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SUPPLY CHAIN DISRUPTION ANALYSIS IN THE MULTI-ECHELON SYSTEM USING DISCRETE EVENT SIMULATION

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Abstract. *As modern supply chain network becomes complex globally dispersed system, vulnerability also increases. Large scale supply chain disruption is rare but the shock-wave created by a disruption creates unforeseen damage in entire supply chain. Because of recent supply chain disruption, many academic researches emerge seeking mitigation strategies. In this paper, we develop a discrete event simulation model for a three-echelon supply chain that assesses the performance of the dual sourcing with respect to various disruption probability, backup options, and recover strategies.*
Keywords: Supply chain disruption, Discrete event simulation, Disruption mitigation, Arena

1. **Introduction.** As the modern supply chain evolves into less vertically integrated globally dispersed network, the complexity and vulnerability inside supply chain increase rapidly. A firm procuring raw materials and parts from multiple oversea suppliers, any disruption in one of suppliers halts production and supply shortages occur. In distribution network, centralized warehouse utilizes economies of scale and risk pooling effects but any failure in a centralized warehouse creates more damage than the decentralized system.

Various supply chain risks are classified as disruptions, delays, systems, forecast, intellectual property, procurement, receivables, inventory, and capacity [1]. Disruption is an unpredictable rare event that disrupts the normal flow of goods and materials within a supply chain that has devastating impacts through supply chain. Recent supply chain disruption events include: Mattel recalled 19 million toys due to lead paint and loose magnets in 2007. Ericsson suffered $2.34 billion loss for the mobile phone division due to 10 minute fire in Phillips semiconductor plant in Albuquerque, New Mexico 2000. Intel suffered $1 billion revenue loss due to severe flooding in Thailand causing shortage of hard drive supply in 2011. Toyota halted 14 assembly plants due to fire in brake parts supplier Aisin Seiko plant in Japan 1997. In 2011, Tohoku earthquake and following tsunami halted automotive semiconductor plants in Japan and North American and European auto makers' entire supply chain stop [2-4].

Sources of disruption are operational contingencies (equipment and system failure, supplier bankruptcy, labor strikes, fire), natural disasters (hurricanes, earthquake), terrorism, political instability, equipment breakdowns, product defects, and transit/custom delays [5].

Previous research on supply chain disruption suggests various mitigation strategies: dual sourcing, inventory mitigation, and facility location and design. Inventory control, dual sourcing, and acceptance strategies are presented for a single-product two-supplier model using base stock policy. Optimal mitigation strategy for frequent-short disruptions in unreliable supplier with infinite capacity/inflexible reliable supplier is backup inventory while for rare long disruptions, dual sourcing is optimal [6,7]. Optimization methodology was also used for optimal design of supply chain network under disruption. A linear programming based optimization model was developed to compute risk-exposure index of downstream nodes of an upstream node failure during predefined periods [8]. Generalized facility location model and a variant of P-median models minimizing expected total cost are also developed when each facility has disruption probability [9].

While many optimization models use static parameters, to evaluate the impact of disruption and to assess mitigation strategies in a more dynamic setting, various simulation models are developed. Simulation models can be used to calculate risk exposures of the existing supply chain network. A discrete event simulation model for a three-echelon network of a consumer packaged goods company was developed [10]. Disruption frequency and duration were modeled using a Monte Carlo simulation package using surveys of client company. Another Monte Carlo simulation combines @Risk and network flow model that computes path flow averages when a node or an arc fails [11]. Adaptive ordering policy is examined in a multi-echelon network using agent simulation [12]. Related with the supply chain risk management, business continuity management (BCM) is a corporate governance standard developed for auditing and assessing organization's preparedness for business disruptions [13].

In this paper, we describe performance of a discrete event simulation model for three-echelon supply chain based on Arena simulation software. In the proposed model, each supply chain node's source, make, and deliver subsystems are separately modeled according to the supply chain operation reference (SCOR) model; disruptions are assumed to occur at make and deliver subsystems independently so the proposed model can capture aggregated upstream node/link failure effects to the downstream node; using generated failure data, one can estimate disruption probability distribution in the proposed model without commercial Monte Carlo simulator.

This paper is organized as follows. In Section 2, SCOR based supply chain and (s, S) inventory policy, disruption models are described. In Section 3, simulation results are presented for two-echelon and three-echelon system with backup strategy, down probability, and ramp up time variations and Section 4 concludes the paper.

