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INTEGRATION DESIGN OF SUPPLY CHAIN HYBRID SIMULATION

Wen Jun Tan
Wentong Cai

School of Computer Science and Engineering
Nanyang Technological University
SINGAPORE

Allan NengSheng Zhang

Singapore Institute of Manufacturing Technology
SINGAPORE

ABSTRACT

A supply chain (SC) consists of multiple entities representing the retailers, manufacturers, distributors or suppliers. A firm can be one of the entities within the whole SC. To study the external effects on its internal operations, the firm needs to construct a SC model. It may have sufficient data to build a detailed model of its operational processes. However, since it has no control or visibility over the external entities, it is difficult to construct the rest of the SC model at the same level of detail. This paper proposes a hybrid model of the SC using integration design. It allows the whole SC to be captured at the broad view through system dynamics, and the target firm to be represented using agent-based model. The proposed hybrid model is therefore able to capture different behaviors of the same system, e.g, strategic planning of the whole SC, and detailed operational process of individual entities. To demonstrate the applicability of the hybrid model, we evaluate the model through a case study of disruption management policies.

1 INTRODUCTION

System dynamics (SD) are frequently used in high level strategic modeling of supply chain (SC) for long term decision-making (Lättilä, Hilletofth, and Lin 2010). Since the SD focus on the macro-level details in the SC, aggregated data is sufficient to calibrate the model. Typically, for public-listed companies, their annual account reports regarding the total sales and production volume are publicly available. Hence, parameters for a simulation of supply chain network (SCN) using SD could be calibrated easily based on publicly available data.

On the other hand, discrete event simulation (DES) is often used in short-term operational planning, due to the advantage of adaptability and modularity in modeling SC processes (Lättilä, Hilletofth, and Lin 2010). Agent-based simulation (ABS) can be used to simulate SCN, where each agent is a business entity within the SC, and the agents interact with each other within an environment through discrete events. However, the complexity of DES/ABS models increases exponentially with the size of the simulated system (Rabelo et al. 2005). In addition, a company may not have visibility and control over the whole SC. Detailed operational behaviors of all SC entities are not available, e.g., inventory or procurement policies of a business entity are not revealed to its business partners. Therefore, building a DES/ABS for the entire SC is difficult without all the operational behaviors and parameters.

To address these issues, this research proposes a hybrid model that combines SD with ABS in an integration design approach to simulate the entire SC. The broad view of the SC is modeled as SD, while the detailed operational processes of the entities are represented using agent-based model (ABM). Each entity within the SC can be either an SD entity, or an agent, depending on the problem scope. The combined model gives a single view of the whole SC. For instance, a firm decides to build a model of its SCN, to study the external effects of the whole SC on its internal operations. Due to the accessibility of external data and lacking of operation details of other entities in the SC, it restricts the applicability of the ABM.

By using a hybrid model, it can then build highly detailed model of its own operations using ABM, while modeling the external effects on the firm through SD.

The remaining of the paper is organized as follows: Section 2 reviews the existing hybrid approaches to model SC. Section 3 describes a hybrid model of SC, integrating SD and ABS. Section 4 illustrates the application of the hybrid model using a case study on supply disruption management. Section 5 describes the experiments to evaluate the trade-offs between different SC disruption management policies. The paper concludes in Section 6 with future works.

2 LITERATURE REVIEW

Previous research focuses on using different methods for different levels of decision domain, e.g. using SD at strategic level, or using DES at operational/tactical level (Tako and Robinson 2012). Hybrid models combine these approaches to provide an integrated decision-making system. There are several design approaches for combining different models.

Sequential design first used the SD model to capture the whole system under study, and then the DES model is used to focus on a specific process of the system (Morgan, Howick, and Belton 2017). There is usually a linear and unidirectional relationship between the models, where the output of one model is used as the input for the other model. Reiner (2005) proposed a combined usage of SD and DES: order fulfillment process using DES, whose performance indicators are used in the customer-orientated process evaluation using SD.

Interaction design is frequently used to capture the operational processes and interactive influences acting upon them (Morgan, Howick, and Belton 2017). Compared to sequential design, interaction design has bi-directional feedback between the models. For example, Wang et al. (2013) proposed a hybrid model: ABM models different departments within the SC, SD is used predict the production output and adjust the production rate based on the input from sale department (agent), and DES simulates the assembling process based on the production rates from the production planning (SD model). The assembled products are input to the sale department (agent) to be sold to customers.

Integration design combines DES and SD in the same model, taking the same view of the system. The two methods are inseparable and need to function together as a single model. This gives a concise and coherent view of the model, instead of separate results from each model to the end-users. Helal et al. (2007) proposed integrating DES and SD to simulate integrated manufacturing enterprise. An overall SD will be built for the enterprise system, and a number of DES models will be designed for the selected entity in the system as dictated by analysis needs.

The proposed model in this paper uses an integration design to integrate SD and ABM to form a single model. However, this model is flexible such that each entity in the SCN can be either a SD entity or an agent. Detailed description of the model is given in the next section.

