Dynamic Simulation and Decision Support for Multisite Specialty Chemicals Supply Chain

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Companies are increasingly shifting from single-site manufacturing to multisite operations to tap into the vast business opportunities offered by globalization. The supply chain of such a multisite enterprise is complex, involving numerous interacting entities with various roles and constraints, resulting in complex dynamics and complexities in decision making. This complexity motivates the development of simulation models of the supply chain that can capture the behavior of the entities, their interactions, the resulting dynamics, and the various uncertainties. In this article, we present a dynamic model of a multisite specialty chemicals supply chain that can serve as a quantitative simulation and decision support tool. The model explicitly considers the different supply chain entities and their interactions across various activities such as order acceptance and assignment, job scheduling, raw material procurement, storage, and production. It has been implemented as a dynamic simulator in Matlab/Simulink, called the integrated lube additive supply chain simulator (ILAS). Different policies, configurations, and uncertainties can be simulated in ILAS, and their impacts on the overall performance of the supply chain, such as customer satisfaction and profit, can be analyzed. The capabilities of ILAS for decision support are illustrated using several case studies.

1. Introduction

A supply chain (SC) is a network of suppliers, manufacturing plants, warehouses, and distribution channels structured to acquire raw materials, convert them into finished products, and distribute these products to customers. Several characteristics distinguish chemical SCs from those of other industries such as automotive, electronic, or general retail.[1] In chemical manufacturing, the concepts of "discrete parts" and "assembly" do not apply. Instead, chemical SCs involve a huge variety of nondiscrete, immiscible, often incompatible and nonsubstitutable, and huge-volume materials, each of which has its own unique characteristics. The chemical industry is highly capital-intensive. It has long and divergent SCs with recycle loops, given the fact that the industry itself is its largest consumer. Other key features include extensive trading; need for safety-first policies; and sensitivity to energy prices, sociopolitical uncertainties, and environmental regulations. On the logistics part, maritime transport is the workhorse of chemical SCs. The hazardous nature and huge volumes of chemicals necessitate the use of highly expensive and sophisticated transport equipment and storage facilities. Although these features distinguish the chemical industry as a whole, there are further fine-grained differences between petrochemicals and specialty chemicals. Some characteristics of petrochemicals are undifferentiated, low-margin, and high-throughput products from continuous processing. In contrast, the specialty chemicals industry is characterized by high-value and low-throughput viscous fluid products with partial differentiation among them. Each product is defined by its performance and formulated through a unique recipe. Operations typically involve reaction and blending carried out in batch operating mode. The specialty chemicals SC typically operates in pull mode, driven by specific customer orders.

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Lubricant (lube) additives are specialty chemical products that enhance the performance characteristics of finished lubricating oils and greases. Additives are combined with base oil to produce a formulated lubricant. Different types of additives perform different functions, for example, corrosion and rust inhibitors, antiwear agents, antioxidants, antifoams, friction modifiers, detergents to reduce buildup of deposits, and so on. A lube additive package typically results from a complex formulation involving 10−15 ingredients. All together, there could be over 4000 formulations from 1500 substances. Specific tailoring of lubricant composition is possible using different base oils and additives. Hence, the key competence of additive suppliers is their ability to formulate unique additive packages that deliver required performance at competitive prices. Details of the intrinsic chemical identities and their proportions in the formulations are proprietary. Information about activities and relationships among component suppliers, formulators, and customers is also confidential business information.

Interesting dynamics abound in global SCs and obviate narrow, univariate analysis. For instance, after a major disruption in August 2005, Chevron Oronite reported taking a number of corrective actions, including increasing inventories, establishing supply chain redundancies, and keeping open a plant that was scheduled to be shut.[2] These measures, which are counter to traditional SC optimization recommendations, illustrate the challenging nature of supply chain management (SCM) when SCs span continents, involve numerous entities, and have to contend with various uncertainties. With the increasing emphasis on globalization and the more competitive business environment, companies try to reach out globally to different markets by shifting from a single-site operation to a multisite manufacturing enterprise. This brings the flexibility of producing more products, focusing on specialization activities, and getting closer to both low-cost raw material sources and targeted markets.[3] However, this also results in a more complex SC with complex dynamics, which could, in turn, lead to unforeseen domino effects. Information delay, limited visibility, and the presence of various

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uncertainties further complicate SC decision making. A decision made by an entity might be optimal for its own objective when the effects on other entities are not considered, but could be counterproductive for the overall enterprise. Whereas enterprises today consider SCM to be a key factor for achieving better profitability and customer satisfaction, the practice of SCM is not straightforward given the above challenges.

This motivates the development of dynamic simulation models of the SC that can capture the behavior of the entities, their interactions, the resulting dynamics, and the various uncertainties.[4] A hierarchy of decisions has to be made in SCM: strategic, tactical, operational, and ad hoc. Simulations can provide support for these decisions by allowing the user to quantitatively evaluate the impact of a particular decision on the SC performance, analyze different SC policies, and identify consequences of a disruption and possible remedial actions.[5] In this article, we present a dynamic model of a multisite lube additive SC. It has been implemented as a simulator, called the integrated lube additive supply chain simulator (ILAS), in Matlab/Simulink.[6]

Mathematical programming approaches have been proposed for multisite SC design and operational planning among other approaches to these problems. Tsiakis and Papageorgiou[7] proposed a mixed-integer linear programming (MILP) model to determine the optimal configuration of a production and distribution network subject to financial and tactical operational constraints taking into account production balancing among the sites. Ferrio and Wassick[8] presented an MILP model focused on the redesign of existing multiproduct SC networks made up of production sites, a number of echelons of distribution centers, and customer sites. You and Grossmann[9] developed a multiperiod mixed-integer nonlinear programming (MINLP) model for the optimization of design and planning of a supply chain with multisite processing facilities under demand uncertainty.

Timpe and Kallrath[10] presented a general MILP model for optimal planning in large multisite production networks, covering production, distribution, and marketing. Verderame and Floudas[11] formulated an MILP model for multisite planning with production disaggregation to determine both production and shipment profiles. Dondo et al[12] proposed an MILP model for the management of logistic activities in a multisite SC, namely, the problem of multiple-vehicle pickup and delivery with time windows. Amaro and Barbosa-Póvoa[13] presented an MILP model for the planning of generalized SCs involving production, storage, and transportation under market demand/price uncertainty while also accounting for different partnerships structures. Puigjaner and Laínez[14] employed a scenario-based multistage stochastic MILP in an MPC scheme to incorporate uncertainty and process dynamics into an enterprise-wide model.

Mathematical programming techniques generally work well for small-scale, short-term SC problems; however, they are limited in dealing with large-scale, long-term, stochastic, dynamic, nonlinear problems.[15,16] Simulation is a popular methodology for describing the inherent complexities in large-scale supply chains; hence, simulation−optimization approaches have been proposed. Mele et al.[15] addressed the SC design and retrofit problem by using genetic algorithms to optimize the operation variables associated with each design candidate and assessing the performance of each SC configuration through a dynamic multiagent model. Moon et al.[17] presented an integrated process planning and scheduling model for a multiplant SC that includes operations sequencing, machine selection, and operations scheduling. Their proposed solution strategy employs a genetic algorithm-based heuristic approach. Jung et al.[18] adopted the simulation−optimization framework for multistage SC safety stock management, employing linear programming to determine optimal safety stock levels and discrete event simulation to obtain performance functions. Pitty et al.[4] proposed a dynamic simulation model of an integrated refinery SC that explicitly considered various activities involving external entities, such as supply and transportation, and intrarefinery activities, such as procurement planning and operations management. Applications of this dynamic simulation model for supporting SC design and operational decisions are described in Koo et al.[5] This article presents a similar dynamic numerical model for a multisite lube additive SC.

Dynamic modeling of SCs based on control theory has previously been proposed to capture the dynamic behavior of SCs.[19] Each SC node (manufacturing plant, plant warehouse, distribution center, retailer) is defined by two properties, namely, inventory and orders, expressed in terms of rates of flow. Control laws are used to represent the decision-making process of deciding how much to order from an upstream node. In contrast to these lumped SC models, we propose a workflow-oriented detailed model that considers each order, each department, and each decision in the enterprise individually and emulates the business processes followed in real-life SCs. The rest of this article is organized as follows: In section 2, we describe the multisite lube additive SC operation and the entities involved. The dynamic model of the system is described in section 3. Various case studies illustrating potential applications of ILAS for decision support are discussed in section 4. Finally, section 5 presents the conclusions and describes future work.

2. Multisite Lube Additive Supply Chain Operation

As shown in Figure 1, the multisite lube additive SC comprises raw material suppliers, third-party logistics (3PL) providers, shippers, the lube additive enterprise, and customers. The lube additive enterprise comprises a global sales department that directly interacts with customers and a number of lube additive plants in various geographical locations (Figure 1 shows two lube plants). The information exchange (shown as broken arrows in Figure 1) between the entities (blocks) facilitates material flow (solid arrow). Each functional department in the enterprise performs a different function. For example, the procurement department is responsible for raw material procurement, and the operations department is responsible for production (i.e., conversion of raw materials into products following a certain recipe). The plant units (shaded blocks) can be further subdivided into storage units (raw material and product tanks), process units (reactors and blend tanks), and packaging units. The functioning of these units and the SC activities are overseen by the functional departments based on certain rules and policies. These departments communicate with one another to get the information necessary to perform their tasks or to call for certain actions. The integrated, overall SC performance and its dynamics emerge from the combined effects of the SC entities. Three different cycles of activities constitute the SC operation: enterprise-level coordination, plant operation, and inventory management.