2. **Simulation Model.** A general supply chain consists of multiple components including manufacturer, supplier, transporter, warehouse, and retailers. The supply chain operation reference (SCOR) is developed by the supply chain council (SCC). SCOR is a process reference model containing standard description of management processes as well as measurement metrics and best practices [14]. A single node in a supply chain network is modeled as five management processes in SCOR: plan, source, make, deliver, and return. In our simulation model, we only include source, make, and deliver.

Generic five management processes composing a supply chain network are presented in Figure 1. The simulation model developed here consists of a distribution center (DC) generating demand, a manufacturing plant (M1) replenishing orders from DC, a backup inventory warehouse (BI), a backup manufacturing plant (M2), and two suppliers (S1, S2) replenishing M1 and M2. Each node in this system are made of source (S), make (M), or deliver (D). Entire model is presented in Figure 2. Using Arena simulation software, M is modeled using 'Process' module, D is modeled using 'Transport' module with truck capacities and truck 'Resource' module, and S is modeled as a generic (s, S) policy with

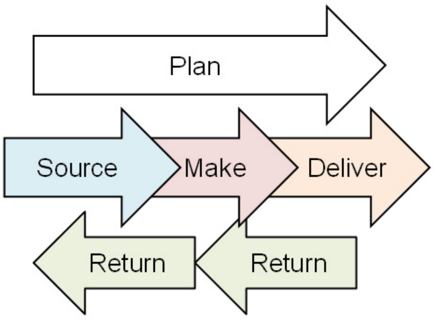

FIGURE 1. SCOR model of a generic supply chain node

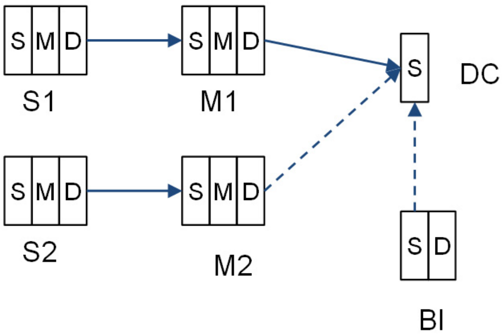

FIGURE 2. Multi-echelon supply chain simulation model

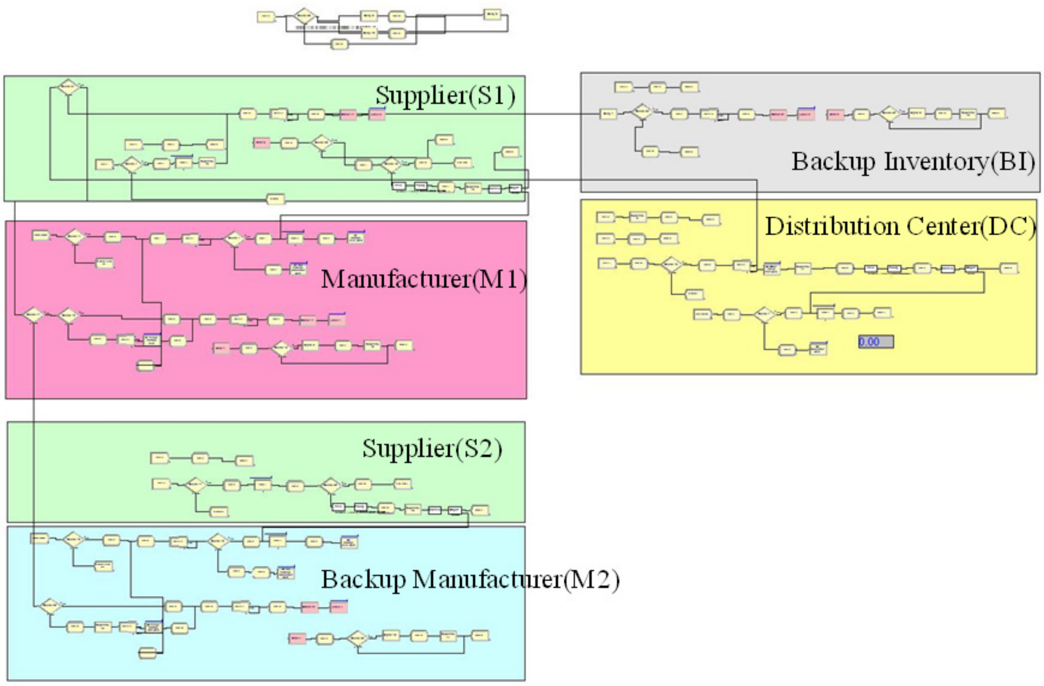

FIGURE 3. Arena simulation model

backorders being held in a 'Hold' module. Details of Arena simulation model are omitted and Figure 3 presents entire Arena model.