3 SUPPLY CHAIN HYBRID MODEL

3.1 Supply Chain Network Model

The SC model studied in this paper is based on a typical multi-echelon manufacturing SC. First, the entire SCN is modeled as a flow network. Each node in the network represents a SC entity, e.g., manufacturers or suppliers. Given a single SC with three entities, upstream entity (e_h), current entity (e_i) and downstream entity (e_j), there are two directed edges between each entity: the information flow (*demand flow*) from the downstream entity to the upstream entity, and physical flow (*supply flow*) from the upstream entity to the downstream entity.

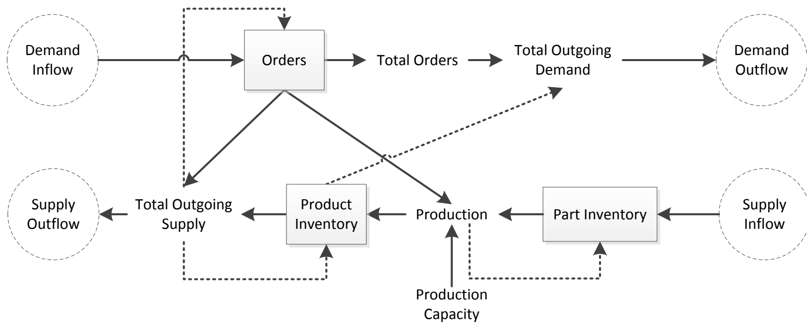


Figure 1: Casual loop diagram of a single SC entity. Solid arrows represent positive feedback loop while dotted arrows represent negative feedback loop.

3.2 System Dynamics Model

The SD model is created by simplifying the SD supplier model, originally proposed in (Tao, Lee, and Chew 2016), only considering the backorders, product inventory and production. It also includes part inventories. The model is extended to support multi-echelon manufacturing SCN instead of a two-echelon retail SCN. Figure 1 shows the casual loop diagram of a SC entity e_i. The definitions of model variables, parameters and generic equations that describe the relationships of the variables are described below, with the corresponding units.

In Figure 1, there are three stocks in the entity (shown in rectangles): orders o_j from each downstream entity e_j, part inventory I^{part} and the product inventory $I^{product}$. The arrows show the cause and effect relationships between the variables, with the solid arrows indicating positive feedback, and dotted arrows indicating negative feedback. The entity e_i has a set of downstream entities E_i^{in} where $e_j \in E_i^{in}$, and a set of upstream entities E_i^{out} where $e_h \in E_i^{out}$. Entities are connected to each other through the demand and supply flows. Each entity is constrained by the *production capacity*, which is the volume of products or services that can be produced by the entity.

First, the current pending orders $o_j(t)$ from each downstream entity e_j is the aggregation of the demand flow from each downstream entity $d_j^{in}(t)$ with the unfulfilled demand from the last period $o_j(t-1)$, minus the out-going supply $s_j^{out}(t)$ which is the fulfilled orders (1a). The total order quantity $O_i(t)$ is the sum of all pending orders (1b). The total outgoing demand $D_i^{out}(t)$ is the total order quantity subtracted by the existing product inventory $I_i^{product}(t)$ (1c). If there are available products in the inventory, it will be used to fulfill the demand directly. Then, the total outgoing demand is distributed according to the available upstream entities (1d).

$$\text{Orders from } e_j,\ o_j(t) = o_j(t-1) + d_j^{in}(t) - s_j^{out}(t-1) \text{ [Orders]} \tag{1a}$$

$$\text{Total Order Quantity, } O_i(t) = \sum_{e_j \in E_i^{in}} o_j(t) \text{ [Orders/Period]} \tag{1b}$$

$$\text{Total Outgoing Demand, } D_i^{out}(t) = O_i(t) - I_i^{product}(t) \text{ [Orders/Period]} \tag{1c}$$

$$\text{Demand Outflow to } e_h,\ d_h^{out}(t) = \frac{D_i^{out}(t)}{|E_i^{in}|} \text{ [Orders/Period]} \tag{1d}$$

The supply inflow $s_h^{in}(t)$ is aggregated with left-over parts from the last period $I_i^{part}(t-1)$ (2a), subtracted by amount of parts used in production $P_i(t-1)$, to form the current part inventory $I_i^{part}(t)$. Based on the production capacity $\mathscr{C}_i$, current total demand $O_i(t)$ and available parts $I_i^{part}(t)$, product is manufactured (2b).

