Selection of the response speed to improve the supply chain responsiveness subject to natural disasters
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Abstract

The objective of this paper is to develop a decision making tool to design a responsive supply chain subject to natural disasters. The contingency rerouting is known as a cost-effective risk management strategy for major disruptions compared to emergency inventories which are economically unsustainable. We propose a mixed integer programming (MIP) based capacity planning tool which generates the contingency plan of the supply chain subject to random disruptions. In order to make an accurate decision, the impacts of response time and flow congestion are considered in the analysis. The appropriate response speed for a given disruption environment is selected through a decision tree analysis by minimizing the expected supply chain costs. The results show the optimality of the faster response speed as the failure probability increases and/or recovery probability decreases.

Keywords: Natural disasters, Contingency strategy, Reconfigurable supplier, Response speed

Ce projet vise l'élaboration d'un outil d'aide à la décision aux fins de la conception d'une chaîne d'approvisionnement adaptée au contexte des catastrophes naturelles. Le réacheminement d'urgence est une stratégie connue de gestion de risque en cas de perturbation majeure. Il est plus avantageux au chapitre des coûts que l'utilisation de stocks d'urgence, solution non viable sur le plan économique. Nous proposons un outil de planification de capacité reposant sur une programmation partiellement en nombres entiers (MIP), qui génère le plan d'urgence relatif à la chaîne d'approvisionnement soumise à des perturbations aléatoires. Afin d'en arriver à une décision adéquate, l'analyse tient compte des impacts du temps de réponse et de la congestion du flux. La sélection de la vitesse de réponse appropriée dans un contexte de perturbation donné s'effectue au moyen d'une analyse par arbre de décision en minimisant les coûts prévus de la chaîne d'approvisionnement. Les résultats montrent l'optimalité d'une vitesse de réponse d'autant plus grande que la probabilité de défaillance augmente ou que la probabilité de redressement diminue.

Mots-clés: catastrophes naturelles, stratégie d'urgence, fournisseur avec possibilité de reconfiguration, vitesse de réponse

1. Introduction

Within the last decade, several supply chains have been affected by natural disasters, showing their vulnerability in the face of catastrophes. Ericsson lost 400 million euros after a random lightning bolt struck its semiconductors supplier firm in New Mexico in 2000 [1]. Japan tsunami in 2011 interrupted Japanese automotive production, as well as automotive companies all over the world, which are supplied by Japanese suppliers [2]. As a result of these, there has been a growing interest to find appropriate risk management strategies when such events occur.

Risk management strategies in supply chains are divided into two categories. Mitigation strategies focus on taking precautions in advance to the risk occurrence through strategic inventory and dual sourcing. On the other hand; strategies such as contingency rerouting and revenue management are implemented in the event of a risk occurrence [1,3]. The contingency rerouting could be a cost efficient strategy to protect the supply chain against major disruptions [4]. This can be achieved by using a flexible backup supplier that is capable of altering its capacity in order to cover for the disrupted source. However, this coverage would be available only after a certain period of time which can hurt the product availability.

The response time is a crucial characteristic of contingency rerouting since only a fraction of the required capacity might be available within this period. Ignoring this fact in the supply chain planning stage leads to the overestimation of the available backup capacity, and may result in product shortage. In order to minimize this effect, the backup supplier can invest in production capabilities to increase the response speed. Therefore, these characteristics should be accurately considered in the design of such contingency mechanisms.

This paper focuses on the optimal selection of the backup supplier's response speed in order to improve the supply chain responsiveness under catastrophic events. The rest of the paper is organized as follows: Section 2 reviews the relevant literature, Section 3 presents the problem statements, Section 4 describes the solution methodology, the numerical results are presented in section 5, and section 6 states the conclusions.

2. Literature review

We focus our literature review to the research that considers the response time and back up facilities to mitigate against the disruptions in a supply chain context. The seminal work by Tomlin [3] presents the inventory as an appropriate strategy for frequent-short disruptions of the main supplier and the dual sourcing for rare-long disruptions. If the backup supplier has flexible capacity, the contingent rerouting might be optimal. However, Tomlin assumes that the whole backup capacity would be available only after the response time. Hopp and Yin [5] consider a similar premise regarding the available capacity within the response time. In order to protect the supply chain against catastrophic failure of supply, the authors conclude that the inventory or backup capacity should be provided at most in one node along each path to the customer.

While Tomlin [3] and Hopp and Yin [5] assume that there is no supply from the backup capacity during the response time, Niroomand et al [6] illustrate partial availability of the capacity within this period in a strategic capacity planning model. The authors consider a two echelon supply chain where the production stage includes a dedicated manufacturing system (DMS) and a reconfigurable manufacturing system (RMS) as a flexible supply. The model incorporates a partial availability of the RMS capacity during the ramp up phase to better represent the modular structure of RMS.

In assessing the operational characteristics of the contingency rerouting such as the available capacity within the response time, the decisions affecting the response speed should be made in the planning stage to improve the robustness of the contingency rerouting [4]. For example, a facility that is designed with parallel machine configuration will possess better scalability and will be able to reach the desired level of capacity faster. On the other hand, a serial configuration will lead to relatively slower response speed [7]. This will create the need to set higher inventory levels to sustain the desired service levels.

