r^{sup,p} dis^{\sup,p} D_r^{sup,p,t,sc} + \sum_{t}\sum_{m}\sum_{wh}\sum_{s\in PR} d_s^{wh,m} dis^{wh,m} D_s^{wh,m,t,sc},$ $s\in PR, r\in R, m\in M, wh\in WH, p\in P, \sup\in SUP, sc\in SC, t\in T$	3
$U_s^{m,t,sc} = U_s^{m,t-1,sc} + Dem_s^{m,t,sc} - \sum_{wh\in WH} D_s^{wh,m,t}, \quad s\in PR, m\in M, t\in T, sc\in SC$	4
$Inv_s^{wh,t,sc} = Inv_s^{wh,t-1,sc} - \sum_{m\in M} D_s^{wh,m,t,sc} + \sum_{p\in PS} D_s^{p,wh,t,sc}, \quad \forall s\in PR, wh\in WH, t\in T, sc\in SC$	5
$Inv_s^{p,t,sc} = Inv_s^{p,t-1,sc} + P_s^{p,t,sc} - \sum_{wh\in WH} D_s^{p,wh,t,sc}, \quad s\in PR, p\in PS, t\in T, sc\in SC$	6
$Inv_r^{p,t,sc} = Inv_r^{p,t-1,sc} - C_r^{p,t,sc} + \sum_{\sup\in SUP} D_r^{\sup,p,t,sc}, \quad r\in R, p\in PS, t\in T, sc\in SC$	7
$Inv_r^{\mathrm{p},t,sc} \le stcap_r^{\mathrm{p}}, \quad \forall r\in R, \mathrm{p}\in PS, t\in T, sc\in SC$	8
$Inv_s^{\mathrm{p},t,sc} \le stcap_s^{\mathrm{p}}, \quad \forall s\in PR, \mathrm{p}\in PS, t\in T, sc\in SC$	9
$Inv_s^{wh,t,sc} \le stcap_s^{wh}, \quad \forall s\in PR, wh\in WH, t\in T, sc\in SC$	10
$P_s^{p,t,sc} \le prcap_s^{p}, \quad \forall s\in PR, p\in PS, t\in T, sc\in SC$	11
$D_s^{p,wh,t,sc} \le trcap_s^{p} + CI_s^{p,wh}, \quad \forall s\in PR, p\in PS, t\in T, sc\in SC$	12
$D_s^{wh,m,t,sc} \le trcap_s^{wh} + CI_s^{wh,m}, \quad \forall s\in PR, wh\in WH, m\in M, t\in T, sc\in SC$	13
$DRisk \le R$	14

$DRisk = \sum_{sc} P_{sc}\psi_{sc} \qquad ,sc \in SC$	15
$\psi_{sc} \geq \Omega - \text{Profit1} - \text{Profit2}_{sc},\ \ \psi_{sc} \geq 0, \qquad \forall sc \in SC$	16
$Sl_{m,s,sc} \geq L \qquad ,\forall m \in M, s \in PR, sc \in SC$	17
$Sl_{m,s,sc} = 1 - \frac{\sum_t U_s^{m,t,sc}}{\sum_t Dem_s^{m,t,sc}} \qquad ,\forall m \in M, s \in PR, sc \in SC, t \in T$	18
$\text{Rev2}_{sc} = \sum_t \sum_s \sum_m sp_{s,m} * \left(Dem_s^{m,t,sc} + U_s^{m,t-1,sc} - U_s^{m,t,sc} \right) \qquad ,\forall s \in PR, m \in M, sc \in SC, t \in T$	19
$\text{Rev1} = \sum_s \sum_m sp_{s,m} * \left(Dem_s^{m,1} - U_s^{m,1} \right) \qquad ,\forall s \in PR, m \in M$	20
$\text{Profit1} = \text{Rev1} - \text{Cost1}$	21
$\text{Profit2}_{sc} = \max\left(\text{Rev2}_{sc} - \text{Cost2}_{sc}\right), \quad \text{sc} \in \text{SC}$	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 equation 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 equation 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 equations 8–10 respectively while the production capacity constraint for production sites is given by equation 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.

6.3.3.2 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, In order 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 to 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 is not able to order the total demand to the warehouses, they update the *requests* and re-send 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 pre-defined. 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 (BOM) 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, In order 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 to 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 re-send 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 pre-defined. 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.

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.

6.3.3.3 Hybrid simulation based optimization methodology

As discussed in sections 6.3.3.1 and 6.3.3.2, 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 6.2, the following variables are used to couple the optimization model with the simulation model in this work: i) production and consumption values from simulation model to optimization model, ii) shipment values obtained from optimization model to simulation model.

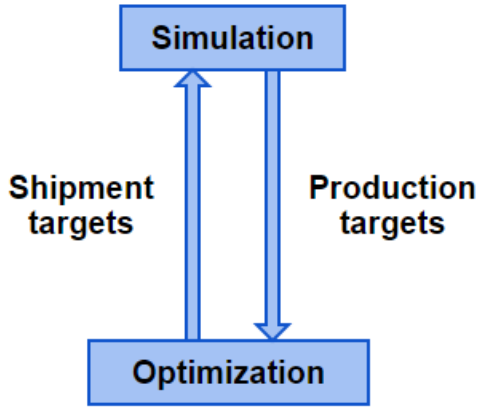

Figure 6.2: Coupling between simulation and optimization

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.

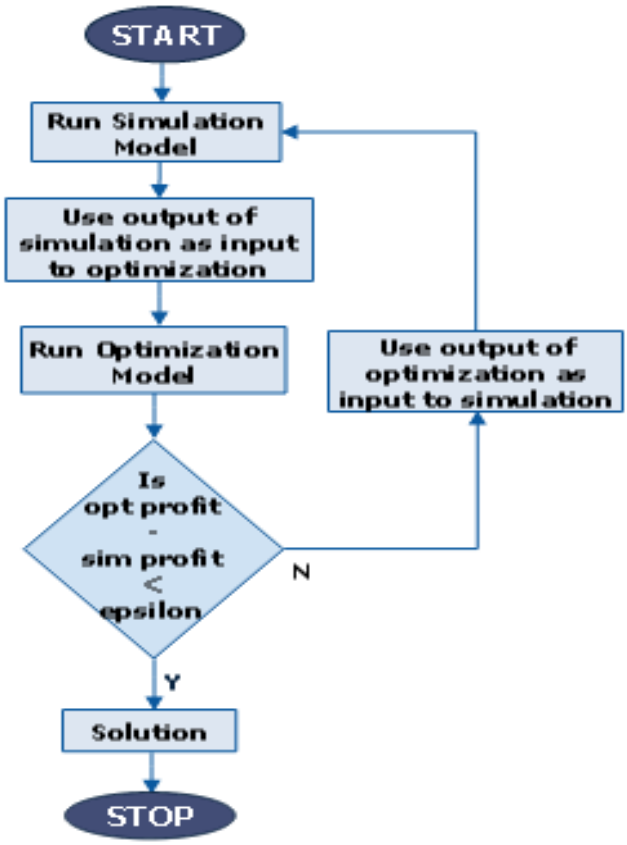

Figure 6.3: Iterative framework for the hybrid simulation-optimization approach

Using the hybrid approach proposed above, the solution methodology proposed in chapter 3 has been used. As shown in figure 6.3, 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 uses the optimization model to guide the simulation model, used as the master model, towards 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.

6.4 Overall Framework

The overall solution framework consists of the hybrid simulation based optimization model incorporated in the rolling horizon. Figure 6.4 shows the different steps of the framework.

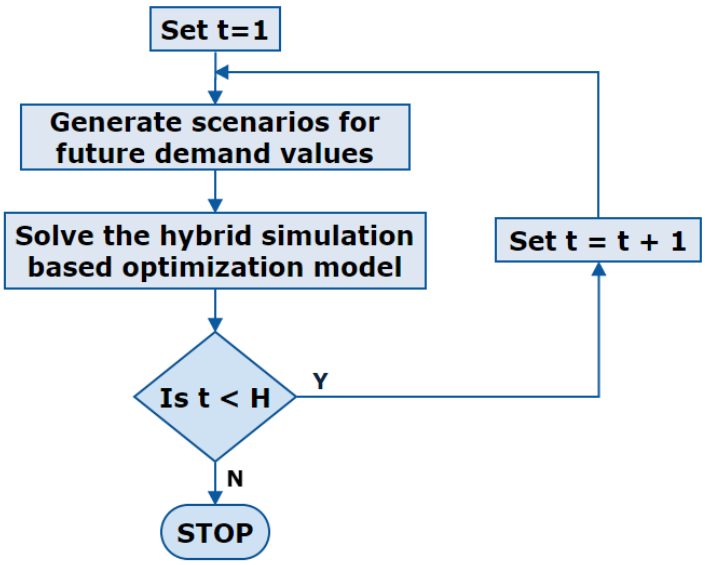

Figure 6.4: Solution framework

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.

6.5 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 [125-127]. You et al. [123] 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 towards higher expected cost. In this work, the downside risk model is used to manage risk. The model can be expressed for profit as follows.

$$\min \ \mathrm{DRisk}(x,\Omega) = \sum_{s} P_s \psi_s \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(14)$$

$$\psi_{sc} \geq \Omega - \mathrm{Profit1} - \mathrm{Profit2}_{sc}, \ \psi_{sc} \geq 0, \qquad \forall sc \in SC \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots(15)$$

In order to solve the multi-objective problem, the ε - constraint method is used.

6.6 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.

6.6.1 Case study 1

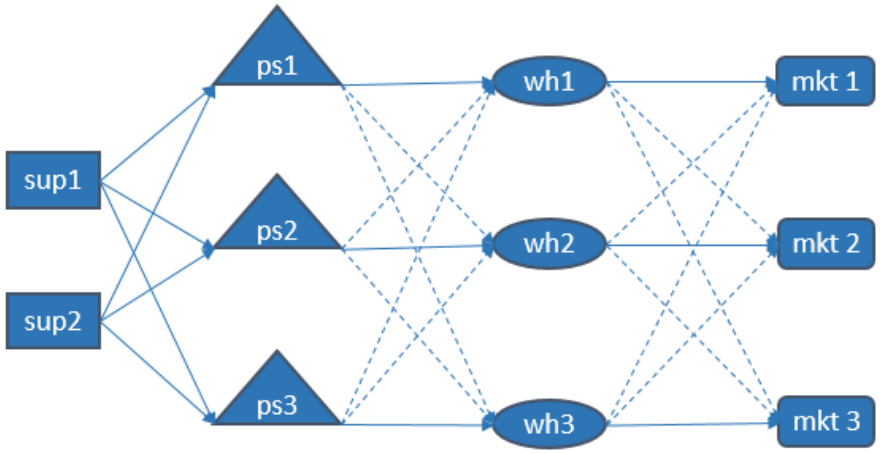

Figure 6.5: Supply chain network for case study 1

The supply chain network considered in the first study consists of 3 markets, 3 warehouses, 3 production sites and 2 suppliers, as shown in figure 6.5. There are 2 products and 3 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 and between production sites and raw material suppliers are provided in Tables A.6.1 and A.6.2.

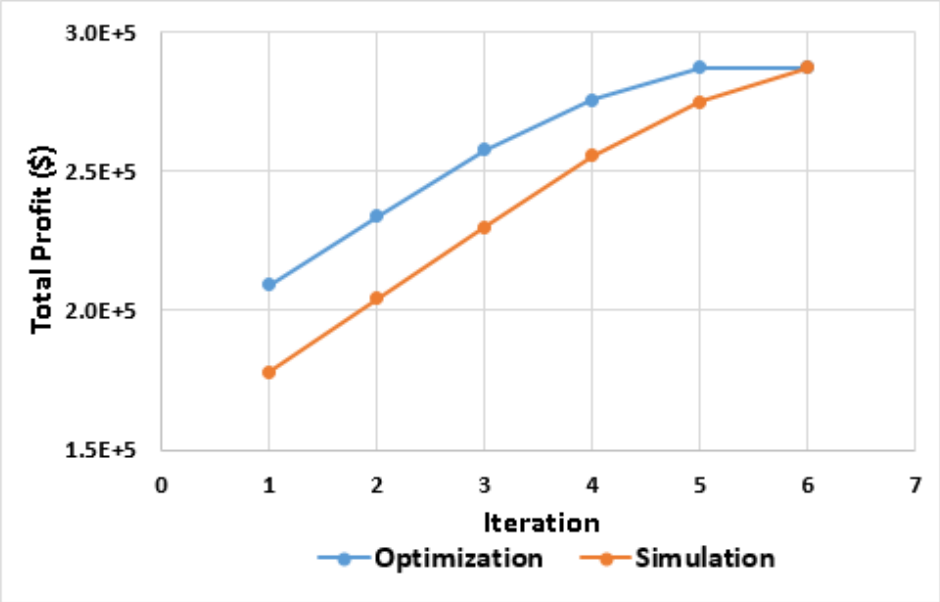

Figure 6.6: Solution of the hybrid simulation based optimization model

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 6.6. It can be seen that the profit values obtained from the simulation model and the optimization for the particular scenario converge in 8 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). Since 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.

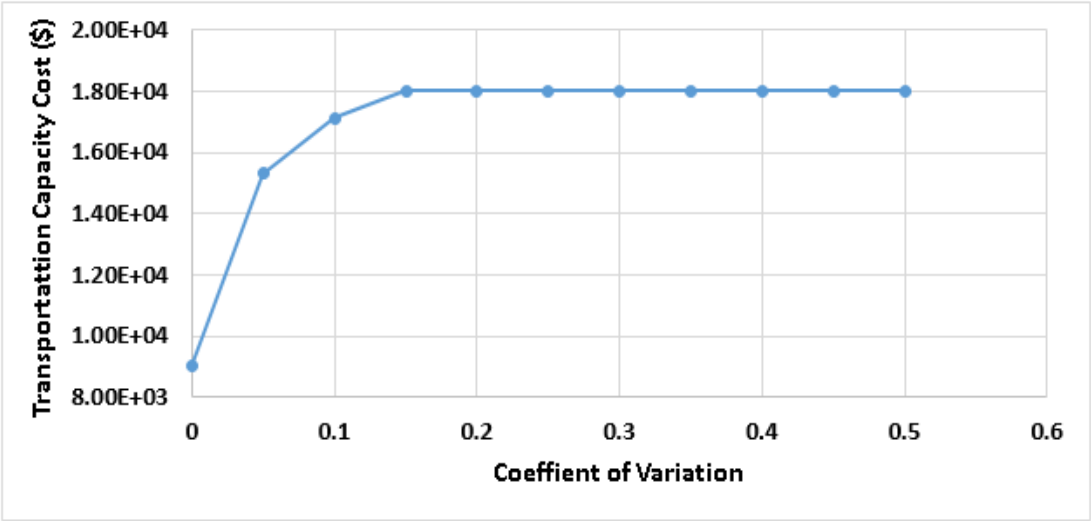

Figure 6.7: Comparison of transportation capacity cost with variability on demand

The different entities can increase their transportation capacity in order 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 6.7 shows a comparison of the transportation capacity cost with demand variability. The y-axis represents the cost due to increasing the transportation capacity in order 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. Since variability in demand is considered to be higher for a future period that is far from the current period compared to 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.