Inventory policy is described using the following variables: inventory level (IL), inventory position (IP), order quantity (Q), reorder point (s), order-up-to-level (S), demand (D), backorder (B), and lead-time (L) [15]. In the following, $x^+ = \max(x, 0)$, $x^- = \max(-x, 0)$.

In the (s, S) policy, in each period, if $IP \le s$, $Q = S - IP$ parts are ordered and it is delivered in L periods. For DC, demand D is observed and variables are updated as $IL = (IL - D)^+$, $B = (IL - D)^-$ and $IP = IL + Q - B$. A disruption in M1 is modeled as 'Resource Failure' in Arena with up time and down time both having exponential distributions with parameters λ_U and λ_D, respectively. Thus, M1's disruption state follows a Markov chain with states 'up' and 'down' and the probability of down is $\lambda_D/(\lambda_U + \lambda_D)$. The performance of system is measured using holding, backorder and order cost, and fill rate in DC. The total cost is represented as $h(IL)^+ + p(IL)^- + c_1(Q_1) + c_2(Q_2) + c_I(Q_I) + K\delta(Q)$ where, h, p, c_1, c_2, c_I are unit holding, stockout penalty, order cost to M1, M2, BI, respectively, and K setup cost and $\delta(z) = 1$ if $z > 0$ and $\delta(z) = 0$, if $z = 0$. We assume that $h < p$, $c_1 < c_2 < c_I$.

3. **Computational Experiment.** We implemented our model using Arena v.14.7 and all simulation run is carried with 10 batches and each batch consists of 100 days warm up time and 10 years of simulation time [16]. In our preliminary simulation, we consider simple two-echelon supply chain consisting of a retailer and a supplier with (s, S) policy. Retailer's demand D is distributed as normal distribution $N(\mu, \sigma)$, $\mu = 20$, $\sigma = 1$, cost parameters are $h = 1$, $p = 20$, $K = 250$. The simplest disruption model considered in literature uses geometric distribution with failure and recovery probability α, β, respectively [17]. This disruption is also a Markov chain with failure probability $\alpha/(\alpha + \beta)$.

When we model 'Resource failure' in Arena, we use exponential distribution as up and down time distribution. We observed that exponential up and down time generates rarer disruption with longer disruption length, while geometric disruption generates frequent and shorter disruption length. This difference is observed in both Figure 4 and Figure 5. As the down probability increases, fill rate decrease and backorder cost increase in geometric disruption are bigger than in exponential function disruption with same failure probability. So, in our main simulation, we use exponential distribution as up/down probability.

For general three-echelon model in Figures 2 and 3, demand process in DC is modeled as a compound Poisson distribution with order size ranging from one to four with equal probability. Average order inter-arrival time is assumed as an exponential with mean 4 hours. In DC's source subsystem, IP is checked every day. We approximated compound Poisson with normal distribution and found that daily demand is approximately N(15.01,

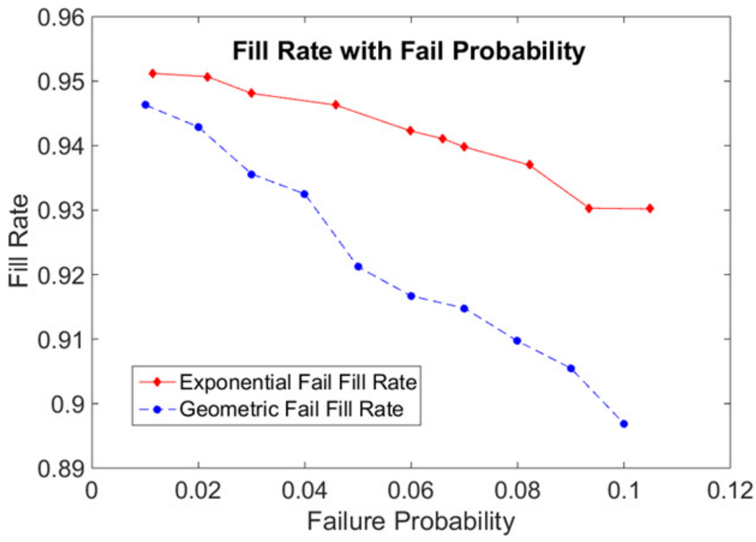

FIGURE 4. Fill rate variation in a simple two-echelon (s, S) policy with respect to different disruption models

