RECOVERY STRATEGIES FROM MAJOR DISRUPTIONS IN SUPPLY NETWORKS

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Abstract - The increase in supply network disruptions has shown that many companies have been caught by surprise and were not able to quickly, if at all, recover from these disruptions. In this paper we propose models for optimal recovery from major unpredictable disruptions in a supply network. We consider a supply network that is comprised of customers and production facilities where disruption may occur at any of the facilities and can cause partial failure or complete shutdown of the supply facilities. The novelty of our model is that it incorporates dynamic pricing as a lever to manage demand during such disruptions. In addition to pricing we also incorporate recovery strategies that are based on inventory, transshipment and outsourcing. We allow for the recovery duration and the disrupted capacity to be uncertain and use pricing to reflect temporary impacts of disruption on demand. Demand is price sensitive and accounts for uncertainty in the customers' willingness to pay during the recovery period.

Keywords - Supply Chain Network; Risk Management; Disruption Recovery Strategies

I. INTRODUCTION AND LITERATURE REVIEW

Supply chain risks are divided into two categories: operational risks and disruption risks. Operational risks are directly related to current flows in the supply chain including uncertainty in customer's demand, supply, and cost. Disruption risks, the subject of this paper, refer to natural disasters and man-made disruptions such as earthquakes, floods, hurricanes and terrorist attacks. Without proper response strategies, supply chains may suffer significant losses while recovering fromdisruptions.With the increase in the occurrence of disruptions, organizations are incorporating disruption risk management in theirsupply chain operations strategies. Two common strategies for disruption risk management are mitigation and contingency strategies (Tomlin, 2006). A mitigation strategyis used in the supply chain before a disruption occurs and consequently its related cost is imposed on the network regardless of the disruption occurrence. For example, a multi sourcing strategy falls in this category. A contingency strategy is only usedafter the disruption occurs such as transportation rerouting. When it comes to the source of risks there are generally two sources for the disruption: random disruption risks that may occur at any physical point of the supply chain network (Lim et al., 2010), e.g., natural hazards,and premeditated disruption risks that are deliberately planned to inflict the supply chain with maximum damages such asterrorist attacks and labor union strikes (see Church et al., 2004; Church and Scaparra, 2006; Scaparra and Church, 2008; Altner et al., 2010; Liberatore et al., 2011 and 2012, among others).Our focus in this paper is on major random disruption to supply networks.

There have been many studies that have looked at supply network disruption risk management (Snyder et al., 2016). Most of these studies focus on mitigation strategies before disruption. To show the merit of a mitigation strategy, it is customary to compare the costs before disruption to those after disruption and argue that it is optimal to increase the costs before disruption (through mitigation strategies) in order to significantly decrease the disruption costs. In these studies the recovery period is often taken as a single period and the main recovery strategy that is adopted is transportation rerouting. This leaves out significant operational and strategic perspectives of the recovery process, including the financial losses after disruption, uncertainty in recovery duration and the process of regaining pre-disruption production capacity levels. Given the apparent increase of major supply network disruptions, companies are interested in finding strategies that would allow them to recover quickly with the least possible costs. Thus, our goal in this paper is to help fill in this gap in the literature by developing models to find optimal recovery strategies from major supply network disruptions.

Our models' assumptions and ideas are derived from recent experiences from major supply network disruptions. For example, the 1998 hurricanes in Guatemala and Honduras damaged banana farms and caused a 10% halt in the world's banana production. Using alternative sources, Chiquita was able to continue to serve its customers while Dole was unable to find a suitable alternative sourcing for banana supply in the area. Thus, it lost 70% of its bananas supply in the area resulting in a financial loss of $100 million.It took over a year for Dole to recover from this disruption. In March 2000, lightning caused fires in the semiconductor production plant of Phillips leading to a six week supply shortage for Ericsson and Nokia. As a result, Ericsson suffered a financial loss of $400 million in the North America mobile market(Tomlin, 2006).As another example, the 2011 tsunami in Japan has

caused production disruption in Toyota manufacturing plants that spread out around the globe, from partial to full shut down. It took the company more than six months to return most of its supply chain to a pre-disruption activity levels (Morteza-Beigi and Hassini, 2014).Hendricks and Singhal(2005) noted that unlike operational risks, disruption risks cause huge negative financial impacts for companies and recovery from disruption to return to normal conditions is often slow. Motivated by these examples, in this paper, we explicitly model the recovery duration after the disruption as well as the possibility that facilities may be partially disrupted.

