Optimizing strategies to mitigate risk in a supply chain disruption

by

Steve Paul

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Cameron MacKenzie, Major Professor
David Cantor
Guiping Hu

The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis/dissertation is globally accessible and will not permit alterations after a degree is conferred.

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DEDICATION

I dedicate this thesis to my mother, my father and my sister for their constant support and motivation throughout my years of education.

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ABSTRACT

With the growth of globalization in the supply chain industry, manufacturing firms and suppliers are more susceptible to disruptions. There is a huge gap between optimization, simulation, and supply chain risk management. Our research is an attempt to bridge this gap, by improving a currently existing supply chain disruption model through Bayesian optimization technique. During a disruption, suppliers of manufacturing firms do not always have an option of moving their facility to an alternate location. This model optimizes a complex simulation to help identify the optimal risk management strategies for a firm who is planning for a severe supply chain disruption. The results of the model are depicted through an illustrative example based out of the 2011 Japanese earthquake and tsunami, and its robustness is tested through sensitivity analysis. Firms need to be prepared for disruptive events and may have the desire to maximize their profit and this model provides techniques to the decision maker to choose cost-effective strategies based on certain parameters.

CHAPTER 1. INTRODUCTION

Supply chain disruptions seem to be occurring more frequently. The COVID-19 pandemic has strained many supply chains due to changing patterns of demand and measures taken to limit the spread of the disease. The 2011 Japanese earthquake and tsunami and Hurricanes Katrina and Rita in 2005 are examples of natural disasters that disrupted many businesses' supply chains for a significant period of time. Whether it is a pandemic or a natural disaster or another event such as a fire or labor strike, disruptions can occur quickly in one part of the world and effect businesses on a global scale.

When a supply chain disruption occurs, manufacturers may rely on a variety of strategies to mitigate the effects of disruption. Firms have to make decisions on how to balance their operations and help recover from the disruption by choosing the right mitigation strategy. Firms need to make optimal decisions before a disruption occurs to determine what to do about inventory, plan to purchase from alternate suppliers, or move production to alternate facility usually with the goal of maximizing profit. Manufacturers may have a diverse supplier base in terms of geography for identical production inputs so that if one supplier is adversely impacted, their other suppliers will still be able to produce. Firms with a diverse supplier base tend to recover back from the disruption earlier. With increasing globalization in the supply chain, vulnerability to the risks due to the disruption have been increasing as well (Kilpatrick and Barter, 2020). Models can help firms manage inventory before a disruption occurs, and the way in which firms manage inventory to mitigate supply chain risk can enhance a firm's performance (Hilman and Keltz, 2007). Schmitt and Singh (2012) propose systematic approaches to improve system resilience by network utilization and proactive planning.

Tang (2005) reviews research in the field of supply chain risk management (SCRM) and advocates the need of having an integrated view of SCRM (Tang and Musa, 2010). Identifying the best risk management strategies before a disruption occurs, is very challenging due to the uncertainty surrounding disruptive events (Kaplan and Anette, 2012). Monte Carlo simulation can help analyze that uncertainty by imitating potential scenarios and including different sources of randomness and uncertainty (Heckmann, 2016). Monte-Carlo simulation can incorporate complexity, real world variability, and uncertainty in the supply chain disruptions to anticipate and forecast a wide range of different outcomes.

Although simulation can capture the variability or uncertainty in supply chain disruptions, using simulation to optimize decision making can be very challenging. Evaluating an alternative, requires running thousands of replications of a simulation and repeating this for each alternative in a feasible set can take a very long time to run or even be impossible for if the decision variables are continuous. Simulation optimization provides techniques to optimize a decision when the objective function is evaluated via simulation. Although SCRM can substantially benefit from complex simulations to analyze the uncertainties in supply chain disruptions, very little research has applied simulation-optimization techniques to identify the best SCRM strategies (Oliviera et al. 2019). The motivation behind this paper is to bridge the disconnect between SCRM, simulation, and optimization. A severe supply chain disruption simulation based on MacKenzie et al. (2013) interrupts the supply for a firm. Before the disruption occurs, a firm may have several strategies to help mitigate the disruption such as holding inventory, arranging with alternate suppliers, helping suppliers recover more quickly, and increasing the loyalty of its customers so that they do not purchase from other firms during the disruption. This paper applies a popular simulation-optimization technique called Bayesian optimization to enable a firm to use Monte Carlo simulation to choose among the most effective strategies while considering the costs of each strategy. This paper uses those risk mitigation strategies as input decision variables to maximize profit as a function of the decision variables. The paper is unique in demonstrating how a firm can determine its optimal risk mitigation strategy when a complex disruption is modeled using a complex simulation.

Firms need to prepare for disruptive events. The model in this paper focuses on preparing for disruptive events before the disruption occurs. Section 2 summarizes the research done in the field of the supply chain risk management. Section 3 discusses the simulation, the optimization framework, and the decision variables. Section 4 provides an illustrative example motivated by MacKenzie et al. (2013) and conducts sensitivity analysis to examine the impacts of parameters that change. Section 5 concludes the research and provides scope for future research.

CHAPTER 2. LITERATURE REVIEW

Different strategies have been proposed to mitigate the risk of supply chain disruptions. SCRM has involved qualitative and quantitative aspects. Marketing strategies (Christopher, 2000) can help mitigate the effects of volatility and uncertainty in demand and supply by using them as frameworks to devise the right supply chain strategy (Lee, 2000). Chopra and Sodhi (2004) categorize risk to show what managers can employ to reduce supply chain risk. In order to deal with these disruptions, it is necessary to have a structured approach (Juttner, 2005), rubrics (Chang et al., 2016), and robust strategies to develop a resilient supply chain (Tang, 2006). Blackhurst et al. (2005) lays the groundwork for the need of robust optimization tools and proactive mitigation strategies (Synder et al., 2015) to mitigate the negative consequences due to a supply chain disruption.

Quantitative models for SCRM are plentiful and examine a wide range of situations and scenarios. Firms selling multiple products deal with a higher level of demand and supply uncertainty, but Tomlin and Wang (2004) show how to dynamically adjust to the supply chain strategy using a two-stage stochastic program. Future supply uncertainty can be analyzed through inventory models based on the interarrival time of the stochastic renewal process (Parlar and Berkin, 1991). Manufacturing planners may need to design a robust supply chain. Synder et al. (2006) show various strategic planning models using network-theory models, protection models and the economic order quantity (EOQ) techniques to develop a resilient supply chain network. Using copula functions (Wagner et al., 2008) and joint default correlation (Babich et al., 2007) among multiple suppliers having default risk, firms can reduce supply chain risk by making better sourcing decisions. Proactive planning can reduce loss due to a disruption by focusing on key locations and vulnerability drivers using simulation-based catastrophic risk estimation methods (Wagner and Bode, 2007; Knemeyer et al., 2008). Firms can make informed decisions using risk-exposure models based on the duration of impact (Simchi-Levi et al., 2015). Hendricks et al. (2008) show how economic parameters can be tapped into a function of the cost strategies and their influence in mitigating the negative consequences in a supply chain disruption.

