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Supply Chain Management Using an Optimization Driven Simulation Approach

Nihar Sahay and Marianthi Ierapetritou
Dept. of Chemical and Biochemical Engineering, Rutgers University, Piscataway, NJ 08854

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In this work, we propose a hybrid simulation-based optimization framework to solve the supply chain management problem. The hybrid approach combines a mathematical programming model with an agent-based simulation model and uses them in an iterative framework. The optimization model is used to guide the decisions toward an optimal allocation of resources given the realistic supply chain representation given by the simulation. Thus, the proposed approach provides a more realistic solution compared to a stand-alone optimization model, often a simplified representation of the actual system, by making use of the simulation model, which captures the detailed dynamic behavior of the system. A multiobjective problem has been formulated by taking into consideration the environmental impact of supply chain operations. The proposed framework has been applied to small-scale case studies to study the effectiveness of the approach for such problems. © 2013 American Institute of Chemical Engineers *AIChE J*, 59: 4612–4626, 2013
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Introduction

A chemical supply chain is a network of suppliers, production facilities, warehouses, and markets designed to acquire raw materials, manufacture, and store and distribute products among the markets. The individual entities in such a network have their own goals and objectives. The entities do not have a view of the whole network, and therefore, their individual objectives are not aligned toward the objective of the whole chain. These entities usually make the operation decisions in isolation or on an individual basis. It has been shown that greater efficiency and reduced costs can be achieved through proper coordination among the entities in terms of material, financial, and information flow.[1,2] This provides the motivation behind developing an integrated model for the whole supply chain.

Traditionally, economic performance has been used to measure the efficiency of supply chains. In the recent past, there has been a growing concern about environmental degradation and limited nonrenewable resources. Supply chain activities have a significant contribution toward greenhouse gases and air pollution, which cause harmful effects on health and global warming. There have been environmental regulations and enterprises have also become more environmentally conscious recently. Thus, there is an increasing interest toward modifying the supply chains so as to consider their environmental impacts. The field of Green supply chain management deals with the relationship between the supply chain and the environment. Techniques have been developed to make a holistic assessment of the environmental performance of the supply chain.

Correspondence concerning this article should be addressed to M. Ierapetritou at marianth@soemail.rutgers.edu.

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.

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, multiobjective programming, stochastic programming, and so forth. As our proposed approach is based on the multiobjective optimization we are reviewing the works in this category. Chen et al.[3] develop a multiobjective production and distribution planning model to study fair profit distribution for a multienterprise 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 multiobjective problems by using one numerical example. Chen and Lee[4] proposed a multiproduct, multistage, and multiperiod 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[5] 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.[6] address the design of hydrogen supply chains. A bicriterion mixed integer linear program (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 bilevel algorithm. You and Grossman[7] 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, whereas 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 Ref. 8.

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,[9–12] discrete event simulation,[13–18] and agent-based simulation.[19–33]

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.[34] 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.[35] 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.[36] Garcia-Flores and Xue Wang[37] described a multiagent 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 Ref. 38.

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.[39–50] Shanthikumar and Sargent[51] 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[52] developed an integrated multiproduct, multiperiod, multishop 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.[53] 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.[54] 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.[55] 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.[56] 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,[57] 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 multiobjective problem is solved by taking the environmental impact of the supply chain as an additional objective for decision-making.

In this article, 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 predetermined. 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, whereas an optimization model is used to guide the simulation toward 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 supply chain (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 article is organized as follows. Problem Formulation Section presents the problem formulation which also describes the independent optimization and simulation models as well as the hybrid simulation-optimization framework. Case Studies Section presents the case studies which have been studied using the hybrid approach which is followed by some concluding remarks in Conclusions Section.

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 that can be manufactured using three raw materials. A bill of material (BOM) 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, whereas 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.

Optimization model

The multisite model includes supplier, production site, warehouse, and market constraints. The set of products ($s \in \mathrm{PR}$) are stored at the warehouses ($\mathrm{wh} \in \mathrm{WH}$). 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 ($p \in \mathrm{PS}$) which in turn manufacture these products from the raw materials ($r \in R$) obtained from raw material suppliers ($\sup \in \mathrm{SUP}$). 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 ($\mathrm{mt} \in \mathrm{MT}$) and production ($\mathrm{mp} \in \mathrm{MP}$), 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, whereas 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 multiobjective 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.

$$
\begin{aligned}
\min & \sum_{t}\sum_{\mathrm{wh}}\sum_{s\in\mathrm{PR}} h_s^{\mathrm{wh}}\mathrm{Inv}_s^{\mathrm{wh},t} + \sum_{t}\sum_{p}\sum_{s\in\mathrm{PR}} h_s^{p}\mathrm{Inv}_s^{p,t} + \sum_{t}\sum_{p}\sum_{r\in R} h_r^{p}\mathrm{Inv}_r^{p,t} \\
& + \sum_{t}\sum_{\sup}\sum_{r\in R} h_r^{\sup}\mathrm{Inv}_r^{\sup,t} + \sum_{t}\sum_{m}\sum_{s\in\mathrm{PR}} u_s^{m}U_s^{m,t} + \sum_{t}\sum_{p}\sum_{\mathrm{mp}}\sum_{s}\left(\mathrm{FixCost}^{p}w_t^{p} + \mathrm{VarCost}^{p}P_s^{p,t}\right) \\
& + \sum_{t}\sum_{\mathrm{mt}}\sum_{m}\sum_{\mathrm{wh}}\sum_{s\in\mathrm{PR}} d_s^{\mathrm{wh},m}D_s^{\mathrm{wh},m,t} + \sum_{t}\sum_{\mathrm{mt}}\sum_{\mathrm{wh}}\sum_{p}\sum_{s\in\mathrm{PR}} d_s^{p,\mathrm{wh}}D_s^{p,\mathrm{wh},t} + \sum_{t}\sum_{\mathrm{mt}}\sum_{\sup}\sum_{p}\sum_{r\in R} d_r^{\sup,p}D_r^{\sup,p,t}
\end{aligned}
\tag{1}
$$

$$\text{st} \quad U_s^{m,t}=U_s^{m,t-1}+Dem_s^{m,t}-\sum_{\text{wh}\in\text{WH}} D_s^{\text{wh},m,t}, \quad \forall s\in\text{PR}, m\in M, t\in T \tag{2}$$