Given our focus on post-disruption recovery, we are interested in finding strategies that would allow a disrupted supply network to recover quickly with the least cost. In the literature the strategy that is commonly used is rerouting given the focus is usually on single period recovery models (e.g., Cui et al. 2010 and Lim et al., 2010). In this paper we consider novel strategies such as dynamic pricing. For example, Dell has been reported to have used pricing as a strategy to remain competitive during the time when its supply network has been disrupted during the 1999 earthquake in Taiwan (Martha and Subbakrishna, 2002 and Olson and Wu, 2008). In 2005, hurricane Katrina has caused the idling of about 10% of the oil refineries capacity in the U.S. due to the disruption of the drilling facilities in the Gulf region. This has led to an overnight increase of the price of a gallon of gas by about 50 cents. During the 2011 Thailand flooding it was reported that prices of hard drives jumped by 300% immediately after the flooding and gradually decreased to 28% higher than pre-disruption levels after about two quarters from the flooding. These examples have motivated us to incorporate dynamic pricing as a post-disruption recovery strategy, in addition to transportation rerouting, outsourcing and production and inventory management strategies. To focus on the impact of pricing as a post-disruption recovery strategy, we assume the price impact is restricted to the supply network. This assumption would hold for products where the firm has market power in setting prices.

II. MULTI-SOURCING MODEL

In this section we present assumptions, model and analysis for a supply network where a single commodity product is being produced in several facilities and sold to multiple customer groups

2.1. Assumptions

We are interested in determining the commodity price, the amount of production and inventory holding in each of the production facilities as well as transportation and outsourcing strategies (from productionand outsourcing facilities to customers) during the post-disruption recovery period. Our objective is to maximize the supply network profit during recovery.

Facilities' capacities are measured based on the production volume of the commodity.Given our focus on the post-disruption period, it is assumed that the disrupted facilities are known. Thus, in our model the disrupted facilities, as well as their location and degree of disruption, are known input parameters. As in Azad et al. (2013) we assume that in the event of a partial disruption, the remaining available capacity can be used to serve customers. Customers can be served either through finished good inventory, which were not damaged during the disruption, and/or through the non-disrupted production capacity. The latter can happen, for example, when a facility has two parallel identical production lines and only one of them is disrupted.

Since we are mainly focusing on major and critical production disruption, it is reasonable to assume that other disruptions do not happen during the recovery period. In other words, we assume that disruptions in different facilities are independent.

The facilities' disrupted capacity is recovered gradually over time. The amount of disrupted capacities in each period and the length of the recovery periods are uncertain. Our capacity recovery model is general enough to capture situations where a facility is instantaneously recovered, after a certain period of repair, or capacity is incrementally built up through the recovery period. To model the recovery uncertainty we use the scenario approach which has been applied in the literature to formulate disruption parameters in supply networks, e.g., see Peng et al., 2011,Shen et al., 2011and Azad and Hassini, 2013. Since disruptions are rare events and do not happen frequently, it is challenging to estimate the distribution of the uncertain recovery parameters. On the other hand, scenario approach does not require restrictive assumptions on the distribution of the random parameters, which increases its generality and flexibility (Pagnoncelli et al., 2012). In this approach, the uncertainty is characterized through a set of admissible situations, and a probability distribution over this set (Campi et al., 2009) and the absence of any distributional assumptions, allows one to use the actual historical data as the set of scenarios (Pagnoncelli et al., 2012). For example, in our work we can determine the scenarios based on the historical data on the impact of previous disruptions in terms of recovery duration and process of disrupted capacities in the facilities. Also, the probability of each scenario can be calculated based on, for example, the number of occurrence of that scenario in the past.

Unlike the existing literature in which one uncertain parameter (e.g. disrupted facilities) is formulated by applying the scenario approach, we develop this

approach to model two uncertain recovery parameters: the amount of disrupted capacities in the facilities and the length of the recovery period.In order to formulate the length of the recovery period in the scenario approach, the maximum time length required for disruption recovery among all possible disruption scenarios is considered as the horizon time length for all the scenarios. This idea is further explained in Section 3.2 with an illustrative example.
Customers' willingness to pay is assumed to be random with a distribution $f(x)$ such that $0 \leq f(x) \leq 1$ for all $x \geq 0$ and has an increasing generalized failure rate (IGFR) as defined in Lariviere and Porteus (2001). The demand, as a function of price, is $d(p) = a \int_p^{\infty} f(x)dx$ where $a = d(0) \geq 1$ is the potential market size.This general function would allow for representing different demand models. It is also assumed that the product price is the same in all facilities and the potential market size remains constant during the recovery period.

In addition to the facilities existing in the network, demand outsourcing is also taken into account. Allocating customers to facilities and (or) outsourcing is formulated by using continuous variables. As such it will be possible to assign each customerto several facilities andtheir demand in each period can be supplied by disrupted or non-disrupted facilities (with respect to capacity) and (or) outsourcing. Each production facility that is used to satisfy customers' demand in a period can use a combination of goods produced in that period and inventory transferred from the previous period with respect to its available (non-disrupted) capacity in that period. Inventory that is transferredto the next period incurs an inventory holding cost based on thevolume of the commodity that is transferred.