Optimization techniques are used frequently to make decisions in SCRM. Optimizing worst-case performance in SCRM through stochastic mixed integer programming methods can mitigate the impact of disruption risks (Sawik, 2016). Firms can benefit from risk pooling and risk diversification through dynamic sourcing strategies (Mak and Shen, 2011) using Lagrangian relaxation algorithm and Markov chain distributions. The optimization behavior of manufacturers and distributors can be tapped to maximize profit and reduce risk in the supply chain (Nagurney et al., 2003; Hopp and Liu, 2008). These optimization models frequently assume that, firms desire to maximize profits during disruptions and use expected profit as an appropriate measure for evaluating different strategies to manage operational risks (Tomlin, 2009).

Monte-Carlo simulation has been used to assess the effect of supply chain disruptions that affect the supply chain network for a significant period of time (Deleris and Erhun, 2005). Simulation can incorporate the correlation among suppliers to help model the risk of severe disruptions that impact multiple suppliers simultaneously. Schmitt and Singh (2009) use the inputs from a Monte-Carlo simulation into a large simulation model to quantify the threats due to the disruption. Also, Schlüter et. al, (2017) use discrete event simulation to quantify the impact of supply chain disruption risk. Lei and MacKenzie (2019) use simulation to solve continuous-time Markov chains that assess risk in a supply chain where the failure of two suppliers are correlated with each other. MacKenzie et al. (2013) simulate a severe supply chain disruption in which the production facilities of multiple suppliers are suddenly closed, and these suppliers are unable to deliver product to multiple firms. This research optimizes a complex scenario based on Monte-Carlo simulation.

Despite the wealth of optimization models and a variety of simulations that explore different features of supply chain disruptions, simulation-optimization has only infrequently been used to optimize risk mitigation strategies for a firm that requires a simulation to analyze the occurrence and effects of risk (Oliveira et al. 2019). Carson and Maria (1997) categorize simulation-optimization methods into (i) gradient based search, (ii) stochastic optimization (iii) response surface methodologies, (iv) heuristic methods, (v) A-team, and (vi) statistical methods. Simulation-based multi-objective optimization models have been applied to high-end server manufacturing using goal programming methodology (Aqlan and Lam, 2016). Ge et al. (2016) develop cost-effective strategies in agricultural supply chains using simulation optimization. A popular simulation-optimization technique is Bayesian optimization (Wang et al., 2016; MacKenzie and Hu, 2018), and to our knowledge, no research has combined a simulation of a supply chain disruption SCRM with Bayesian optimization.

The 2011 Japanese earthquake and tsunami causes a very severe supply chain disruption throughout the world especially in the automobile and electronic industries. Multi-regional input-output models (MacKenzie et. al 2012, Arto et. al 2015) and equilibrium model of production networks (Carvalho et. al 2016) have been used to quantify the worldwide economic impacts of the Japanese tsunami. The Japanese tsunami stresses the importance of supply chain managers understanding the entire network of their supply chains and incorporating systems thinking into their supply chain planning (Ghadge et al., 2011). MacKenzie et al. (2013) apply their simulation of a severe supply chain disruption to the disruption in the automobile industry caused by Japanese tsunami in order to analyze how different disruption management strategies could help firms recover from a severe supply chain disruption. Our research builds upon this simulation model in MacKenzie et al. (2013) in order to optimize over the set of SCRM strategies available to a firm.

As discussed above, a plethora of models exist that solve for the optimal SCRM strategy and other supply chain disruption models rely on simulation, but no research has optimized a SCRM strategy based on Monte Carlo simulation using Bayesian optimization. This paper uses both techniques together to analyze what a firm should do before a disruption occurs. The paper is based on the model presented in MacKenzie et al. (2013). MacKenzie et al. (2013) discuss post-disruption decisions that suppliers and firms must make on whether to move their production to an alternate facility, how much inventory should be held, and whether to purchase from alternate suppliers. This paper applies Bayesian optimization to SCRM and ties in the benefits of both simulation and optimization to provide effective cost strategies for the decision maker in a firm.

CHAPTER 3. SIMULATION-BASED OPTIMIZATION MODEL

The disruption simulation is derived from MacKenzie et al. (2013) and is motivated by the severe supply chain disruption resulting from the 2011 Japanese earthquake and tsunami. The simulation contains multiple firms and suppliers. As depicted in Fig. 1, a disruptive event suddenly closes the facilities for each of the suppliers, and each of the suppliers is unable to deliver supplies to the firms. A firm may have several methods to minimize this disruption. It may have supply inventory that it can use to continue production. If a firm does not have supply inventory, then it may be able to purchase supplies from an alternate supplier. If the alternate supplier is too expensive, the firm may have finished goods inventory to satisfy demand from its customers. If the firm is unable or unwilling to meet its customer demand, those customers may buy from one of the other firms in the simulation. At the end of each period, there is a probability that a supplier's facility reopens. If the supplier's facility reopens, it will be able to deliver supplies to firms. The simulation continues until all of the suppliers' facilities are reopened.