$$\text{Inv}_s^{\text{wh},t}=\text{Inv}_s^{\text{wh},t-1}-\sum_{m\in M} D_s^{\text{wh},m,t}+\sum_{p\in\text{PS}} D_s^{p,\text{wh},t}, \quad \forall s\in\text{PR}, \text{wh}\in\text{WH}, t\in T \tag{3}$$

$$\text{Inv}_s^{p,t}=\text{Inv}_s^{p,t-1}+P_s^{p,t}-\sum_{\text{wh}\in\text{WH}} D_s^{p,\text{wh},t}, \quad \forall s\in\text{PR}, p\in\text{PS}, t\in T \tag{4}$$

$$\text{Inv}_r^{p,t}=\text{Inv}_r^{p,t-1}-C_r^{p,t}+\sum_{\text{sup}\in\text{SUP}} D_r^{\text{sup},p,t}, \quad \forall r\in R, p\in\text{PS}, t\in T \tag{5}$$

$$\text{Inv}_r^{\text{sup},t}\le \text{stcap}_r^{\text{sup}}, \quad \forall r\in R, \text{sup}\in\text{SUP}, t\in T \tag{6}$$

$$\text{Inv}_r^{p,t}\le \text{stcap}_r^{p}, \quad \forall r\in R, p\in\text{PS}, t\in T \tag{7}$$

$$\text{Inv}_s^{p,t}\le \text{stcap}_s^{p}, \quad \forall s\in\text{PR}, p\in\text{PS}, t\in T \tag{8}$$

$$\text{Inv}_s^{\text{wh},t}\le \text{stcap}_s^{\text{wh}}, \quad \forall s\in\text{PR}, \text{wh}\in\text{WH}, t\in T \tag{9}$$

$$P_s^{p,t}\le \text{prcap}_s^{p}, \quad \forall s\in\text{PR}, p\in\text{PS}, t\in T \tag{10}$$

$$E=\sum_t\sum_{\text{mt}}\sum_m\sum_{\text{wh}}\sum_{s\in\text{PR}} et^{\text{wh},m} D_s^{\text{wh},m,t}+\sum_t\sum_{\text{mt}}\sum_{\text{wh}}\sum_p\sum_{s\in\text{PR}} et^{p,\text{wh}} D_s^{p,\text{wh},t}$$
$$+\sum_t\sum_{\text{mt}}\sum_{\text{sup}}\sum_p\sum_{r\in R} et^{\text{sup},p} D_r^{p,\text{sup},t}+\sum_t\sum_p\sum_{\text{mp}}\sum_s \left(ep^p P_s^{p,t}\right) \tag{11}$$

$$E\le \text{ecap} \tag{12}$$

The objective function in Eq. 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, whereas Eq. 10 is the production capacity constraint for production sites. Equations 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, whereas 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.

Simulation model

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. An agent-based simulation model of the entire supply chain has 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.

The different entities of the supply chain have been modeled as the agents. 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. As 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.

Each agent is represented by a collection of attributes and behaviors. Java programming language has been used to code the agents. 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. The classes also contain implementations of different methods to define the behaviors of the agents.

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.

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 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. 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 predefined. 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. Although 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.

Production site agent

The production site agent is responsible for the manufacture of products from raw materials. A 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 as 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 predefined. 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 BOM relationship is used to calculate the consumption of raw materials and production of products. Although 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

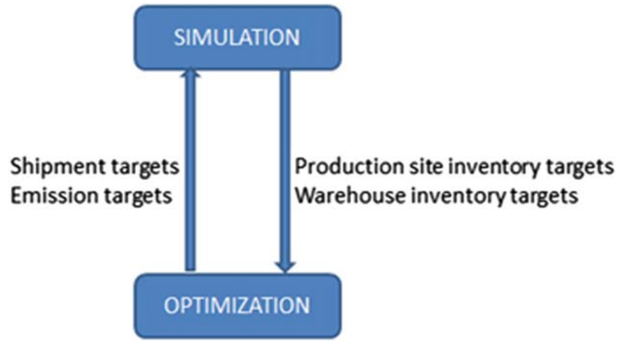

Figure 1. Coupling between simulation and optimization.

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

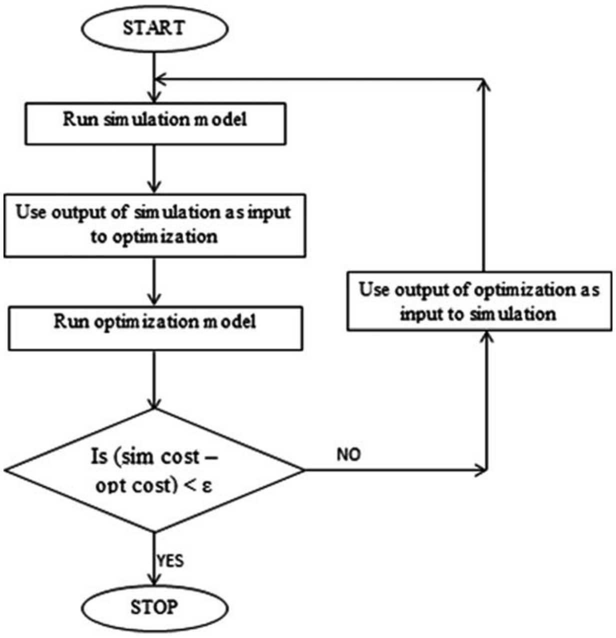

Figure 2. Iterative framework for the hybrid simulation–optimization approach.

component is proportional to the amount of products produced.

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. Although 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.

Hybrid simulation-optimization approach

The independent optimization and simulation models are developed independently as discussed in Optimization model and Simulation model sections, 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 above in Figure 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 to the model. The simulation model is forced to restrict its total carbon emissions below the level, which is set in the optimization model.