2.2. Model

Indices and sets

k	Index for customers types; $k \in K$
j	Index for production facilities; $j \in J$
t	Index for time periods; $t \in T$
s	Index for recovery process scenarios; $s \in S$

Parameters

C_{jkt}	Transportation cost from facility j to customers type k in period t
CP_{jt}	Production cost in facility j in period t
CO_{kt}	Outsourcing cost of customers typek in period t
IC_{jt}	Inventory carrying cost of product in facility j in period t
IN_{j0}	Inventory at the beginning of period one in facility j
Cap_j	Production capacity of facility j
α_{jts}	Fraction of unavailable production capacity of disrupted facility j in period t in scenario s
a_k	The market size for customers of type k demand
UP	The upper bound for product price
w_s	The probability that scenario soccurs
M	Large number

Decision variables

XP_{jt}	Amount of product produced by facility j in period t
YP_{jkt}	Amount of shipped goods from facility j to customer k in period t
OS_{kt}	Amount of outsourcing of customer k's demand in period t
P_t	Product price in period t
IN_{jt}	Amount of commodity held in stock in facilityj at the end of period t
π_{MS}	Profit in multiple-sourcing model

Problem formulation
Model A:

$$Max \quad \pi_{MS} = \sum_{k,t}\left(a_k \int_{P_t}^{\infty} f(x)dx\right)P_t - \left[\sum_{j,t} CP_{jt}XP_{jt} + \sum_{j,t} IC_{jt}IN_{jt} + \sum_{k,t} CO_{kt}OS_{kt} + \sum_{j,k,t} C_{jkt}YP\right. \quad (1)$$

Subject to:

$$\sum_j YP_{jkt} + OS_{kt} \geq a_k \int_{P_t}^{\infty} f(x)dx \qquad \forall k,t \qquad (2)$$

$$\sum_k YP_{jkt} + IN_{jt} = XP_{jt} + IN_{j,t-1} \qquad \forall j,t \qquad (3)$$

$$XP_{jt} \le \left(1 - \sum_s w_s \alpha_{jts}\right) Cap_j \qquad \forall j,t \qquad (4)$$

$$P_t \le UP \qquad \forall t \qquad (5)$$

$$XP_{jt}, IN_{jt}, YP_{jkt}, OS_{kt}, P_t \ge 0 \qquad \forall j,k,t \qquad (6)$$

Objective function (1) is aimed to maximize the total profit of the network. The first term of the objective function represents the total sales revenue of the network. The second term is the total cost of the network including the production cost, the inventory holding cost in the production facilities, the outsourcing cost and the transportation cost of the commodity from production facilities to customers. Constraints (2) address the transshipment, outsourcing and pricing recovery strategies which are related to supplying customers demand in each period with respect to product price and it should be provided via transshipment from production facilities and (or) outsourcing. Constraints (3) address the transshipment, inventory and production recovery strategies and they are the equilibrium equations of production and inventory for each facility in each period. They state that the sum of transshipment to the customers and the inventory of the period should equal the sum of the commodity production in that period and the inventory transferred from the previous period. Constraints (4) address the recovery process scenarios for the facilities where the amount of commodity production must be less than or equal to the expected value of the available capacity in each period with respect to the disruption recovery scenarios. Constraints (5) enforce the product price limit for each recovery period. The UP represents the limit on the price during recovery periods. This limit may represent the producer's economies (such as prices that would guarantee a positive sale) or the customers' purchasing power (such as desire to not increase prices significantly during disruption). Constraints (6) enforce the non-negativity restriction on the decision variables.

It is worth noting here that unlike previous network design models which consider before and after the disruption decisions simultaneously, the scenarios in our model appear only in the constraints related to the available capacity of the disrupted facilities in each period. This is due to the fact that we are focusing on post-disruption recovery where disrupted facilities are known and our costs and revenues are scenario independent. In particular we do not model the cost of recovery and assume that it is a sunk constant cost that is independent of our model decision variables.

III. BENEFITS OF CONSIDERING PRICING AS A DISRUPTION RECOVERY STRATEGY

Since this is the first time pricing has been considered as a recovery strategy for supply network disruptions, wenumerically analyze the performance of this strategy. For this purpose the results are compared with the case where the pricing strategy is not applied and a fixed price (as a parameter) is considered.Figure1 compares the results for the US case study. The figure shows the increase in price and the improvement (%) in profit of the network when compared to the fixed price case.