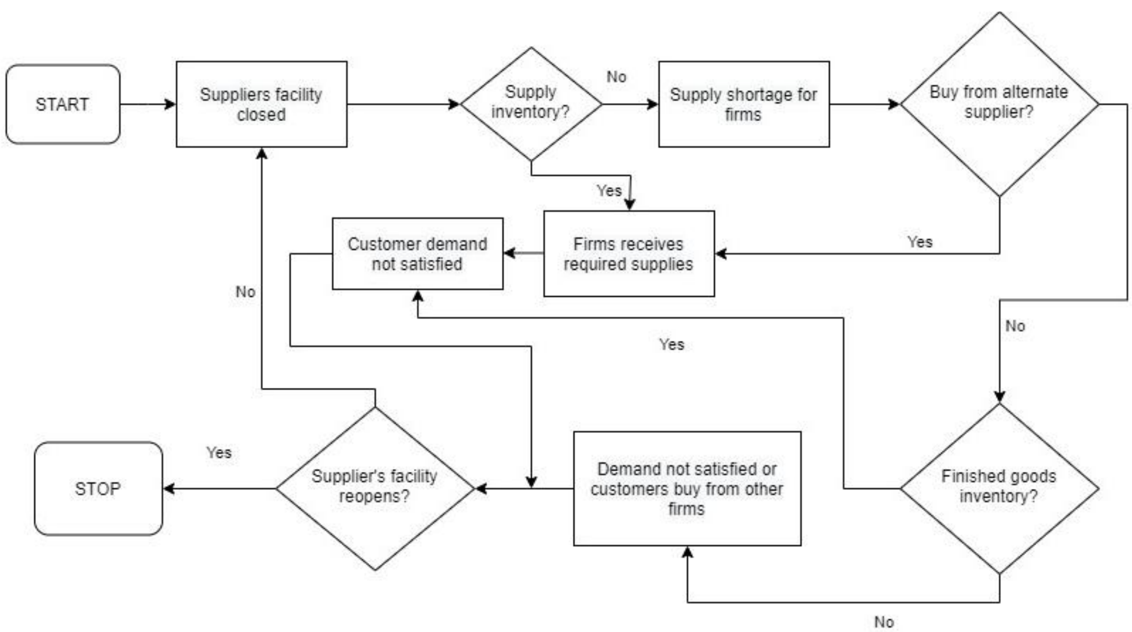

Fig. 1. *Flow chart for the simulation of a severe supply chain disruption*

The goal of this research is to identify the optimal risk management strategies for a firm who is planning for a severe supply chain disruption as represented by the simulation. We assume one out of the n firms is planning how it should prepare for the supply chain disruption. The firm has several risk management strategies from which to choose: (i) build up supply inventory for each of its suppliers, (ii) hold finished goods inventory, (iii) arrange with alternate suppliers to allow the firm to be able to purchase supplies in case of a disruption, (iv) work closely with one or more of its suppliers so that these suppliers can reopen their facility more quickly in case it is closed, and (v) create more loyalty with its customers so that they do not buy from other firms.

Each of these strategies has a cost that the firm would need to pay before the disruptive event. Since the supply chain disruption is a complex event with many uncertainties and independent actions, developing equations to describe the cost-effectiveness of each strategy is impractical. The simulation can be used to identify the optimal risk management strategies. The optimization model calls the simulation model (depicted in Fig. 1) in order to evaluate the firm's profit during the disruptive event given a set of risk management strategies. The optimization model continues to iterate over the risk management strategies (the decision variables) in order to identify the set of strategies that maximizes the firm's expected profit during the disruption.
As seen in Fig. 2., the optimization model initializes the decision variables. The risk management model calculates the cost of these strategies and executes the supply chain disruption simulation assuming the firm has selected those strategies. The simulation calculates the firm's expected profit. This expected profit is used to update a surrogate model using Bayesian optimization.

Bayesian optimization is a method that uses simulation to update a surrogate model (Shahriari et al., 2016; Martinez-Cantin, 2014). The Bayesian optimization algorithm assumes a Gaussian prior over the objective function, which is expected profit in this paper. When the simulation evaluates a continuous decision variable—which may be a set of continuous decision variables—the algorithm uses Bayesian techniques to update the Gaussian distribution and calculate a posterior Gaussian distribution (Lizotte, 2008; Snoek et al., 2012). The next set of decision variables to evaluate in the simulation is the set of decision variables that is expected to offer the most improvement. Expected improvement is calculated as a combination of the likelihood that the mean and standard deviation of the posterior distribution are large (Mokus et al., 1978). This paper uses the Random Embedding Bayesian Optimization (REMBO) developed by Wang et al. (2016) to implement the Bayesian optimization algorithm. If the expected improvement is larger than small threshold, it is assumed that optimal solution has not been found. The algorithm chooses a new set of decision variables and the process repeats itself. The algorithm continues in this manner until the expected profit converges.