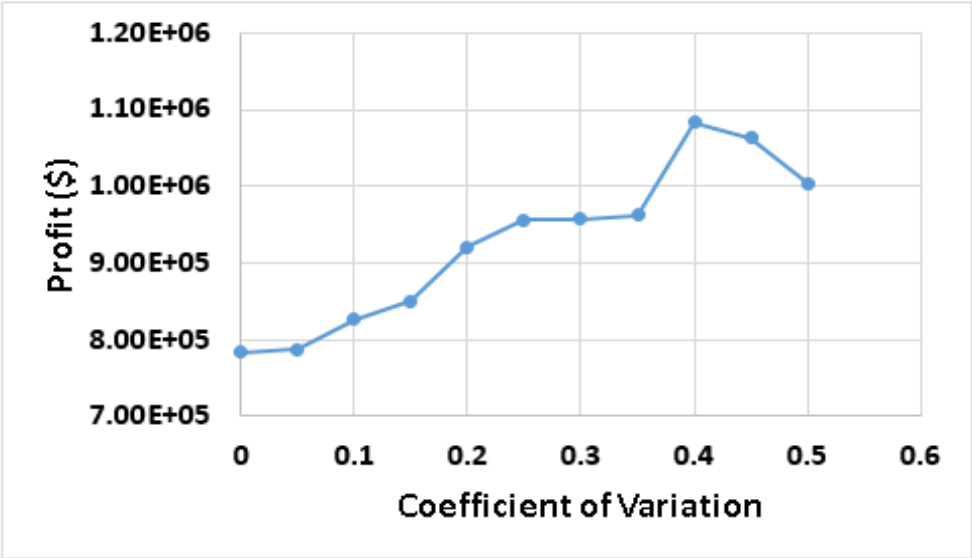

Figure 6.8: Variation of profit with demand variability

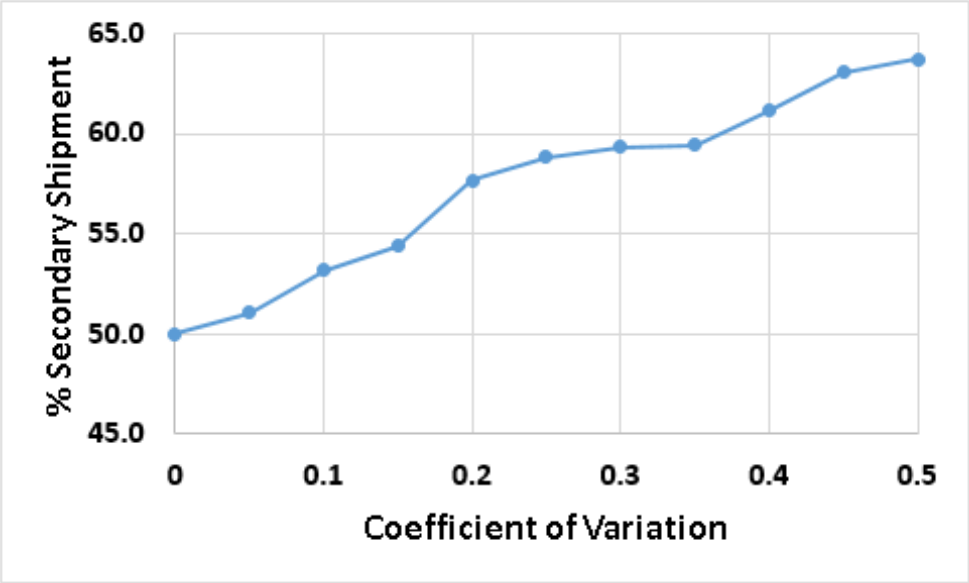

Figure 6.9: Variation of secondary shipment with demand variability

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 6.8 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, since a minimum service level is maintained, the revenue also increases. It is to be noted that the trend obtained in figure 6.8 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 6.7,

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 6.9 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.

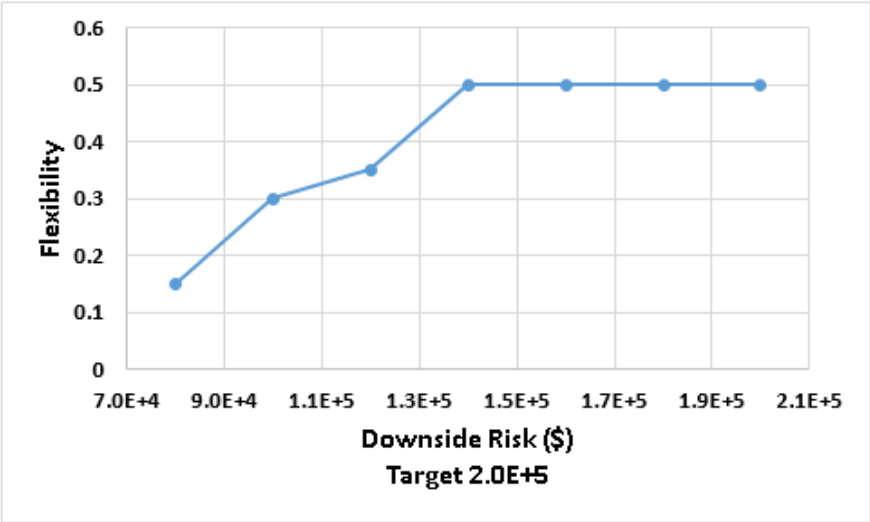

Figure 6.10: Variation of flexibility with risk

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. In order 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. In order 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 6.10 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 towards the end of the planning horizon is lower. A higher target profit towards 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 13893 sec. 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.

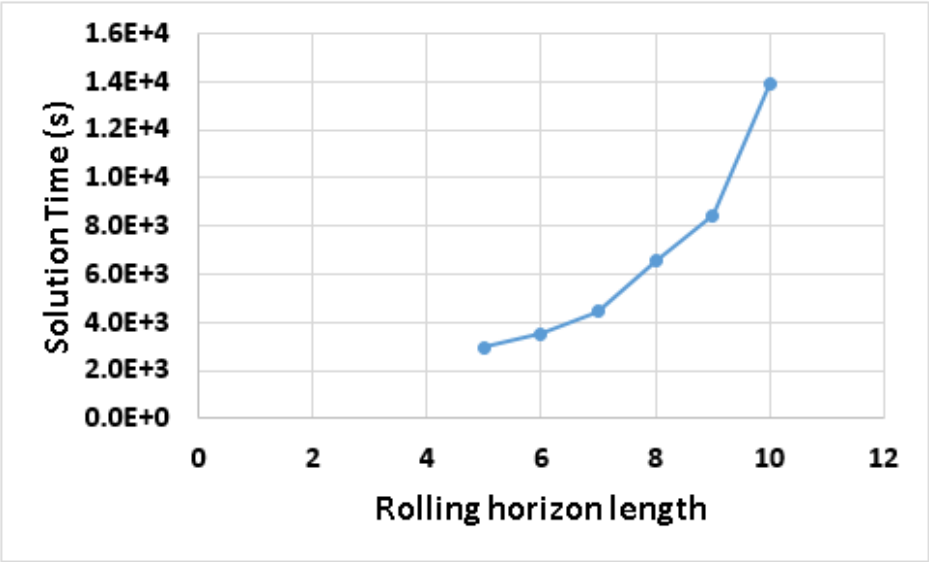

Figure 6.11: Variation of solution time with rolling horizon length

The effect of the length of rolling horizon on the solution time is investigated. Figure 6.11 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 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.

6.6.2 Case Study 2

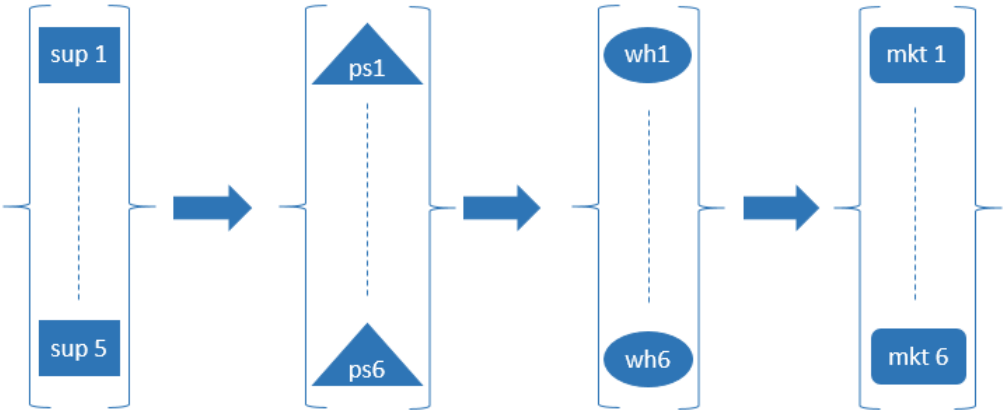

Figure 6.12: Supply chain network for case study 2

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 6 markets, 6 warehouses, 6 production sites and 5 suppliers, as shown in Figure 6.12. There are 2 products and 3 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 A.6.3, A.6.4 and A.6.5 contain the values of distances between the different entities of the supply chain network.

Figure 6.13 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 since 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.

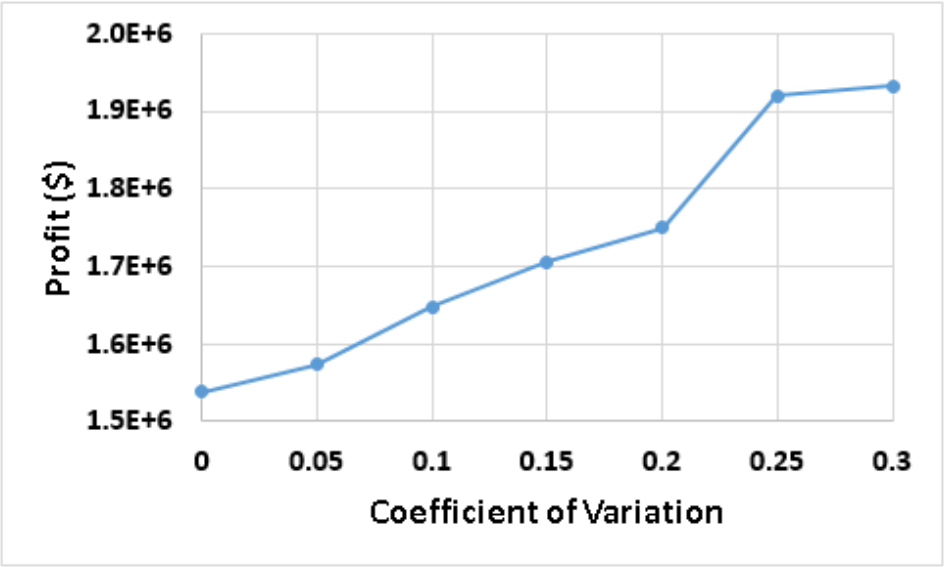

Figure 6.13: Variation of profit with demand variability

Figure 6.14 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 6.15 shows the variation in secondary shipment with demand variability. It can be seen that increased secondary shipment is required to meet the required service level in case of increased demand variability.

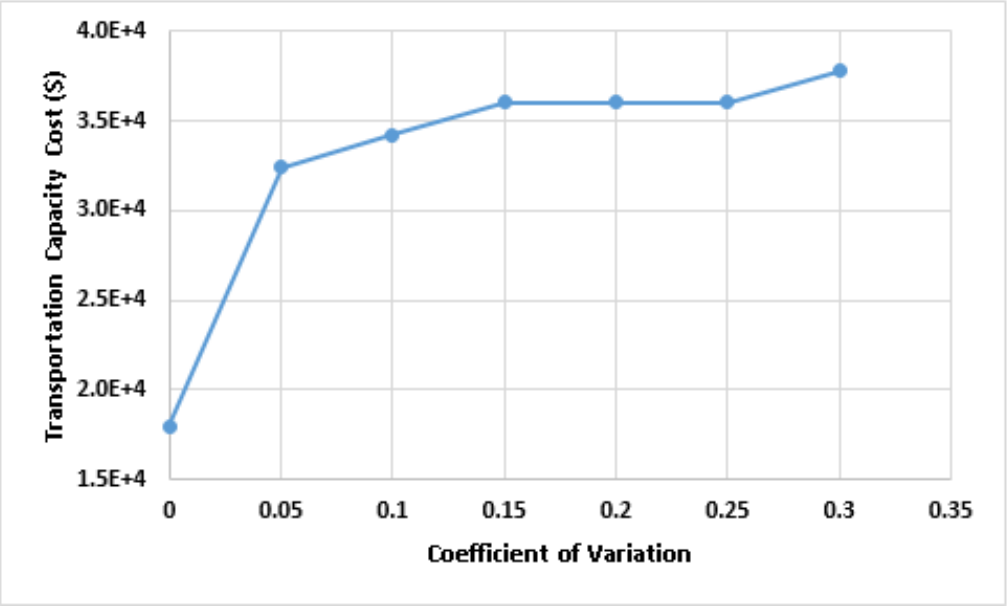

Figure 6.14: Comparison of transportation capacity cost with variability

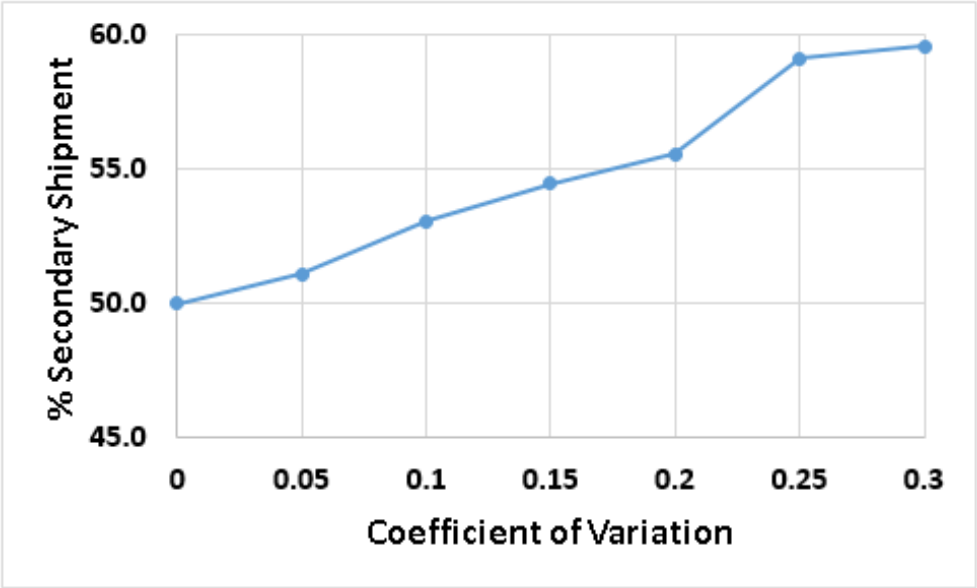

Figure 6.15: Variation of secondary shipment with demand variability

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 6.16 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.