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 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

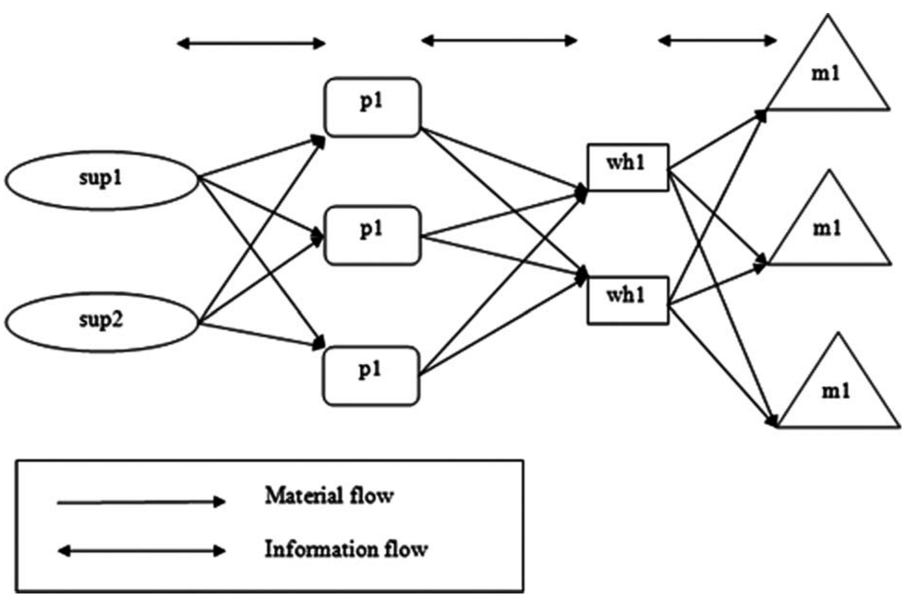

Figure 3. Supply chain network for the case study 1.

Table 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
PI	3	75	35	28
P2	3	112	42	17
P1	4	58	16	74
P2	4	38	3 2	3
P1	5	55	55	16
P2	5	96	45	95
P1	6	58	4 2	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 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	0ptimization Cost	% Difference
1	7.13E+06	1.08E+06	84 8 1
2	5.03E+06	1.79E+06	6 4 3 3
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	1 3.7 1
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

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 toward the best solution it can achieve.

Case Studies

In this section, the hybrid simulation-optimization approach has been tested in two rather small-scale supply chain management problems.

Case study 1

The supply chain consists of three markets, two warehouses, three production sites, and two raw material suppliers. There are two products and three raw materials. Transportation can be done using two different modes of transport and production can also be done using two different modes. Figure 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 1. 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 2 and Figure 4 below. The results illustrate that the framework converges to the optimal solution within 20 iterations. The total computation time was 684 s 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 5 above shows the variation in different components of total cost obtained from the simulation model over the iterations, whereas Figure 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.

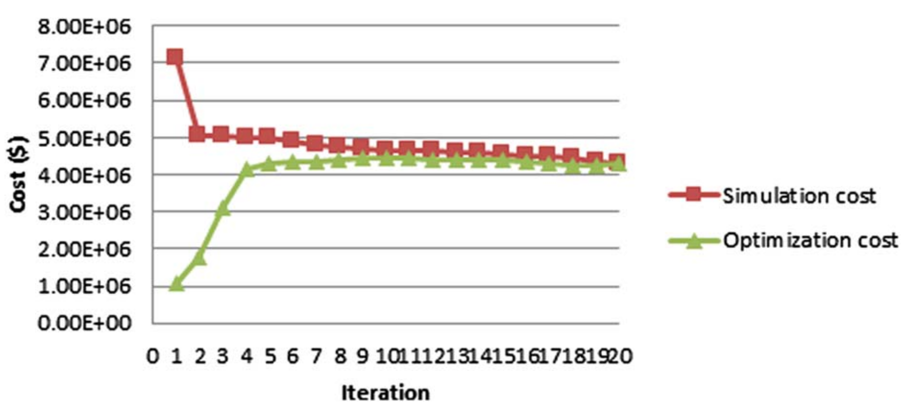

Figure 4. Objective values of simulation and optimization models at each iteration for emission equal to 1.4E+06 kgCO_2e.

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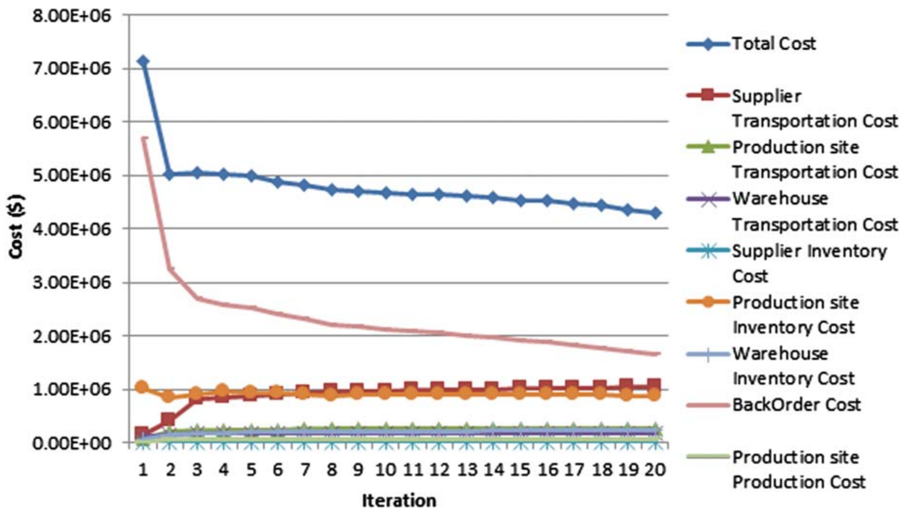

Figure 5. Breakdown of different cost components during the algorithm iterations.

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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 toward 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 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.

Figures 8 and 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 9 that the total cost decreases with increasing warehouse capacity with a slight fluctuation in the region of

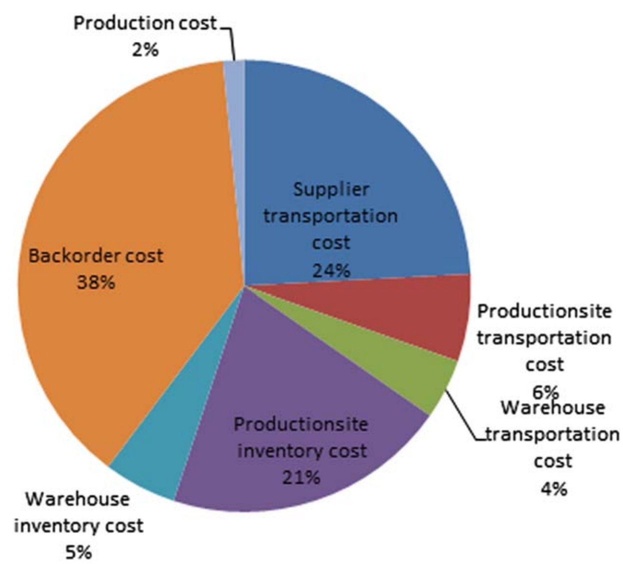

Figure 6. Breakdown of different cost components for the final solution.