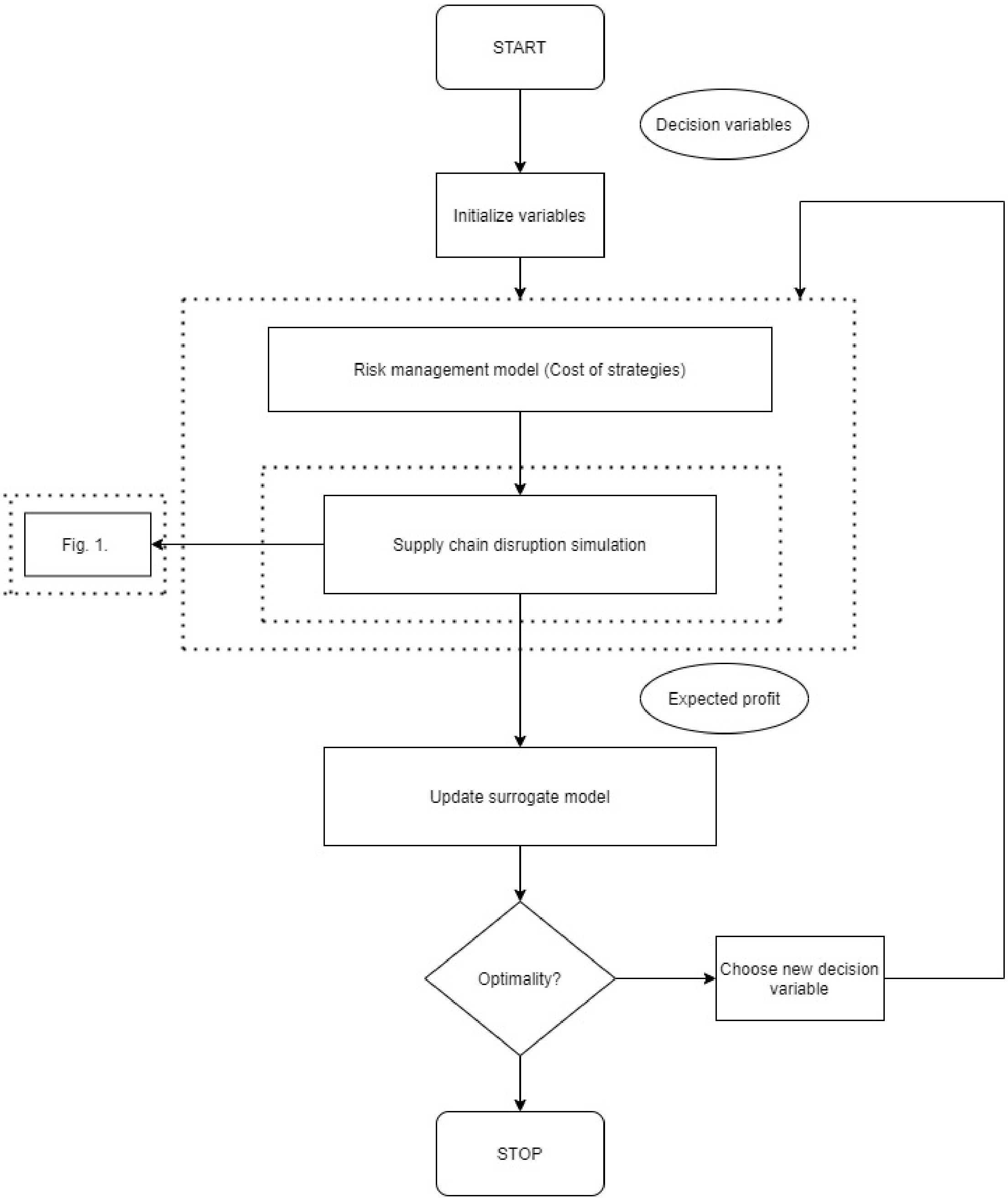

Fig. 2. *Flow of the optimization model with the supply chain disruption simulation*

The algorithm uses the knowledge of the simulation to determine how well the objective function performs. It works on the idea of finding the less wrong with more data values for the decision variables based on the past evaluation results. The optimization model iterates for several times from its previous best point trying to find the next best possible value. With sufficient simulations, we can say with a certain level of confidence that values obtained are closest to the true value to make the system robust.

Table 1 presents the decision variables used in this model. Table 2 depicts the parameters of the cost functions used to evaluate the cost of each decision, and Table 3 displays other model parameters.

Table 1. *Decision variables*

Symbol	*Description*
$i_1, i_2, \dots, i_n$	supply inventory for each of the firm's n suppliers
i_{n+1}	finished goods inventory
a_{jk}	amount of supplies that can be purchased at w_k prices for alternate supplier to j
p_j	probability that supplier j's facility reopens in each period
q	probability that a firm's customer will not purchase from another firm

Table 2. *Cost function parameters*

Symbol	*Description*
w_k	per-unit cost of purchasing supplies from an alternate supplier
α_j	fixed cost for inventory for supply j
β_j	variable cost for inventory for supply j
$\gamma_{j,k}$	cost of arranging 1 unit from alternate supplier j at a purchase cost of w_k
$\eta_j, \delta_j, \kappa_j, \hat{p}_j$	parameters for the cost to help supplier j reopen more quickly
$\theta, \lambda, \rho, \hat{q}$	parameters for cost of keeping the customers loyal to the firm

Table 3. *Other parameters*

$Symbol$	$Description$
m	number of firms
n	no. of suppliers
n'	number of suppliers with whom the firm works to reopen their facility more quickly
j, k, r	limit parameters
C	Budget for strategies
$c_j(\cdot)$	cost function for decision strategy j
π	total expected profit

3.1.Risk management strategies

The supply chain simulation includes m firms, and a firm receives different goods from each of its n suppliers. The risk management model seeks to optimize the strategies for one firm and the decision model is described from the perspective of that one firm.

The firm receives supplies from n suppliers. Let $i_1, i_2, \dots, i_n$ be the supply inventory the firm holds before the disruption occurs from each supplier. The variable i_{n+1} represents the finished goods inventory for the firm.

The firm can prearrange with alternate suppliers to purchase from those suppliers if the firm's original suppliers cannot deliver the product. These alternate suppliers are exogenous to the supply chain disruption simulation and can always deliver supplies during the simulation. We assume the per-unit cost of purchasing supplies during the disruption is $\mathbf{w}$ where $w_1 < w_2 < \cdots < w_r$ where w_r is the highest per-unit cost of purchasing supplies. The matrix $\mathbf{A}$ is a $n \times r$

matrix representing the amount of supplies the firm can purchase from alternate suppliers during a disruption and a_{jk} is the amount of supplies the firm can purchase from an alternate supplier to supplier j, $j = 1, \dots, n$ and a per-unit cost of w_k. The firm determines before the disruption the matrix **A** of how much alternate supplies it wants to have available at the different costs.

Before the disruption, the firm can work with some of its suppliers to help those suppliers reopen more quickly if those suppliers' facilities are closed by the disruption. The supplier's facility opens with a certain probability at the beginning of the next period. The decision variables p_j is the probability that a supplier's facility reopens in each period of the simulation. If there are n total suppliers, the firm may only have a close enough relationship with $n' \leq n$ suppliers that it would help that supplier reopen more quickly. The subscript j in the decision variable p_j only corresponds to those suppliers whom the firm works with before the disruptive event to plan for a quicker reopening. In a practical scenario, the probability would increase as the firm tries to help the suppliers reopen the facility, but we assume the probability that a supplier's facility reopens in each period remains constant through the simulation.

The final risk management strategy is the firm can increase the loyalty of its customers and q represents the probability that one of the firm's customers will not purchase from another firm given that the firm is not able to produce in a period during the disruption.

3.1.Cost function for risk mitigation strategies

The firm must bear a cost for each mitigation strategy and a firm will want to select strategies that are most cost-effective. We assume the cost of inventory for supplier j, $c_j(i_j)$, is comprised of a fixed cost and a variable cost where α_j is the fixed cost and β_j is the variable cost:

$$c_j(i_j) = \alpha_j + \beta_j i_j \tag{1}$$

where $j = 1, \dots, n+1$. The cost $c_n(i_{n+1})$ is the cost of holding finished goods inventory. If $i_j = 0$, then $\alpha_j = 0$, and therefore, $c_j(i_j) = 0$, since, the model assumes no fixed cost for no finished goods inventory

The firm can prearrange with alternate suppliers to purchase supplies at different per-unit as represented by the vector **w**. The firm determines the amount of supplies $a_{j,1}, a_{j,2}, \dots a_{j,r}$, at each of those prices and the cost of arranging for alternatives to supplier j is

$$c_{j+n+1}(a_{j,1}, a_{j,2}, \dots a_{j,r}) = \sum_{k=1}^{r} \gamma_{j,k} a_{j,k} \tag{2}$$

where $\gamma_{j,1} > \gamma_{j,2} > \cdots > \gamma_{j,r}$ and $j = 1, \dots, n$. The firm is required to pay more in order to prearrange purchasing supplies at a lower per-unit cost w_j.