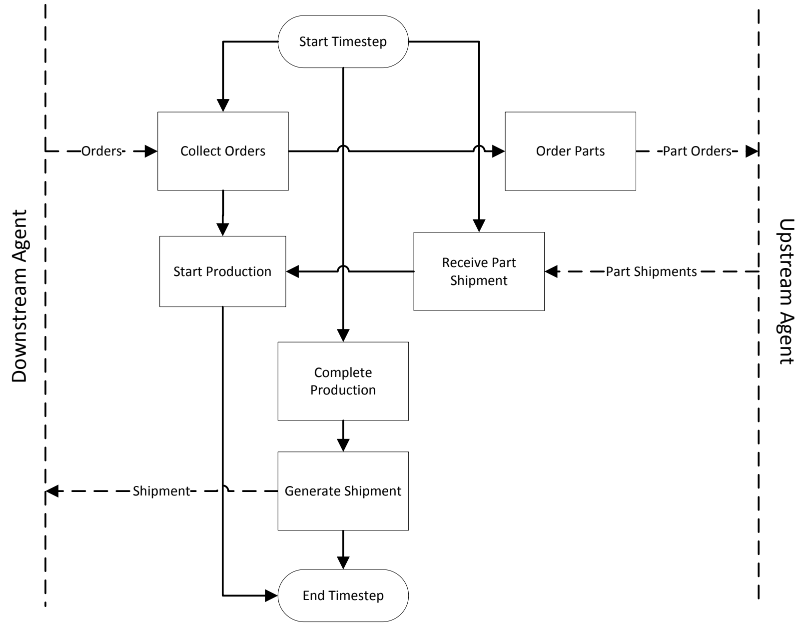


Figure 2: Agent model for a single SC entity.

The manufactured product is added to the product inventory $I_i^{product}(t)$, including surplus of products from last period $I_i^{product}(t-1)$ (2c), and subtracting the fulfilled supply $s_j^{out}(t-1)$. The total outgoing supply $S_i(t)$ depends on the current orders $O_i(t)$ and existing products in the inventory (2d). Outgoing supply $s_j^{out}(t)$ is distributed among the downstream entities proportional to the pending demand (2e).

$$\text{Part Inventory, } I_i^{part}(t) = I_i^{part}(t-1) + \sum_{e_h \in E_i^{out}} s_h^{in}(t) - P_i(t-1) \text{ [Parts]} \tag{2a}$$

$$\text{Production, } P_i(t) = \min(O_i(t), \mathscr{C}_i, I_i^{part}(t)) \text{ [Products/Period]} \tag{2b}$$

$$\text{Product Inventory, } I_i^{product}(t) = I_i^{product}(t-1) + P_i(t) - S_i(t-1) \text{ [Products]} \tag{2c}$$

$$\text{Total Outgoing Supply, } S_i(t) = \min(O_i(t), I_i^{product}(t)) \text{ [Products/Period]} \tag{2d}$$

$$\text{Supply Flow to } e_j\text{, } s_j^{out}(t) = \frac{o_j(t)}{O_i(t)} \times S_i(t) \text{ [Products/Period]} \tag{2e}$$

3.3 Agent-Based Model

In ABM, each entity is modeled as agents, which interacts with others by generating discrete events. There are two types of discrete events: *orders* represent the demand, and *shipment* represent the supply. The simulation is executed by time-step, where each time step represents a day of operation in the SC. At every time step, each agent interacts with each other by exchanging orders and shipments. Every agent has the same general behavior, which is shown in Figure 2. This is an extension of the agent-based model of manufacturing SC, originally proposed in (Tan, Li, and Cai 2015), including production operations in the entity.

At the start of each time step, the agent will collect all the pending orders from its downstream agent in an order queue. Assuming one unit of part is required to manufacture one unit of product, the agent makes part orders to its upstream agents based on its inventory policy. When the inventory level falls below the safety stock, the agent will generate a replenishment order to the upstream agent that will restore the inventory to the safety stock. The review period is set to every time step. When the upstream agent fulfills the part orders and delivers the part downstream, the agent will collect the part shipments and increase the part inventory according to the shipment quantity received.

Based on the availability of parts, pending orders and production capacity ($\mathscr{C}_i$), new *production* is generated. The manufacturing process completes the production based on the production time, and adds the produced quantity to the product inventory. According to the pending orders and available product in the inventory, shipment will be created and sent downstream.

3.4 Hybrid Model

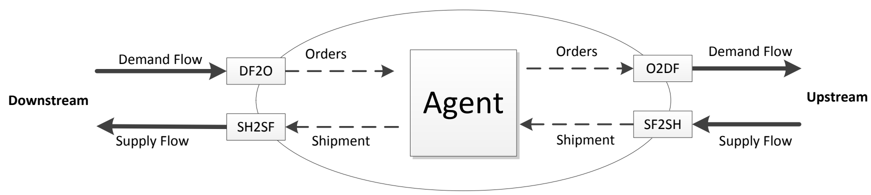


Figure 3: Integration of Agent model with SD.

This hybrid model uses the *integration design* (Morgan, Howick, and Belton 2017), where both models have the same view of the system and executes together. SD uses continuous time (executing in fixed time step with integration interval) to interact with ABS executing at fixed time step. ABS executes at time step (t_D), while SD is executes in time step (t_C). To synchronize between the continuous and discrete simulation, t_C is at a finer time resolution compared to t_D. The data exchange occurs at the discrete time step t_D.

By replacing a SC entity in the SD model with the corresponding agent model, this allows the agent model represents the high level details of a SC entity, while allowing the SD model to capture the broad view of the whole SC. Adapters need to be created to wrap around an agent to convert between the discrete events and corresponding flows, as shown in Figure 3.