The SC operation can be represented clearly and conveniently using sequence diagrams. Figure 2a shows the sequence diagram of the enterprise-level coordination cycle. The diagram shows the sequence of activities (or tasks) performed by the different entities and the interactions involved within one cycle. Each entity has a vertical bar (thread of activities). The entity's name is listed at the top, and the human stick figure indicates whether the entity consists of just one or multiple instances. A vertical

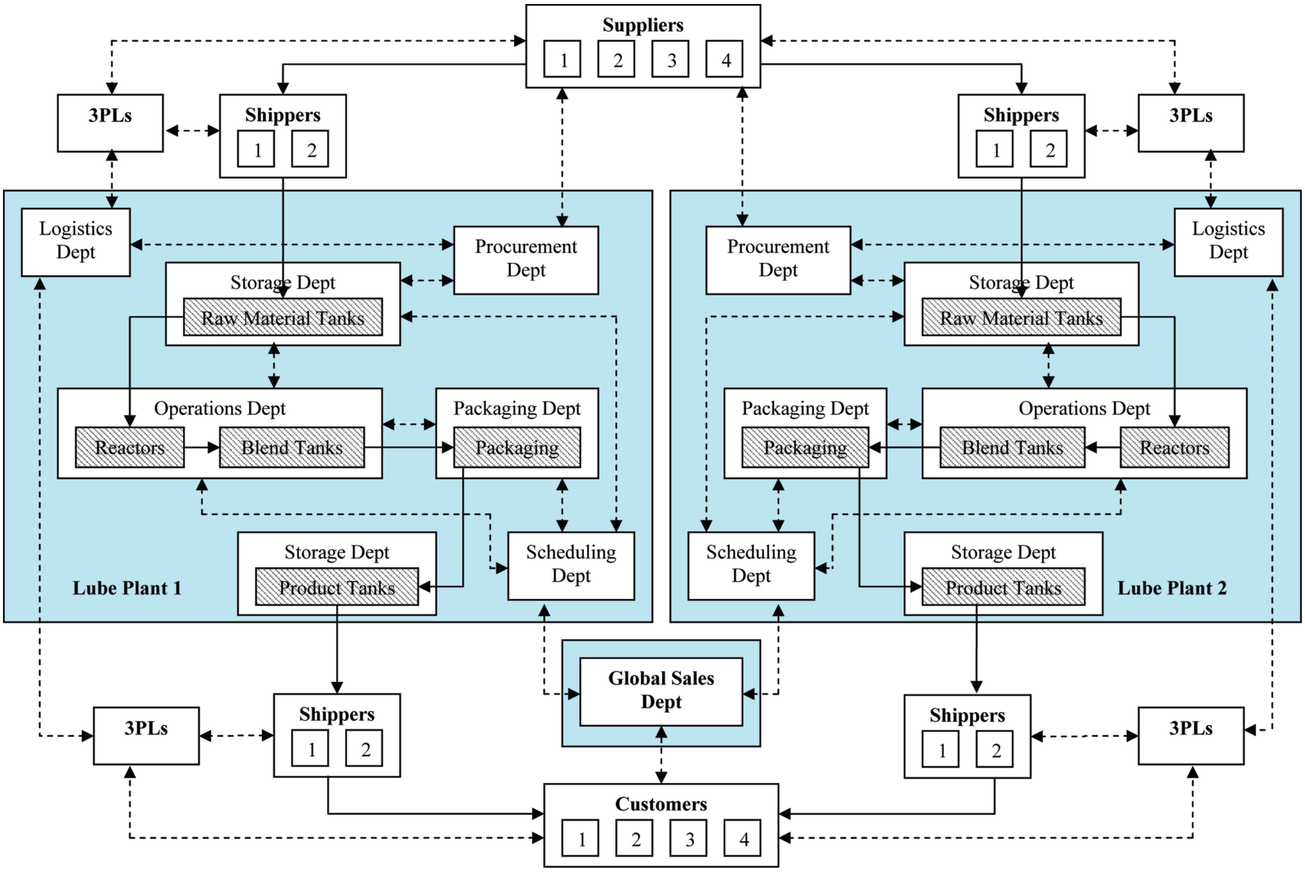

Figure 1. Schematic of multisite lube additive supply chain.

dotted line is the time axis on which a task, represented by a rectangle, is placed. A solid arrow represents a message from one entity to another, whereas a dotted arrow represents a reply. The vertical position of a task shows its sequence relative to other tasks of any entity; earlier tasks are placed higher on the time axis. Note that the actual duration of a task or between tasks is not represented in this diagram; only the relative sequence is. The vertical bar shows when an entity is active within the cycle. It starts when the entity first receives a message or performs its first task and ends after it sends its last message or performs the last task in its thread.

The enterprise-level coordination cycle involves (multiple) customers; the global sales department; and the different plants, specifically their scheduling departments, as shown in Figure 2a. The cycle starts with a customer placing an order with the sales department, which then forwards the order details to the scheduling departments of the different plants to invite bids. The schedulers in the plants estimate the delivery date and costs of the potential order and send proposals to sales. Based on the proposals and following a certain job assignment policy, the sales department selects a plant for the job. The job assignment policy can be based on, for example, customer location, earliest projected delivery date, or lowest projected costs. The sales department then assigns the job to the selected plant, and the scheduler inserts the job into the plant's schedule based on a scheduling policy. Each subsequent customer order follows the same cycle.

The other two cycles are at the plant level. Figure 3a shows the sequence diagram of the plant operation cycle. Once an order is received, the scheduling department then inserts it into the job schedule following a scheduling policy, such as earliest due date. Scheduling is important to minimize lateness in order delivery to customers. The scheduler is also in charge of assigning orders to the production line. Before releasing a job to the operations department, the scheduling department checks with the storage department to ensure that there are sufficient raw materials for that order. The operations department supervises the processing (reaction and blending) required to manufacture the product. The manufactured product is then sent for packaging and subsequently sent out to the customers through logistics and 3PLs. When the manufacturing of an order is completed, the next job in the schedule is released by the scheduler, and the cycle repeated.

The inventory management cycle ensures the availability of raw materials necessary for manufacturing. The sequence diagram of the inventory management cycle is given in Figure 4a. The storage department monitors the inventories of all raw materials and triggers their procurement as necessary. The procurement policy defines the trigger for procurement; for example, in the reorder point policy, procurement is triggered when raw material inventory falls to or below the reorder point. When triggered, storage informs procurement of the amount and type of raw material to be purchased from the supplier. The material is delivered to storage through logistics and 3PLs.

The three cycles are interrelated: The job schedule of the scheduler connects enterprise-level coordination and plant operation, and raw material inventory of storage connects plant operation and inventory management.

From the above description, it is clear that managing the SC involves decision making by the different entities. In enterprise-level coordination, the scheduler decides how to slot a potential job into the existing schedule and what completion date it can commit. The sales department then

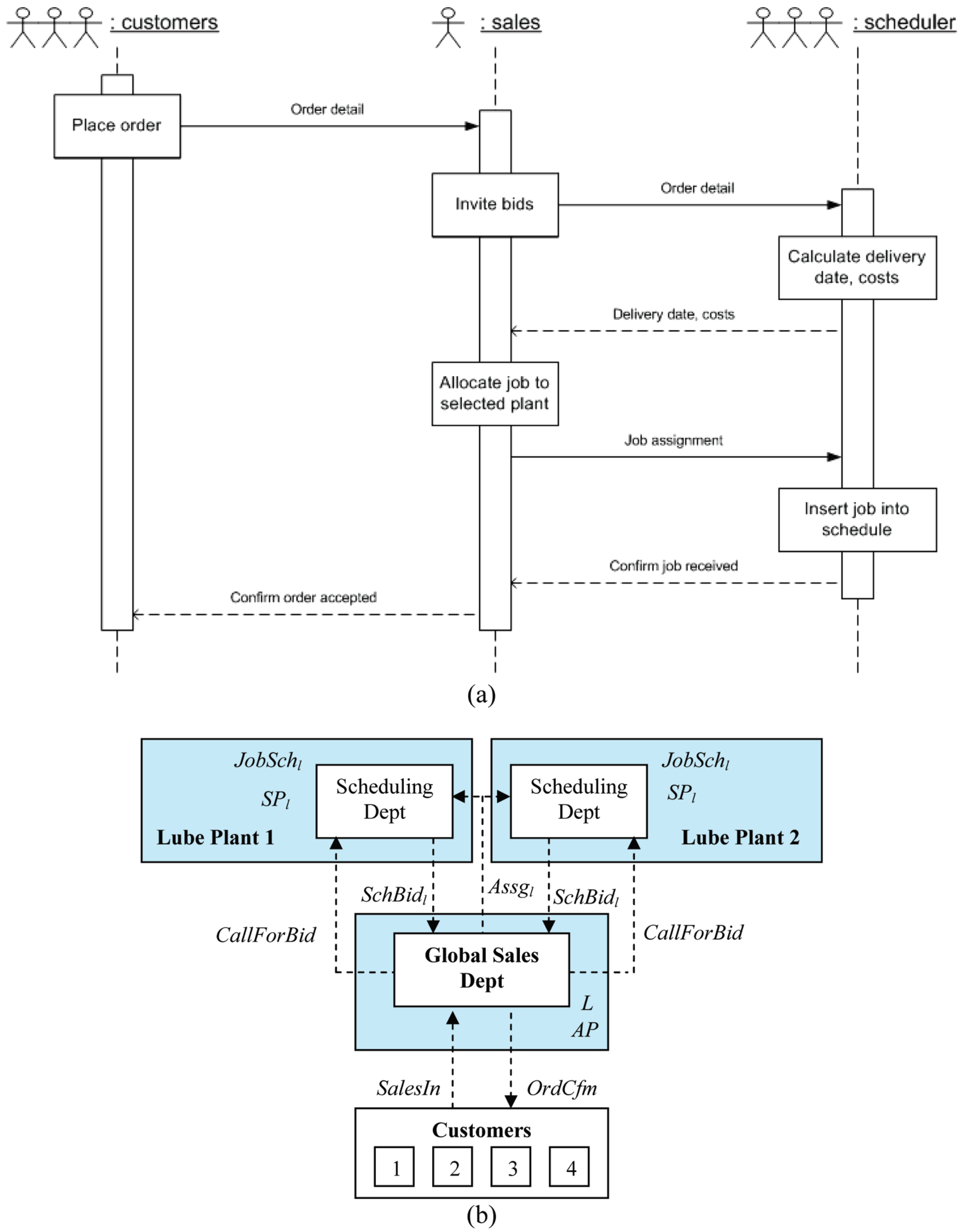

Figure 2. (a) Sequence diagram of enterprise-level coordination. (b) Entities and variables in enterprise-level coordination.

decides the plant to which the job should be assigned. The scheduler of the corresponding plant has to update its schedule. In plant operation, the scheduler decides which job to process. The scheduler can follow the existing schedule or might need to reschedule to react to changing condition, such as if a raw material for a particular job is not available. In inventory management, storage and procurement decide when, how much, and which raw materials to buy. In addition to these routine decisions, there are decisions to be made in exceptional circumstances, for example, how to deal with events such as plant disruption or supply disruption. The varied interactions and the resulting material flow and decisions result in complex dynamics. Decision support for managing the SC can be enabled by a dynamic integrated model of the enterprise and the SC, as described in the next section.