The cost of helping a supplier recover more quickly is represented by $c_{j+2n+1}(p_j)$ where $j = 1, \dots, m$. If the firm chooses not to help a supplier recover, the probability that supplier j reopens in each period is $\hat{p}_j$. Since the time until a supplier reopens follows a geometric distribution, the expected number of periods until the supplier reopens is the reciprocal of the probability. The cost of improving the probability is based on an exponential function of the expected number of periods until the supplier reopens:

$$c_{j+2n+1}(p_j) = \frac{\eta_j \left(1 - \exp\left(\delta_j \left[\frac{1}{\hat{p}_j} - \frac{1}{p_j}\right]\right)\right)}{\kappa_j} \tag{3}$$

where $\delta_j, \eta_j, \kappa_j > 0$ are parameters of the cost function. The exponential distribution assumes marginally increasing costs so that the first dollar spent improves the probability more than second dollar.

The cost of increasing customer loyalty $c_{2n+n\prime+2}(q)$ as represented by the probability q has a similar functional form to the cost of increasing the probability that a supplier's facility reopens. The variable $\hat{q}$ is the probability that a customer does not purchase from an alternate supplier if the firm chooses to spend no money to improving the probability.

$$c_{2n+m+2}(q) = \frac{\lambda\big(1 - \exp\big(\theta(q - \hat{q})\big)\big)}{\rho} \tag{4}$$

where $\theta, \lambda, \rho > 0$ are parameters of the cost function.

We assume the firm is going to choose a set of risk management or mitigation strategies in order to maximize its expected profit subject to a budget constraint. Each simulation trial calculates the firm's profit during the disruption and the firm's expected profit during the disruption. $\bar{\pi}$ is the average profit over multiple simulation trials. The firm's total expected profit π is calculated as the total cost of the risk management strategies subtracted from the average profit from the simulation:

$$\pi = \bar{\pi} - \sum_{j=1}^{2n+n\prime+2} c_j(\cdot) \tag{5}$$

The model also assumes the total cost of the mitigation strategies must be less than or equal to a predefined budget C:

$$\sum_{j=1}^{2n+n\prime+2} c_j(\cdot) \leq C \tag{6}$$

Finally, each decision variable is constrained by a lower and upper bound. The inventory and alternate supplier strategies have lower bounds of 0. The supply inventory finished goods and alternate suppliers have an upper bound of 200, 300 and 25 respectively. The lower bounds for p_j and q are $\hat{p}_j$ and $\hat{q}$, respectively, and the upper bounds for the probabilities are 1.0.

CHAPTER 4. ILLUSTRATIVE EXAMPLE

4.1. Inputs

An illustrative example provides a demonstration for how this model can identify the optimal strategy for a firm desiring to mitigate the effects of a supply chain disruption. This illustrative example is based on MacKenzie et. al (2013) situation where there are m= 3 firms. Firm 2, which loosely represents how Toyota and Honda were impacted by the 2011 Japanese earthquake and tsunami, suffers the most of the three firms in the simulation. Consequently, the simulation-optimization framework in this paper will focus on firm 2's risk-mitigation decision making, and we will refer to it as the firm. The firm has $n = 3$ suppliers, all of whom have their production facility closed at the beginning of the simulation. Each supplier produces a different product for the firm and each of the three supplies is necessary for the firm to produce. Each period in the simulation represents 1 week. The amount of demand for the firm in each week is 21 units. The firm's per-unit cost to purchase from each of the three primary suppliers is 1. The per-unit revenue is 4, and the firm has a per-unit profit equal to 1 if it purchases from each of its primary suppliers. Demand is assumed to be constant for each week except for the possibility that demand that is not satisfied in one week could be added to demand in the following week or become for competing firms. Future research could explore the impact of more variable or uncertain demand patterns.

Supplier 3 is more vertically integrated with the firm than the other two suppliers, and this example assumes that the firm can work with supplier 3 to enhance its recovery before the disruption. Since supplier 3 is the only supplier the firm can work to increase its probability of reopening, $n' = 1$ and p_3 is the firm's only decision variable corresponding to the reopening of a supplier's facility.

This model includes 18 decision variables. Each risk management strategy bears a cost. As presented earlier, the costs are functions of the decision variables. The parameters associated with these cost functions are shown in Table 4. The supply inventory (i_1, i_2, i_3) have an upper bound of 200 units each, and the finished goods inventory (i_4) has an upper bound of 300 units. The firm can arrange to purchase from alternate suppliers to each of the three primary suppliers if the primary suppliers are unable to deliver supplies to the firm. The per-unit prices that the firm can purchase from the alternate suppliers are $r = 1,2,3,4$. The maximum amount that the firm can purchase at each of those four prices is 25. Supplier 3's expected time of closure is 26 weeks, and its initial probability of reopening is 1/26 = 0.038. This parameter comes from Mackenzie et. al (2013) based on new articles (Bunkley, 2011) describing that Toyota and Honda took 6 months to return full production following the Japanese tsunami and earthquake. The probability a customer does not purchase from alternate firms is 0.25. The budget for the risk mitigation strategies is $C = 250$.

Table 4. *Parameter values for the cost functions*

$Cost\ strategy$	$Parameter\ values$
Cost of supply inventory at supplier	$\alpha_j = 5; \beta_j = 0.1$; where $j = 1,2,3$
Cost of finished goods inventory at the firm	$\alpha_4 = 12; \beta_4 = 3.1$
Per-unit cost of alternate suppliers	$w_1 = 1; w_2 = 2; w_3 = 3; w_4 = 4;$
Cost of supply inventory from alternate supplier	$\gamma_{j,1} = 0.5, \gamma_{j,2} = 0.2, \gamma_{j,3} = 0.05, \gamma_{j,4} = 0.01;$ where $j = 1,2,3,4$
Cost of increasing probability of reopening	$\eta = 250; \delta = 0.037; \kappa = -1.6;\ \hat{p} = 26$
Cost of increasing customer loyalty	$\lambda = 100; \theta = 0.24;, \rho = -0.2;\ \hat{q} =\ 0.25$

The REMBO algorithm calls the supply chain risk mitigation model to find the optimal set of decision strategies. MATLAB is used as a platform to run REMBO and simulate the supply chain disruption.

4.2.Base-case results

The REMBO optimization is run to obtain values of the decision variables and their corresponding expected profit. The initial point is updated based on the previous maximum value of the expected profit to improve the expected profit in the next trial. The REMBO algorithm is repeated for 60 trials to ensure that it covers the true maximum and the simulation model is run for 40 iterations and 3000 simulations within the optimization model to obtain the base-case result. Table 5 shows the base case results of the decision variables and the expected profit.