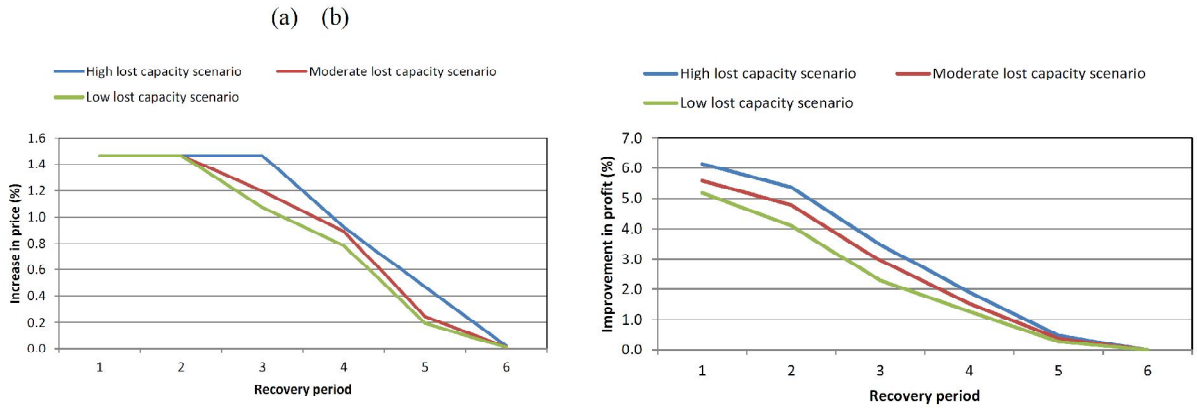


Fig. 1. The impact of considering a pricing strategy l in the US case study (a) on the price of the product (b) on the profit of the network

According to Figure 1,the increase in price and improvement in profit in the multi-sourcing model shows a non-increasing trend during the recovery periods, compared to the fixed-price model.During the initial periods when the disruption occurs and there is a considerable lost capacity, the network

profitis improved considerably. When the lost capacity of facilities improves, price returns to the normal conditions before the disruption and improvement in profit tends towards zero.

CONCLUSION

In this paper we propose model for recovering from disruptions in a supply network. Unlike previous studies in the literature,the recovery duration is uncertain and a dynamic pricing recovery strategy is considered in addition to inventory, transportation and outsourcing strategies. In addition, the advantages of the pricing strategy in dealing withdisruption were analyzed and compared with the case where the price is fixed after disruption.

There are several interesting future directions in this area. First, in practice prices may not decrease immediately when the network recovers from disruptions. This can happen due to presence or lack of competitive pressures. Thus, to understand such pricing behaviors we would add competition in the model. The second direction concerns modelling substitutable multi-commodity supply chain networks in which the price of a commodity may affect the demand of other commodities.

REFERENCES

[1] Altner DS, Ergun O, Uhan NA. The maximum flow network interdiction problem: valid inequalities, integrality gaps, and approximability. Operations Research Letters 2010;38(1):33-38.

[2] Church RL, Scaparra MP. Protecting critical assets: the R-interdiction median problem with fortification. Geographical Analysis 2006; 39(2):129-146.

[3] Church RL, Scaparra MP, Middleton RS. Identifying critical infrastructure: the median and covering facility interdiction problem. Annals of the Association of American Geographers 2004; 94(3):491-502.

[4] Cui T, Ouyang Y, Shen ZJ. Reliable facility location design under the risk of disruptions. Operations Research 2010; 58(4):998-1011.

[5] Hendricks KB, Singhal VR. An empirical analysis of the expectation of supply chain disruptions on long-run stock price performance and equity risk of the firm. Production and Operations Management 2005; 14(1):35-52.

[6] Liberatore F, Scaparra MP, Daskin MS. Analysis of facility protection strategies against an uncertain number of attacks: the stochastic R-interdiction median problem with fortification. Computers and Operations Research 2011; 38(1):357-366.

[7] Liberatore F, Scaparra MP, Daskin MS. Hedging against disruptions with ripple effects in location analysis. Omega 2012; 40:21-30.

[8] Lim M, Daskin M, Bassamboo A, Chopra S. A Facility Reliability Problem: Formulation, Properties and Algorithm. Naval Research Logistics 2010; 57(1):58-70.

[9] Martha, J. and Subbakrishna, S. Targeting a just-in-case supply chain for the inevitable next disaster. Supply Chain Management Review, 2002, 6(5):18-23.

[10] Morteza-Beigi L, Hassini E. A Model for risk propagation in supply chains with case studies of Toyota and Honda's global supply netoworks, Working Paper, DeGroote School of Business, McMaster University, 2014.

[11] Olson, DL, and Wu, DD. Enterprise risk management. Singapore: World Scientific, 2008.

[12] Scaparra MP, Church RL. A bi level mixed-integer program for critical infrastructure protection planning. Computers and Operations Research 2008; 35(6):1905-1923.

[13] Tomlin B. On the value of mitigation and contingency strategies for managing supply chain disruption risks. Management Science 2006; 52(5):639-657.

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