3. Dynamic Lube Additive Supply Chain Simulation Model

The proposed model uses a discrete-time representation, where one day is divided into T time ticks t. Day 1 consists of T ticks from $t = 1$ to T, day 2 from $t = T + 1$ to $2T$, and so on. The location of a plant or a customer is represented through a pair of coordinates (x, y). An important element in any real-life SC is the presence of numerous stochastic factors. Uncertainties in the lube additive SC operation include order details and

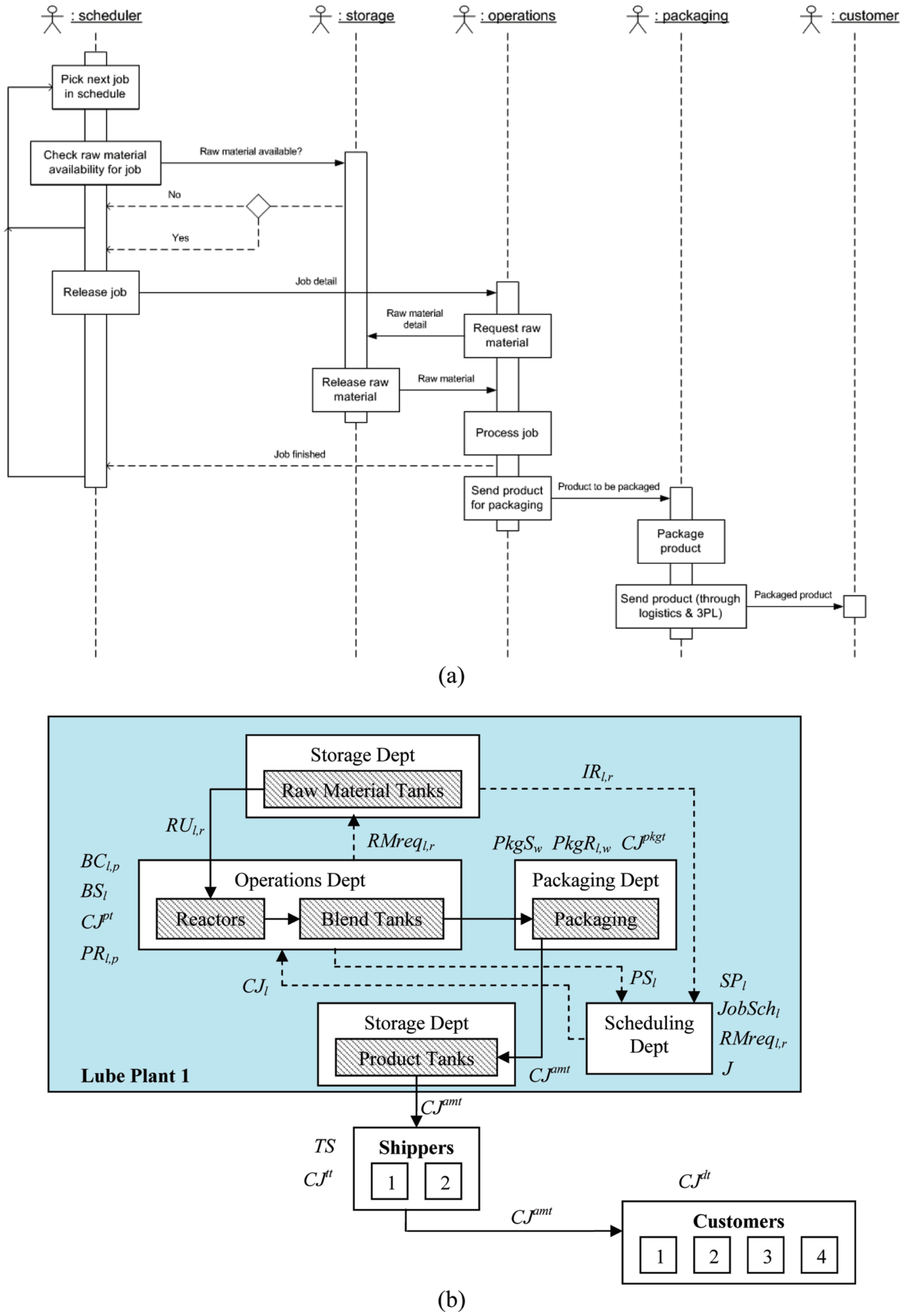

Figure 3. (a) Sequence diagram of plant operation. (b) Entities and variables in plant operation.

arrivals, raw material transportation times, processing times, and packaging times. These are abstracted through stochastic variables in the model.

3.1. Enterprise-Level Coordination. The enterprise-level cycle involves the customer, the global sales department, and the scheduling department of each local plant (Figure 2b). It starts with a customer placing an order with sales.

The customer order is modeled as a structure with nine components: (1) CO^{id} is the index number to identify a particular order. (2) CO^{amt} represents the amount ordered. (3) CO^{pdt} represents the product type. (4) CO^{grd} represents the grade within the product type. (5) CO^{dd} is the due date. (6) CO^{pkg} represents the packaging type. (7) CO^{xloc} is the x coordinate of the customer location. (8) CO^{yloc} is the y coordinate of the customer location. (9) CO^{time} is the time when the order is placed.

Customer orders for each product type are randomly generated by sampling from a prespecified demand curve and order frequency. Other order details, including grade, due date, packaging type, and customer location, are also randomly generated within prespecified limits (see section 3.4).

The sales department receives a customer order, CO

$$\mathrm{SalesIn}(t) = \begin{cases} \mathrm{CO} & \text{at } t = \mathrm{CO}^{\mathrm{time}} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Sales then decides the plant to which the order should be assigned following a job assignment policy. In most policies, sales communicates with the scheduler of each eligible plant to get information required by the policy. For example, if assignment is based on the earliest completion date, sales asks for the projected completion date for that order from the schedulers, by forwarding the order information to the schedulers

$$\mathrm{CallForBid} = \mathrm{CO} \quad (2)$$

where CallForBid is the information sent by sales to the schedulers to ask for bids.

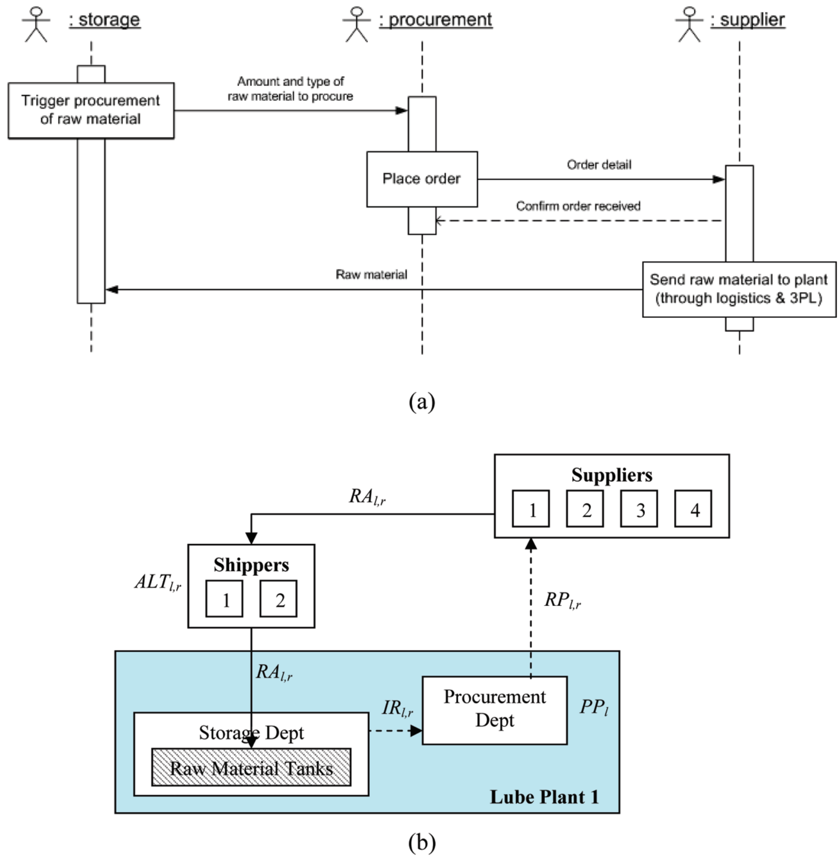

Figure 4. (a) Sequence diagram of inventory management. (b) Entities and variables in inventory management.

Each scheduler maintains a schedule of the jobs the plant, designated by the index l, has to process, JobSch_l. The job schedule is an array of customer orders sorted in the sequence in which they will be processed by the plant. The scheduler determines the projected completion date by inserting the potential order into its schedule, following its scheduling policy, to get a projected job schedule

$$\text{ProjJobSch}_l = \text{SP}(\text{CO}, \text{JobSch}_l)_l \quad (3)$$

where ProjJobSch_l is the projected job schedule of plant l including the potential order CO, SP_l is the scheduling policy employed by the scheduler of plant l, and JobSch_l is the job schedule of plant l before the arrival of order CO.

Based on this projected schedule, each scheduler sends a bid SchBid_l containing the projected completion date for the order to sales

$$\text{SchBid}_l = f(\text{ProjJobSch}_l) \quad (4)$$

Sales might negotiate with the customer if the earliest completion date from all plants is beyond the due date. Once a satisfactory due date, CO^{dd}, has been accepted by the customer, sales assigns the order to the selected plant following the job assignment policy. If an acceptable due date cannot be negotiated, the customer will walk away, and the order will be lost.

$$\text{OrdCfm} = \begin{cases} 1 & \text{if order is accepted} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

$$L = \text{AP}(\text{CO}, \text{SchBid}_l) \quad (6)$$

$$\text{Assg}_l = \begin{cases} \text{CO} & \text{if OrdCfm} = 1 \text{ and } l = L \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

In eqs 6 and 7, L is the selected plant for order CO, AP is the job assignment policy, and Assg_l is the job assignment from sales to plant l.

The number of customer orders assigned to plant l, NCO_l, and the number of missed orders, NMO, can then be updated as

$$\text{NCO}_L \leftarrow \text{NCO}_L + 1 \quad (8)$$

$$\text{NMO} \leftarrow \text{NMO} + (1 - \text{OrdCfm}) \quad (9)$$

The scheduler of the selected plant L then uses the projected schedule that incorporates CO as the new job schedule

$$\text{JobSch}_L \leftarrow \text{ProjJobSch}_L \quad (10)$$

3.2. Plant Operation. This cycle takes place within each plant l and involves the scheduling, operations, storage, and packaging departments (Figure 3b). The plant operates in batch mode, that is, production is done batchwise in noncontinuous processing units. The series of processing units can be considered as one big reactor unit. Raw materials are fed into this unit, and after a certain processing time, products are discharged. All plants are assumed to operate in make-to-order mode. Processing is done for each order from start to finish before the plant moves on to the next order; hence, intermediates are exclusive to each order and are not considered explicitly here. Also, after production, products are packaged and delivered; again, inventory-related issues are ignored for these stages.

Production is carried out following the job schedule, which consists of a sequence of jobs to be processed. Each job CJ is modeled as a structure with 20 components: (1−8) the first eight components of its corresponding customer order CO; (9) CJ^{nb}, the number of batches; (10) CJ^{pt}, the processing time; (11) CJ^{np}, the number of packages; (12) CJ^{pkgt}, the packaging time; (13) CJ^{tt}, the transportation time; (14) CJ^{st}, the processing start time; (15) CJ^{dt}, the delivery time; (16) CJ^{rev}, the revenue; (17) CJ^{pc}, the processing cost; (18) CJ^{pkgc}, the packaging cost; (19) CJ^{tc}, the transportation cost; and (20) CJ^{pen}, the late delivery penalty.