Table 5. *Base-case result*

$Cost\ strategy$	$Value$	$Cost\ of\ strategy$
Supply inventory at supplier 1,2,3	$i_1 = 190;\ i_2 = 194;\ i_3 = 198;$	$c_1 = 24;\ c_2 = 24.4\ ;\ c_3 = 24.8$
Finished goods inventory at the firm	$i_4 = 0;$	$c_4 = 0$
Amount purchased from alternate suppliers to primary supplier 1	$a_{11} = 0;\ a_{12} = 25;\ a_{13} = 0;\ a_{14} = 25;$	$c_5 = 7.875$
Amount purchased from alternate suppliers to primary supplier 2	$a_{21} = 0; a_{22} = 3; a_{23} = 25; a_{24} = 25;$	$c_6 = 3.15$

Amount purchased from alternate suppliers to primary supplier 3	$a_{31} = 0; a_{32} = 0; a_{33} = 25; a_{34} = 0;$	$c_7 = 1.875$
Probability of reopening of supplier 3	$p = 0.088193;$	$c_8 = 112.5377$
Probability of customers remaining loyal to the firm	$q = 0.25;$	$c_9 = 0$
	$\text{Expected profit} = 665$	$\text{Total cost of strategies} = 198.81$

These results show that the firm should prepare for the supply chain disruption by purchasing supply inventory from the primary suppliers but should not have any finished goods inventory. The lack of finished goods inventory is because the input parameters make carrying finished goods inventory more expensive than carrying supply inventory. If it is unrealistic to recommend a firm carry no finished goods or supply inventory, we can add a minimum amount of finished goods or supply inventory as a constraint in the risk management model. The firm should also spend a substantial portion of its budget to help supplier 3 reopen more quickly. Supplier 3's probability of reopening increases from 0.038 to 0.088, and the expected time the supplier is closed is reduced from 26 weeks to approximately 11 weeks. The supply inventory and helping supplier 3 reopen more quickly consumes most of the budget of 250.

The parameters $(a_{1,1}, a_{1,2}, a_{1,3}, a_{1,4})$, $(a_{2,1}, a_{2,2}, a_{2,3}, a_{2,4})$, and $(a_{3,1}, a_{3,2}, a_{3,3}, a_{3,4})$ represent the amount that the firm prearranges to purchase from alternate suppliers to primary supplier 1, 2 and 3, respectively. Purchasing from an alternate supplier at a cost of 1 is less cost effective than holding supply inventory and helping supplier 3 recover more quickly, and $a_{1,j} = 0$ for $j = 1,2,3$. The firm should arrange to purchase from alternate suppliers at 2-4 times the price of the primary supplier, but the cost to enter into these arrangements is relatively small ($c_5 = 8, c_6 = 3$, and $c_7 = 2$). These results could be partly due to the heuristic and partially random way in which the REMBO chooses different variables to analyze in the simulation. Despite having run several tests, it might be that pre-arranging to purchase from alternate suppliers at any price is not really optimal. The firm may not actually use these alternate suppliers during the disruption.

The firm should not use its entire budget to mitigate the risk of this supply chain disruption. The cost of all these strategies only totals 199 and the firm has a budget of 250. This means the budget is not a binding constraint. Since the firm desires to maximize its expected profit, spending more than 199 would mean that firm is spending too much to mitigate the risk and would actually hurt its expected profit. These base case values are then run independently in the supply chain risk simulation model for 10,000 times to obtain an expected profit with a 95% confidence interval. The firm's expected profit with these optimal strategies is 665.

4.3. Sensitivity analysis

Sensitivity analysis provides insight into the robustness of optimal strategies to changes in model parameters. For this illustrative example, sensitivity analysis can generate insights into how this type of model adjusts to changes in these parameters. We perform sensitivity analysis on the budget**,** one of the cost parameters for inventory, one of the cost parameters for the probability of supplier 3 reopening, and one of the cost parameters for customer loyalty. The REMBO algorithm was run 5 separate times for each set of parameters. Each run of REMBO had 40 iterations in which it called the risk management model, and each iteration conducted 300 replications of the supply chain disruption simulation. The REMBO algorithm produced a solution at the end of each run. Since we are provided with 5 potential optimal solutions (sets of decision variables), we separately run 10,000 replications of the simulation for each of these 5 sets of decision variables. The set of decision variables that generates the largest expected profit is selected as the optimal decision.

4.3.1. Budget

Firms almost always operate within a budget, and many firms may have a fixed budget for how much they will spend to mitigate risk. Increasing the budget in this model means the firm has more resources to hold more inventory, arrange to purchase supplies from alternate suppliers, and help its suppliers recover more quickly. The base-case results indicate that if the firm has a budget of 250, the firm should only spend 199, and increasing the budget beyond 250 would provide no additional benefit. Sensitivity analysis on the budget C means that the budget is decreased from 250 to 95. Figure 3. displays the change in the expected profit with respect to the budget.

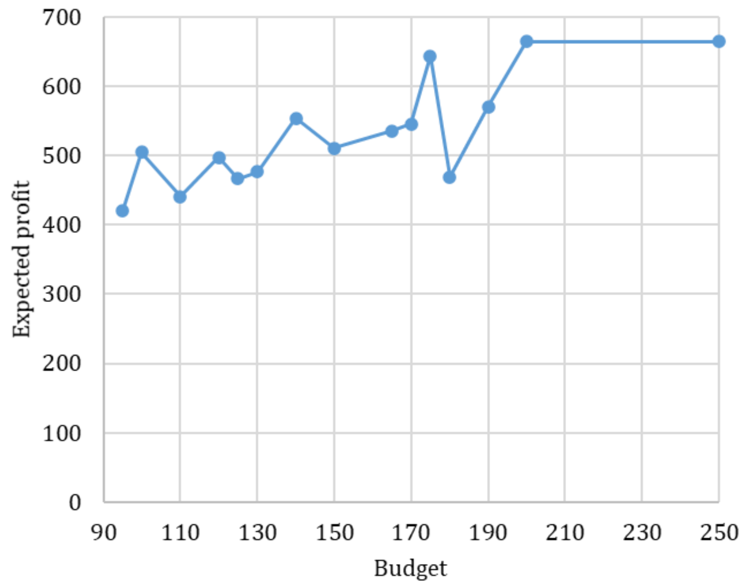

Fig. 3. *Change in the expected profit of the firm w.r.t the dedicated budget*

The firm's expected profit does not change when the budget is reduced from 250 to 200, and the optimal amount to spend remains 199. When the budget is reduced from 200, the expected profit generally decreases as the budget decreases. The decline in the expected profit as the budget decreases is not consistent, however. These random fluctuations are likely due to the combined randomness in the optimization algorithm and the simulation. Three hundred replications of the simulation may not be sufficient in order to accurately determine the expected profit for a set of decision variables, and REMBO may be converging on what it thinks is the optimal solution but could be local maxima. However, conducting more than 300 replications for the simulation and 40 iterations for the optimization algorithm for so many parameters in this sensitivity analysis did not really seem feasible.