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Table 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	4 7.77
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	0.63

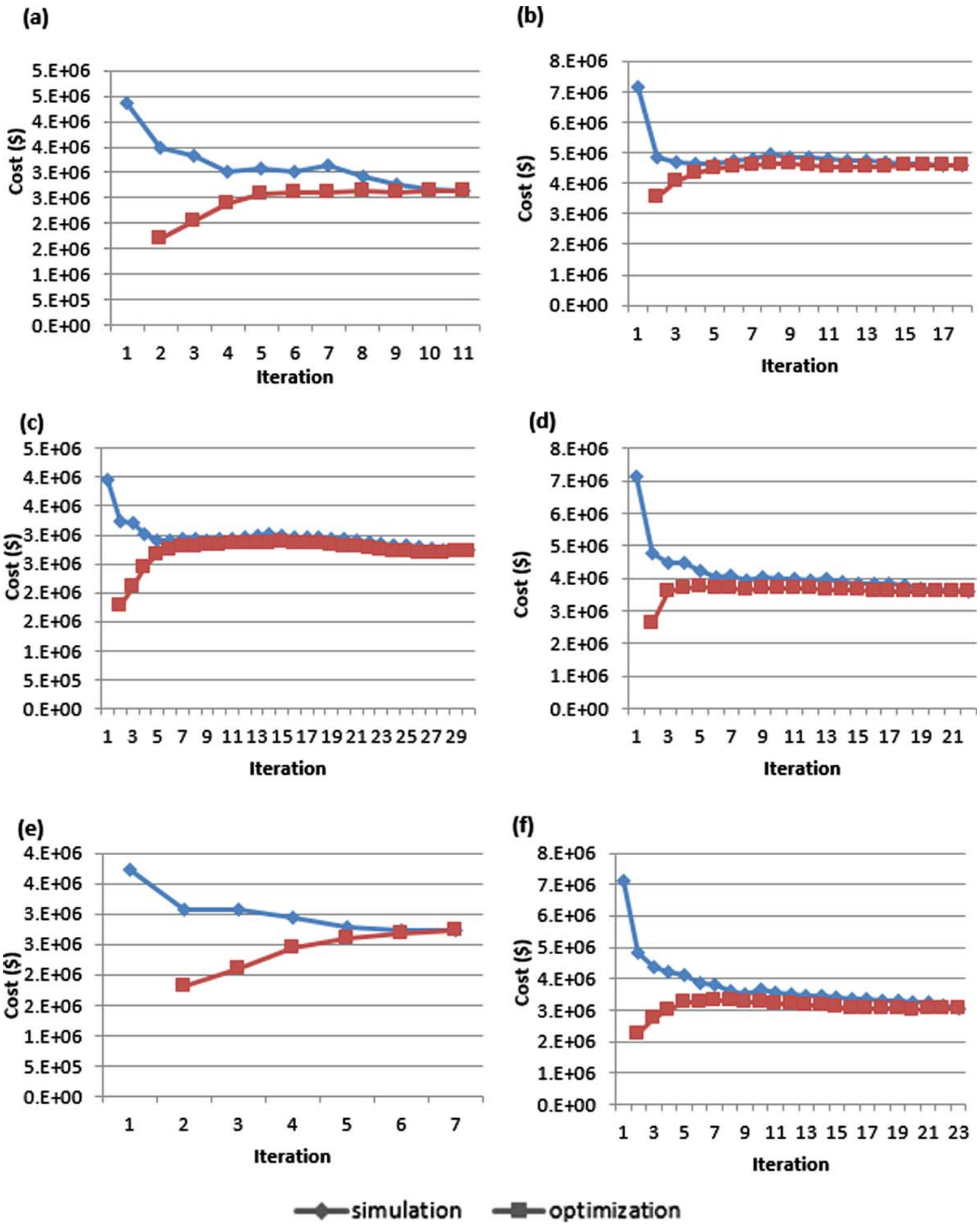

Figure 7. Hybrid approach results for different capacities: (a) warehouse capacity = 375 production site capacity = 75, (b) warehouse capacity = 200 production site capacity = 60, (c) warehouse capacity = 425 production site capacity = 75, (d) warehouse capacity=200 production site capacity = 75, (e) warehouse capacity = 450 production site capacity = 75, (f) warehouse capacity = 200 production site capacity = 90.

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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

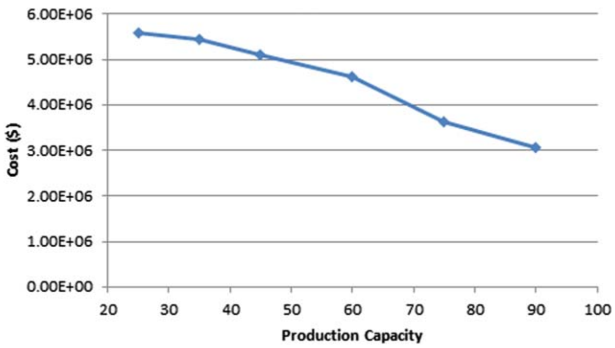

Figure 8. Cost for different production capacities.

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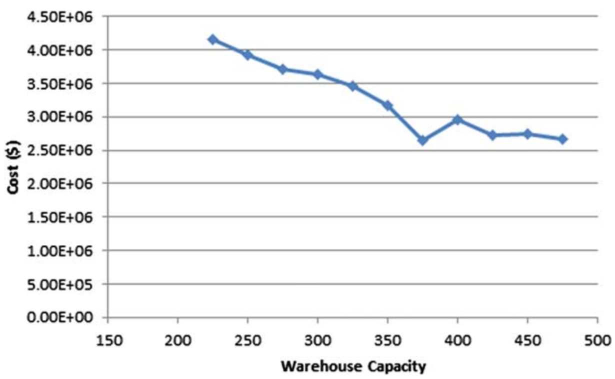

Figure 9. Cost for different warehouse capacities.