The processing status PS_l of a plant l indicates the amount of time remaining to complete the current job in the unit. The job is completed when PS_l reaches 0; at that time, the unit is said to be free and ready to accept the next job. When the unit is free, the scheduler checks whether there is any other job remaining in the schedule. If the job schedule is nonempty, the scheduler identifies the next job CJ_l to be processed. CJ_l is usually the first job in the schedule, $JobSch_{l,1}$, since the job schedule is sorted based on the scheduling policy.

Before releasing this job to operations, the scheduler checks with storage to determine whether there are enough raw materials for this job. A unique product recipe defines the types and amounts of raw materials needed to make a certain product of a certain grade. The amount of raw material r required for the job is calculated based on the recipe

$$RMreq_{l,r} = RCP_{r,P,G}CJ_l^{amt} \tag{11}$$

where $P = CJ_l^{pdt}$ and $G = CJ_l^{grd}$ are the product type and grade of job CJ_l, respectively. $RMreq_{l,r}$ is the amount of raw material r required for processing the current job at plant l, and $RCP_{r,p,g}$ is the recipe specifying the amount of raw material r required to make one unit of product p of grade g. If there are enough raw materials for $JobSch_{l,1}$, the scheduler releases this job to operations. Otherwise, the scheduler checks raw material availability for the second job in the schedule, and so on, until identifying the earliest job in the schedule for which raw materials are available.

In general, let $JobSch_{l,j}$ be the jth job in the schedule, and let the Jth job be the earliest job for which raw materials are available

$$J = \min_{[1\ \mathrm{size}(JobSch_l)]} j \quad \text{s.t.} \quad IR_{l,r}(t) \geq RCP_{r,P,G}JobSch_{l,j}^{amt} \tag{12}$$

where $IR_{l,r}(t)$ is the inventory level for raw material r at plant l at time t. If such a J is found, then $JobSch_{l,J}$ is the next job to be processed

$$CJ_l = JobSch_{l,J} \quad \text{if} \quad PS_l(t) = 0 \tag{13}$$

$$CJ_l^{st} = t \tag{14}$$

where CJ_l is the next job to be started and released to operations at plant l and CJ_l^{st} is its processing start time. The scheduler then updates the processing status

$$PS_l(t + 1) = CJ_l^{pt} \tag{15}$$

where CJ_l^{pt} is the total processing time for job CJ_l. The required raw materials are transferred from storage to the reactor

$$RU_{l,r}(t) = RMreq_{l,r} \tag{16}$$

where $RU_{l,r}(t)$ is the amount of raw material r transferred from storage to the reactor at plant l at time t.

Processing is carried out in batches, where each batch has a fixed and a variable processing time. The number of batches is first calculated as

$$CJ_l^{nb} = \mathrm{ceil}\left(\frac{CJ_l^{amt}}{BS_l}\right) \tag{17}$$

where CJ_l^{nb} is the number of batches for job CJ_l and BS_l is the batch size as limited by the reactor size of plant l. The fixed processing time is linearly dependent on the number of batches, whereas the variable processing time is linearly dependent on the total product amount. The total processing time for job CJ_l, including uncertainty, is then calculated as

$$CJ_l^{pt} = (BC_{l,P}CJ_l^{nb} + PR_{l,P}CJ_l^{amt})(1 + \beta PTU_l) \tag{18}$$

where $BC_{l,P}$ is the batch-dependent processing time per batch of product P at plant l, $PR_{l,P}$ is the amount-dependent processing time per unit of product P at plant l, β is a uniform [0, 1] random variable for processing time uncertainty, and PTU_l is the maximum percentage delay for processing at plant l.

As time progresses, the processing status is updated to keep track of the amount of time remaining to complete the current job

$$PS_l(t + 1) = \begin{cases} PS_l(t) - 1 & \text{if } PS_l(t) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

The total processing time of plant l, NPT_l, is also updated at every tick

$$NPT_l \leftarrow \begin{cases} NPT_l + 1 & \text{if } PS_l(t) > 0 \\ NPT_l & \text{otherwise} \end{cases} \tag{20}$$

When processing is completed [i.e., $PS_l(t) = 0$], the product is discharged and sent to packaging. The operations department informs the scheduler that the processing unit is free and ready for the next job. The scheduler removes the completed job from the schedule and continues with the next job in the schedule

$$JobSch_l \leftarrow JobSch_l - CJ_l \tag{21}$$

Packaging is carried out in a first-in-first-out manner and is assumed to be faster than processing so that it will never be a bottleneck. Different packaging types have different sizes. Packaging time depends on the packaging type and the number of packages. First, the number of packages required is calculated

$$CJ_l^{np} = \mathrm{ceil}\left(\frac{CJ_l^{amt}}{PkgS_W}\right) \tag{22}$$

where $W = CJ_l^{pkg}$ is the packaging type of job CJ_l; CJ_l^{np} is the number of packages for job CJ_l; and $PkgS_W$ is the packaging size of type W, which is the amount of product contained in a package of type W.

The packaging time, including uncertainty, is calculated as

$$CJ_l^{pkgt} = (PkgR_{l,W}CJ_l^{np})(1 + \gamma PkgTU_l) \tag{23}$$

where CJ_l^{pkgt} is the total packaging time for job CJ_l, $PkgR_{l,W}$ is the packaging time per package of type W at plant l, γ is a uniform [0, 1] random variable for packaging time uncertainty, and $PkgTU_l$ is the maximum percentage delay for packaging at plant l.

After packaging, the packaged product is assumed to be immediately dispatched to the customer. No product inventory is kept. The delivery time is calculated based on the straight-line distance between the plant and the customer

$$\mathrm{CJ}_l^{\mathrm{tt}} = \mathrm{TS}\sqrt{(x_l - \mathrm{CJ}_l^{\mathrm{xloc}})^2 + (y_l - CJ_l^{\mathrm{yloc}})^2} \tag{24}$$

where $\mathrm{CJ}_l^{\mathrm{tt}}$ is the transportation time for job CJ_l, TS is the transportation speed (in days per unit distance), and x_l and y_l are the location coordinates of plant l.

Finally, the product is delivered to the customer at $\mathrm{CJ}_l^{\mathrm{dt}}$

$$\mathrm{CJ}_l^{\mathrm{dt}} = \mathrm{CJ}_l^{\mathrm{st}} + \mathrm{CJ}_l^{\mathrm{pt}} + \mathrm{CJ}_l^{\mathrm{pkgt}} + \mathrm{CJ}_l^{\mathrm{tt}} \tag{25}$$

where $\mathrm{CJ}_l^{\mathrm{dt}}$ is the delivery time of job CJ_l. The total tardiness and number of late deliveries for plant l can then be updated as

$$\mathrm{NLD}_l \leftarrow \mathrm{NLD}_l + \max(0, \mathrm{CJ}_l^{\mathrm{dt}} - \mathrm{CJ}_l^{\mathrm{dd}}) \tag{26}$$

$$\mathrm{NLO}_l \leftarrow \begin{cases} \mathrm{NLO}_l + 1 & \text{if } \mathrm{CJ}_l^{\mathrm{dt}} > \mathrm{CJ}_l^{\mathrm{dd}} \\ \mathrm{NLO}_l & \text{otherwise} \end{cases} \tag{27}$$

where NLD_l is the total tardiness (in days) for plant l and NLO_l is the number of late deliveries by plant l. CJ_l is now complete and inserted into the list of completed jobs $\mathrm{JobComp}_l$

$$\mathrm{JobComp}_l \leftarrow \mathrm{JobComp}_l + \mathrm{CJ}_l \tag{28}$$

3.3. Inventory Management. The inventory management cycle takes place within each plant and involves the storage department, the procurement department, and the suppliers (Figure 4b). This cycle primarily deals with the replenishment of raw materials through procurement. The procurement department gets inventory updates from the storage department and procures raw material based on its procurement policy PP_l

$$\mathrm{RP}_{l,r}(t) = \mathrm{PP}_l[\mathrm{IR}_{l,r}(t)] \tag{29}$$

where $\mathrm{RP}_{l,r}(t)$ is the amount of raw material r purchased at time t by plant l.

In the current version of the model, the logistics department and the 3PL are not modeled explicitly, and their functionality is approximated by a time lag between raw material purchase and its arrival at the plant, incorporating uncertainty

$$\mathrm{RA}_{l,r}(t) = \mathrm{RP}_{l,r}(t - \mathrm{ALT}_{l,r}) \tag{30}$$

$$\mathrm{ALT}_{l,r} = (1 + \lambda \mathrm{LTU}_{l,r})\mathrm{LT}_{l,r} \tag{31}$$

where $\mathrm{RA}_{l,r}(t)$ is the amount of raw material r arriving at plant l at time t, $\mathrm{ALT}_{l,r}$ is the lead time between purchase and arrival for raw material r at plant l, λ is a uniform [0, 1] random variable for lead time uncertainty, $\mathrm{LTU}_{l,r}$ is the maximum percentage delay for transportation of raw material r to plant l, and $\mathrm{LT}_{l,r}$ is the nominal lead time for raw material r to plant l.

The material balance on raw material inventory is given by

$$\mathrm{IR}_{l,r}(t + 1) = \mathrm{IR}_{l,r}(t) + \mathrm{RA}_{l,r}(t) - \mathrm{RU}_{l,r}(t) \tag{32}$$

3.4. Order Generation. We use a simple model of the global lube additives market demand that incorporates annual growth as well as seasonal variation over the course of a year. This is implemented as a demand curve, $\mathrm{DD}_{p,d}$, from which customer orders are generated

$$\mathrm{DD}_{p,d} = \mathrm{CA}_p \sin\left(d\mathrm{CN}_p \frac{\Pi}{180}\right) + \mathrm{BD}_p \exp(d\mathrm{DG}_p) + \alpha_d \mathrm{DDU}_p \tag{33}$$

$$d = \mathrm{floor}\left(\frac{t - 1}{T}\right) \tag{34}$$

where $d = 1, 2, ..., D$, for a simulation horizon of D days. The first term on the right-hand side of eq 33 represents the effect of fluctuating seasonal demand, where CA_p is the cycle amplitude for product p and CN_p is the number of cycles in one year (360 days) for product p. The second term represents the effect of a gradual growth in demand, where BD_p is the base demand level for product p and DG_p is the demand growth factor for product p. The third term represents the daily uncertainty in demand, where α_d is a uniform [−1, 1] random variable and DDU_p is the daily demand uncertainty limit for product p.

This economic demand curve for product p is translated into discrete orders by first calculating the cumulative monthly demand $\mathrm{MD}_{p,m}$

$$\mathrm{MD}_{p,m} = \sum_{d=30(m-1)+1}^{30m} \mathrm{DD}_{p,d} \tag{35}$$

where $m = 1, 2, ..., \mathrm{ceil}(D/30)$.