Continuous to discrete adapters contain buffers to accumulate flows during the continuous time. Discretization of the flows depends on the *lot size* defined for the order and shipment. In the real world SC, the lot size is determined by the two entities when they are performing the transaction. The value of lot size depends on the modeler. At each discrete time step, the adapter will generate discrete events based on the lot size. Similarly, *discrete to continuous* adapters receive the discrete event, and generate the corresponding flow quantity. Given the order lot size L^{order}, and shipment lot size $L^{shipment}$, conversion procedure for continuous to discrete adapters are shown in Table 1, and discrete to continuous adapters in Table 2.

There are four types of adapters to convert between the flows and the discrete events, as shown in Figure 3. Demand flow to Orders (DF2O) converts the demand flow into discrete orders to be sent to the agent. It accumulates the demand flow during the continuous time into a buffer, and discretizes into discrete orders based on the order lot size. After processing the orders, the agent may submit orders to suppliers if there are insufficient parts. Orders to Demand Flow (O2DF) receives the part orders, and convert them to demand flow upstream. The upstream entity processes the demand flow, and generates the corresponding supply flow downstream. Supply Flow to Shipment (SF2SH) accumulates the supply flow into a buffer, and discretizes into discrete part shipment based on the shipment lot size. Shipment to Supply Flow (SH2SF) receives the product shipment, and convert them to supply flow downstream.

Table 1: Continuous to Discrete Adapters.

Adapter	Continuous	Discrete

Demand Flow to Orders (DF2O)	$\text{Buffer}_d \mathrel{+}= d_j$	**while** $\text{Buffer}_d > L^{order}$ **do**
		Generate new Order(Quantity = L^{order}, Time = t_D)
		$\text{Buffer}_d \mathrel{-}= L^{order}$
		end while

Supply Flow to Shipment (SF2SH)	$\text{Buffer}_s \mathrel{+}= s_h$	**while** $\text{Buffer}_s > L^{shipment}$ **do**
		Generate new Shipment(Quantity = $L^{shipment}$)
		$\text{Buffer}_s \mathrel{-}= L^{shipment}$
		end while

Table 2: Discrete to Continuous Adapters.

Adapter	Discrete	Continuous
Orders to Demand Flow (O2DF)	$d_h \mathrel{+}=$ Order.Quantity	$d_h \rightarrow$ upstream
Shipment to Supply Flow (SH2SF)	$s_j \mathrel{+}=$ Shipment.Quantity	$downstream \leftarrow s_j$

4 CASE STUDY

4.1 Disruption Management Policies

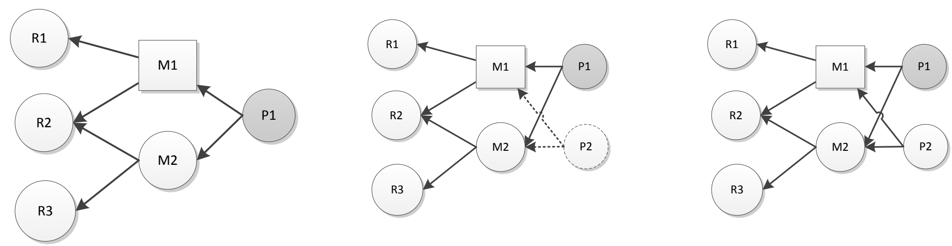
There are two general approaches to handle the impact of disruptions. *Mitigation policies* are those in which the firms take some action in advance of a disruption, and thus incur cost of the action regardless of whether the disruption occurs (Tomlin 2006). One of the common practices for mitigation policies is sourcing from more than one supplier. If the one of the suppliers is down during the disruption, other suppliers can still fulfill the demand of the firm. However, multi-suppliers can be more costly due to the increase in ordering costs (Arda and Hennet 2006). During normal scenario, the demand is split between the suppliers, reducing the quantities ordered per supplier. Therefore, it is difficult to negotiate for lower price of the supplies due to economies of scale.

Contingency policies are actions that are only taken when the disruption occurs. Hence, the cost of action is incurred only during activation of the contingency policy. Contingent re-routing seeks alternative suppliers during disruption, where the demand will be rerouted to the backup supplier when the primary supplier is not available (Tomlin 2006). However, a backup supplier often charges a higher cost than regular suppliers (Tomlin 2009). The backup supplier may need to activate additional manpower in order to fulfill the increase in demand, which transmit into higher costs.

4.2 Supply Chain Network

One of the SCNs (`SC01`) from the data set of multi-echelon SCs has been selected to be used in the case study (Willems 2007). This SCN is simplified to consider a single product, where the manufacturer only requires one type of parts to manufacture one type of products. There are three retailers in the network (*R1*, *R2* and *R3*), two manufacturers (*M1* and *M2*), and one part supplier (*P1*), as shown in Figure 4a. The arrows in the network represent the supply flow. The firm of interest is *M1*, where it is modeled using an agent. Other entities are modeled using SD.