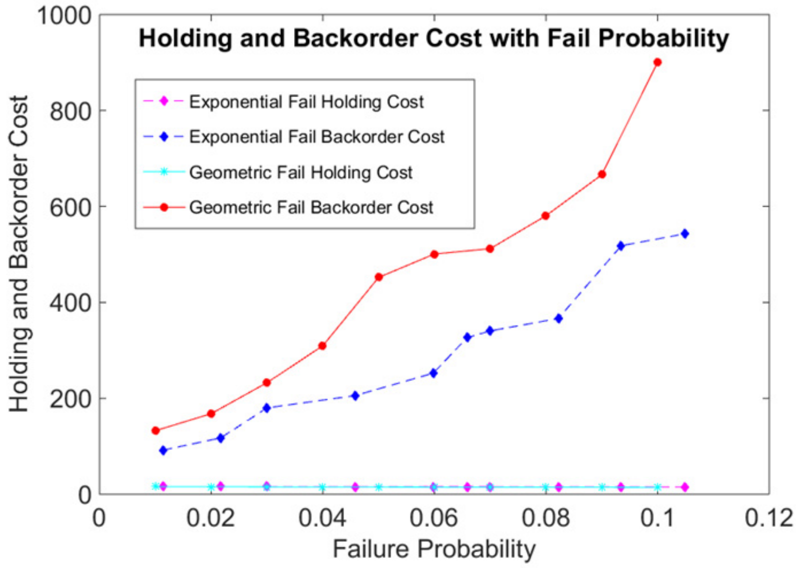

FIGURE 5. Holding and backorder cost in a simple two-echelon (s, S) policy with respect to different disruption models

6.69) and average lead time is 4 days. The optimal reorder point s and order-up-to-level S are computed using an iterative heuristic for (R, Q) policy [15]. The iterative heuristic finds $R = 81$, $Q = 335$, and we set $s = 81$, $S = 416$.

For our model, we assume that when the 'Resource' in M1 is failed, after τ days (ramp up time), if there is enough storage in BI, orders can be transfered to BI and if there is not enough storage in BI, orders are replenished from backup manufacturer M2. If 'Resource' in M1 becomes 'Active' state, M1 receives orders from DC.

Figure 6 shows total cost with respect to reserve inventory level when $\tau = 0$ and only BI is used as a backup. For DC, average order quantity $\overline{Q} = 190.2$ and backup inventory level in Figure 6 corresponds to multiples of $\overline{Q}$. When up time is exponential(792) and down time exponential(4), the total cost remains flat with over 97% fill rate. However, for up/down = 392/3 and 1000/8, to achieve similar low total cost, reserve inventory level increases: for 392/3 and 1000/8 cases, total costs become flat when reserve inventories

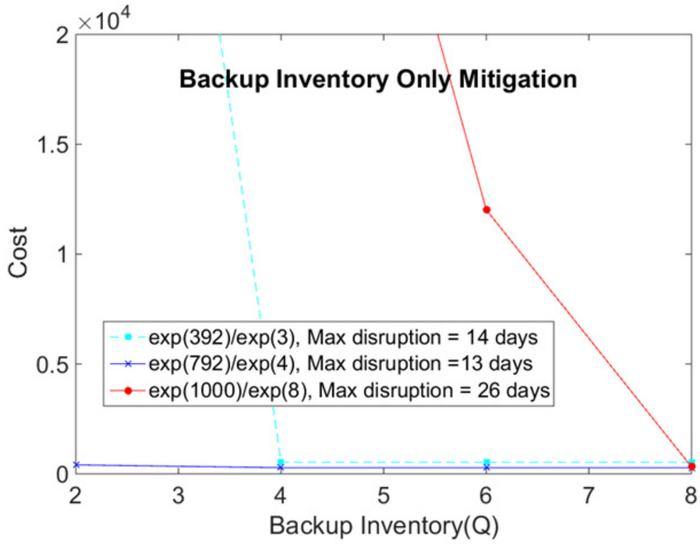

FIGURE 6. Total cost according to different disruptions when inventory only backup is used