Similar to how the firm should only spend 199 if the budget is between 200 and 250, the firm should not use all of its budget even when the budget is reduced. If the budget is 150, the firm should only spend 118 for an expected profit of 510. If the budget is 100, the firm should only spend 89 for an expected profit of 505. The budget may constrain the firm because the firm cannot spend 199, but always spending to the budget may actually decrease the firm's expected profit even if the budget is less than 199. We should caveat this conclusion by recognizing that this interesting result could be due to a failure to identify the true optimal set of risk management strategies for a given budget constraint.

As the budget continues to decrease the firm, the firm should have supplier 1 hold low inventory and compensate it by purchasing from its alternate suppliers. Even though, the supply inventory with the primary supplier 1 should be lowered, the firm should not hold much finished goods inventory. Purchasing from alternate suppliers would be profitable to the firm.

4.3.2. Inventory with the supplier

The cost of holding supply inventory is composed of a fixed cost and variable cost as depicted in Equation (1). The variable cost β_j is initially set at 0.1 and varied for supplier 1. Here, the budget remains constant at 250. Figure 4 shows how the firm should alter its inventory for supplier 1 as β_1 changes. The inventory for supplier 1 remains constant at 190 units for $\beta_1 \leq 0.3$. When $\beta_1 \geq 0.4$, holding supply inventory suddenly becomes too expensive and the firm should hold very little or no inventory for supplier 1.

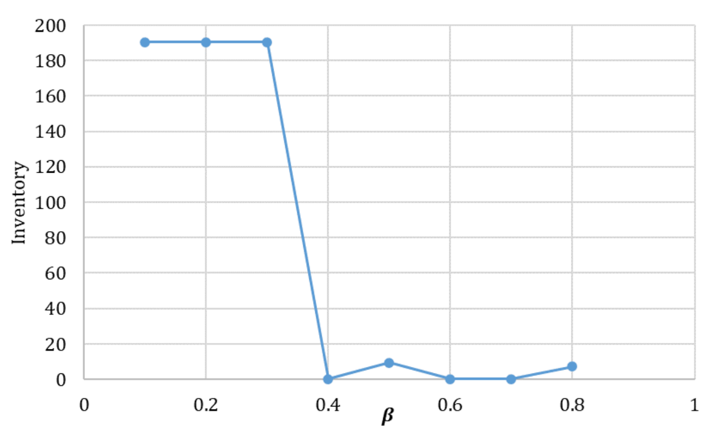

Fig. 4. *Inventory for suppliers as variable cost of the inventory changes*

Table 6 depicts how the inventory and purchasing from alternate suppliers should change as β_1 changes. If $\beta_1 \leq 0.3$, the optimal decision remains relatively constant, and the firm should primarily relay on supply inventory to mitigate the effects of the disruption. If $\beta_1 \geq 0.4$, the optimal decision changes. The firm should begin to hold a little bit of finished goods inventory. For example, the finished goods inventory should be 13 and 14 if $\beta_1 = 0.5$ and 0.6. The firm should also begin to prearrange to purchase from alternate suppliers at the same price as which it purchases from the primary suppliers. If $\beta_1 = 0.8$, the firm should arrange to purchase 25 units every week from an alternate supplier to supplier 1 at the same price as the primary supplier. If $\beta_1 = 0.5$, the firm should arrange to purchase from alternate suppliers to suppliers 2 and 3 at the same price as the primary suppliers. The table demonstrates, again however, in the random nature of the optimization algorithm, which may explain why the results are not as consistent as we would expect them to be.

Table 6 *Optimal mitigation decisions as the variable cost for supplier changes*

	$Primary\ Suppliers$			$Fin.\ goods$	$Alternate\ suppliers\ to\ 1$				$Alternate\ suppliers\ to\ 2$				$Alternate\ suppliers\ to\ 3$			
β	i_1	i_2	i_3	i_4	a_{11}	a_{12}	a_{13}	a_{14}	a_{21}	a_{22}	a_{23}	a_{24}	a_{31}	a_{32}	a_{33}	a_{34}
0.1	190	194	198	0	0	25	0	25	0	3	25	25	0	0	25	0
0.2	190	192	199	0	0	25	2	25	0	3	25	23	0	0	25	1
0.3	190	194	198	0	0	25	2	25	0	3	25	25	0	0	25	0
0.4	0	198	109	0	1	3	0	25	23	0	25	25	0	25	13	25
0.5	9	6	195	13	1	25	0	25	25	1	0	13	24	24	25	25
0.6	0	27	20	14	1	0	25	2	0	2	22	24	2	2	20	0

0.7	0	2	17	5	0	25	25	25	0	24	0	25	23	22	25	1
0.8	7	188	172	0	25	0	25	24	1	3	25	1	2	25	25	23

Next, we altered the variable cost for primary supplier 2 and primary supplier 3. The supply inventory drops at the same point of β_j = 0.4. The results of increasing the variable cost for all supply inventory echoes the results from increasing the variable cost for inventory of supplier 1. The variable cost β_j was also altered for all three suppliers simultaneously. At $\beta_j \geq 0.2$ The firm should drastically reduce its inventory for all three suppliers and purchase more from alternate suppliers.

4.3.3. Probability of reopening

Each supplier's facility will reopen at the beginning of the next period with a certain probability, but the firm can only choose to increase supplier 3's likelihood of reopening. We perform sensitivity analysis on η_3, which is a multiplicative factor in the cost function in Equation (3) for the probability of supplier 3 reopening. In the base case, $\eta_3 = 250$, and the firm should choose $p_3 = 0.088$. If η_3 decreases to 55, the firm should increase the probability to 0.16.