The most common way to model disruption is to assume that the supply process has two states: functioning normally, and disrupted (Snyder et al. 2016). During disruption, supplier P_1 will be down, and it will be up after the disruption. Disruptions can be infrequent but long, or frequent but short. Figure 4 shows three disruption management policies that are examined in this case study. The acceptance policy is shown in Figure 4a, where there is only a single supplier. Contingent policy is shown in Figure 4b, where the backup supplier *P2* is only utilized during disruption. As a contingent supplier, *P2* is configured with the same parameters as *P1*. The demand will be re-routed to *P2* during the disruption. Figure 4c is shows



(a) Single Supplier. (b) Contingent Supplier. (c) Multi-Suppliers.

Figure 4: Different SC disruption management policies.

the mitigation policy where dual suppliers (*P1* and *P2*) are used. The demand is split evenly between the two suppliers, where each supplier provide half of the total supply required by *M1*. During disruption, only the remaining supplier will be able to fulfill half of the total demand.

The impact of various costs on the attractiveness of a given policy is of an interest to the firm. By simulating across a spectrum of disruption profiles, we can analyze the cost-effectiveness in terms of two metrics: *backorder cost* and *ordering cost*. Backorder cost is the cost incurred by a firm when it is unable to fill an order and must complete it later. The backorder cost accumulates at a constant rate proportional to both the backorder volume and backlog duration (Hu, Kim, and Banerjee 2009). Purchasing or ordering cost is the cost involved in sourcing the product from the suppliers, which a simple model assumes the cost to be linear to the amount purchased (Scarf 1959).

Trade-offs between these policies and trade-off between backorder cost and ordering cost are analyzed and shown in the next section.

5 EXPERIMENT

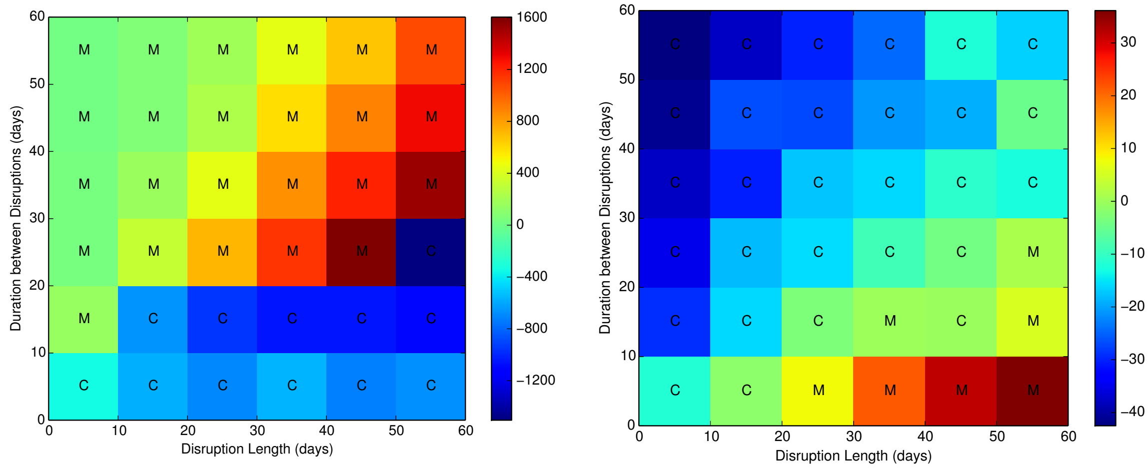
5.1 Setup

The SD model is calibrated with the demand data from Willems (2007). Based on the demand data, the supply or production capacity for each entity is assumed to be 10% more than the demand on the entity. This is to allow flexibility in the SC such that it is possible to clear the back-orders.

The entity *M1* is modeled as an agent. Other than the demand data, the production lead time and ordering cost from Willems (2007) is also used to calibrate the parameters for the agent. The remaining parameters are based on assumptions. There is an ordering lead time of 1 day, and shipment lead time of 1 day (Tan, Li, and Cai 2015). The order lot size L^{order} and shipment lot size $L^{shipment}$ are both set to 50 units. Assuming that the production lead time for e_i is $t_i^{production}$, ordering lead time t^{order}, and shipment lead time $t^{shipment}$, the safety stock for e_i is $s_i = \mathscr{C}_i \times (t_i^{production} + t^{order} + t^{shipment})$.

The simulation is executed for a period of 2 years, after running for 1 year as warm up. The agent is executed with a time step of 1 day, while the system dynamic entities execute at a time step of $\frac{1}{2}$ day. Disruption length and interval between disruptions are configured according to the experiment in the next sections. However, a firm may not respond immediately to a disruption at a supplier (Arda and Hennet 2006). For this case study, contingent supplier is activated at the middle of the disruption, for a period equals to the disruption length. Assume that the start of the disruption is at time t_s for a duration of T_d, the time when contingent supplier is activated equals $t_s + \frac{T_d}{2}$.