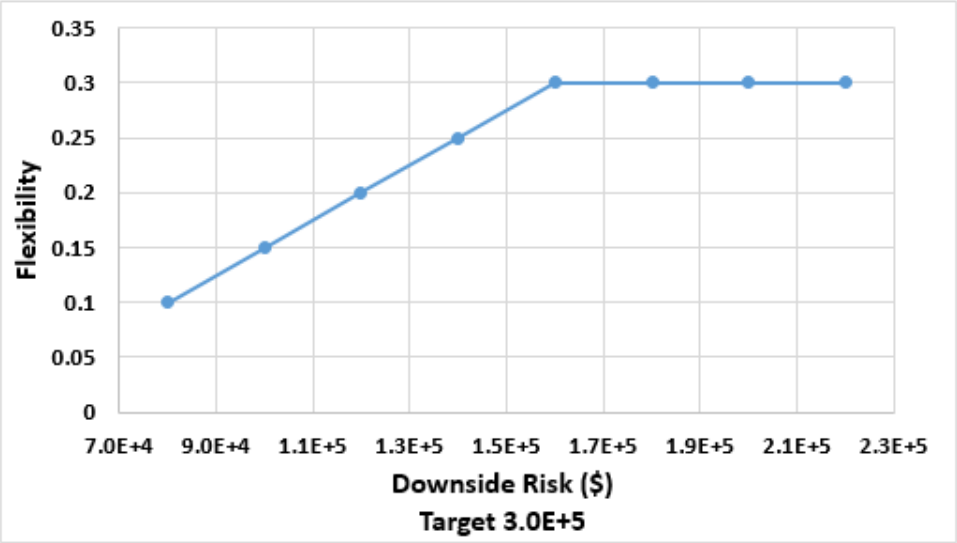

Figure 6.16: Variation of flexibility with risk

The computational time required to solve the case study at a particular risk level and demand variance is 30581 sec. 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.

6.7 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. In order 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.

Nomenclature:

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*
$dis^{wh,m}$	distance between warehouse *wh* and market *m*
$dis^{p,wh}$	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*
$Dem_s^{m,t,sc}$	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
$Cost2_{sc}$	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*
$Inv_s^{wh,t,sc}$	inventory level of product *s* at the end of the planning period *t* at warehouse *wh* for scenario *sc*
$Inv_s^{p,t,sc}$	inventory level of product *s* at the end of the planning period *t* at production site *p* for scenario *sc*
$Inv_r^{p,t,sc}$	inventory level of raw material *r* at the end of the planning period *t* at production site *p* for scenario sc
$Inv_r^{\sup,t,sc}$	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

$CI_s^{wh,t,sc}$	Increase in transportation capacity at warehouse *wh* for product *s* at planning period *t* for scenario *sc*
$CI_s^{p,t,sc}$	Increase in transportation capacity at production site *p* for product *s* at planning period *t* for scenario *sc*
$DRisk$	Value of downside risk
$Sl_{m,s,sc}$	Service level for product *s* at market *m* for scenario *sc*
$sp_{s,m}$	Selling price of product *s* at market *m*
$\mathrm{Rev}_{\mathrm{sc}}$	Revenue for scenario *sc*

7 Derivative Free Optimization for Expensive or Black-box Objective Functions

Derivative free optimization (DFO) methods are used for solving problems where the analytic derivatives of the objective function are unavailable as well as difficult to compute. Such problems are frequently encountered in various fields of engineering like computational fluid dynamics, process flowsheet design, mechanical engineering design, and large scale nonlinear partial differential equations. The complex processes associated with such problems are usually described by expensive computational models. While the analytic derivatives of such models are unavailable, their high computational cost does not allow a large number of function evaluations thus making the calculation of derivatives impractical. To overcome the issue of high computational cost, these methods frequently employ surrogate approximations in place of the actual high fidelity complex models.

Surrogate models have become increasingly popular in engineering and a lot of research has been done in the area[128-134]. Besides reducing the computational time, the use of surrogate models offers other benefits related to statistical analysis since they are usually developed using a Design of Experiments (DOE) technique. Also, fitting surrogate models can provide input-output relationships in cases where such functions are unavailable. Most of the surrogate-based optimization methods proposed in the literature follow some common steps, as shown in Figure 7.1. The first step involves fitting a surrogate model using a few initial sampling points. An experimental design is used to determine the initial sampling points. The next step is to improve the surrogate model by evaluating the original function at promising locations, either in the regions of low

objective function values (in the case of minimization) or where there is less information about the function. Evaluation of the original function and refitting of the surrogate model are done iteratively until an improved model of the original function has been obtained. Finally the surrogate model is optimized instead of the original objective function to obtain local optima.

Although most of the algorithms follow these common steps, they differ in terms of the models and the sampling technique they adapt. The surrogate models used can be broadly classified into interpolating and non-interpolating models, among which interpolating models have been shown to perform better[135]. The sampling techniques proposed in the literature can be either two-step or one-step methods. In case of two-step methods, a surrogate model is fitted based on the initial sampling points in the first step and that model is used to determine the adaptive sample points in the second step. On the other hand in case of one-step methods, model fitting and determination of adaptive sample points are combined into a single step with the idea that the errors in model fitting are not passed on to the determination of adaptive sample points.

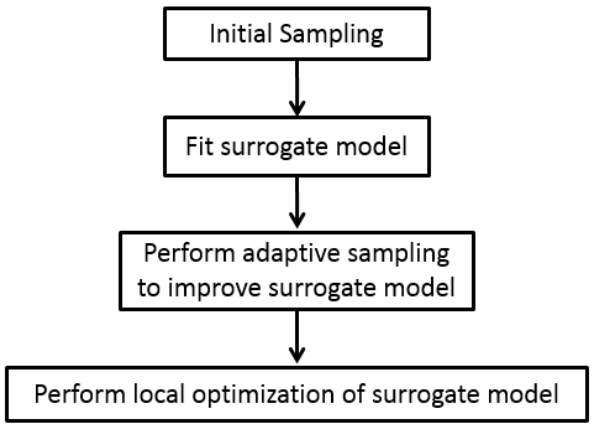

Figure 7.1: Steps for surrogate-based optimization

In this chapter, we propose a surrogate based optimization framework for expensive objective functions and also analyze the performance of different adaptive sampling techniques. The problems considered are bounded unconstrained optimization cases. The objective of the algorithm is to obtain the global minimum as well as local minima with low number of function evaluations.

7.1 Background

A number of derivative free optimization methods have been proposed in the literature addressing the different challenges associated with various optimization problems. Rios and Sahinidis[136] provide a comprehensive review of the derivative free optimization algorithms and software implementations. They address the solution of bound constrained optimization problems where the objective function values are available but there is no derivative information. Amaran et al.[137] review the algorithms related to simulation optimization where the objective function and constraints can be evaluated through a stochastic simulation. Among surrogate based methods, different surrogate models have been proposed, such as kriging[138], radial basis functions (RBF)[139-141], splines[142], support vector regression[143] etc. Cozad et al.[144] proposed the automated learning of algebraic models for optimization (ALAMO). The approach uses the best subset technique to consider a large number of functional components in the model and then builds a low-complexity surrogate model. As mentioned in the previous section, interpolating models have been found to perform better than non-interpolating models. In this work, we use the kriging model as the surrogate model in the optimization algorithm.

Kriging was originally developed in geostatistics by Daniel Krige [145]. Later on, it was applied to both deterministic and stochastic simulation models for developing input-output relationships. Sacks et al.[138] introduced it to the optimization literature. The deterministic output was modeled as a realization of a stochastic process and the model was also shown to be capable of identifying high uncertainty regions. Since then, kriging has been used extensively to model black-box functions. Since kriging provides the predicted value as well as the error at an unsampled point, its use allows the use of Expected Improvement (EI)[146], a function that gives the probability of any unsampled point to have an improved objective function value or higher uncertainty. Therefore most of the work involving kriging use the EI function for adaptive sampling. Davis and Ierapetritou[147] use a hybrid kriging-RSM methodology for the optimization of NLP black-box systems lacking a closed-form mathematical description. They extended the methodology to solve MINLP problems where the formulation contains black box functions[148]. Boukouvala and Ierapetritou[149] proposed an optimization methodology for constrained black box functions. The methodology uses separate surrogate models for the objective and feasibility functions. A modified EI function is used to locate the boundaries of the feasible region. In a more recent work, Regis[150] develops a new kriging based optimization method for steep and narrow optima. The algorithm uses a trust region method where each iterate maximizes the expected improvement function. Kriging also has the ability to be used for highly nonlinear functions with noisy input output data. In such cases, a nugget effect parameter is introduced that makes the model noninterpolating. The nugget effect parameter controls the smoothing ability of the model [151].

The EI approach for adaptive sampling is widely used along with the kriging model and it has been shown to work very well for most of the cases[146]. The approach uses the kriging model determined beforehand and therefore its performance is also affected by how good the surrogate model is. Therefore, for problems with steep optima or with sparse sampling, where it is difficult to have a good surrogate model, the approach also may fail to detect regions of optima. This drawback is addressed by one-step approaches for adaptive sampling. The one-step approaches overcome the issue of poor parameter estimation by performing estimation of parameters for the surrogate model and determination of location of the next promising point in a single step. In particular, we look at the goal seeking approach and EI with conditional lower bound. The goal-seeking approach uses different goal values and maximizes the conditional likelihood function to find the optimum locations of the goals. The method of EI with conditional lower bound calculates a statistical lower bound for a goal using the likelihood ratio test. The lower bound is used to calculate a variance estimate which is used in the EI function. In a way, it incorporates the benefits of EI with the goal seeking approach.

7.2 Solution Methodology

The overall solution framework is shown in Figure 7.2. As shown in the figure, the algorithm starts with an initial sampling based on DOE. In particular, Latin Hypercube Sampling is used. We use 10n+1 samples where n is the number of dimensions. Using the initial samples, an initial surrogate model is fitted. We use the Kriging model in this work. After the initial model development, adaptive sampling is performed using either

the Expected Improvement or Goal-Seeking approaches. The performance of the Expected Improvement and Goal-Seeking approaches are compared in the results section. The final step is the local search step for which the trust region method is used. Local search is performed starting from multiple starting points that are determined by obtaining clusters containing the best points. The details of the different steps are included below.

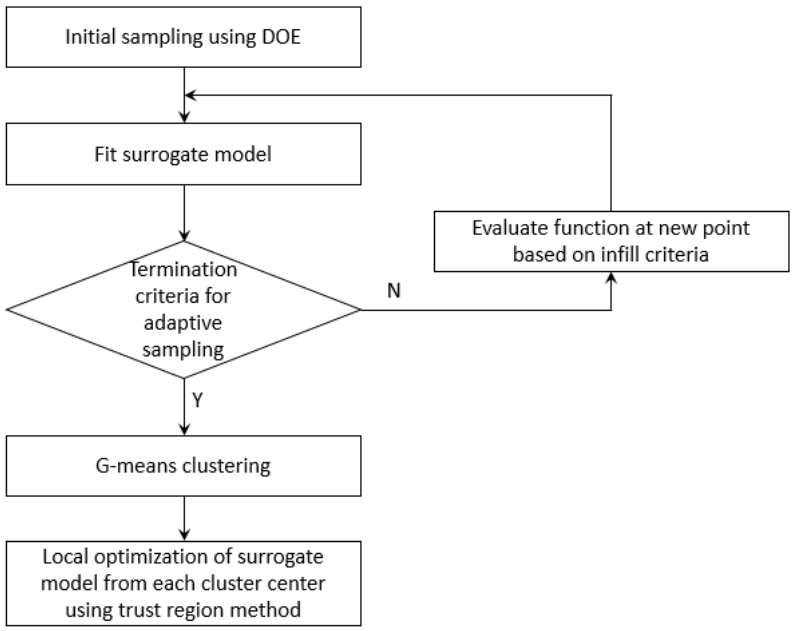

Figure 7.2: Solution framework

7.2.1 Surrogate model

Kriging is an inverse distance weighting method. It was first used in the field of geostatistics to study the distribution of mineral deposits. But it has also become popular in the area of optimization owing to the relatively low number of parameters and its ability to identify promising regions of high uncertainty. Kriging models the function as a

realization of a random variable to capture the uncertainty in the value of the function at an unsampled point. The random variable is considered to be normally distributed with a mean μ and variance σ^2. The kriging predictor is a linear function of the observed yi's. However the coefficients are nonlinear functions of x.