Each monthly demand is redistributed throughout the days in the month according to the order frequency index f_p, representing the probability of a customer order on a given day for product p, where $0 \le f_p \le 1$. We assume that, on each day, there can be at most one order for each product type. The higher the f_p value, the more frequent the orders throughout the month. A uniform [0, 1] random variable, $\mu_{p,d}$, is generated for every day in the month and compared to f_p to capture the uncertainty of order occurrence on a particular day

$$\mathrm{ratd}_{p,d} = \begin{cases} \mu_{p,d} & \mu_{p,d} \le f_p \\ 0 & \mu_{p,d} > f_p \end{cases} \tag{36}$$

The demand amount following an order occurrence is generated as

$$\mathrm{DR}_{p,d} = \frac{\mathrm{ratd}_{p,d}}{\sum_{d=30(m-1)+1}^{30m} \mathrm{ratd}_{p,d}}(\mathrm{MD}_{p,m}) \tag{37}$$

for each month m

$$\mathrm{AD}_{p,d} = \begin{cases} 0 & \mathrm{DR}_{p,d} < \mathrm{Dmin} \\ \mathrm{DR}_{p,d} & \mathrm{Dmin} \le \mathrm{DR}_{p,d} \le \mathrm{Dmax} \\ \mathrm{Dmax} & \mathrm{DR}_{p,d} > \mathrm{Dmax} \end{cases} \tag{38}$$

where $\mathrm{ratd}_{p,d}$ represents the portion of demand for product p on day d out of the monthly demand $\mathrm{MD}_{p,m}$; $\mathrm{DR}_{p,d}$ is the raw demand amount for product p on day d; and $\mathrm{AD}_{p,d}$ is the actual demand amount after accounting for the minimum and maximum order size limits, Dmin and Dmax, respectively. Each $\mathrm{AD}_{p,d}$ represents one customer order.

If $\mathrm{AD}_{p,d} > 0$, then a customer order CO will be created

$$\mathrm{CO}^{\mathrm{amt}} = \mathrm{AD}_{p,d} \tag{39}$$

$$\mathrm{CO}^{\mathrm{pdt}} = p \tag{40}$$

Other order details, including grade, due date, packaging type, and customer location, are randomly generated from their respective predefined ranges.

3.5. Performance Indicators. The performance of the SC is measured through various key performance indicators (KPIs) such as profit and customer satisfaction. Profit is calculated as revenue from product sales minus costs. The various costs considered are raw material purchase costs, fixed and variable operating costs, packaging costs, delivery costs, inventory costs, and penalties for late delivery of products.

Revenues, processing costs, packaging costs, transportation costs, and penalties are specific to each job and can be calculated as follows

$$\mathrm{CJ}_l^{\mathrm{rev}} = \mathrm{Price}_{P,G}\mathrm{CJ}_l^{\mathrm{amt}} \tag{41}$$

$$\mathrm{CJ}_l^{\mathrm{pc}} = \mathrm{CostOV}_l\mathrm{CJ}_l^{\mathrm{pt}} \tag{42}$$

$$\mathrm{CJ}_l^{\mathrm{pkgc}} = \mathrm{CostPkg}_{l,W}\mathrm{CJ}_l^{\mathrm{np}} \tag{43}$$

$$\mathrm{CJ}_l^{\mathrm{tc}} = \mathrm{CostD}_l\mathrm{CJ}_l^{\mathrm{amt}}\sqrt{(x_l - \mathrm{CJ}_l^{\mathrm{xloc}})^2 + (y_l - \mathrm{CJ}_l^{\mathrm{yloc}})^2} \tag{44}$$

$$\mathrm{CJ}_l^{\mathrm{pen}} = \mathrm{Pen} \times \max(0, \mathrm{CJ}_l^{\mathrm{dt}} - \mathrm{CJ}_l^{\mathrm{dd}}) \tag{45}$$

where $P = \mathrm{CJ}_l^{\mathrm{pdt}}$, $G = \mathrm{CJ}_l^{\mathrm{grd}}$, and $W = \mathrm{CJ}_l^{\mathrm{pkg}}$ are the product type, grade, and packaging type of job CJ_l, respectively; $\mathrm{Price}_{P,G}$ is the price of product P of grade G; CostOV_l is the processing cost (charged when the plant is processing a job) of plant l; $\mathrm{CostPkg}_{l,W}$ is the cost of one package of type W at plant l; CostD_l is the delivery cost per unit distance per unit product for plant l; and Pen is the penalty cost per late day.

The profit for each plant l is calculated as

$$\mathrm{Profit}_l = \sum_{\mathrm{CJ}_l \in \mathrm{JobComp}_l} \mathrm{CJ}_l^{\mathrm{rev}} - \Bigg[\sum_{\mathrm{CJ}_l \in \mathrm{JobComp}_l} (\mathrm{CJ}_l^{\mathrm{pc}} + \mathrm{CJ}_l^{\mathrm{pkgc}} + \mathrm{CJ}_l^{\mathrm{tc}} + \mathrm{CJ}_l^{\mathrm{pen}}) + \sum_t \sum_r \mathrm{CostR}_{l,r}\mathrm{RA}_{l,r}(t) + \sum_t \sum_r \mathrm{CostI}_l\mathrm{IR}_{l,r}(t) + (\mathrm{CostOF}_l \times D \times T)\Bigg] \tag{46}$$

where $\mathrm{CostR}_{l,r}$ is the price of raw material r as purchased by plant l, CostOF_l is the fixed operating cost (charged at each tick regardless of whether the plant is processing or idle) of plant l, and CostI_l is the inventory cost per unit raw material per tick for plant l.

Customer satisfaction is measured as the percentage of deliveries that are on time out of the total number of orders accepted. For each plant l

$$\mathrm{CS}_l = \left(1 - \frac{\mathrm{NLO}_l}{\mathrm{NCO}_l}\right) \times 100\% \tag{47}$$

In addition to profit and customer satisfaction, plant utilization is another performance indicator

$$\mathrm{Util}_l = \frac{\mathrm{NPT}_l}{T} \times 100\% \tag{48}$$

Whereas each plant has its own local performance measures, we are also interested in the profit and customer satisfaction of the overall enterprise, which are obtained by combining the profits and customer satisfactions from all local plants

$$\mathrm{Profit} = \sum_l \mathrm{Profit}_l \tag{49}$$

$$\mathrm{CS} = \left(1 - \frac{\sum_l \mathrm{NLO}_l}{\sum_l \mathrm{NCO}_l}\right) \times 100\% \tag{50}$$

Other performance indicators of the overall enterprise are the number of missed orders, NMO, and the total tardiness

$$\mathrm{NLD} = \sum_l \mathrm{NLD}_l \tag{51}$$

3.6. Policies. 3.6.1. Job Assignment Policy. The simplest job assignment policy is equal assignment, where orders are assigned to all plants equally. If there are three plants, the first order is assigned to plant 1, the second to plant 2, the third to plant 3, the fourth again to plant 1, and so on

$$L = \mathrm{mod}\left(\frac{\mathrm{CO}^{\mathrm{id}}}{\mathrm{NL}}\right) \tag{52}$$

where NL is the number of plants.

Under the earliest completion date policy, the job is assigned to the plant that can deliver the product at the earliest. Here, the bids from schedulers contain the projected completion (delivery) dates

$$L = \arg\min_l(\mathrm{SchBid}_l) \tag{53}$$

Under the nearest customer location policy, the job is assigned to the plant that is nearest to the customer

$$L = \arg\min_l\left[\sqrt{(x_l - \mathrm{CO}^{\mathrm{xloc}})^2 + (y_l - \mathrm{CO}^{\mathrm{yloc}})^2}\right] \tag{54}$$

3.6.2. Scheduling Policy. Each customer order comes with a due date. The processing due date (PDD) for a job is calculated as

$$\mathrm{PDD} = \mathrm{CJ}^{\mathrm{dd}} - \mathrm{CJ}^{\mathrm{TT}} - \mathrm{CJ}^{\mathrm{PkgT}} - \mathrm{CJ}^{\mathrm{PT}} \tag{55}$$

PDD refers to the latest date that the plant should start processing the job in order for the finished product to reach the customer by the agreed-upon due date, considering the required processing, packaging, and transportation times. Under the PDD scheduling policy, new jobs are sequenced such that the jobs with the earlier PDDs are placed with higher priorities

$$\mathrm{JobSch}_l = \text{sort ascending}(\mathrm{JobSch}_l) \text{ according to PDD} \tag{56}$$

3.6.3. Procurement Policy. Different procurement policies can be adopted, such as fixed interval or reorder point. Under the fixed-interval policy, raw materials are purchased at a regular interval PC_l to bring the inventory up to certain top-up levels $\mathrm{RT}_{l,r}$

$$\mathrm{RP}_{l,r}(t) = \begin{cases} \mathrm{RT}_{l,r} - \mathrm{IR}_{l,r}(t) - \sum \mathrm{RW}_{l,r}(t) & \text{if } \mathrm{RP}_{l,r}(t) > 0, \quad t = i\mathrm{PC}_l, \quad i = 1, 2, 3, ... \\ 0 & \text{otherwise} \end{cases} \tag{57}$$

where $\mathrm{RT}_{l,r}$ is the inventory top-up level for raw material r at plant l, $\sum \mathrm{RW}_{l,r}(t)$ is the amount of raw material r that has been ordered but is yet to arrive at plant l, and i is the procurement cycle index.

Under the reorder point policy, raw material will be purchased when its inventory falls below the reorder point $\mathrm{RR}_{l,r}$

$$\mathrm{RP}_{l,r}(t) = \begin{cases} \mathrm{RT}_{l,r} - \mathrm{IR}_{l,r}(t) - \sum \mathrm{RW}_{l,r}(t) & \text{if } \mathrm{IR}_{l,r}(t) + \sum \mathrm{RW}_{l,r}(t) < \mathrm{RR}_{l,r} \\ 0 & \text{otherwise} \end{cases} \quad (58)$$

where $\mathrm{RR}_{l,r}$ is the reorder point for raw material r at plant l.

4. Illustrative Supply Chain Management Problems

The model described above has been implemented in Matlab/Simulink,[6] as shown in Figure 5. The value $T = 100$ and a fixed step solver with a step size of 0.01 day were used. Model parameters can be specified in the corresponding block, and product recipe can be specified in the corresponding m-file. The outputs from the simulation, namely, costs incurred, product revenue, profit, and various SC operational metrics including raw material inventory, current job processing time, are calculated in the display panel block. An ILAS simulation run for a 360-day horizon requires ∼600 s on an Intel Xeon, 3.0 GHz processor.

In the following seven case studies, the following settings were used: (1) There were three product types with five different grades for each product; each grade was produced using a specific combination of eight raw materials. (2) There were three plants: H, J, and S. (3) There was no time delay between operations and packaging (i.e., products from operations were instantly transported to packaging). (4) The processing time was the same for each product type regardless of grade, but differed between product types. (5) There was only one processing unit and one packaging unit. Only one job could be processed at a time; likewise for packaging.