Two metric are used to measure the performance of the agent *M1*: backorder cost B and ordering cost C. To differentiate the additional expense of applying disruption management policies, there is a cost multiplier on the backorder cost α and the ordering cost β for both polices. Assume that the cost



(a) Optimal Policies for Backorder Cost.

(b) Optimal Policies for Ordering Cost.

Figure 5: Optimal Disruption-management Policies (M $\rightarrow$ Multi-suppliers, C $\rightarrow$ Contingent Supplier).

of ordering from the regular supplier is 1, if the ordering cost per unit for multi-suppliers or contingent supplier is 20% more than regular supplier, $\beta = 1.2$. For an agent e_i, the backorder cost for time step t is defined as $B(t) = O_i(t) \times \alpha$. While the ordering cost for time step t is defined as:

$$C(t) = \begin{cases} d_h^{out}(t) \times \beta & \text{, if } h \text{ is contingent or multi-supplier} \\ d_h^{out}(t) & \text{, if } h \text{ is regular supplier} \end{cases} \tag{3}$$

The cost multiplier for each policy may not be the same, depending on the experiment.

5.2 Disruption Scenarios

Figure 5 shows the optimal disruption-management policies across different disruption scenarios. The length of disruption, and the duration between each disruption are varied. Disruptions are frequent but short at the bottom left of the figure, and rare but long at the top right. Cost multipliers are set as $\beta = 1$ and $\beta = 1.2$. The heat map shows the region for a more optimal policy. If multi-suppliers is more optimal compared to contingent supplier, the heat map will be labeled as M, with reddish color as the intensity of comparison. Otherwise, if contingent supplier is more optimal, it is labeled as C, with bluish color as the intensity of comparison.

Figure 5a shows a heat map of the *range* of average per day backorder cost for multi-suppliers or contingent supplier. Color intensity represents the average backorder cost, with darker color for higher cost. The policy with lower backorder cost is more optimal. We can see that when the interval between the disruptions is low, contingent suppliers will have a lower backorder cost compared to multi-suppliers. Even thought the disrupted supplier recovered after disruption, it does not have sufficient capacity to fulfill the back-orders. Since the contingent supplier is engaged even after the disruption ended, it is able to clear the backorders.

When the interval between the disruptions increases, a multi-suppliers has a lower backorder cost compared to contingent suppliers. With sufficient time between disruption, multi-suppliers are able to clear the backorders. Since contingent supplier is only activated after certain period after the disruption, the firm is unable to manufacture anything during this period, resulting in high backorder cost. Whereas with multi-suppliers, at least the firm is able to continue with production at lower capacity, depending on the remaining supplier. At around 20 to 30 days between disruptions with disruption length of 50 to 60 days,

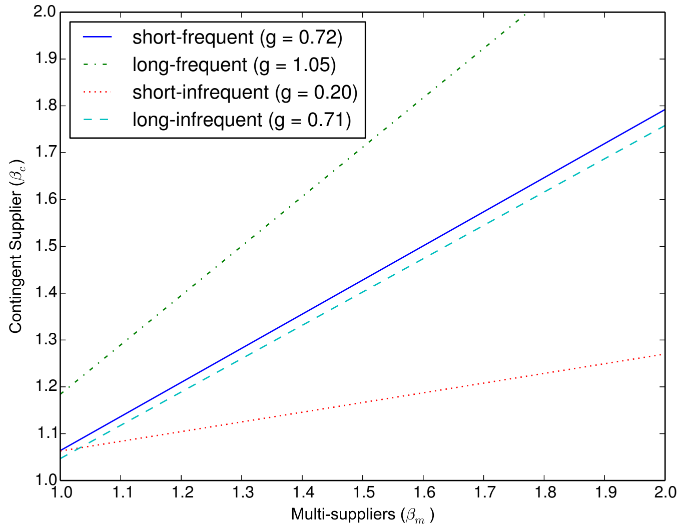


Figure 6: Ordering Cost trade-off between Contingent Supplier and Multi-Suppliers. Gradient g of each line is shown in the legends.

both policies result in high backorder cost (showing dark red or dark blue). When the length of disruption increases, backorder cost will have the most impact when there is insufficient time to clear the back-orders.

Figure 5b shows a heat map of the *difference* between average per day ordering cost for multi-suppliers and contingent suppliers. Color intensity represents the amount of the absolute difference, with darker color for higher amount. When the interval between the disruptions is low and disruption length is high, multi-suppliers seem to have a lower ordering cost compared to contingent supplier. This is due to the multi-suppliers having lower order fulfillment compared to contingent supplier, resulting in lower overall ordering cost. The cost difference is highest at both up-left and bottom-right corners. Multi-suppliers incur higher ordering cost over time if there are few disruptions. The firm is paying for additional costs without any benefits from using multi-suppliers. Overall, contingent supplier will be cost-effective in terms of ordering costs if the multi-suppliers and contingent suppliers have the same cost multiplier.