For a continuous function, the predicted values $y(x_i)$ and $y(x_j)$ at the points x_i and x_j are close if the points are close to each other. Therefore the correlation between the random variables $Y(x_i)$ and $Y(x_j)$ will be high if the points are close and close to zero if the points are very far apart. Equation 1 has these properties and can be used to define the correlation between predicted values at different points.

$$Corr\left[Y\left(x_i\right),Y\left(x_j\right)\right]=\exp\left(-\sum_{l=1}^{d}\theta_l\left|x_{il}-x_{jl}\right|^{pl}\right) \quad \text{.....(1)}$$

where θ_l determines the influence of change in direction l on the predicted values. For high values of θ_l, there is a large change in function value with change in the x values in the direction l. The smoothness of the function is determined by the parameter p_l. For smooth functions, the value is close to 2 while for rough, non-smooth functions, it is close to 0.

The parameters of the model μ,σ^2,θ,p are determined by maximizing the likelihood function. Using the correlation in equation 1, the predicted value at any point $x*$ is given by equation 2. Here the optimal value of μ, denoted by $\hat{\mu}$, is defined as shown in equation 3. Similarly the optimal value of σ^2 is defined by equation 4. For n sampled points, R is defined as the $(n\times n)$ matrix where the (i,j) element is the correlation

between $Y(x_i)$ and $Y(x_j)$. r is defined as the correlation vector between $Y(x^*)$ and $Y(x_i)$, for i=1,…n.

$$\hat{y}(x^*) = \hat{\mu} + r' R^{-1}(y - 1\hat{\mu}) \quad \text{.....(2)}$$

$$\hat{\mu} = \frac{1' R^{-1} y}{1' R^{-1} 1} \quad \text{.....(3)}$$

$$\hat{\sigma}^2 = \frac{(y - 1\hat{\mu}) R^{-1} (y - 1\hat{\mu})}{n} \quad \text{.....(4)}$$

$$s^2(x^*) = \hat{\sigma}^2 \left[1 - r' R r + \frac{(1 - r' R^{-1} r)^2}{1' R^{-1} 1} \right] \quad \text{.....(5)}$$

The Mean Squared Error (MSE) of the predictor, derived using the standard stochastic process approach is given by equation 5. Error calculation makes the model particularly advantageous since it can be used to determine the high uncertainty regions in the adaptive sampling stage. It should be noted that the predicted value and the mean squared error are derived assuming that the parameters of the model are correct. However, the correct values of the parameters are unknown and what we have are estimated values based on the sampled points.

7.2.2 Adaptive Sampling

7.2.2.1 Expected Improvement

Depending on the search methodology used, DFO methods can be classified into local and global methods. The drawback associated with local search methods is that the convergence depends on the initial point and can get stuck in the local optimum closest to

the initial point. It is important to recognize that the response surface is uncertain and there is a need to explore the sample space. Expected improvement is one of the popular methods that balances between local and global search. It is commonly used as a criterion in adaptive sampling to determine regions where the objective function values are low or the function has not been sampled enough[146,152].

The improvement at any point is a random variable and can be calculated as shown in equation 6. Here improvement is calculated over the current best function value, $f_{\min}$. Y is a normally distributed random variable with mean and standard deviation given by the DACE predictor and its standard error. The expected value of this improvement is given by equation 7. ϕ and Φ denote the standard normal density and distribution functions in equation 7. The expression for expected value has very desirable properties. As shown in equations 8 and 9, its partial derivative with respect to $\hat{y}$ and s are always negative and positive, respectively. Thus maximization of the expected improvement leads to lower values of $\hat{y}$ and higher values of s. Therefore this figure of merit provides a balance between local and global search.

$$I = \max(f_{\min} - Y, 0) \quad \text{.....} \quad (6)$$

$$\mathrm{E}\left[I(\mathrm{x})\right] = (f_{\min} - \hat{y})\Phi\left(\frac{f_{\min} - \hat{y}}{s}\right) + s\phi\left(\frac{f_{\min} - \hat{y}}{s}\right) \quad \text{.....} \quad (7)$$

$$\frac{\partial \mathrm{E}(I)}{\partial \hat{y}} = -\Phi\left(\frac{f_{\min} - \hat{y}}{s}\right) < 0 \quad \text{.....} \quad (8)$$

$$\frac{\partial \mathrm{E}(I)}{\partial s} = \phi\left(\frac{f_{\min} - \hat{y}}{s}\right) > 0 \quad \text{.....} \quad (9)$$

In case of Kriging model, the prediction error s is equal to the root mean square error (MSE).

7.2.2.2 Goal seeking approach

As mentioned earlier, the goal-seeking approach proposed by Jones[146] tries to overcome the issue of poor parameter estimation in the first step of the EI approach due to poor sampling. It is a one-step method where a hypothesis is made that the response surface passes through a point x^* where it achieves a goal f^*. This hypothesis is evaluated by calculating the conditional likelihood of the observed data under the assumption that the surface passes through the point (x^*, f^*). By maximizing the conditional likelihood given by equation 10, the optimal parameters of the surrogate model along with x^* can be determined for a given f^*. Therefore the optimal parameters of the model are found so that the hypothesis is true. It should be noted that this method would require the value of f^* for which the conditional likelihood needs to be maximized. Since the value of f^* is not readily available, several values of f^* less than f_{min}, the minimum value of response sampled so far, are used and the conditional likelihood function is maximized for each of these goal values. Balance between local and global search can be obtained by adjusting the goal values. A very low goal value leads to exploration of the search space while goal values close to f_{min} leads to local search. It has been shown that the optimal values of x^* for the different goal values are obtained in clusters[135]. For each of the clusters, the points associated with the least goal value can be sampled next. This approach has been shown to provide robustness in case the initial sampling is not very good.

$$L_{cond} = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}(\hat{\sigma}^2) - \frac{1}{2}\ln|C| - \frac{(\text{y-m})^{\text{T}}\text{C}^{-1}(\text{y-m})^{\text{T}}}{2\hat{\sigma}^2} \quad \text{.....} \quad (10)$$

where $m = \hat{m} + \gamma\,(y^g - \hat{m})$ ..... (11)

and $C = \Psi - \psi\psi^T$ ..... (12)

Jones[135] suggests using 27 values for the goals. In order to reduce the computational time, we use only 15 goal values. These values are less than f_{min} and the obtained points are clustered into 2 clusters. Then the original function is evaluated in each of the clusters at the point where the goal value is the least. This is repeated until a better point cannot be obtained for three consecutive iterations.

7.2.2.3 One-Step Expected Improvement with Conditional Lower Bound

Since it is known that EI performs well, it is desired that a one-step adaptive sampling technique incorporates EI. The goal-seeking approach described in the previous section tries to address the issue of poor parameter estimation but does not include the benefits of EI. The one-step EI method uses a goal for the predicted value that is determined statistically using the likelihood ratio test as described by equation 13.

$$\Lambda = 2\ln\frac{L_0}{L_{cond}} < \chi^2_{critical}(\text{limit,dof}) \quad \text{.....} \quad (13)$$

where L_0 is the conditional likelihood of $\hat{y}(\mathrm{x})$ at x, while L_{cond} is the conditional likelihood of the goal value. By solving the maximization problem using the appropriate limit as shown in equation (14), the standard deviation can be obtained.

$$\max_{\mathrm{x},y^h,\theta} \quad \hat{y}(\mathrm{x}) - y^h$$

$$\text{subject to} \quad 2\ln\frac{L_0}{L_{cond}(\mathrm{x},\theta,y^h)} < \chi^2_{critical}(\text{erf}\,(1/\sqrt{2}),\text{dof}) \quad \text{.....} \quad (14)$$

The estimate of the standard deviation is then used to calculate the EI. The overall infill criterion can be implemented as shown in equation 15.

$$\max_{\mathrm{x}} E\left[I\left(\mathrm{x}, \begin{cases} \max\limits_{y^h,\theta} & \hat{y}(\mathrm{x}) - y^h \\ \text{subject to} & 2\ln \dfrac{L_0}{L_{cond}(\mathrm{x},\theta,y^h)} < \chi^2_{critical}(\mathrm{erf}\,(1/\sqrt{2}),\mathrm{dof}) \end{cases} \right) \right] \quad \text{.....} \quad (15)$$

7.2.3 Local search

The global search methods do not guarantee convergence to optimal points. Therefore once the adaptive sampling has been performed and a good surrogate model has been obtained, a local search method is used to optimize it. Local search methods guarantee convergence to first order and second order optimal points by reducing the search space to zero. In particular, by ensuring that the surrogate model represents the original function accurately, it can be proven that as the trust region radius reduces when a descent direction is not found, the method will converge to a local optimum when the radius is very small[153].

Since trust region method is a local search method, it is able to find minima close to the starting point. This lays importance to the selection of good starting points for the algorithm. In order to increase the chances of finding the global minimum, clustering is used to find good starting points that act as initial trust region centers. The g-means clustering algorithm is used[154]. This method represents a wrapper around the k-means algorithm that helps find clusters without the need to specify the number of clusters. Since the number of clusters is not obvious, this method is used as it learns the number of

clusters as it proceeds. It is based on a statistical test for the hypothesis that a subset of data follows a Gaussian distribution. The algorithm runs k-means with increasing k until the hypothesis that the data assigned to each k-means center is Gaussian is accepted.

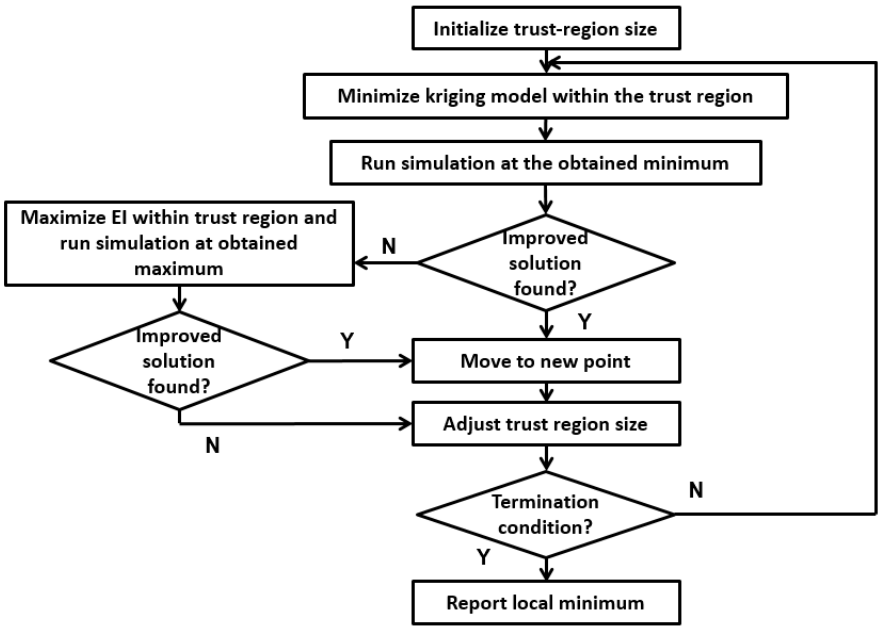

Figure 7.3: Trust region method

Once the clusters are determined, trust region search is used from each of the cluster centers successively. During the search, the trajectory of search for each of the clusters is stored. If the trajectory for a cluster gets very close to a previous one, the search for that particular cluster is abandoned and the optimum associated with the previous cluster is reported as the one for the current cluster. In a recent work, it is shown that maximizing EI within the trust region performs well for steep and narrow minimum basins[150]. As shown in Figure 7.3, this idea is incorporated in the trust region method implemented in this work. If an improved solution is not obtained on optimizing the surrogate model

within the trust region, the EI is maximized. The adjustment of the trust region radius then depends on a comparison of the expected improvement and the actual improvement.

7.3 Case Studies

The proposed algorithm is tested using standard mathematical functions. In order to test the performance of the algorithm and compare the performance of the different infill criteria on functions where the global optimum is difficult to find, we have included functions with many local minima or very steep ridges. In particular, we investigated the Branin, Shubert, Easom, Michalewicz, and the Ackley functions. The actual plots for these functions are shown in figure 7.4. All these functions have multiple local minima. Easom, Ackley and Michalewicz function have very steep minima. For comparison, the results obtained from the EGO solver are also presented.

Since the initial sampling is random, we run the algorithm a number of times to observe the average performance of the algorithm. The results shown here are for a total number of 30 runs.