This model can be used to study various supply chain problems. The nominal values for the model parameters are given in Tables 1 and 2. The product recipe is given in Table 3. The specific parameters used in each case study are listed in Table 4. Because of stochastic variations, the customer orders and the various SC operational metrics were different in each simulation run. Accordingly, the KPIs were different across simulation runs even for the same SC configuration and policies. Thus, for each case study, we performed 100 ILAS simulation runs and report the mean and standard deviation for each KPI.[20]

4.1. Case Study 1: Earliest Completion Date Assignment Policy. In the nominal case, the global sales department assigns jobs based on the equal assignment policy. Simulation reveals that this policy results in a low overall customer satisfaction (66%) and a high total tardiness (295 days), as shown in Table 5 (mean value followed by standard deviation within parentheses). This is because the orders are of varying sizes and due dates, but no consideration of these or the plants' existing commitment is taken in the assignment policy. An order might be assigned to a busy plant with large orders pending in its schedule rather than a plant with a lighter load that could deliver the order faster, leading to low customer satisfaction and high tardiness. In this case study, the job assignment policy is modified to consider the expected completion date from the plants. Under the earliest completion date policy, the sales department communicates with the scheduler of each plant to get the projected completion date for the current order from the schedulers. Sales assigns the order to the plant that can deliver at the earliest. For fair comparison with the previous equal assignment policy, all orders are accepted even when none of the plants' projected completion dates can meet the customer's due date. The effectiveness of this policy can be seen in Table 5. The earliest completion date policy results in a higher profit (15% increase), higher customer satisfaction (29% increase), and significantly lower tardiness (74% decrease), as orders are always assigned to the earliest plant. This case study shows that coordination between the global sales department and the plants can improve overall performance.

4.2. Case Study 2: Nearest Customer Location Assignment Policy. This case study compares the previously described earliest completion date assignment policy of the global sales department with another policy based on customer location. The

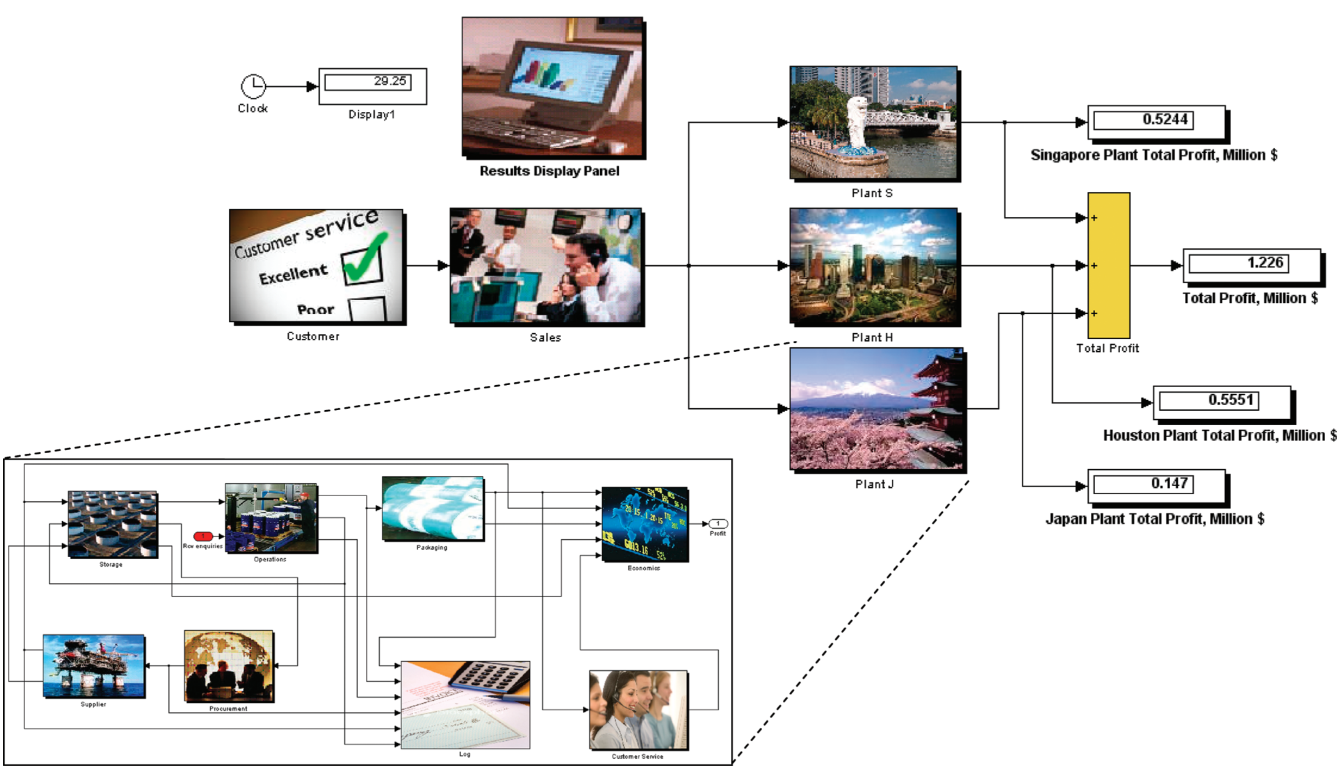

Figure 5. Integrated lube additive supply chain simulator (ILAS).

Table 1. Nominal Values for Global Entities' Model Parameters

ILAS block	parameter description	notation	value(s)
customer	frequency index	f_p	[0.3 0.4 0.6]
	minimum order size (unit)	Dmin	500
	maximum order size (unit)	Dmax	5000
	demand random seed		varies
	number of cycles in 360 days	CN_p	[2 2 2]
	amplitude of cycles (unit)	CA_p	[4 4 4]
	demand growth factor	DG_p	[8 8 8]/37000
	base daily demand (unit)	BD_p	[200 250 300]
	daily uncertainty limit ± (unit)	DDU_p	[5 5 5]
	product grade range		1−5
	due date range (days)		15−25
	packaging type range		1, 2
	customer location *x*-coordinate range		0−10
	customer location *y*-coordinate range		0−10
plant S	location coordinates	x_S, y_S	[3 3]
plant H	location coordinates	x_H, y_H	[7 3]
plant J	location coordinates	x_J, y_J	[5 8]
sales	job assignment policy		earliest completion date
	customer tolerance (days)		5

Table 2. Nominal Values for All Local Plant Entities' Model Parameters

ILAS block	parameter description	notation	value(s)
operations	processing time per unit product (days)	$PR_{l,p}$	[0.005 0.002 0.003]
	batch size (unit)	BS_l	1000
	processing time per batch (days)	$BC_{l,p}$	[2 2 2]
	scheduling policy	SP_l	PDD with late jobs consideration
	maximum processing delay (%)	PTU_l	10
	plant disruption start time		0
	plant disruption end time		0
packaging	packaging size (unit)	$PkgS_w$	[100 500]
	packaging time per package (days)	$PkgR_{l,w}$	[0.1 0.1]
	maximum packaging delay (%)	$PkgTU_l$	0
	transportation speed (days/unit distance)	TS	1
procurement	procurement policy	PP_l	reorder point procurement
	procurement cycle time (days)	PC_l	7
	reorder point (unit)	$RR_{l,r}$	[700 700 700 700 700 4500 4500 4500]
	top-up point (unit)	$RT_{l,r}$	[1000 1000 1000 1000 1000 5000 5000 5000]
supplier	raw material lead time (days)	$LT_{l,r}$	[4.3 4.3 4.3 4.3 4.3 4.3 4.3 4.3]
	maximum raw material delivery delay (%)	$LTU_{l,r}$	0
economics	product price ($/unit)	$Price_{p,g}$	[100 110 120 130 140; 200 210 220 230 240; 300 310 320 330 340]
	raw material price ($/unit)	$CostR_{l,r}$	[30 60 90 70 50 35 130 25]
	processing cost ($/tick)	$CostOV_l$	120
	fixed operating cost ($/tick)	$CostOF_l$	20
	packaging cost ($/package)	$CostPkg_{l,w}$	[100 200]
	raw material inventory cost [$/(unit tick)]	$CostI_l$	0.001
	late penalty ($/day)	Pen	500
	delivery cost {$/[unit(unit distance)]}	$CostD_l$	5
storage	initial raw material inventory (unit)	$IR_{l,r}(0)$	[1500 1500 1500 1500 1500 6000 6000 6000]

customer location policy assigns an order to the plant nearest to the customer if it can meet the due date. Otherwise, it will try the next-nearest plant. If no plant can meet the order's due date, the order will not be taken (i.e., missed order). This will minimize total transportation costs and might result in better profit. A simulation was run to compare the two assignment policies. The results are summarized in Table 6. The customer location policy results in lower customer satisfaction (4% decrease) and higher tardiness (55% increase). Orders are not assigned to the earliest plant, so there is less buffer from the due date compared to the earliest completion date policy, which always assigns orders to the earliest plant. This buffer helps to guard against processing time uncertainty (maximum processing delay of 10%, Table 2), so less buffer means a higher chance of tardiness due to processing delay. On the other hand, the customer location policy gives a higher profit (2.3% increase) as savings in transportation costs (13% decrease) more than offset the late penalties.

4.3. Case Study 3: Plant Disruption and Job Reassignment. This case study focuses on decision support in the case of a plant disruption. When a plant is disrupted, it cannot operate, and production is stopped. In this case, plant S is disrupted from day 75 to day 100. This will impact the job that is in process and the subsequent jobs in the schedule and might result in late deliveries and lower customer satisfaction. One possible mitigation strategy is through job reassignment. This can be done by sending the in-process job and subsequent jobs in the schedule of the disrupted plant back to the global sales department, which then reassigns these jobs to the other two plants. The disruption impact and the efficacy of this strategy can be evaluated through simulation. Three scenarios were

Table 3. Product Recipe ($RCP_{r,p,g}$)

		raw material type							
product	grade	1	2	3	4	5	6	7	8
A	1	0.1	0	0	0	0.1	0.8	0	0
	2	0	0.15	0	0	0.1	0.75	0	0
	3	0.05	0	0.15	0	0	0.8	0	0
	4	0	0.15	0.15	0	0	0.7	0	0
	5	0	0	0.2	0	0.1	0.7	0	0
B	1	0.15	0	0	0	0.15	0	0.7	0
	2	0	0.1	0	0	0.1	0	0.8	0
	3	0.2	0	0.1	0	0	0	0.7	0
	4	0	0.05	0	0.15	0	0	0.8	0
	5	0	0	0.15	0	0.1	0	0.75	0
C	1	0.1	0	0	0	0.15	0	0	0.75
	2	0	0	0.15	0	0.05	0	0	0.8
	3	0	0.2	0	0.1	0	0	0	0.7
	4	0.1	0	0	0.1	0	0	0	0.8
	5	0	0.15	0	0	0.15	0	0	0.7