5.3 Ordering Costs Trade-off

Figure 6 compares the trade-off between the policies based on different cost multiplier for each policy. The x-axis shows the cost multiplier for the multi-supplier (β_m), while y-axis shows the cost multiplier for the contingent supplier (β_c). There are four different disruption scenarios, varying between the disruption length (short or long), and interval between disruptions (frequent with short intervals or infrequent with long intervals). The lines represent the ordering cost where multi-suppliers is equals to the contingent supplier.

For most disruption scenarios, contingent suppliers are generally more cost effective in terms of ordering cost compared to multi-suppliers ($g < 1$). This is more prominent when the disruption is short and infrequent (dot line), where $g = 0.20$. It is because it only incurs very little addition cost to engage the contingent supplier only during a few short disruptions. However, multi-suppliers seems more cost-effective than contingent supplier for long and frequent disruption (dot-dash line), where $g = 1.05$. From the previous subsection, the lower ordering cost comes from lower order fulfillment.

To interpret this diagram, we can compare the ordering cost between polices under different disruption scenarios. For example, given a short and infrequent disruption, and the cost multipliers for different policies are $\beta_m = 1.8$ and $\beta_c = 1.1$. The point $(1.8, 1.1)$ is under the dot line. This indicates that contingent supplier will be more cost-effective in terms of ordering cost compared to multi-suppliers given the cost multiplier and disruption scenario. For another example, if $\beta_c = 1.3$, the point $(1.8, 1.3)$ is above the dot line. This means that multi-suppliers will be more cost-effective.

5.4 Total Relative Cost

Assuming $\beta = 1$, given that the average backorder cost for multi-suppliers is $\overline{B_m}$, and contingent supplier is $\overline{B_c}$, the normalized backorder cost for the multi-suppliers $\widehat{B_m}$ and for contingent supplier $\widehat{B_c}$ is shown below:

$$\widehat{B_m} = \frac{\overline{B_m}}{\max(\overline{B_m}, \overline{B_c})} \times \alpha \qquad\qquad \widehat{B_c} = \frac{\overline{B_m}}{\max(\overline{B_m}, \overline{B_c})} \times \alpha$$

Similarly, the average amount of orders fulfilled for multi-suppliers is defined as $\overline{C_m}$, and contingent supplier is $\overline{C_c}$. Assuming $\beta = 1.5$, the normalized ordering cost for the multi-suppliers $\widehat{C_m}$ and for contingent supplier $\widehat{O_c}$ is shown below:

$$\widehat{C_m} = \frac{\overline{C_m}}{\max(\overline{C_m}, \overline{C_c})} \times \beta \qquad\qquad \widehat{C_c} = \frac{\overline{C_c}}{\max(\overline{C_m}, \overline{C_c})} \times \beta$$

After normalizing the costs (back-order cost and ordering cost) between the policies, the total relative cost is calculated by aggregating the weighted metrics. Assume the weight for the ordering cost is w_1 where $0 \leq w_1 \leq 1$, and the weight for the backorder cost is $w_2 = 1 - w_1$. The total relative cost for multi-suppliers $TotalCost_m$ and contingent supplier $TotalCost_c$ is shown below:

$$TotalCost_m = \widehat{B_m} \times w_1 + \widehat{C_m} \times w_2 \qquad\qquad TotalCost_c = \widehat{B_c} \times w_1 + \widehat{C_c} \times w_2$$

Figure 7 shows the trade-off between backorder cost and ordering cost based on the two policies. X-axis represents the weight of the ordering cost w_1. Increasing w_1 will decrease the weight for the backorder cost w_2. Y-axis is the total relative cost. Policy with lower total relative cost is a more optimal.