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environmental impacts. The hybrid approach has been used to solve the multiobjective optimization problem. The multiobjective 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 10 below.

The two curves in the plot of Figure 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, whereas 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 as 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 as the simulation model represents the more realistic scenario and thus leads to higher cost and higher emissions.

Case study 2

In this case, the supply chain consists of three markets, six warehouses, eight production sites, and six raw material suppliers. There are two products and three raw materials. Transportation can be done using two different modes and production can also be done using two 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 and Figure 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 s 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 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

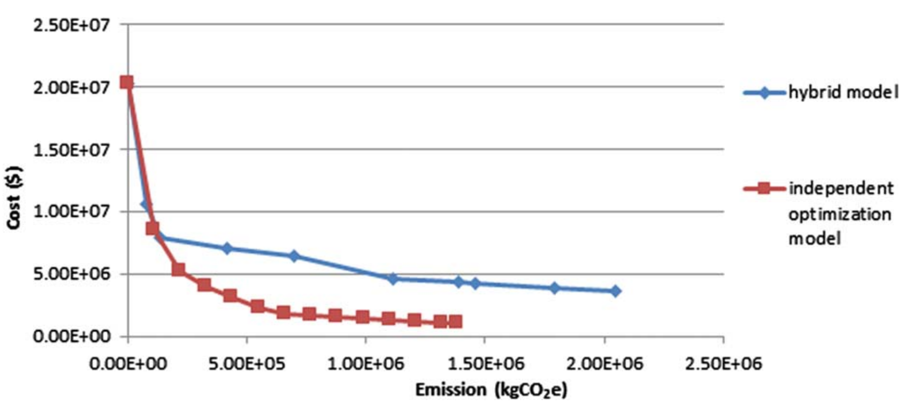

Figure 10. Comparison of results from hybrid model and independent optimization model for different values of emission.

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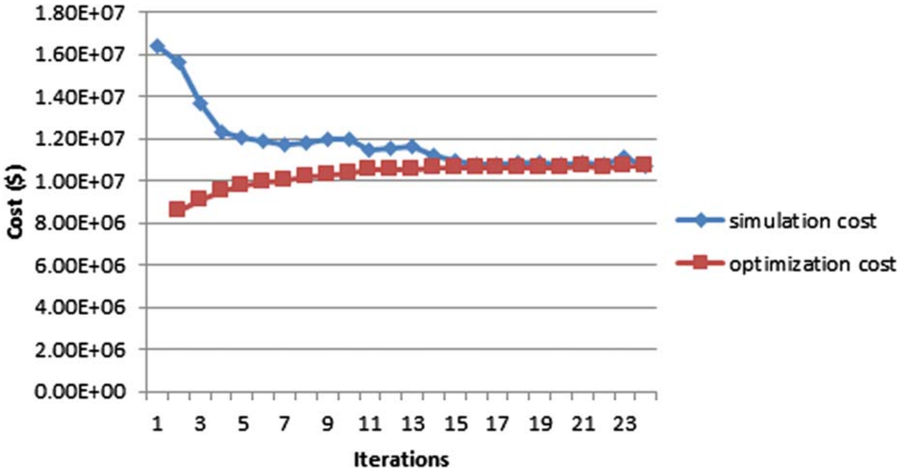

Figure 11. Objective values of simulation and optimization models at each iteration for emissions equal to 1.9E+06 kgCO_2e.

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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 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 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.

Figures 14 and 15 show the trend of cost predicted by the model for varying production capacity and warehouse capacity, respectively. In Figure 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 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.

Like case study 1, ε-constraint method is used to solve the multiobjective 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 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.

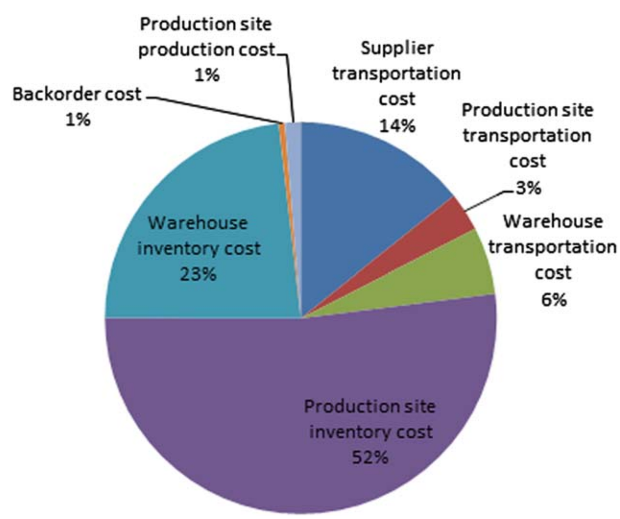

Figure 12. Breakdown of different cost components for the final solution.