Table 4. Parameters for the Case Studies

case study	changes from nominal case		
1	job assignment policy	AP	equal assignment, earliest completion date
	take all orders?		yes
2	job assignment policy	AP	earliest completion date, customer location
3	plant S disruption start time		75
	plant S disruption end time		100
4	scheduling policy	SP_l	PDD, PDD-LJS
5	procurement policy	PP_l	fixed-interval procurement
	procurement interval (days)	PC_l	7, 10, 14
	top-up point (unit)	$RT_{l,r}$	[100 100 100 100 100 160 400 270] × 1, ×1.4, ×2
	min order size (unit)	Dmin	200
	max order size (unit)	Dmax	1400
	raw material inventory cost [$/(unit tick)]	$CostI_l$	0.003
6	plant S processing time per unit product (days)	$PR_{S,p}$	[0.005 0.002 0.003] × 1, ×1.5
	plant S processing cost ($/tick)	$CostOV_S$	120, 90
	plant S max processing delay (%)	PTU_S	10, 25
7	maximum raw material delivery delay (%)	$LTU_{l,r}$	5, 20
	maximum order size (unit)	Dmax	2500
	reorder point (unit)	$RR_{l,r}$	[700 700 700 700 700 4500 4500 4500] × 0.8, ×1

Table 5. Comparison of KPIs for Case Study 1

	equal assignment	earliest completion date
overall profit (M$)	13.69 (0.86)	15.68 (0.87)
overall customer satisfaction	66% (12%)	85% (14%)
overall plant utilization	89% (3%)	90% (4%)
total tardiness (days)	294.53 (178.58)	75.62 (99.16)
simulation horizon	360 days	
BD_p multiplier	×1	
number of orders	±250	

Table 6. Comparison of KPIs for Case Study 2

	earliest completion date	customer location
overall profit (M$)	9.01 (0.88)	9.22 (0.90)
transportation cost (M$)	1.98 (0.13)	1.71 (0.09)
overall customer satisfaction	93% (3%)	89% (4%)
overall plant utilization	98% (1%)	97% (1%)
total tardiness (days)	2.88 (1.26)	4.47 (1.86)
number of missed orders	26.59 (4.21)	27.01 (4.15)
simulation horizon	180 days	
BD_p multiplier	×1.3	
number of orders	±125	

simulated: normal operation (i.e., no disruption), disruption with no reassignment, and disruption with reassignment. As shown in Table 7, the disruption causes significantly higher tardiness

Table 7. Comparison of KPIs for Case Study 3

	no disruption	no reassignment	with reassignment
overall profit (M$)	7.77 (0.68)	7.60 (0.66)	7.58 (0.67)
overall customer satisfaction	99% (1%)	98% (2%)	99% (1%)
plant S tardiness (days)	0.25 (0.66)	37.33 (29.2)	0.14 (0.40)
plant H tardiness (days)	0.21 (0.50)	0.39 (0.80)	0.60 (1.02)
plant J tardiness (days)	0.18 (0.48)	0.29 (0.84)	0.32 (0.94)
overall plant utilization	85% (5%)	84% (4%)	83% (4%)
number of missed orders	1.27 (1.23)	2.69 (2.06)	3.16 (2.21)
simulation horizon	180 days		
BD_p multiplier	×1.2		
number of orders	±125		

for plant S (37.33 days) compared to normal operation (0.25 day). With job reassignment, the tardiness of plant S can be brought down to 0.14 day, with very small increases in the tardiness of the other two plants and slightly more missed orders. This shows that cooperation among the plants, in this case through job reassignment, can help to manage disruption and mitigate its impacts.

4.4. Case Study 4: Scheduling Policy. This case study illustrates how the simulation model can be used to evaluate a new scheduling policy. Here, the global sales department employs the earliest completion date assignment policy. Before job assignment, each scheduler submits a proposed completion

Table 8. Comparison of KPIs for Case Study 4

	PDD	PDD-LJS
overall profit (M$)	19.14 (1.19)	19.37 (1.07)
overall customer satisfaction	65% (4%)	92% (2%)
overall plant utilization	97% (1%)	97% (1%)
number of missed orders	54.16 (5.76)	56.88 (5.93)

simulation horizon	360 days
BD_p multiplier	×1.3
number of orders	±250

Table 9. Comparison of KPIs for Case Study 5

	procurement interval (days)/top-up level		
	7/×1	10/×1.4	14/×2
overall profit (M$)	9.62 (0.95)	9.27 (0.96)	8.73 (1.04)
total inventory cost (M$)	2.02 (0.07)	2.36 (0.06)	2.92 (0.05)
total tardiness (days)	7.47 (4.83)	3.78 (2.19)	2.87 (1.70)
customer satisfaction	93.7% (2.8%)	94.7% (2.8%)	95.1% (2.9%)
overall plant utilization	98% (1%)	98% (1%)	98% (1%)
no of missed orders	21.95 (4.67)	21.78 (4.50)	21.88 (4.51)

simulation horizon	180 days
BD_p multiplier	×1.2
number of orders	±125

Table 10. Comparison of KPIs for Case Study 6

	sell	stay as is	upgrade
overall profit (M$)	13.12 (2.52)	15.95 (3.94)	16.32 (4.03)
overall customer satisfaction	89% (7%)	95% (4%)	96% (3%)
overall plant utilization	93% (8%)	86% (17%)	84% (19%)
number of missed orders	62.24 (40.10)	32.99 (22.05)	25.54 (17.18)

simulation horizon	180 days
BD_p multiplier	×1.2, ×0.8
number of orders	±125

Table 11. Comparison of KPIs for Case Study 7

	low-reliability 3PL		high-reliability 3PL	
	low reorder point	high reorder point	low reorder point	high reorder point
overall profit (M$)	13.68 (1.22)	15.94 (1.46)	19.69 (1.45)	19.51 (1.31)
overall customer satisfaction	68% (4%)	73% (5%)	91% (3%)	92% (2%)
overall plant utilization	67% (4%)	76% (4%)	97% (1%)	97% (1%)
number of missed orders	112.32 (8.78)	93.48 (8.97)	58.84 (5.42)	58.71 (5.30)

simulation horizon	360 days
BD_p multiplier	×1.3
number of orders	±250

date for the potential job to sales. This proposed completion date is obtained by inserting the potential job into its existing job schedule based on a scheduling policy and estimates the completion date considering all earlier jobs in the schedule. Sales assigns the job to the plant with the earliest proposed completion date. Currently, the scheduling departments of all three plants employ the PDD (processing due date) scheduling policy.

The SC manager notices that a number of customer orders are delivered late. Upon studying the scheduling policy, he finds that, when a new job is inserted into a slot in the schedule, this policy does not consider the due dates of the jobs in the slots after it. Therefore, he proposes a new policy similar to PDD with one modification: the scheduler will check to ensure that the insertion of the new job into the schedule will not result in any of the jobs behind it becoming late. Otherwise, the new job will be moved to the next slot, until no jobs behind it become late with its insertion. With this modification, a new job insertion should not affect the completion times of previously committed jobs such that they become late. These two policies, namely, PDD and PDD with late jobs consideration (PDD-LJS), were examined through simulation, and the results are reported in Table 8. The new policy significantly improves customer satisfaction from 65% to 92%. The new policy has slightly more missed orders because a potential job will be assigned a later position in the schedule compared to the PDD policy, so there is a higher chance of this later proposed completion date falling beyond the customer negotiation tolerance limit. Nevertheless, the profit from the new policy is still higher because less late delivery penalty is incurred. This case study shows that a small modification to a policy can have a significant impact.

4.5. Case Study 5: Procurement Policy. This case study focuses on the raw material procurement policy employed by the plants. Under the fixed interval procurement policy, the procurement department of each plant procures raw material at every fixed interval to a certain top-up level. The top-up level is set to be proportional to the interval length. A shorter interval means more frequent procurement; a lower top-up level is used, as less material will be required in the shorter interval compared to a longer interval. Three cases with different intervals and top-up levels were simulated, and the results are reported in Table 9. As the interval length increases, profit decreases as a result of higher inventory costs from having a higher top-up level. On the other hand, customer satisfaction increases, and tardiness decreases with a longer interval as a result of having a higher inventory buffer and fewer out-of-stock situations. This case study shows that the simulation uncovers and quantifies the tradeoff between profit and tardiness.

4.6. Case Study 6: Strategic Decision. This case study shows how simulation provides strategic decision support. In this scenario, plant S is aging, having 50% longer processing times than the other two plants and 2.5 times higher maximum processing delays, but 25% lower processing costs. The market is predicted to move in two possible directions: 0.7 probability of a 20% demand increase and 0.3 probability of a 20% decrease. Three strategic moves are considered by the enterprise: selling the old plant, upgrading it, or leaving it as is. Upgrading will restore plant S to its original processing time, maximum processing delay, and processing cost, which are equal to those of the other two plants. Selling and upgrading costs are assumed to be absorbed into the fixed operating costs. Simulation can quantify the enterprise performance for each strategic option in terms of both profit and customer satisfaction. For each option, a total of 100 simulation runs were conducted: 70 runs with 120% of the demand and 30 runs with 80% of the demand (BD_p in Table 1). Table 10 shows that, under this demand outlook, although staying as is might give similar profit and customer satisfaction in a number of cases, upgrading is the best option, as it gives the highest profit (16.32 M$) and customer satisfaction (96%).

4.7. Case Study 7: Dealing with Unreliable 3PL. In this scenario, there have been frequent late arrivals of raw materials due to low 3PL reliability. The enterprise is considering the possible options for dealing with this situation. One option is to have a higher reorder point to guard against supply uncertainty. (In this case study, all plants are using the reorder point procurement policy.) A second option is to switch to a more reliable 3PL. A simulation was run to quantify the benefits of these options. Four cases were considered: low-reliability 3PL (20% maximum delivery delay) and high-reliability 3PL (5%), each with a low reorder point and a high reorder point (25% higher). The results are shown in Table 11. The low-reliability 3PL with a low reorder point results in low utilization (67%) and low customer satisfaction (68%) because of the time spent waiting for raw materials to arrive. Having a high reorder point improves performance (76% utilization, 73% customer satisfaction), but not as significantly as switching to a high-reliability 3PL. In the high-reliability 3PL case, the performances for the two reorder points are comparable. Both are significantly better than the low-reliability 3PL case, so it is recommended to switch to the high-reliability 3PL.

In summary, these case studies demonstrate how the simulation model provides decision support for different decisions in multisite SCM: policy, disruption management, and strategic decisions.

5. Concluding Remarks

The complex dynamics in a multisite specialty chemicals SC necessitates the development of a simulation model to support SCM. The dynamic model presented in this article adequately captures the integrated SC operation. Its implementation in Matlab/Simulink, called ILAS, serves as a versatile tool for decision support in a variety of scenarios. Seven case studies demonstrate how the model enables experiments to analyze policies, optimize parameters, evaluate impacts of a disruption, devise disruption management strategies, and provide strategic decision support. It can also be coupled with an optimizer in a simulation−optimization framework for optimization studies.[21] Future work includes explicitly modeling negotiations between the different entities to study the benefits of different negotiating strategies between the customers and the global sales department, adding learning capabilities to enable the entities to adapt their policies to changes in the business environment, and further studies of collaboration and competition between the plants.