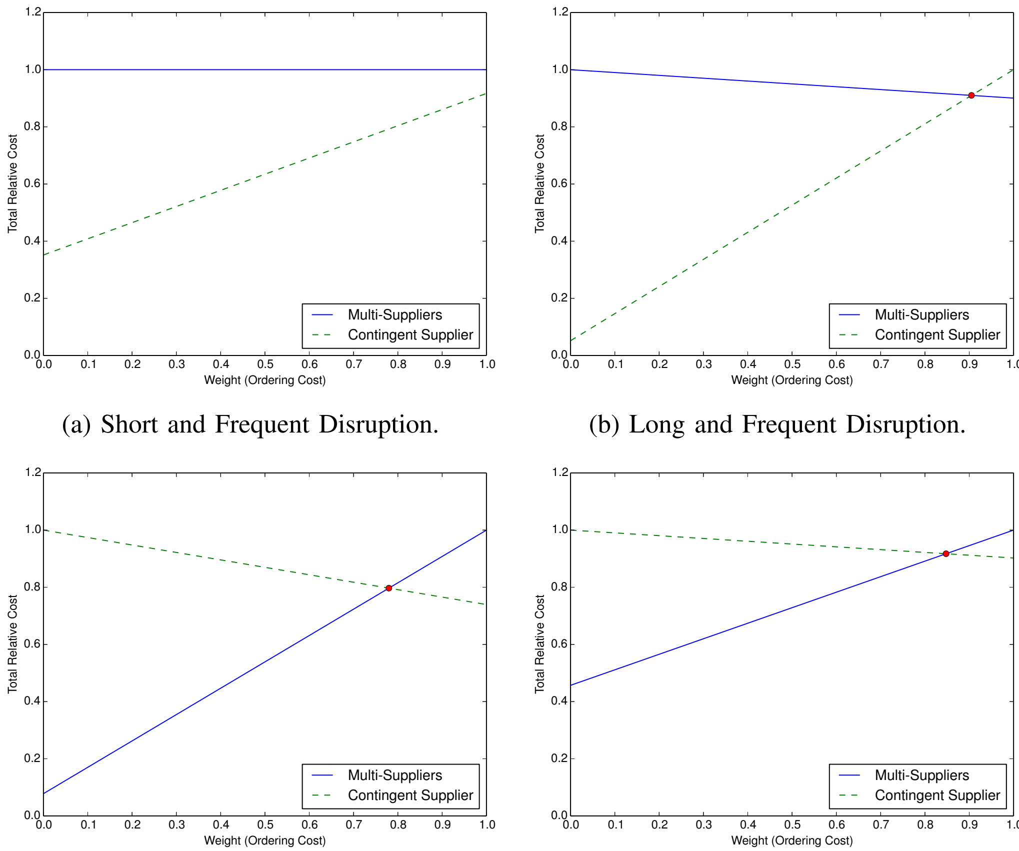
In Figure 7a, multi-suppliers is always more expensive than contingent supplier, as it is difficult to clear the backorders. These results shows that considering only ordering cost as shown in Figure 6 is insufficient for comparison between policies under short and frequent disruptions. In Figure 7b, multi-suppliers is generally more expensive than contingent suppliers due to the unfulfillment of back-orders. Multi-suppliers only becomes cheaper when $w_1 > 0.9$. This is similar in Figure 6 for the long and frequent disruptions (dot dash line), where multi-suppliers seems more cost-effective. Hence, frequent disruptions has a huge impact on the backorder cost for multi-suppliers (large gap between policies at lower w_1).

On the other hand in Figure 7c, multi-suppliers is cheaper compared to contingent supplier when w_1 is low. This is because multi-suppliers tend to have lower backorder cost compared to contingent supplier, as shown in Figure 5a at the top left. When w_1 increases, contingent supplier will be more cost-effective due lower ordering cost. This is similar in Figure 7d.

In summary, when the backorder cost is high (lower w_1): for frequent disruptions, multi-suppliers is more expensive due to the inability to clear backorders; for infrequent disruptions, contingent supplier is more expensive due to higher backorders. On the contrast, when the ordering cost is high (higher w_1), contingent supplier is generally more cost-effective.

6 CONCLUSION

A hybrid model of SC is proposed, combining SD and ABS using an integration design approach. Each entity in the SC can be represented by either a SD entity or an agent, interacting with each other through special adapters that convert between the continuous flow and discrete events. The number of agents in the model depends on (i) the availability of data to calibrate agent model parameters, or (ii) the level of detail needed for the study. There are several benefits of using the hybrid model. First, this allows the firm to



(a) Short and Frequent Disruption.

(b) Long and Frequent Disruption.

(c) Short and Infrequent Disruption.

(d) Long and Infrequent Disruption.

Figure 7: Trade-off between Backorder Cost and Ordering Cost.

construct a broad view of the whole SCN based on aggregated data through SD. Next, it allows the firm to perform in-depth analysis regarding its own performance by modeling detailed processes using an agent.

A case study on disruption management policies is used to illustrate the applicability of the hybrid model. A firm is interested to find out the optimal disruption management policies during disruption. Two disruption management policies are studied: mitigation policy using multi-suppliers and contingency policy using contingent supplier. Trade-offs between these policies and trade-offs between backorder cost and ordering cost are analyzed and shown in the experimental results.

As for future works, further validation on the interaction between SD model and agent model is required, especially considering the effects of lead-time delays in the SC. This will involve performing the same experiment with different mixture of SD models and agent models. Additional operational behaviors, e.g. production scheduling, can be implemented in the agent model, to study the external effects on the internal operations of the firm. Similarly, internal disruptions, such as changes to the production process, can be investigated. This will extend the applicability of this model to the analysis of real world issues.

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AUTHOR BIOGRAPHIES

WEN JUN TAN is a PhD student at Nanyang Technological University (NTU). His main research interests are modeling and simulation of complex supply chains. His e-mail address is wtan047@e.ntu.edu.sg.

WENTONG CAI is a Professor in the School of Computer Engineering at Nanyang Technological University (NTU), Singapore. His expertise is mainly in the areas of Modeling and Simulation, and Parallel and Distributed Computing. His email address is aswtcai@ntu.edu.sg.

ALLAN NENGSHENG ZHANG is a Senior Scientist in the Singapore Institute of Manufacturing Technology (SIMTech). His research interests include knowledge management, data mining, machine learning, artificial intelligence, computer security, software engineering, software development methodology and standard, intelligent control systems and enterprise information systems, Color management and control systems. His email address is nzhang@simtech.a-star.edu.sg.