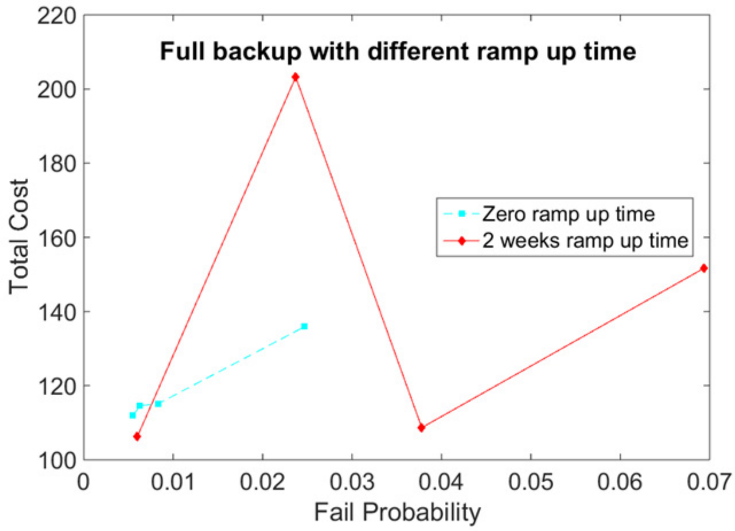

FIGURE 7. Effect of disruption location in the three echelon inventory system

TABLE 1. Full backup with different ramp up time

Problem	Cost	Fill rate	M2 (%)	BI (%)	Up time	Down time	Down prob.
1	112±4.86	0.9756	1.044	0.7036	792	4	0.0055
2	115.11±4.56	0.976	1.04	0.71	392	4	0.0083
3	114.6±5.22	0.9758	1.36	0.71	1000	8	0.0063
4	135.92±9.79	0.974	3.09	0.708	1000	16	0.0247
5	106.34±0.58	0.977	0	0	792	4	0.0060
6	108.68±2.5	0.9757	0	0.69	100	4	0.0378
7	151.72±23.82	0.9652	0.375	0.712	100	8	0.0694
8	203.22±166.78	0.9694	1	0.712	1000	16	0.0237

are higher than $4\overline{Q}$ and $8\overline{Q}$, respectively. We note that the required reserve inventory is affected by down probability $\lambda_D/(\lambda_U + \lambda_D)$ and maximum down days.

Table 1 shows detailed result when both BI and M2 backups are used. Problems 1-4 correspond $\tau = 0$ and Problems 5-8 correspond to $\tau = 2$ weeks. Second column shows the average total cost with 95% half width. Remaining columns are fill rate, percentage of total orders covered by M2, percentage of total orders covered by BI, mean up time, mean down time, and down probability. For ramp up time $\tau = 0$, as the down probability increases, the total cost also increases, but the fill rate remains flat. We can see that as more disruption occurs, the percentage of total demand covered by M2 increases. For $\tau = 2$ weeks, Problem 8 has higher cost than Problem 7. This is caused by longer disruption period during simulation run. As in Problems 1-4, as the disruption probability increases, backup by M2 increases. For problems 1-8, BI has $4\overline{Q}$ initial inventory.

4. **Conclusions.** In this paper, we developed a discrete event simulation model that represents multi-echelon supply chain network. Previous simulation models for supply chain with disruption scenarios assume simple structures for analysis. For periodic review model, base-stock and (s, S) policy simulation models with deterministic lead time are introduced in [17].

Even though our model is three-echelon model, each tier in our model consists of three business processes and Arena processes are modeled individually. Our model can cover both base-stock, (s, S), and (R, Q) policies with general disruption scenarios.

We found that as the disruption probability increases, inventory alone is not a secure mitigation plan and reserve inventory and backup manufacturer are secure mitigation plan. The study on the supply chain disruption is still at the early stage and further research is required to examine different disruption impacts such as full/partial inventory loss or effects of the disruption response strategies.

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