In a related study, Schmitt [8] tries to find the optimal inventory level and the response time such that a required service level would be satisfied under all plausible future scenarios. While this work contributes by representing the partially lost sales as a function of the disruption duration, the model ignores a critical aspect in the supply flow. In a situation where the main supplier is disrupted, its demand would be transferred to the backup supplier under a contingency strategy. This may create an overload of demand at the backup supplier and leads to the overestimation of the production capacity due to the congestion.

In order to consider the impact of the congestion over the system throughput, the relationship between the workload and throughput should be identified [9]. Vidyarthi [10] represents the congestion effect in a capacity planning model under the random demand arrivals albeit this phenomenon so far is ignored in the works which focus on the management of major disruptions [5,8]. In this work, we focus on supply chain design decisions to recover from the natural disasters. The contingency rerouting is applied where the backup supplier is assumed to be equipped with an RMS facility. The differentiating approach in this paper is to precisely represent the partially available capacity during response time. This will allow developing a decision making tool to determine an appropriate response speed of the backup supplier.

3. Problem statement

In order to implement an appropriate contingency strategy, the operational characteristics such as response time should be considered in the planning stage [4]. In this paper, we analyze the available backup capacity during the response time. This analysis is based on modeling the available capacity with respect to the response time characteristics and congestion effect.

We consider a single product supply chain that includes a warehouse with dual sourcing. One of the suppliers has DMS facility and the other one is equipped with RMS. In the case of the DMS disruption, the RMS could change its capacity level to sustain the supply flow at the required rate. The time and the magnitude of these changes are decided in a contingency capacity planning model as described in sections 4.1. The RMS changes its capacity level by adding or removing modules. However, the target capacity would be gradually achieved within the response time. Therefore a fraction of the target capacity is available during the response period. In addition to that, an accurate evaluation of the partial capacity during the response time is gained upon considering the impact of the congestion. The amount of the available capacity during the response time depends on the reconfiguration speed. However, the RMS reconfiguration cost increases in the reconfiguration speed. As result of these, the appropriate reconfiguration speed of the RMS should be selected with respect to the tradeoff between reconfiguration cost and shortage cost.

4. Solution methodology

In order to find the optimal response speed of RMS, a solution methodology based on mixed integer programming and decision tree analysis is proposed. We first develop a mixed integer programming (MIP) based multi period capacity planning model to generate supply chain configuration. Afterwards, capacity plan is subjected to a set of possible DMS disruption scenarios where each scenario's probability of occurrence is calculated using discrete Markov chain distribution. Each disruption scenario is then inserted to the MIP model to represent the capacity disruptions to DMS facility which in turn will trigger the need for RMS to ramp up its capacity and supply the demand. Three different response speeds are proposed $RS_k, k \in \{1,2,3\}$ where a certain capacity level is available during the response time corresponding to each speed. For each level, the MIP model generates the contingency capacity plans and their resulting costs corresponding to different disruption scenarios (m, n) where m represents the time of occurrence and n is the length of disruption. The costs of the contingency capacity plans as well as the probabilities of disruption scenarios are then represented in a decision tree.

For a given failure and recovery probability, the optimal response speed under all plausible future scenarios is selected through this decision tree analysis. Since the selection of the response speed can depend on the attitude of the decision maker towards risk, we can determine the optimal policy under risk neutral, and risk averse conditions.

4.1 Capacity Planning model

The first step of the proposed methodology consists of the mixed integer programming model to determine the capacity, production, inventory and work in process (WIP) levels of DMS and RMS suppliers for a predetermined planning horizon. The list of notations and decision variables are shown Table 1.

		Indices	
T	Time horizon	$i \in 0,1,2,3$	Number of added modules
$t \in 1,\ldots,T$	Current time	$j \in 100,200,300,400$	Nominal capacity levels
t_D	Time of Disruption	N^d	Approximation lines, DMS
M	A big number	$N^r_{0,j}$	Approximation lines, RMS with fixed capacity level j
d	DMS supplier	$V^r_{i,j}$	Approximation planes, RMS with reconfiguration
r	RMS supplier		
		Input parameters	
D^{tot}_t	Demand at time t	Crm^d	Release material cost of DMS
CP^d	Production cost of DMS	Crm^r	Release material cost of RMS
CP^r	Production cost of RMS	C^d_{Max}	Maximum DMS capacity
RC	Reconfiguration cost	C^r_{Max}	Maximum RMS capacity
SC	Shortage cost	C^r_{ml}	RMS Module capacity
EC^d	Excess capacity cost of DMS	θ^U_i	coefficient of upper limit for RMS capacity changes
EC^r	Excess capacity cost of RMS	θ^L_i	Coefficient of lower limit for RMS capacity changes
HC^d	Finished good holding cost of DMS	Y^{DMS}_t	DMS status at time t
HC^r	Finished good holding cost of RMS	$I^{d,ini}_t$	DMS inventory value before disruption
$C\omega^d$	WIP holding cost of DMS	$I^{r,ini}_t$	RMS inventory value before disruption
$C\omega^r$	WIP holding cost of RMS	$Y^{i,ini}_t$	The RMS capacity plan before disruption
		Decision variables	
$D\lambda_t$	DMS production at time t	ω^d_t	DMS Work in process at t
$R\lambda_t$	RMS production at time t	ω^r_t	RMS Work in process at t
$R\Delta\xi^+_t$	RMS added capacity at t	rm^d_t	DMS release material at t
$R\Delta\xi^-_t$	RMS removed capacity at t	rm^r_t	RMS release material at t