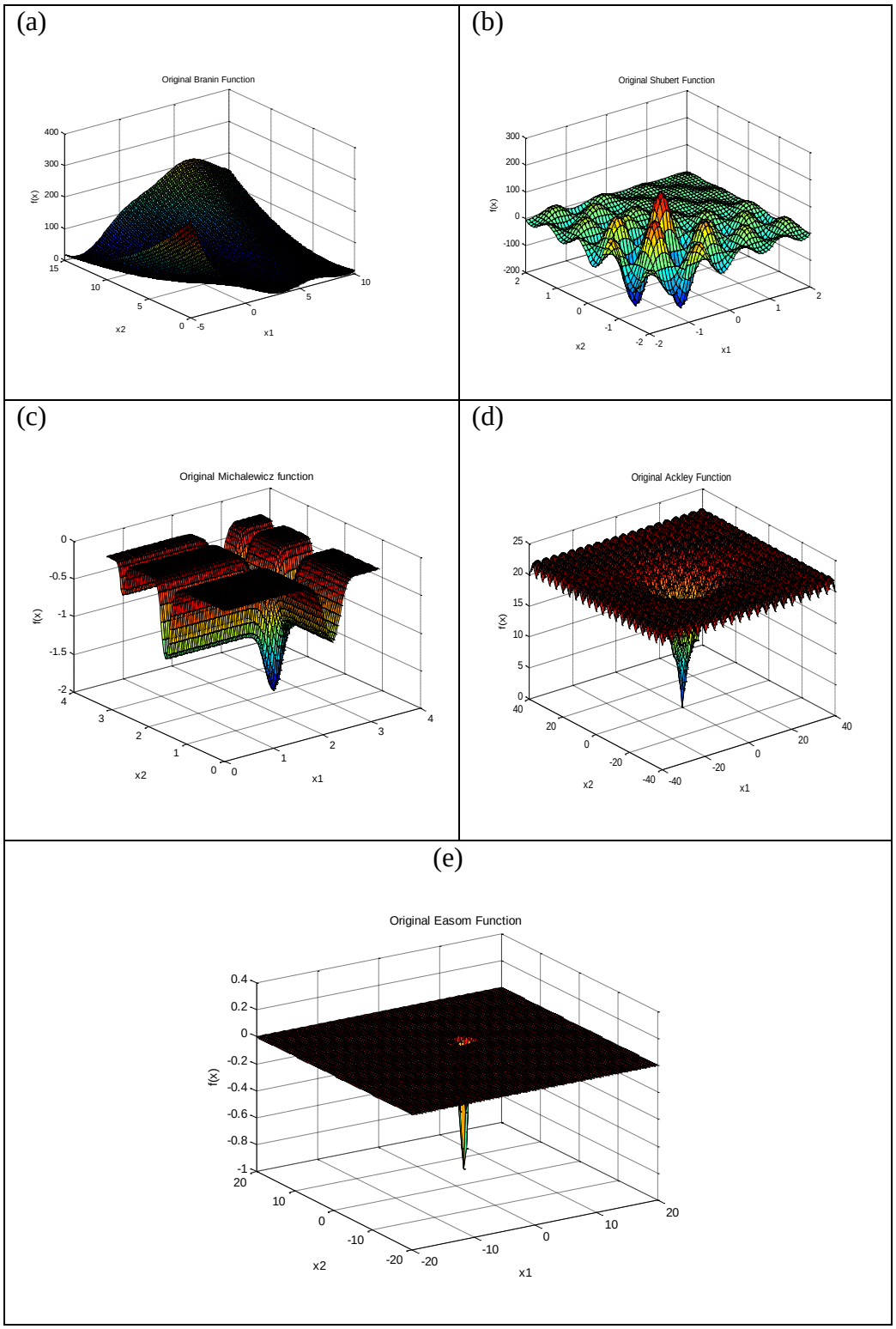

Figure 7.4: Original function plots for (a) Branin, (b) Shubert, (c) Michalewicz, (d) Ackley, (e) Easom functions

7.4 Results

The performance of the algorithm is evaluated on the basis of three factors, namely the number of times the global minimum is obtained out of a given number of runs, the average number of function calls and the average computational time required. There are three stages during which the original function is evaluated during the algorithm. In the initial sampling stage, it is evaluated for a pre-specified number of times. Then it is evaluated during the adaptive sampling stage and the local search stage. In the local search stage, the number of function calls depends on the number of clusters found by the g-means algorithm. It is observed that the number of clusters vary from 1 to 12 for the functions investigated. Clustering is performed on points over a mesh grid. By making the grid fine or coarse or adjusting the number of points over the grid used for clustering, the number of clusters obtained can be adjusted. It should be noted that although finding more clusters provides more initial starting points for local search and thus increases the chances of finding the global optimum, the total number of function calls and computational time also increase.

Table 7.1 shows the number of times the global minimum was found out of the 30 runs. The same initial samples are used for all the different methods compared. It can be seen that the proposed algorithm, both in case of EI and goal-seeking, is able to find the global minimum almost as frequently as EGO in case of the Branin, Easom and Michalewicz functions. EGO performs slightly better for the Shubert function. The functions where EGO does not perform well are the Easom function and the Ackley function. Both of these functions have larger number of local minima. In case of Easom, the region of

global minimum occupies a very small area compared to the overall search domain. It is observed that the proposed method performs very well when the goal seeking method is used, finding the global minimum 29 times out 30, compared to only 21 times by EGO.

Table 7.1: Number of times the global minimum is found (total runs = 30)

	Number of times the global opt is found		
Function	**EI**	**Goal seeking**	**EGO**
Branin	30	30	30
Shubert	23	25	30
Easom	21	18	17
Michalewicz	30	28	30
Ackley	16	29	21

Table 7.2 shows a comparison of the number of function calls used by the different methods. The average value over the 30 runs is presented. It can be seen that EGO uses higher number of function calls for the Shubert, Easom and Ackley functions. Among these, it performs better than the proposed method only in the case of the Shubert function. For the rest of the functions, despite the higher number of function calls, EGO is unable to find the global minimum more frequently and actually finds it less frequently for the Ackley function. As mentioned earlier, the proposed method finds clusters and uses them to perform local optimization. Therefore the number of function calls in Table 7.2 include the calls made during the local optimization step.

Table 7.2: Average number of function calls

Function	Average number of function calls		
	EI	Goal seeking	EGO
Branin	175.47	170.87	44.07
Shubert	222.73	193.63	308.79
Easom	249.30	208.60	368.00
Michalewicz	135.90	130.43	45.03
Ackley	125.20	65.20	247.83

For comparison, the function calls in the initial and adaptive sampling stages of the proposed method are presented in Table 7.3. It is to be noted that the number of function calls before local optimization in case of the Easom function using EI is very low which indicates that the adaptive sampling step does not perform sufficient number of iterations. This is possibly due to the low area occupied by the region of global minimum compared to the overall search space. The table shows that a majority of function calls are used in the local optimization stage where a trust region method is executed starting from each cluster center. The average number of clusters detected are presented in Table 7.4.

Table 7.3: Average number of function calls before local optimization

Function	Average number of function calls before local optimization	
	EI	Goal seeking
Branin	47.13	28.57
Shubert	50	31
Easom	23.53	29
Michalewicz	49.96	33.26
Ackley	30.47	29.43

Table 7.4: Average number of clusters

	Clusters	
Function	**EI**	**Goal seeking**
Branin	3.00	3.13
Shubert	4.73	4.20
Easom	3.40	2.70
Michalewicz	2.67	3.00
Ackley	2.33	1.03

For the Shubert and Easom functions, where the EI and goal seeking approaches do not perform well, the performance of one-step EI is evaluated. This method is computationally more expensive due to the nested optimization that is solved to determine the adaptive sampling point in each iteration. The method is executed for 10 replications. Out of the 10 replications, it is able to find the global minimum all 10 times for the Shubert function while 6 times for the Easom function.

7.5 Conclusions

The optimization algorithm presented in this work combines local and global search and is tested with problems that are difficult to minimize, either due to too many local optima or steep and narrow minima. In the local optimization step, maximization of Expected Improvement is incorporated to improve the chances of detecting steep and narrow minima close to another region of minimum. Local optimization is done starting from different cluster centers. The g-means algorithm is used for clustering. This bypasses the requirement of specifying the number of clusters and enables the determination of multiple local minima.

Different infill criteria are used for the adaptive sampling stage. Among the different functions for which the results are presented, it is seen that the proposed method performs better for the Ackley function when the goal seeking approach is used. However the goal seeking approach is a parametric method since it depends on the goal values chances. In a future work, the determination of goal values used for the approach will be investigated.

8 Multi-Enterprise Supply Chain Operation

Most of the work described in the earlier chapters considers single enterprise supply chain networks. The previous chapters have not explicitly considered the interactions among the different enterprises constituting a supply chain network. The advancements in web technologies have seen the limitations with multi-enterprise global supply chain networks dissolve. In fact, it is rare for a single enterprise to operate its supply chain independently in the present scenario. Multi-enterprise supply chain operations can be significantly different from that in a monolithic supply chain belonging to a single enterprise.

Minimization of costs or maximization of profits is considered as a single objective in most of the work related to integration of supply chain networks. These strategies lead to the optimal solution for the entire network. However, those solutions might not be suitable for the individual entities in the network. For instance, the optimal solution strategy might require shipment of products at frequent intervals from a warehouse to a downstream location. However that could mean increased transportation costs for the warehouse, making the solution not suitable for the particular warehouse. In case of a single enterprise network, it might be alright to not take into account such considerations. However they gain more importance when the network consists more than one enterprise and the optimal solution for the overall network is not beneficial for all the participating enterprises. Under such circumstances, the model needs to take into consideration the interaction among the entities in terms of transfer prices, coalition formation, negotiations. When transactions among different enterprises are involved, the optimal solution for the overall network might not be possible from a practical standpoint unless

the individual objectives of the entities are also satisfied. In this work, we consider the supply chain network to be composed of more than one enterprise and incorporate decision-making rules regarding transactions among different enterprises.

8.1 Background

Unlike the traditional methodology of supply chain optimization that takes a centralized view, recent work include more studies involving multi-enterprise networks. Among the initial studies discussing multi-enterprise networks, D'Amours et al.[155] proposed a network approach with multiple firms. The firms are selected and scheduled with the objective of fulfilling demand at minimum cost. Collaborative approach is shown to be more profitable and it suggested that electronic data exchange should be implemented for communication among the firms. Over these years, companies have started widely using electronic data exchange in order to communicate with each other. During the late 1990's, many new supply chain paradigms evolved which were studied by many authors[156-158]

Among the different ways enterprises may interact with each other for transactions, auctions have been gained some emphasis recently. Although buyers usually rely on contracts with suppliers for the critical products, auctions have become an efficient and effective means to procure non-critical products. They help achieve lower acquisition costs as well as enable new suppliers to enter the market. Advances in information technology have enabled online marketplaces where auctions can be carried out and buyers and sellers can exchange goods and money. Another advantage such marketplaces

offer is that they allow the buyers and sellers to determine price elasticity and dynamically adjust their prices based on supply and demand. In the recent past, there has been a growing body of literature in the field of operations management. Jin and Wu study auctions in electronic markets. They show that apart from price-determination, auctions also act as a coordination mechanism for the supply chain. They study the buyer-supplier interactions for different kinds of market mechanisms. Beil and Wein[159] consider a manufacturer who uses a procurement auction to determine which supplier will be awarded the contract. They consider bids with both and price and non-price attributes. The manufacturer learns from the bids of the suppliers in the previous rounds of auction and then uses a scoring rule choose the bid such that its utility is maximized. Chen[160] study a problem with one buyer and multiple suppliers. The price and the purchase quantity are determined through an auction. The buyer first designs a contract specifying the payment for each possible purchase quantity. Then the suppliers bid for the contract. The strategy is applied to a newsvendor model. Gallien and Wein[161] propose a procurement auction where multiple units can be awarded. A bidding support system is proposed since the mechanism is not truth-inducing. Chen et al. propose VCG auctions that include not only the price schedules but also the transportation costs. In this way, they ensure that the allocation decisions are efficient for the whole supply chain. Moyaux et al.[162] study the supply chain as a network of auctions. The model is implemented using the JASA simulator. They show that the price dynamics are more complicated than just fulfilling consumer demand, using raw material supplies and using the capacities for transformation. Gimpel and Makio[163] propose a multi-attribute continuous time double auction. The auction mechanism addresses how to choose a particular order among

multiple orders and also how to choose a particular point within the entire acceptable attribute space. In this work we consider a multi-enterprise supply chain network. The production sites and warehouses are considered to belong to one particular enterprise while the retailers are different enterprises. The transaction between warehouses and retailers happens through auctions.

8.2 Problem Statement

A multi-enterprise supply chain consisting of different entities is considered. Specifically, the constituting entities are retailers, warehouses, production sites and raw material suppliers. The warehouses, production sites and raw material suppliers are considered to belong to one enterprise while the retailers belong to different enterprises. Similar to the problems that have been studied in the earlier chapters, the different entities of the network follow have their own roles in the network and perform their functions based on their individual policies. The warehouses store products and transport them to fulfill market demand. They regulate their inventory by following their own inventory replenishment policy. Similarly, production sites also transport products to fulfill warehouse demand. They manufacture products to regulate their product inventory by following a production policy. They maintain their raw material inventory by following an inventory replenishment policy. The transactions between warehouses and retailers are considered as inter-enterprise transactions and occur in the form of auctions. During every period, both the warehouses and the retailers bid in terms of the price and the quantity of products which results in multi-attribute double auctions. The participating

parties are considered to be able to learn from the previous rounds of auction and adjust their bids accordingly.

8.3 Solution Methodology

The multi-enterprise supply chain operation is modeled using an agent-based simulation model. The roles and functions that the agents retain from the previous work have been included in the model. The changes that are made in the model for this work are related to how the transactions take place between the warehouses and the retailers. Since these two entities are considered to belong to different enterprises, the process of buying and selling products by the retailers and the warehouses respectively is carried out in the form of auctions. Also an auctioneer agent is added to the model. This agent is responsible for executing the auctions among the warehouses and the retailers. Below is a description of the auction mechanism that is implemented by the auctioneer agent.

8.3.1 Auction mechanism

The auction mechanism considered is a multi-attribute double auction. It is a double auction since both the warehouses and the retailers submit their ‘asks’ and ‘bids’. It is multi-attribute since the ‘asks’ and ‘bids’ contain not just the price but also the amount of products. There are four general properties that double auctions should satisfy. *Budget balance* implies that the auctioneer should not lose or gain money from the auction. The transactions should take place between the buyers and sellers only. An auction is *pareto optimal* if there is no other trade that makes all traders at least as well off and at least one trader strictly better off. *Individual rationality* implies that the participants prefer taking part in the auction to not taking part. An auction should also be *coalition proof*. This

implies that the traders should not find it profitable to form coalitions with each other and trade outside the auction.

In every period, a round of auction takes place for each warehouse. In one round of auction, a warehouse enters the auction as the seller and multiple retailers enter as buyers. The auction mechanism proposed by Gimpel and Makio[163] is used in this work The auction mechanism between the warehouse and the retailers can be considered to consist of two steps. The first step is *matching* which is followed by *arbitration*. As shown in figure 8.1, in the matching phase first the buyers and the seller place their bids and 'asks'. These consist of two attributes, price and risk. The seller states the minimum price it is willing to sell one unit of product for and the maximum amount of product it can sell. Similarly the buyer states the maximum price it is willing to pay for one unit of product and the maximum quantity it is willing to buy. As can be seen in figure 8.1, there are overlapping regions of bids by the buyers and the seller. Trade can happen only within these regions. So trade can happen between the seller and buyer 1 in the region (A+C) while it can happen with buyer 2 in the region (B+C). Since there is only one seller, it calculates its maximum possible payoff by trading with each of the buyers. The buyer that provides that highest potential maximum payoff is chosen by the seller for trade.