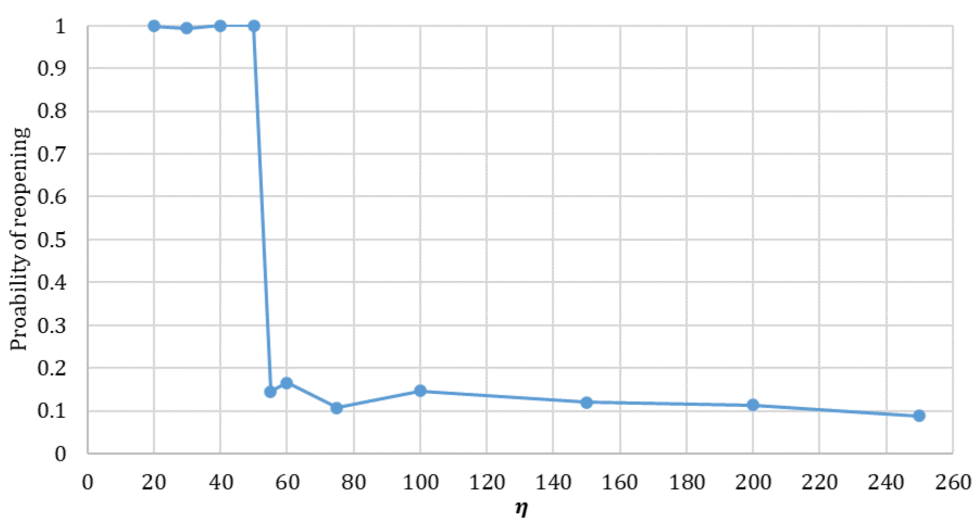

Fig. 5. *Probability that supplier 3 reopens versus the cost to help supplier 3 reopen*

From figure 5. it is evident that, if, $\eta_3 \leq 50$, the cost to increase the probability becomes so inexpensive that the firm should choose $p_3 = 1.0$. Firm should buy from the alternate suppliers to (i) primary supplier 1 selling at 2-4 times (ii) primary supplier 2 selling at 3-4 times and (iii) primary supplier 3 selling at 3 times the same price. Since the probability that supplier 3 reopens is 100%, the firm should not purchase supply inventory from supplier 3.

4.3.4. Loyalty of the customer

If the firm is not able to satisfy the demand of the customers because it does not have enough inventory or purchasing from alternate suppliers is too expensive, customers may buy from other firms in the simulation. Each customer has the same probability that it will buy from a competitor to the firm, and $\hat{q} = 0.25$ is the initial probability that a customer will not buy from the firm's competitor. In the base case, the firm should not choose to increase this probability and $q = 0.25$. The parameter $\lambda = 100$ is associated with the cost to increase the firm's customer loyalty in Equation (4). This parameter is varied to see if decreasing λ should change the firm's decision. However, even if $\lambda = 10$, the firm should not choose increase customer loyalty. Enhancing the loyalty of the firm's customer is a less effective strategy than the other mitigation strategies such as holding inventory or helping supplier 3 recover more quickly because the latter strategies help the firm satisfy demand as opposed to leaving customer demand unsatisfied.

Through sensitivity analysis on these parameters, the decision maker can identify the appropriate strategy if there is a certain variation in the parameters. The firm could decide their expenditure based on the cost of each strategy and how would it benefit or adversely affect other parameters.

CHAPTER 5. CONCLUSION

This research proposes a SCRM model that uses a supply chain disruption simulation and applies a simulation-optimization algorithm in order to determine the optimal risk mitigation strategies for a firm. The supply chain disruption simulation begins by closing the facilities of several suppliers, and the firms that rely on these suppliers may not be able to satisfy their customers. Within the risk management model, the firm could choose from among several different strategies, to include holding supply inventory, finished goods inventory, prearranging to purchase from alternate suppliers, working with suppliers to increase their capability to reopen more quickly, and increasing their customer loyalty. Since these risk management strategies are all continuous variables and evaluating each strategy requires the supply chain disruption simulation, we use a Bayesian optimization algorithm in order to determine the optimal set of risk management strategies.

An illustrative example demonstrates how this risk management model works. Under the base-case scenario, the firm should hold a significant amount of supply inventory and also increase the probability that one of its key suppliers reopens. The base-case results demonstrate how some strategies may be very appealing and other strategies may be less appealing. Further research can explore the extent to which it is best to focus the majority of the budget on a few cost-effective risk mitigation strategies rather than spreading the budget evenly over every strategy. The base-case results also reveal that a firm should not always use the entire budget on risk mitigation strategies because the costs of continuing to spend money on risk mitigation may outweigh the benefits. Sensitivity analysis on some of the key parameters shows that there may be sudden changes in a decision variable as parameters change. For example, as the cost of inventory increases, the firm should keep the same amount of inventory until a certain threshold is reached and then decide to hold hardly any inventory.

Simulation-optimization has hardly been applied to SCRM, and yet, supply chain disruptions are so complex that, they frequently require simulation to analyze and combine the different uncertainties. Although, our model applies a simulation-optimization algorithm to a SCRM framework, this framework has certain limitations. The Bayesian optimization-algorithm is not guaranteed to find the optimal solution and it has some randomness as it searches for a new decision variable to sample. Each time the decision variable is selected, the supply chain disruption simulation is run several hundred times. Consequently, the entire process takes some time to run. When the algorithm finishes, we cannot be certain that the identified solution is truly optimal. Running the algorithm multiple times with different initial starting points and increasing the number of replications in the simulation can generate more confidence that the identified solution is optimal. The base-case results were run a significant amount of time that we are confident that the identified solution is very close to the true optimal. However, the solutions discovered during the sensitivity analysis are more suspect. Some of the trends that we find are perhaps more due to the heuristic nature and randomness of the simulation-optimization framework. Future research can explore how the algorithm could be made more efficient or the proper number of times to run the simulation or optimization algorithm to be confident the identified solution is optimal.

Other elements to explore within this simulation-optimization framework could be to include objectives other than maximizing profit such as minimizing the time to recover. The simulation model of MacKenzie et al. (2013) assumes that firms also seek to minimize the amount of lost demand during the disruption, and this objective could also be included within this framework. The simulation assumes a severe disruption such as a natural disaster that impacts multiple suppliers, but the framework could be applied to other types of disruption such as man-made disruptions. The simulation would need to be adjusted in order to reflect the particular features of the supply chain disruption, and many disruptions may not impact multiple suppliers like the simulation presented here. Firms learn from previous disruptions, and a firm could use this framework to learn about the impacts of a severe supply chain disruption. It is difficult, however, to model the learning behavior of a firm in this type of static simulation.

Despite these limitations, this simulation-optimization framework for SCRM represents a significant advancement to help firms identify the optimal risk management strategies. Firms should prepare for supply chain disruptions and using simulation to explore the uncertainties in those disruptions is a good method for understanding different scenarios. If the firm wishes to identify the best strategies that will help it manage those scenarios, then a simulation-optimization framework is another helpful tool for the firm. This paper demonstrates how that tool can be applied to particularly severe and complex supply chain disruption.

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