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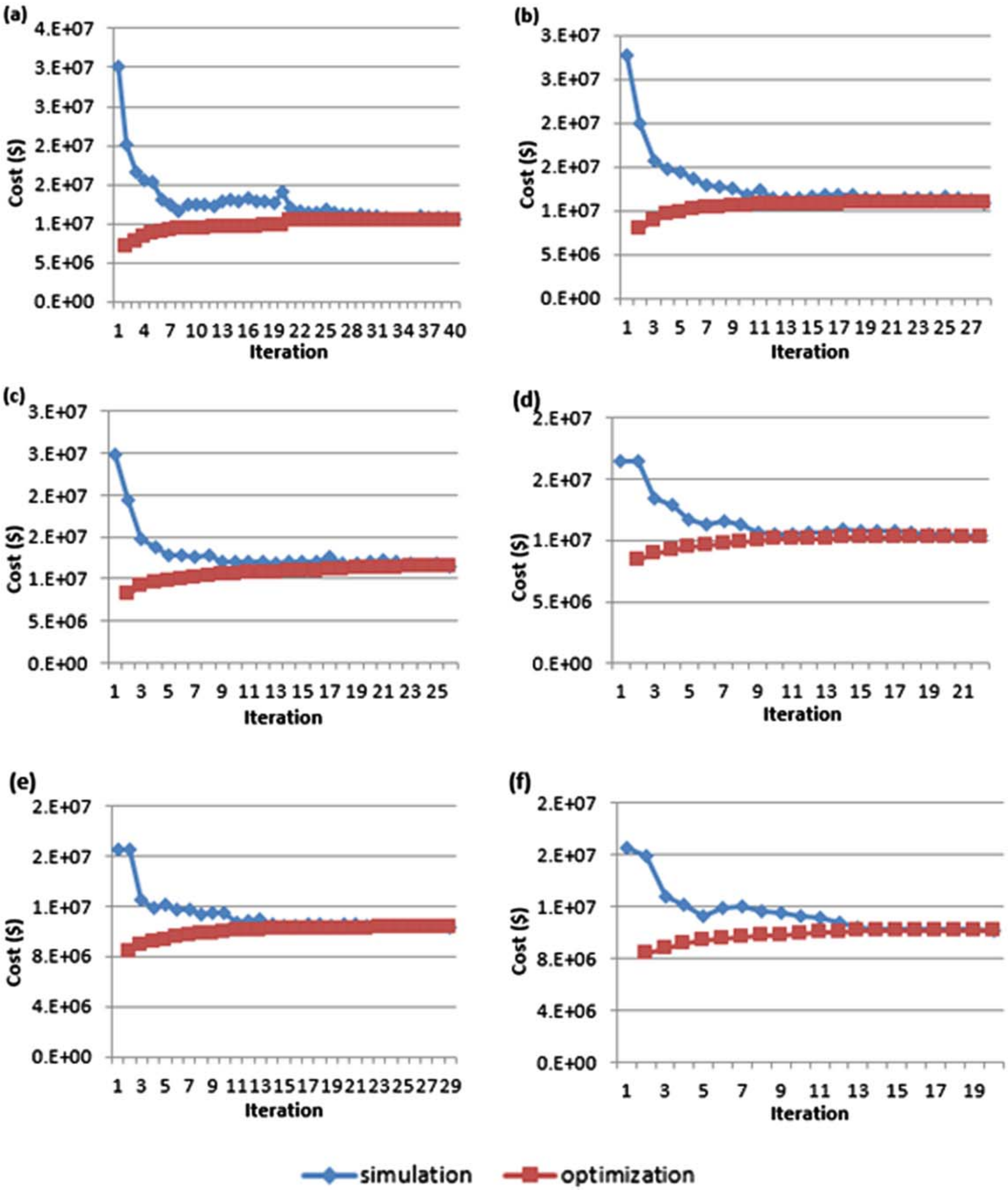

Figure 13. Hybrid approach results for different capacities: (a) production capacity = 75, warehouse capacity=200, (b) production capacity = 75, warehouse capacity = 225, (c) production capacity = 75, warehouse capacity = 250, (d) production capacity = 40, warehouse capacity = 350, (e) production capacity = 50, warehouse capacity = 350, (f) production capacity = 60, warehouse capacity = 350.

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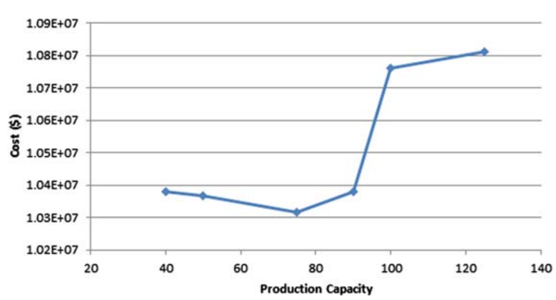

Figure 14. Cost for different production capacities.

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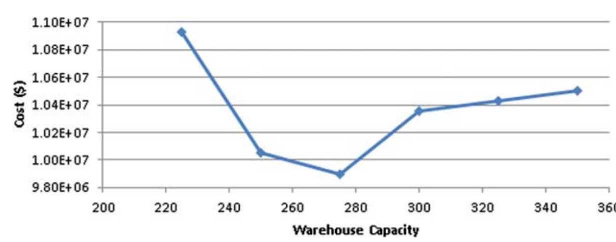

Figure 15. Cost for different warehouse capacities.

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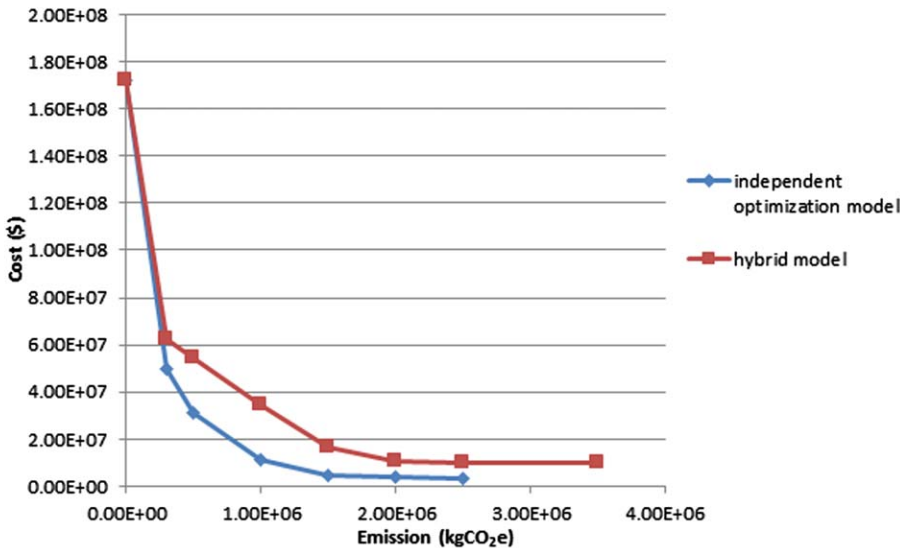

Figure 16. Comparison of results from hybrid model and independent optimization model for different values of emission.

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

Conclusions

In this article, 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 multiobjective optimization problem was addressed using the hybrid framework. It was shown that the framework can be utilized for multiobjective 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.