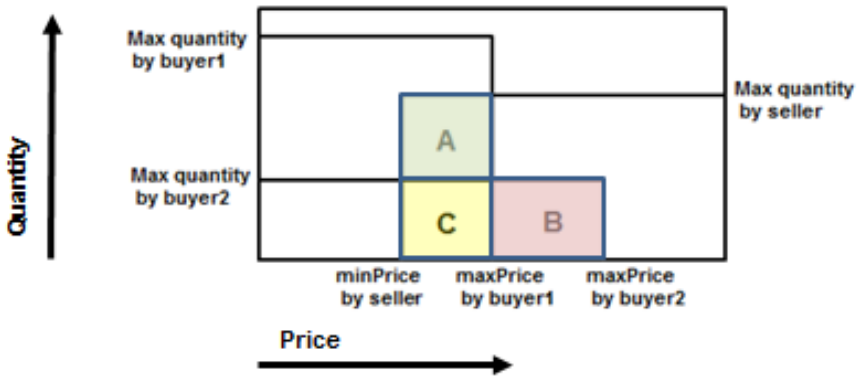

Figure 8.1: Bidding in the multi-attribute double auction

This is followed by the arbitration phase. As shown in figure 8.1, trade can happen in the shaded overlapping regions of the bids. The arbitration phase determines the actual trade parameters within the shaded regions. So if the seller chooses buyer 1 in the figure shown above, the arbitration phase determines the value of price and quantity with the region (A+C) at which the trade actually happens. The Nash bargaining solution is used for arbitration. The Nash solution determines the fair solution based on the payoffs. In this work, the payoff for the warehouse is calculated based on the revenue obtained by selling the products while that for the retailer is calculated based on the profit earned. These calculations do not include the costs related to the overall supply chain like the production cost, inventory cost and transportation cost. Incorporating those costs in the calculations would provide a fair solution from the overall supply chain context. The status quo point for the warehouse is the next highest maximum payoff possible for the warehouse by trading with any of the other retailers. The status quo point for the retailer is zero.

As mentioned earlier, a single warehouse and multiple retailers enter one round of auction. Since the arbitration phase could lead to partial fulfillment of demand of a retailer and there could be inventory left with the warehouse, a warehouse is allowed to re-enter into auction after the other warehouses have already had their auctions. Therefore the auctioneer keeps executing auctions in every period as long as there are willing warehouses and retailers.

8.3.2 Bidding Strategy

Since the auction mechanism does not enforce truthfulness, a pricing strategy is incorporated for the warehouses. The pricing strategy enables them to adjust their bids in different periods. The price bids in a particular depend on the bids in the previous period, the outcome of the previous round of auction and the state of the supply chain network (demand for retailers and inventory for warehouses).

In case of retailers, it adjusts its bid on whether it had won the last round of auction with the warehouse or not. In every period, the retailer tries to earn some profit on selling the products to the customers. So its basic strategy is to adjust the profit it seeks in every period. If it had won the last round of auction, it increases the profit it seeks by a pre-specified amount. If not, it uses the information about the transaction price from the last round of auction to adjust its bid. The current bid of the retailer is a function of the transaction price in the previous round and its learning rate. The learning rate is the factor that determines how much the retailer adjusts its profit percent to get close to the trade price in the last round. So if the learning rate for the retailer is 1.0, the current bid by the retailer becomes equal to the trade price in the previous round.

For the warehouses, the bidding strategy involves factors such as the trade price in the previous round, their inventory level and their target inventory level. There is a minimum bid which the warehouse can place. The minimum bid depends on the valuation of the product by the warehouse. Valuation of the products is a non-trivial issue. It can be based on scarcity of the products, effort needed for the manufacture of the products or the value obtained by the sale of the products. Determination of true valuation of the products has been considered out of scope of the present work and therefore a pre-specified value is assigned. The bid by the warehouse in the current period is given by equation 8.1.

$$Bid(t) = P(t-1) * B(\bar{f}) \quad \text{.....} \quad (8.1)$$

where

$$B(\bar{f}) = 1.2^{(1-\bar{f})} \quad \text{.....} \quad (8.2)$$

$$\bar{f} = \frac{inv(t)}{\text{target inventory}} \quad \text{.....} \quad (8.3)$$

The strategy is adapted from Steiglitz et al.[164] The formulation proposed by them has a term for the gold inventory. Since gold inventory is ignored in this work, it is possible to use a constant term like 1.2. The value 1.2 has been chosen to keep the bids comparable to the bids of the retailers so that trade is enabled. This strategy makes the warehouse bid a lower price if its inventory rises above the target inventory and a higher price if it falls below the target inventory. Thus it reflects the desire of the warehouse to sell more if it has higher inventory and sell less if it has lower inventory.

The bidding strategy related to quantities of products is simple. In case of retailers, the bid is equal to the demand value during that period. Warehouses bid their inventory value current available inventory.

8.4 Case Studies

Two small-scale case studies are presented to demonstrate how the bids of the warehouses and the retailers vary over time. A third case study is also presented where the derivative free optimization algorithm presented in chapter 7 is used to find the optimal warehouse capacities. The performance of the supply chain network is investigated in terms of the total cost of supply chain operations and the service level. Service levels is defined in terms of the average backorders per period and the average demand.

$$ServiceLevel = 1 - \frac{\text{Expected backorders per time period}}{\text{Expected period demand}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (8.4)$$

8.4.1 Case Study 1

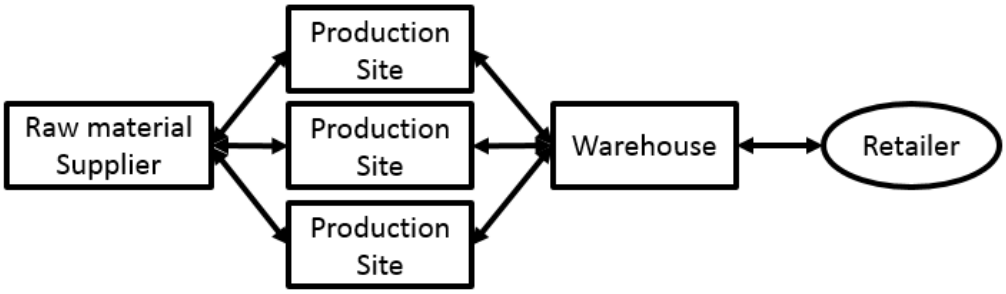

Figure 8.2: Supply chain network for case study 1

As shown in figure 8.2, a supply chain network with 1 raw material supplier, 3 production sites, 1 warehouse and 1 retailer is considered. The planning horizon considered is 10 planning periods. The demand values of the retailer are provided in figure A.8.1. Since there are just one retailer and one warehouse in the network, the case study is used to observe how the bid of the warehouse changes. As mentioned earlier, warehouse price bid depends on the current inventory level relative to the target inventory. Figure 8.3 shows how the warehouse price bid changes over every period for different values of target inventories. The warehouse capacity considered is 200 units. A target=0.2 means that the target level is 20% of the total warehouse capacity.

It can be seen that the fluctuations in the warehouse price bids increase as the target inventory increases. This is because the warehouse inventory falls below the target level and the relative inventory level gets lower if the target value is higher. It can be seen that the warehouse bid does not decrease below a value close to $520. This is the minimum bid for the warehouse based on its valuation of the product.

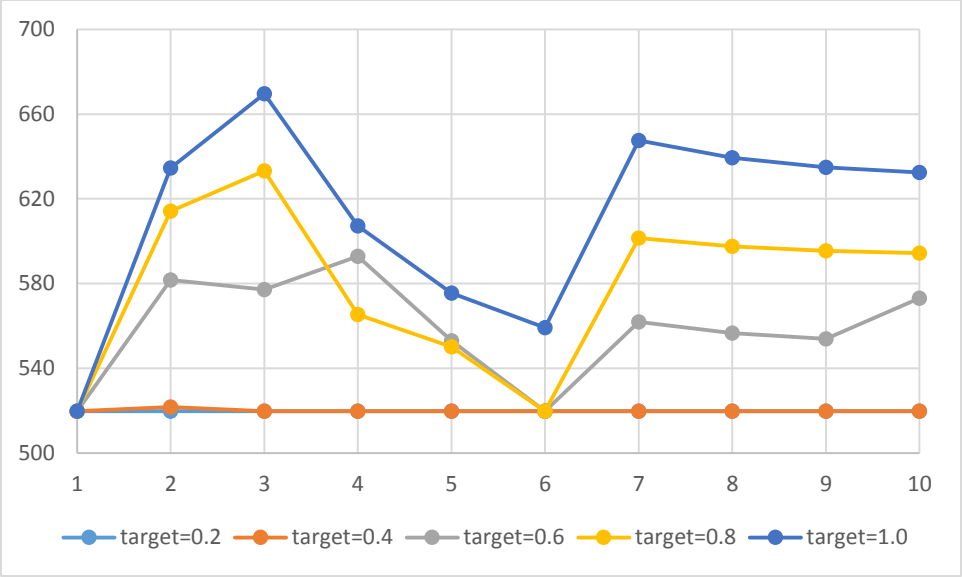

Figure 8.3: Warehouse price bid for warehouse capacity=200

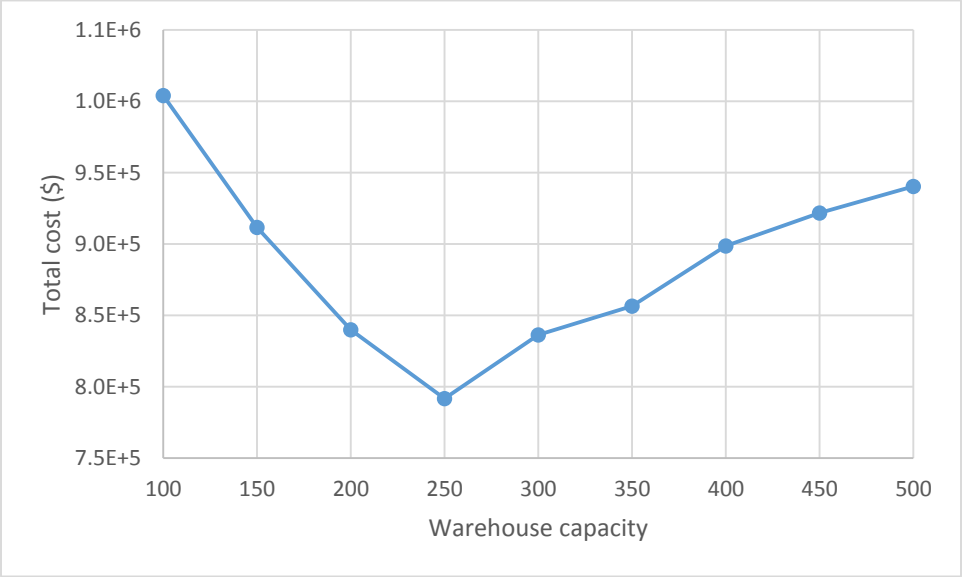

Figure 8.4: Effect of warehouse capacity on total cost (target inventory=0.2)

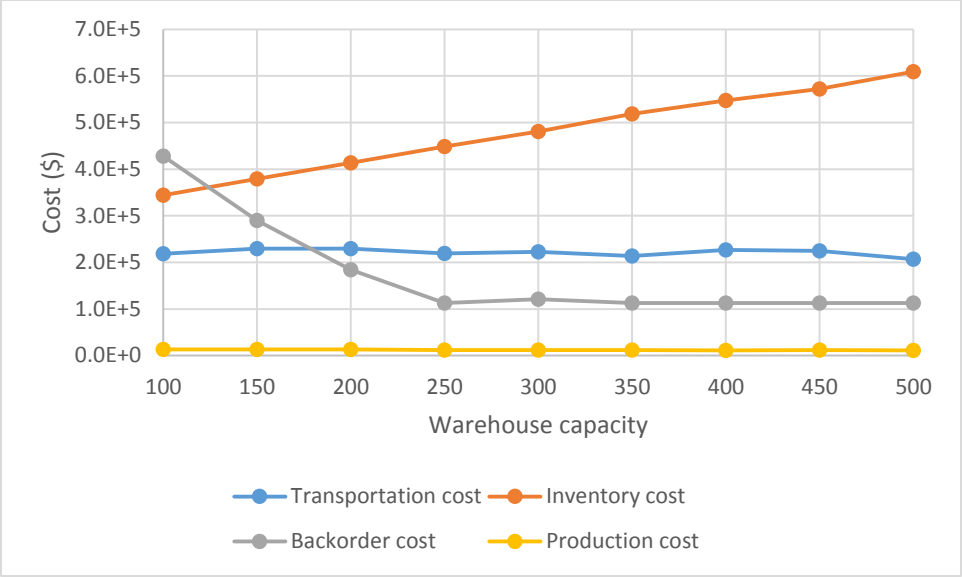

Figure 8.5: Effect of warehouse capacity on cost components

The effect of warehouse capacity on the performance of the supply chain is evaluated. Performance is evaluated on the basis of total cost and service level. Figure 8.4 shows the effect of warehouse capacity on total cost while figure 8.6 shows the effect on service level. The target inventory level used is 0.2. It can be seen that the total cost first decreases as the warehouse capacity increases and then starts to increase. Total cost is the aggregate of different cost components. The effect of warehouse capacity on the different cost components is shown in figure 8.5. It can be seen that among the 4 components, inventory cost and backorder cost have contradicting trends. While inventory cost increases with increasing capacity, backorder cost keeps decreasing until it reaches a steady value. This causes the initial decrease in total cost with capacity followed by an increase.