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Nomenclature

Indexes

d = day
g = grade
i = procurement cycle index
j = position in job schedule
l = plant
m = month
p = product
r = raw material
t = time tick
w = packaging type

Parameters

AP = job assignment policy of global sales department
$BC_{l,p}$ = batch-dependent processing time per batch of product p at plant l
BD_p = base demand level for product p
BS_l = batch size as limited by the reactor size at plant l
CA_p = cycle amplitude for product p
CN_p = number of cycles in one year (360 days) for product p
$CostD_l$ = delivery cost per unit distance per unit product for plant l
$CostI_l$ = inventory cost per unit raw material per tick for plant l
$CostOF_l$ = fixed operating cost of plant l
$CostOV_l$ = processing cost (charged when the plant is processing a job) of plant l
$CostPkg_{l,w}$ = cost of one package of type w at plant l
$CostR_{l,r}$ = price of raw material r as purchased by plant l
D = number of days in simulation horizon
DDU_p = daily demand uncertainty limit for product p
DG_p = demand growth factor for product p
Dmax = maximum order size limit
Dmin = minimum order size limit
f_p = order frequency index
$LT_{l,r}$ = nominal lead time for raw material r to plant l
$LTU_{l,r}$ = maximum percentage delay for transportation of raw material r to plant l
PC_l = procurement cycle interval at platn l
Pen = penalty cost per late day
$PkgR_{l,w}$ = packaging time per package of type w at plant l
$PkgS_w$ = packaging size of package type w
$PkgTU_l$ = maximum percentage delay for packaging of plant l
PP_l = procurement policy of plant l
$Price_{p,g}$ = price of grade g of product p
$PR_{l,p}$ = amount-dependent processing time per unit of product p at plant l
PTU_l = maximum percentage delay for processing of plant l
$RCP_{r,p,g}$ = recipe specifying the amount of raw material r required to make one unit of product p of grade g
$RR_{l,r}$ = reorder point for raw material r at plant l
$RT_{l,r}$ = inventory top-up level for raw material r at plant l
SP_l = scheduling policy employed by the scheduler of plant l
T = number of time ticks in one simulation day
TS = transportation speed
x_l = x coordinate of location of plant l
y_l = y coordinate of location of plant l

Variables

$AD_{p,d}$ = actual demand amount for product p on day d
$ALT_{l,r}$ = lead time between purchase and arrival for raw material r at plant l
$Assg_l$ = job assignment from global sales department to plant l
CallForBid = information sent by sales to schedulers to ask for bids
CJ^{amt} = amount ordered of job CJ
CJ^{dd} = due date of job CJ
CJ^{dt} = delivery time of job CJ
CJ^{grd} = product grade of job CJ
CJ^{id} = order index number of job CJ
CJ_l = job to be processed in plant l
CJ^{nb} = number of batches of job CJ
CJ^{np} = number of packages of job CJ
CJ^{pc} = processing cost of job CJ
CJ^{pdt} = product type of job CJ
CJ^{pen} = late delivery penalty of job CJ
CJ^{pkg} = packaging type of job CJ
CJ^{pkgc} = packaging cost of job CJ
CJ^{pkgt} = packaging time of job CJ
CJ^{pt} = processing time of job CJ
CJ^{rev} = revenue of job CJ
CJ^{st} = processing start time of job CJ
CJ^{tc} = transportation cost of job CJ
CJ^{tt} = transportation time of job CJ
CJ^{xloc} = customer location x coordinate of job CJ
CJ^{yloc} = customer location y coordinate of job CJ
CO = customer order
CO^{amt} = amount ordered in order CO

CO^{dd} = due date of order CO
CO^{grd} = product grade in order CO
CO^{id} = index number to identify a particular order CO
CO^{pdt} = product type in order CO
CO^{pkg} = packaging type in order CO
CO^{time} = time at which order CO is received by global sales department
CO^{xloc} = customer location x coordinate of order CO
CO^{yloc} = customer location y coordinate of order CO
CS = customer satisfaction
CS_l = customer satisfaction of plant l
$\mathrm{DD}_{p,d}$ = demand curve for product p
$\mathrm{DR}_{p,d}$ = raw demand amount for product p on day d
$\mathrm{IR}_{l,r}(t)$ = inventory level of raw material r at plant l at time t
J = index for earliest job in the schedule for which raw materials are available
$\mathrm{JobComp}_l$ = list of completed jobs of plant l
$\mathrm{JobSch}_{l,j}$ = job at sequence j in the schedule of plant l
JobSch_l = job schedule of plant l
L = plant selected by global sales department to be assigned an order
$\mathrm{MD}_{p,m}$ = monthly demand
NCO_l = number of customer orders assigned to plant l
NL = number of plants
NLD = total tardiness (in days)
NLD_l = total tardiness (in days) for plant l
NLO_l = number of late deliveries by plant l
NMO = number of missed orders
NPT_l = total processing time of plant l
OrdCfm = order acceptance confirmation from global sales department to customer
PDDmc = processing due date
Profit = profit
Profit_l = profit of plant l
$\mathrm{ProjJobSch}_l$ = projected job schedule of plant l
$\mathrm{PS}_l(t)$ = amount of time remaining to complete the current job in plant l at time t
$\mathrm{RA}_{l,r}(t)$ = amount of raw material r arriving at plant l at time t
$\mathrm{ratd}_{p,d}$ = portion of demand for product p on day d out of the monthly demand
$\mathrm{RMreq}_{l,r}$ = amount of raw material r required for processing the current job at plant l
$\mathrm{RP}_{l,r}(t)$ = amount of raw material r purchased at time t by plant l
$\mathrm{RU}_{l,r}(t)$ = amount of raw material r transferred from storage to the reactor at plant l at time t
$\Sigma\mathrm{RW}_{l,r}(t)$ = amount of raw material r that has been ordered but is yet to arrive at plant l at time t
$\mathrm{SalesIn}(t)$ = customer order received by global sales department at time t
SchBid_l = bid sent by scheduler of plant l to global sales department
Util_l = utilization of plant$l$

Stochastic Variables

α_d = stochastic variable governing daily uncertainty in demand curve
β = stochastic variable governing uncertainty in processing time
γ = stochastic variable governing uncertainty in packaging time
λ = stochastic variable governing uncertainty in raw material lead time
$\mu_{p,d}$ = stochastic variable governing demand occurrence and quantity

Literature Cited

(1) Srinivasan, R., Karimi, I. A., Vania, A. G. Business decision making in the chemical industry: PSE opportunities. In *Computer-Aided Chemical Engineering*; Marquardt, W., Pantelides, C., Eds.; Elsevier: New York, 2006; Vol. 21, pp 107−117.

(2) Sullivan, T. Special Report: Road to Recovery. Oronite Strives to Regain Customer Confidence. *Lube Rep.* **2006**, *6* (25).

(3) Maritan, C. A.; Brush, T. H.; Karnani, A. G. Plant roles and decision autonomy in multinational plant networks. *J. Oper. Manage.* **2004**, *22*, 489–503.

(4) Pitty, S. S.; Li, W.; Adhitya, A.; Srinivasan, R.; Karimi, I. A. Decision support for integrated refinery supply chains: Part 1. Dynamic simulation. *Comput. Chem. Eng.* **2008**, *32*, 2767–2786.

(5) Koo, L. Y.; Adhitya, A.; Srinivasan, R.; Karimi, I. A. Decision support for integrated refinery supply chains: Part 2. Design and operation. *Comput. Chem. Eng.* **2008**, *32*, 2787–2800.

(6) *Simulink User's Guide*; The MathWorks, Inc.: Natick, MA, 2007.

(7) Tsiakis, P.; Papageorgiou, L. G. Optimal production allocation and distribution supply chain networks. *Int. J. Prod. Econ.* **2008**, *111*, 468–483.

(8) Ferrio, J.; Wassick, J. Chemical supply chain network optimization. *Comput. Chem. Eng.* **2008**, *32*, 2481–2504.

(9) You, F.; Grossmann, I. E. Design of responsive supply chains under demand uncertainty. *Comput. Chem. Eng.* **2008**, *32*, 3090–3111.

(10) Timpe, C. H.; Kallrath, J. Optimal planning in large multi-site production networks. *Eur. J. Oper. Res.* **2000**, *126* (2):), 422–435.

(11) Verderame, P. M.; Floudas, C. A. Operational planning framework for multisite production and distribution networks. *Comput. Chem. Eng.* **2009**, *33*, 1036–1050.

(12) Dondo, R.; Mendez, C. A.; Cerda, J. Optimal management of logistic activities in multi-site environments. *Comput. Chem. Eng.* **2008**, *32*, 2457–2569.

(13) Amaro, A. C. S.; Barbosa-Póvoa, A. P. F. D. The effect of uncertainty on the optimal closed-loop supply chain planning under different partnership structures. *Comput. Chem. Eng.* **2009**, *33* (12):), 2144–2158.

(14) Puigjaner, L.; Laínez, J. M. Capturing dynamics in integrated supply chain management. *Comput. Chem. Eng.* **2008**, *32*, 2582–2605.

(15) Mele, F. D.; Guillén, G.; Espuña, A.; Puigjaner, L. An agent-based approach for supply chain retrofitting under uncertainty. *Comput. Chem. Eng.* **2007**, *31*, 722–735.

(16) Wan, X.; Pekny, J. F.; Reklaitis, G. V. Simulation-based optimization with surrogate models—Application to supply chain management. *Comput. Chem. Eng.* **2005**, *29*, 1317–1328.

(17) Moon, C.; Kim, J.; Hur, S. Integrated process planning and scheduling with minimizing total tardiness in multi-plants supply chain. *Comput. Ind. Eng.* **2002**, *43* (1−2):), 331–349.

(18) Jung, J. Y.; Blau, G.; Pekny, J. F.; Reklaitis, G. V.; Eversdyk, D. Integrated safety stock management for multi-stage supply chains under production capacity constraints. *Comput. Chem. Eng.* **2008**, *32*, 2570–2581.

(19) Perea-López, E.; Grossmann, I. E.; Ydstie, B. E.; Tahmassebi, T. Dynamic Modeling and Decentralized Control of Supply Chains. *Ind. Eng. Chem. Res.* **2001**, *40*, 3369–3383.

(20) Tan, J. H. *A Model-Based Simulation−Optimization Decision Support Strategy for Multi-Site Specialty Chemical Manufacturer Supply Chain*; Final Year Project Report. Department of Chemical and Biomolecular Engineering, National University of Singapore: Singapore, 2009.

(21) Tan, J. H., Adhitya, A., Srinivasan, R. (2009). Multi-site specialty chemicals enterprise decision support through simulation−optimization. Presented in AIChE Annual Meeting, Nashville, TN8−13 November.

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