Acknowledgment

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Notation

Indices

t = planning period
p = production site
sup = supplier
m = distribution market
wh = warehouse
s = product states
r = raw materials 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
$d_s^{\mathrm{wh},m}$ = unit transportation cost of product s from warehouse wh to market m
$d_s^{p,\mathrm{wh}}$ = unit transportation cost of product s from production site p to warehouse wh
$d_r^{\mathrm{sup},p}$ = unit transportation cost of raw material r from supplier sup to production site p
$\mathrm{FixCost}^p$ = fixed production cost of operation of production site p
$\mathrm{VarCost}^p$ = unit variable cost of production at site p
$\mathrm{Dem}_s^{m,t}$ = demand of product s at market m for period t
$\mathrm{et}^{wh,m}$ = Carbon emission due to unit transportation from warehouse wh to market m
$\mathrm{et}^{p,wh}$ = Carbon emission due to unit transportation from production site p to warehouse wh
$\mathrm{et}^{\mathrm{sup},p}$ = 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
$\mathrm{stcap}_r^{\mathrm{sup}}$ = Inventory holding capacity of raw material r at 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
$\mathrm{stcap}_s^{\mathrm{wh}}$ = Inventory holding capacity of product s at warehouse wh
prcap_s^p = Production capacity or product s at production site p

Variables

$D_s^{\mathrm{wh},m,t}$ = Amount of product s transported from warehouse wh to market m at period t
$D_s^{p,\mathrm{wh},t}$ = 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

$\mathrm{Inv}_s^{\mathrm{wh},t}$ = inventory level of product s at the end of the planning period t at warehouse wh

$\mathrm{Inv}_s^{p,t}$ = inventory level of product s at the end of the planning period t at production site p

$\mathrm{Inv}_r^{p,t}$ = inventory level of raw material r at the end of the planning period t at production site p

$\mathrm{Inv}_r^{\sup,t}$ = 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

Literature Cited

1. Stadtler H. Supply chain management and advanced planning—basics, overview and challenges. *Eur J Oper Res*. 2005;163(3):575–588.
2. Varma VA, Reklaitis GV, Blau GE, Pekny JF. Enterprise-wide modeling & optimization—an overview of emerging research challenges and opportunities. *Comput Chem Eng*. 2007;31(5–6):692–711.
3. Chen C-L, Wang B-W, Lee W-C. Multiobjective optimization for a multienterprise supply chain network. *Ind Eng Chem Res*. 2003; 42(9):1879–1889.
4. Chen C-L, Lee W-C. Multi-objective optimization of multi-echelon supply chain networks with uncertain product demands and prices. *Comput Chem Eng*. 2004;28(6–7):1131–1144.
5. Chern CC, Hsieh JS. A heuristic algorithm for master planning that satisfies multiple objectives. *Comput Oper Res*. 2007;34(11):3491–3513.
6. Guillen-Gosalbez G, Mele FD, Grossmann IE. A bi-criterion optimization approach for the design and planning of hydrogen supply chains for vehicle use. *AIChE J*. 2010;56(3):650–667.
7. You FQ, Grossmann IE. Balancing responsiveness and economics in process supply chain design with multi-echelon stochastic inventory. *AIChE J*. 2011;57(1):178–192.
8. Mula J, Peidro D, Díaz-Madroñero M, Vicens E. Mathematical programming models for supply chain production and transport planning. *E J Oper Res*. 2009;204(3):377–390.
9. Higuchi T, Troutt MD. Dynamic simulation of the supply chain for a short life cycle product—lessons from the Tamagotchi case. *Comput Oper Res*. 2004;31(7):1097–1114.
10. Georgiadis P, Vlachos D. The effect of environmental parameters on product recovery. *Eur J Oper Res*. 2004;157(2):449–464.
11. Spengler T, SchrÖter M. Strategic management of spare parts in closed-loop supply chains—a system dynamics approach. *Interfaces*. 2003;33(6):7–17.
12. Schwaninger M, Vrhovec P. Supply system dynamics: distributed control in supply chains and networks. *Cybernet Syst*. 2006;37(5): 375–415.
13. Angulo A, Nachtmann H, Waller MA. Supply chain information sharing in a vendor managed inventory partnership. *J Bus Logist*. 2004;25(1):101–120.
14. Ganeshan R, Boone T, Stenger AJ. The impact of inventory and flow planning parameters on supply chain performance: an exploratory study. *Int J Prod Econ*. 2001;71(1–3):111–118.
15. Gupta M, Ko H-J, Min H. TOC-based performance measures and five focusing steps in a job-shop manufacturing environment. *Int J Prod Res*. 2002;40(4):907–930.
16. van der Vorst JGAJ, Beulens AJM, van Beek P. Modelling and simulating multi-echelon food systems. *Eur J Oper Res*. 2000;122(2): 354–366.
17. Hung WY, Kucherenko S, Samsatli NJ, Shah N. A flexible and generic approach to dynamic modelling of supply chains. *J Oper Res Soc*. 2004;55(8):801–813.
18. Koh SCL, Gunasekaran A. A knowledge management approach for managing uncertainty in manufacturing. *Ind Manage Data Syst*. 2006;106(3–4):439–459.
19. Hicks C, Hines SA, Harvey D, McLeay FJ, Christensen K. An agent based model of supply chains. *Simulation: Past, Present and Future*. Manchester: SCS Europe, 1998:609–613.
20. Ferrarini A, Labarthe O, Espinasse B. Modelling and simulation of supply chains with a multi agent system. *Simulation in Industry 2001*. Marseille, France: SCS Europe, 2001:893–897.
21. Guillen G, Mele FD, Urbano F, Espuna A, Puigjaner L. An agent-based approach for supply chain retrofitting under uncertainty. *European Symposium on Computer-Aided Process Engineering-15, 20A and 20B, Vols. 20a–20b*. Barcelona, Spain: Elsevier, 2005:1555–1560.
22. Allwood JM, Lee JH. The design of an agent for modelling supply chain network dynamics. *Int J Prod Res*. 2005;43(22):4875–4898.
23. Wang YC, Fang LP. Design of an intelligent agent-based supply chain simulation system. *2007 IEEE International Conference on Systems, Man and Cybernetics, Vols. 1–8*. Montreal: IEEE, 2007:3629–3634.
24. Tan L, Xu SH, Meyer B, Erwin B. An agent-based formal framework for modeling and simulating supply chains. *Proceedings of the 2009 IEEE International Conference on Information Reuse and Integration*. Las Vegas, NV: IEEE, 2008:224–229.
25. Wang JR, Li J, Zhang YH, Hu ZW. Simulation study on influences of information sharing to supply chain inventory system based on multi-agent system. *2008 IEEE International Conference on Automation and Logistics, Vols. 1–6*. Qingdao, China: IEEE, 2008:1001–1004.
26. Chan HK, Chan FTS. Effect of information sharing in supply chains with flexibility. *Int J Prod Res*. 2009;47(1):213–232.
27. Bahroun Z, Moalla M, Baazaoui G, Campagne JP. Multi-agent modelling for replenishment policies simulation in supply chains. *Eur J Ind Eng*. 2010;4(4):450–470.
28. Manataki A, Chen-Burger YH, Rovatsos M. Towards improving supply chain coordination through agent-based simulation. *Trends in Practical Applications of Agents and Multiagent Systems, Vol. 71*. Salamanca, Spain: Springer Berlin Heidelberg, 2010:217–224.
29. Li J, Sheng ZH. A multi-agent model for the reasoning of uncertainty information in supply chains. *Int J Prod Res*. 2011;49(19): 5737–5753.
30. Sinha AK, Aditya HK, Tiwari MK, Chan FTS. Agent oriented petroleum supply chain coordination: co-evolutionary particle swarm optimization based approach. *Expert Syst Appl*. 2011;38(5):6132–6145.
31. Behdani B, Adhitya A, Lukszo Z, Srinivasan R. Negotiation-based approach for order acceptance in a multiplant specialty chemical manufacturing enterprise. *Ind Eng Chem Res*. 2011;50(9):5086–5098.
32. Santa-Eulalia LA, D'Amours S, Frayret JM. Agent-based simulations for advanced supply chain planning and scheduling: the FAMASS methodological framework for requirements analysis. *Int J Comput Integr Manuf*. 2012;25(10):963–980.
33. Mohebbi S, Li XP. Designing intelligent agents to support long-term partnership in two echelon e-supply networks. *Expert Syst Appl*. 2012;39(18):13501–13508.
34. Swaminathan JM, Smith SF, Sadeh NM. Modeling supply chain dynamics: a multiagent approach*. *Decis Sci*. 1998;29(3):607–632.
35. Julka N, Srinivasan R, Karimi I. Agent-based supply chain management-1: framework. *Comput Chem Eng*. 2002;26(12):1755–1769.
36. Julka N, Srinivasan R, Karimi I. Agent-based supply chain management-2: a refinery application. *Comput Chem Eng*. 2002b;26:1771.
37. Garcia-Flores R, Wang XZ. A multi-agent system for chemical supply chain simulation and management support. *OR Spectr*. 2002;24: 343.
38. Lee JH, Kimz CO. Multi-agent systems applications in manufacturing systems and supply chain management: a review paper. *Int J Prod Res*. 2008;46(1):233–265.
39. Kim B, Kim S. Extended model for a hybrid production planning approach. *Int J Prod Econ*. 2001;73(2):165–173.
40. Lee YH, Kim SH, Moon C. Production-distribution planning in supply chain using a hybrid approach. *Prod Plan Control*. 2002;13(1): 35–46.
41. Subramanian D, Pekny JF, Reklaitis GV. A simulation—optimization framework for addressing combinatorial and stochastic aspects of an R&D pipeline management problem. *Comput Chem Eng*. 2000;24(2–7):1005–1011.
42. Napalkova L, Merkuryeva G. Multi-objective stochastic simulation-based optimisation applied to supply chain planning. *Technol Econ Dev Econ*. 2012;18(1):132–148.
43. Truong TH, Azadivar F. Simulation based optimization for supply chain configuration design. *Proceedings of the 2003 Winter Simulation Conference, Vols. 1–2*. New Orleans, LA: IEEE, 2003:1268–1275.
44. Chen Y, Mockus L, Orcun S, Reklaitis GV. Simulation-optimization approach to clinical trial supply chain management with demand scenario forecast. *Comput Chem Eng*. 2012;40:82–96.