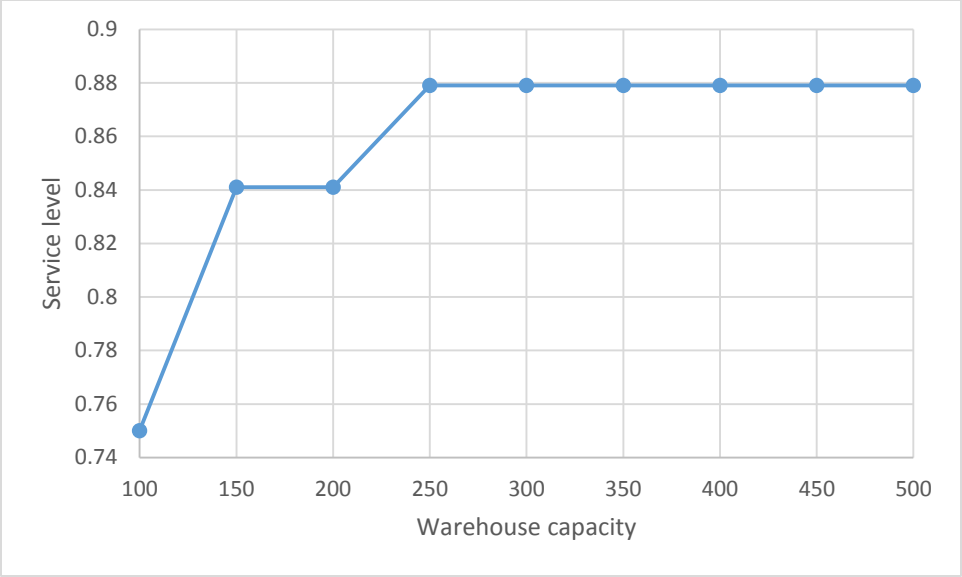

Figure 8.6: Effect of warehouse capacity on service level

As can be seen in figure 8.5, service level keeps increasing with increase in warehouse capacity. This is because more demand is fulfilled with the increase in capacity.

The trends of price bids by the retailer and the warehouse were also investigated. For this the planning horizon was increased to 30 instead of 10. Also the demand values for both the products were made equal to a constant value of 100. It can be seen that for all the target inventory levels, the price bids of the retailer and the warehouse come closer with every period. Retailer bid decreases from its initial value while warehouse bid increases. For target inventory levels of 0.2 and 0.4, the bids reach a steady value while for the higher target levels, they are still decreasing. On running the simulation for longer planning horizons of 100 and 150, it was found that steady values were reached for targets levels of 0.6 and 0.8 as well.

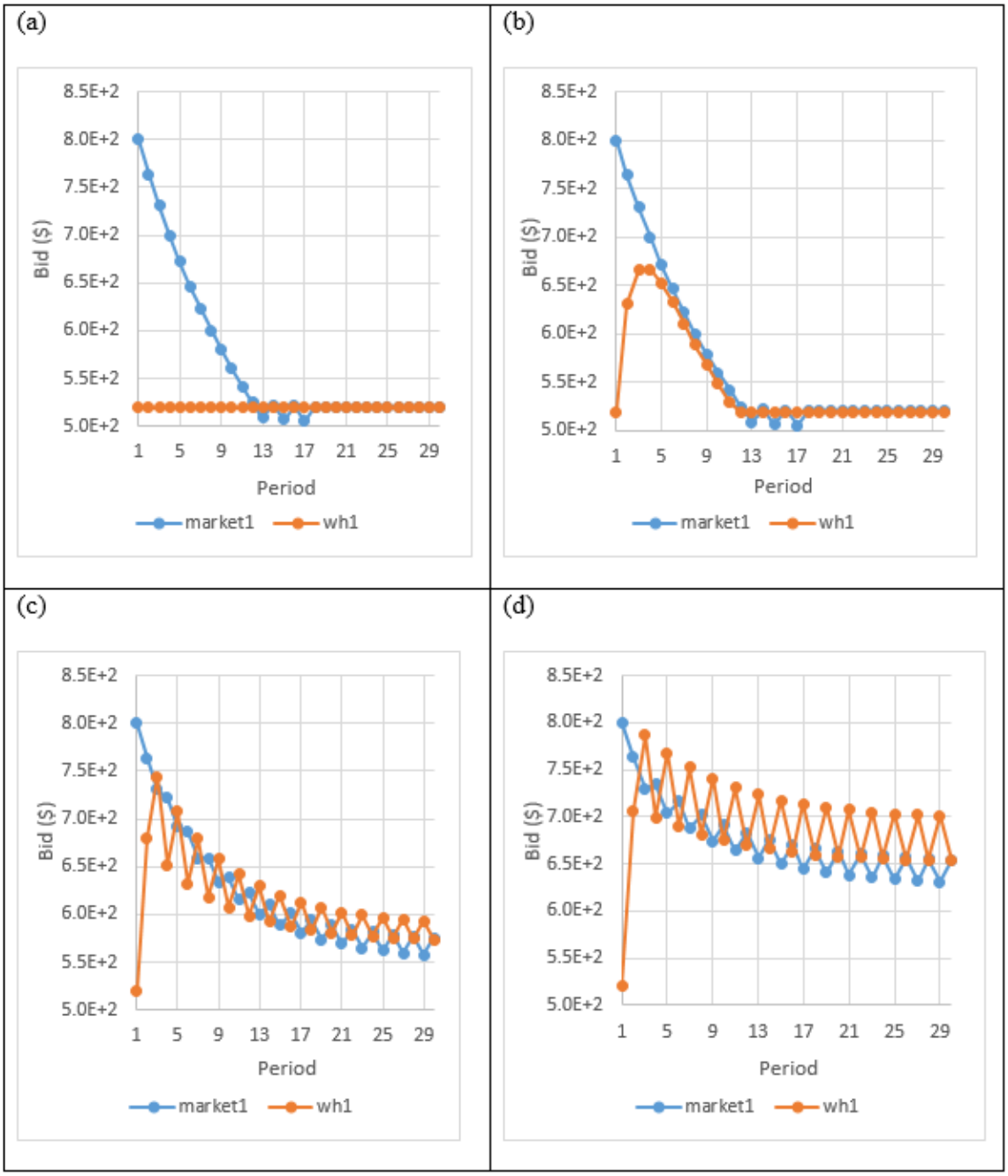

Figure 8.7: Retailer and warehouse price bids during the planning horizon (a) target inventory=0.2, (b) target inventory=0.4, (c) target inventory=0.6, (d) target inventory=0.8

8.4.2 Case Study 2

As shown in figure 8.8, the second case study considers a supply chain network with 1 raw materials supplier, 3 production sites, 1 warehouse and 2 retailers. The demand values for both the retailers are fixed at a constant value of 100.

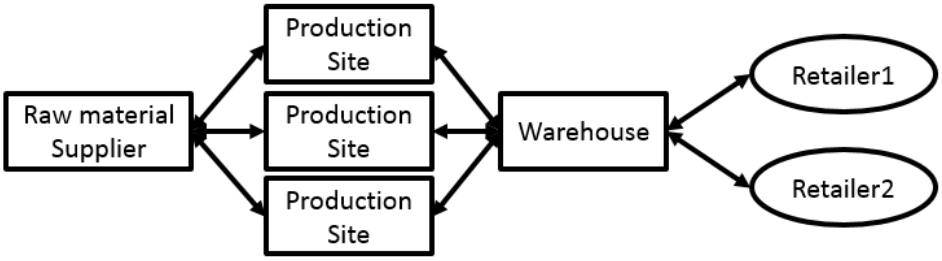

Figure 8.8: Supply chain network for case study 2

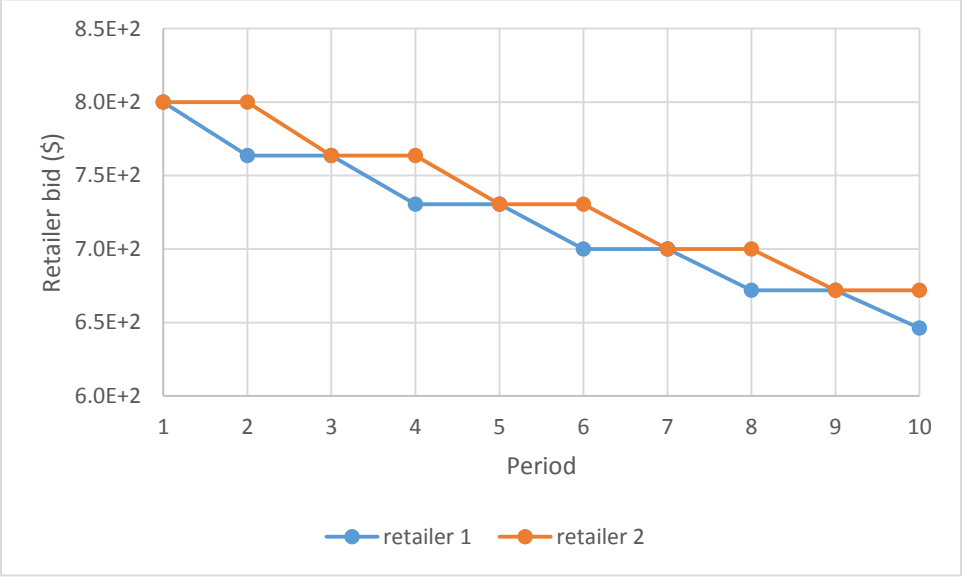

Figure 8.9: Retailer price bids during the planning horizon

This case study is used to show how the retailers adjust their price bids in the presence of other retailers. The effect of learning rates is shown. Figure 8.9 shows the price bids of

the two retailers when the learning rates for both of them are 0. It can be seen that the retailers do not adjust their bids in a period even if they had lost the auction in the previous period. In period 1, retailer 1 wins the auction and therefore places a lower bid in period 2. However retailer 2 does not adjust its bid even though it had lost the auction in period 1. Figure 8.10 shows two plots. Plot (a) shows the case where retailer 1 has a learning rate of 1 while retailer 2 has a rate of 0. Plot (b) shows the case where both the retailers have learning rates of 1.

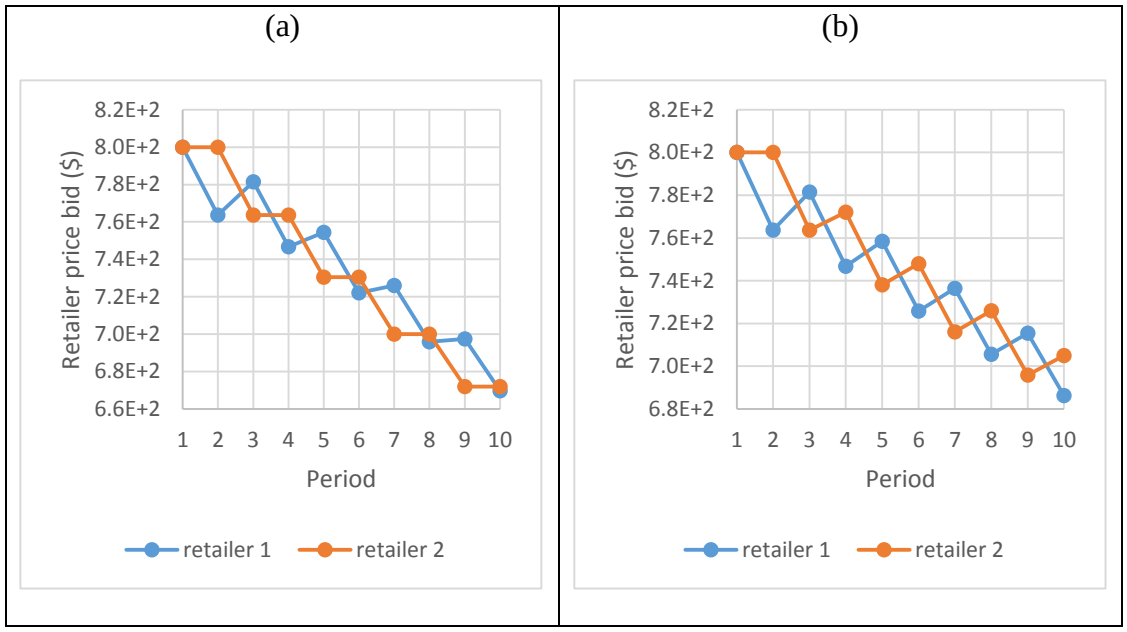

Figure 8.10: Retailer price bids (a) learning rate=1,0 (b) learning rate=1,1

8.4.3 Case Study 3

The supply chain network used in this case study consists of 1 raw material supplier, 3 production sites, 2 warehouses and 2 retailers. The derivative free optimization algorithm proposed in chapter 7 is used to find the optimal warehouse capacities. The other parameters are considered fixed. The target inventory levels for both the warehouses are

fixed at 0.2 and the learning rates of both the retailers are fixed at 1. The demand for both the retailers are provided in Table A.8.2. The search space for capacities is [200,500].

Both 'Expected Improvement' and 'Goal seeking' methods are used for adaptive sampling. Figure 8.11 shows the surface plot obtained from the kriging model obtained after the initial sampling.

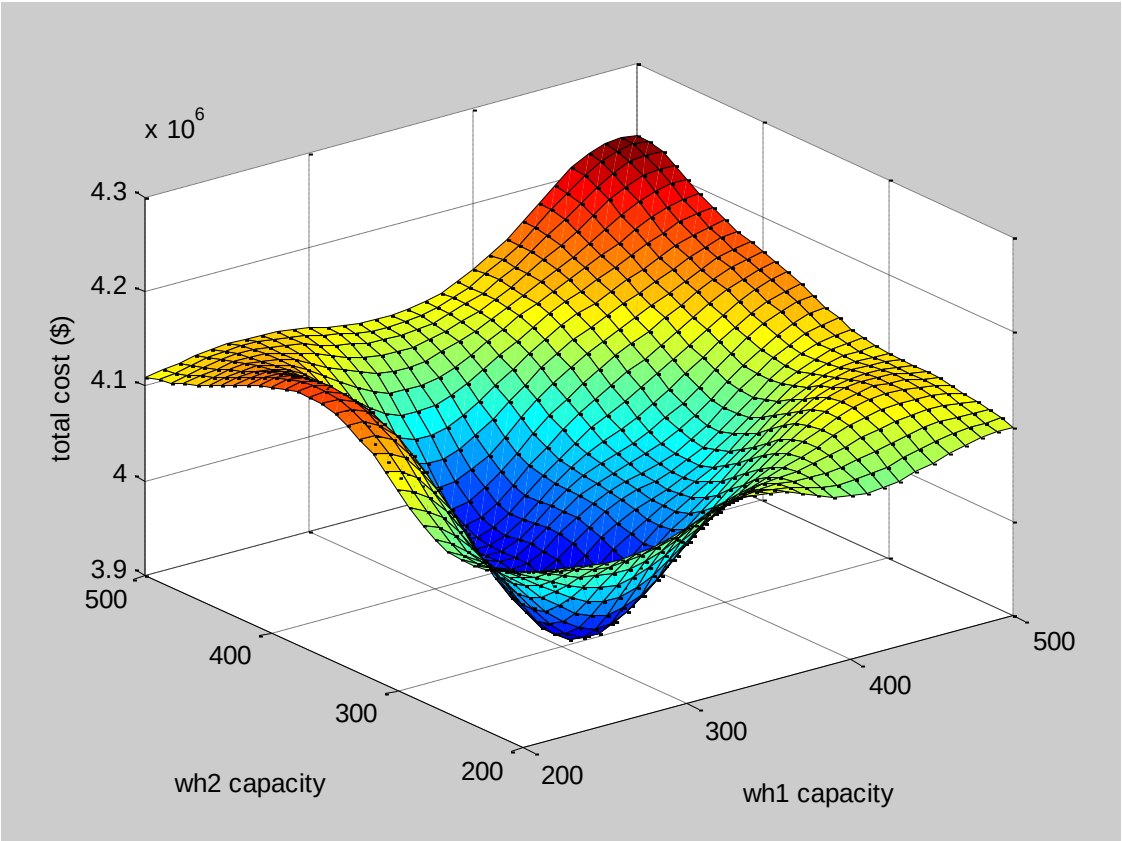

Figure 8.11: Surrogate model after initial sampling

The algorithm was run for 10 times using both the adaptive sampling methods. Tables 8.1 and 8.2 show the results obtained. It can be seen that using EI leads to a higher number of clusters on which the local search is performed. Goal-seeking leads to only one cluster in every replication. Truncating the results to whole numbers, the optimal warehouse

capacities predicted by both the methods are 288 and 288 respectively. The average number of function calls used in case of EI is 140.75 while that in case of goal-seeking is 92.2.

Table 8.1: Optima obtained using EI

Wh1 capacity	Wh2 capacity	Total cost ($)	Replication
288	288	3.9071E+06	1
288	288	3.9070E+06	2
288	289	3.9074E+06	3
288	290	3.9086E+06	4
288	289	3.9077E+06	5
290	288	3.9088E+06	5
289	289	3.9080E+06	5
289	289	3.9081E+06	6
289	294	3.9126E+06	6
289	289	3.9088E+06	6
289	284	3.9180E+06	6
288	289	3.9078E+06	7
290	292	3.9118E+06	7
289	292	3.9108E+06	8
288	288	3.9070E+06	9
288	288	3.9074E+06	10

Table 8.2: Optima obtained using goal-seeking

Wh1 capacity	Wh2 capacity	Total cost ($)	Replication
288	288	3.9072E+06	1
288	288	3.9071E+06	2
289	289	3.9081E+06	3
288	305	3.9205E+06	4
290	288	3.9086E+06	5
288	288	3.9072E+06	6
288	293	3.9115E+06	7
289	289	3.9080E+06	8
289	289	3.9080E+06	9
289	288	3.9075E+06	10

8.5 Conclusion

Multi-enterprise supply chains have a lot of additional factors affecting their dynamics and performance compared to monolithic single enterprise supply chains. Factors related to competition, cooperation, negotiation etc. become more significant in such a scenario. Traditional studies have often ignored the effect of these factors. The study presented above uses one particular approach of auctions to simulate these factors. The study provides insights into how conveniently such scenarios can be represented through agent based simulation models. A particular auction mechanism for the double auction between warehouses and retailers has been implemented. However the model is flexible to incorporate other mechanisms as well. Heuristic rules for the bidding strategies of the agents have been implemented. Determination of optimal bid of the agents has not been covered in this work, which leaves scope for improvement. It was observed that different factors impact the performance of the supply chain. However it is assumed that the

behavior of the supply chain entities is fixed and therefore the optimal capacities of the warehouses are determined using a derivative free optimization approach.

9 Conclusion

Obtaining optimal supply chain operation is a challenging task, especially with the growing size of the global networks. Traditional optimization methods can only be used to solve a simplified version of the real problem. It is not practical to represent the actual supply chain dynamics in terms of mathematical equations. Both the size of the problem and nonlinear dynamics pose a challenge to the optimization methods. In this work, agent based simulation models have been shown to be an effective tool for realistic representation of supply chain dynamics. These models overcome the challenges posed by the large scale nature of the supply chain networks and are also efficient in capturing the detailed dynamics resulting due to the individual decision-making of the supply chain entities. The hybrid simulation based optimization framework proposed in this work allows the simulation model to improve its solution on being guided by an approximate optimization model of the problem. Since the algorithm only guides the simulation towards improved solutions, the behaviors of the different supply chain entities are not disturbed.

The application of the hybrid simulation based optimization method in chapters 4 and 5 demonstrates its effectiveness in being used as a framework which can be conveniently applied to different problems without the need to make radical changes in the methodology. In chapter 6, the framework is applied to a stochastic problem. The solution methodology for the stochastic problem presents a way to make decisions as uncertain events occur and trigger potential trajectories of events. The hybrid simulation based optimization framework enables optimal decision making at the occurrence of each

such uncertain event. It is also shown how such a solution methodology can be applied to study important aspects such flexibility of the supply chain network or to manage risk.

Chapter 7 presents a derivative free optimization methodology for non-convex functions. Such problems can be widely found in the field of supply chain management. When trying to optimize the performance of supply chains, derivatives are usually not available and detailed simulation models can be too time consuming to be used to calculate derivatives. The proposed surrogate based method is especially suitable for problems where the simulation model is computationally very expensive. The algorithm is applied to a multi-enterprise supply chain problem.

Acknowledgement of Previous Publications

Several sections of this dissertation have been published elsewhere or are being prepared for publication. Following are acknowledged.

- Chapter 3 has been published in full under the citation:

Sahay N, Ierapetritou M. Supply chain management using an optimization driven simulation approach. *AIChE Journal.* 2013;59(12):4612-4626.

- Chapter 4 has been published in full under the citation:

Sahay N, Ierapetritou M. Hybrid Simulation Based Optimization Framework for Centralized and Decentralized Supply Chains. Industrial & Engineering Chemistry Research. 2014/03/12 2014;53(10):3996-4007.

- Chapter 5 has been published in full under the citation:

Sahay N, Ierapetritou M, Wassick J. Synchronous and asynchronous decision making strategies in supply chains. Computers & Chemical Engineering. 2014;71:116-129.

- Chapter 6 has been published in full under the citation:

Sahay N, Ierapetritou M. Flexibility assessment and risk management in supply chains. AIChE Journal. 2015;61(12):4166-4178.

- Chapter 7 has been submitted under the citation:

Sahay N, Ierapetritou M. Derivative free optimization for expensive or black-box optimization problems. AIChE Journal.

- Chapter 8 is being prepared for publication under the citation:

Sahay N, Ierapetritou M. Multi-Enterprise Supply Chains: Simulation and Optimization.

Appendix

Appendix Chapter 3

Table A.3.1: Backorder costs for markets

Market	Backorder cost ($/lb)
Market 1	1000.00
Market 2	1200.00
Market 3	800.00

Table A.3.2: Distance of markets from warehouses

	Distance (miles)		
	Market 1	Market 2	Market 3
Warehouse 1	20.0	25.0	30.0
Warehouse 2	30.0	20.0	25.0

Table A.3.3: Holding cost for warehouses

	Holding cost ($/lb/day)
Warehouse 1	40
Warehouse 2	40

Table A.3.4: Distance between production sites and suppliers

	Distance (miles)		
	Production site 1	Production site 2	Production site 3
Supplier 1	20.0	25.0	15.0
Supplier 2	20.0	30.0	20.0

Table A.3.5: Distance between production sites and warehouses

	Distance (miles)		
	Production site 1	Production site 2	Production site 3
Warehouse 1	25.0	40.0	50.0
Warehouse 2	50.0	25.0	40.0

Table A.3.6: BOM relationship for production sites

	A	B	C
P1	1.00	1.50	1.75
P2	1.30	2.00	0.80

Table A.3.7: Production cost in different modes ($/lb)

Production site	**P1**		**P2**	
	Mode 1	**Mode 2**	**Mode 1**	**Mode 2**

Ps 1	20.0	22.0	25.0	27.0
Ps 2	25.0	27.0	20.0	22.0
Ps 3	30.0	32.0	15.0	17.0

Table A.3.8: Holding cost at production sites ($/lb/day)

	P1	P2	A	B	C
Ps1	100	100	100	120	80
Ps2	120	120	100	120	80
Ps3	180	180	100	120	80

Appendix Chapter 4

List of parameter values

h_s^{wh}	$15/lb/day
h_s^{p}	$15/lb/day
h_r^{p}	$15/lb/day
u_s^{m}	$20/lb
$d_s^{wh,m}$	$1/lb/mile
$d_s^{p,wh}$	$1/lb/mile
$d_r^{\sup,p}$	$1/lb/mile

$VarCost^{p}$	\$50/lb
$stcap_{r}^{p}$	\$200 lb
$stcap_{s}^{p}$	\$200 lb

Table A.4.1: Distance between markets and warehouses

	wh1	**wh2**	**wh3**	**wh4**	**wh5**	**wh6**
Market 1	10	50	70	50	10	70
Market 2	15	55	75	55	15	75
Market 3	50	10	50	70	50	50
Market 4	55	15	55	75	55	55
Market 5	70	50	10	50	70	10
Market 6	75	55	15	55	75	15
Market 7	50	70	50	10	50	50
Market 8	55	75	55	15	55	55

Table A.4.2: Distance between warehouses and production sites

	wh1	**wh2**	**wh3**	**wh4**	**wh5**	**wh6**
PS 1	10	10	10	20	20	20
PS 2	20	20	20	10	10	10

Table A.4.3: Distance between production sites and raw material suppliers

	sup1	**sup2**
PS 1	10	25
PS 2	20	15

Appendix Chapter 5

List of parameter values

h_{pr}^{wh}	\$1/lb
h_{pr}^{p}	\$5/lb
h_{r}^{p}	\$5/lb
$VarCost^{p}$	\$2/lb
$d_{pr}^{wh,m}$	\$1/lb/mile
$d_{pr}^{p,wh}$	\$1/lb/mile
$d_{r}^{\sup,p}$	\$1/lb/mile
$stcap_{pr}^{wh}$	200 lb
$stcap_{pr}^{p}$	200 lb
$\alpha_{i,j}$	2/3*mean processing time

Table A.5.1: Maximum capacity of units when processing task

Unit	Max. capacity
heater	100
rtr1	50
rtr2	80
still	200

Table A.5.2: Mean processing times of tasks in different units (hrs)

	heater	rtr1	rtr2	sill
heating	1	0	0	0
rxn1	0	2	2	0
rxn2	0	2	2	0
rxn3	0	1	1	0
sepn	0	0	0	2

Table A.5.3: Transportation cost between market and warehouses ($/lb)

	wh1	wh2
market	5	20

Table A.5.4: Distance between production sites and warehouses

	wh1	**wh2**	**wh3**	**wh4**
ps1	10	22	15	20
ps2	20	10	22	15
ps3	15	20	10	22
ps4	22	15	20	10

Table A.5.5: Proportion of state produced by tasks

	heating	**rxn1**	**rxn2**	**rxn3**	**sepn**
A	0	0	0	0	0
B	0	0	0	0	0
C	0	0	0	0	0
HA	1	0	0	0	0
IAB	0	0	0.6	0	0.1
IBC	0	1	0	0	0
IE	0	0	0	1	0
P1	0	0	0.4	0	0
P2	0	0	0	0	0.9

Table A.5.6: Proportion of state consumed by tasks

	heating	rxn1	rxn2	rxn3	sepn
A	1	0	0	0	0
B	0	0.5	0	0	0
C	0	0.5	0	0.2	0
HA	0	0	0.4	0	0
IAB	0	0	0	0.8	0
IBC	0	0	0.6	0	0
IE	0	0	0	0	1
P1	0	0	0	0	0
P2	0	0	0	0	0

Table A.5.7: Distance between production sites and suppliers

	ps1	ps2	ps3	ps4
sup1	10	20	0	0
sup2	25	15	0	0

Appendix Chapter 6

Table A.6.1: 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 A.6.2: Distance of production sites from raw material suppliers

	sup1	**sup2**
ps1	10	15
ps2	20	10
ps3	15	10

Table A.6.3: 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 A.6.4: 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 A.6.5: 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

Appendix for Chapter 8

List of parameters

Transportation cost	$3/lb/m
Holding cost at wh	$40/lb/day

Table A.8.1: Demand values during the planning horizon

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
P1	57	66	53	36	50	53	38	43	59	52
P2	36	45	46	53	31	53	67	34	59	69

Table A.8.2: Demand for products at retailers

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
retailer 1	**P1**	57	66	53	36	50	53	38	43	59	52
	P2	36	45	46	53	31	53	67	34	59	69
retailer 2	**P1**	54	59	42	48	32	45	44	42	63	48
	P2	62	62	41	33	32	56	47	66	47	36

Table A.8.3: Backorder cost

	Backorder cost ($/lb/day)
Retailer 1	500.00
Retailer 2	600.00

Table A.8.4: Production cost ($/lb)

	P1	P2
Ps1	20.0	25.0
Ps2	25.0	20.0

Table A.8.5: Holding cost at production sites ($/lb/day)

	P1	P2	A	B	C
Ps1	10.0	10.0	10.0	12.0	8.0
Ps2	12.0	12.0	10.0	12.0	8.0
Ps3	18.0	18.0	10.0	12.0	8.0

Table A.8.6: Distance between production sites and suppliers

	Ps1	Ps2	Ps3
Sup1	20.0	25.0	15.0
Sup2	20.0	30.0	20.0

Table A.8.7: Distance between production sites and warehouses

	Ps1	Ps2	Ps3
Wh1	25.0	40.0	50.0
Wh2	50.0	25.0	40.0

Table A.8.8: Distance between warehouses and retailers

	Wh1	Wh2
Retailer 1	20.0	30.0
Retailer 2	20.0	20.0

Table A.8.9: BOM for production sites

	A	B	C
P1	1.00	1.50	1.75
P2	1.30	2.00	0.80

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