45. Tunali S, Ozfirat PM, Ay G. Setting order promising times in a supply chain network using hybrid simulation-analytical approach: an industrial case study. *Simul Model Pract Theory.* 2011;19(9):1967–1982.

46. Wan XT, Pekny JF, Reklaitis GV. Simulation based optimization of supply chains with a surrogate model. *European Symposium on Computer-Aided Process Engineering-14, Vol. 18.* Lisbon, Portugal: Elsevier, 2004:1009–1014.

47. Ding HW, Benyoucef L, Xie XL. A simulation-based optimization method for production-distribution network design. *2004 IEEE International Conference on Systems, Man & Cybernetics, Vols. 1–7.* The Hague: IEEE, 2004:4521–4526.

48. Wan XT, Pekny JF, Reklaitis GV. Simulation-based optimization with surrogate models-application to supply chain management. *Comput Chem Eng.* 2005;29(6):1317–1328.

49. Almeder C, Preusser M. A toolbox for simulation-based optimization of supply chains. *Proceedings of the 2007 Winter Simulation Conference, Vols. 1–5.* Washington, DC: IEEE, 2007:1911–1918.

50. Jung JY, Blau G, Pekny JF, Reklaitis GV, Eversdyk D. A simulation based optimization approach to supply chain management under demand uncertainty. *Comput Chem Eng.* 2004;28(10):2087–2106.

51. Shanthikumar JG, Sargent RG. A unifying view of hybrid simulation/analytic models and modeling. *Oper Res.* 1983;31(6):1030–1052.

52. Young Hae L, Sook Han K. Optimal production-distribution planning in supply chain management using a hybrid simulation-analytic approach. *Proceedings of Winter Simulation Conference.* Orlando, FL, 2000.

53. Gjerdrum J, Shah, Nilay, Papageorgiou, Lazaros G. A combined optimization and agent-based approach to supply chain modelling and performance assessment. *Prod Plan Control.* 2000;12(1):81–88.

54. Paul D, Jan AP, Johan H. On the integration of agent-based and mathematical optimization techniques. *Proceedings of the 1st KES International Symposium on Agent and Multi-Agent Systems: Technologies and Applications.* Wroclaw, Poland: Springer, 2007.

55. Mele FD, Guillen G, Espuna A, Puigjaner L. A simulation-based optimization framework for parameter optimization of supply-chain networks. *Ind Eng Chem Res.* 2006;45(9):3133–3148.

56. Almeder C, Preusser M, Hartl R. Simulation and optimization of supply chains: alternative or complementary approaches? Supply Chain Planning. Berlin, Heidelberg: Springer, 2009:1–25.

57. Nikolopoulou A, Ierapetritou MG. Hybrid simulation based optimization approach for supply chain management. *Comput Chem Eng.* 2012;47:183–193.

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