D_t^l	Lost demand at time t	$R\xi_t$	RMS actual capacity at t
D_t^s	Satisfied demand at time t	$IR\xi_t$	RMS nominal capacity at t
D_t^d	Satisfied demand by DMS at t	$U\xi_t^r$	Upper limit for changes in RMS capacity
D_t^r	Satisfied demand by RMS at t	$L\xi_t^r$	Lower limit for changes in RMS capacity
$E\xi_t^d$	DMS excess capacity at t	Y_t^i	Binary variables represent capacity changes
$E\xi_t^r$	RMS excess capacity at t	Y_t^j	Binary variables represent nominal capacity
I_t^d	DMS finished good inventory at t	Y_t^5	Binary variable controls shortage or inventory
I_t^r	RMS finished good inventory at t	Y_t^{10}	Binary variable controls capacity addition or deletion

Table 1.Notations and decision variables

The objective function includes the production cost (1), the system reconfiguration cost (2), the excess capacity and the lost demand costs (3), the holding cost of the finished good inventory (4), the WIP holding cost (5) and the raw material purchasing cost (6).

$$Min(Z) = \sum_t (CP^d * D\lambda_t + CP^r * R\lambda_t) \quad (1)$$

$$+\sum_t RC * (R\Delta\xi_t^+ + R\Delta\xi_t^-) \quad (2)$$

$$+\sum_t (SC * D_t^l + EC^d * E\xi_t^d + EC^r * E\xi_t^r) \quad (3)$$

$$+\sum_t HC^d * I_t^d + HC^r * I_t^r \quad (4)$$

$$+\sum_t c\omega^d * \omega_t^d + c\omega^r * \omega_t^r \quad (5)$$

$$+\sum_t crm^d * rm_t^d + crm^r * rm_t^r \quad (6)$$

After the demand is realized for a period, it could be satisfied through the inventory or the current RMS and DMS production (7),(8). The unsatisfied demand is lost (9),(10). We assume that it is not possible to have both demand loss and the inventory at the end of a period (11),(12). The work in process inventories consist of the jobs in the queue or under operation. Constraints (13) and (14) represent the balance equations between the raw material release, production quantity and WIP level for each period. The production of DMS and RMS are limited to the available capacity of each system (15),(16). The maximum workload in any period is bounded by the available capacity during that period (17),(18).

Constraints

$$I_t^d = I_{t-1}^d + D\lambda_t - D_t^d \qquad \forall\ t \in T \quad (7)$$

$$I_t^r = I_{t-1}^r + R\lambda_t - D_t^r \qquad \forall\ t \in T \quad (8)$$

$$D_t^d + D_t^r = D_t^s \qquad \forall\ t \in T \quad (9)$$

$$D_t^s + D_t^l = D_t^{tot} \qquad \forall\ t \in T \quad (10)$$

$$D_t^l \le M * (1 - Y_t^5) \qquad \forall\ t \in T \quad (11)$$

$$I_t^d + I_t^r \leq M*(Y_t^5) \qquad \forall\ t \in T \quad (12)$$
$$\omega_t^d = \omega_{t-1}^d + rm_t^d - D\lambda_t \qquad \forall\ t \in T \quad (13)$$
$$\omega_t^r = \omega_{t-1}^r + rm_t^r - R\lambda_t \qquad \forall\ t \in T \quad (14)$$
$$D\lambda_t + E\xi_t^d = C_{\max}^d \qquad \forall\ t \in T \quad (15)$$
$$R\lambda_t + E\xi_t^r = R\xi_t \qquad \forall\ t \in T \quad (16)$$
$$\omega_t^d + rm_t^d \leq C_{\max}^d \qquad \forall\ t \in T \quad (17)$$
$$\omega_t^r + rm_t^r \leq R\xi_t \qquad \forall\ t \in T \quad (18)$$

In order to have an appropriate estimation of the available capacity of RMS during the reconfiguration, we assume that only a portion of the added capacity is available during reconfiguration. Therefore, during reconfiguration period we deal with two characteristics of the reconfigurable capacity: the nominal capacity and the actual capacity. The nominal capacity determines the amount of capacity that the system is set to reach for the following period (19).

$$IR\xi_t = IR\xi_{t-1} + R\Delta\xi_t^+ - R\Delta\xi_t^- \qquad \forall\ t \in T \quad (19)$$
$$R\xi_t = IR\xi_{t-1} + U\xi_t^r - L\xi_t^r \qquad \forall\ t \in T \quad (20)$$
$$IR\xi_t \leq C_{\max}^r \qquad \forall\ t \in T \quad (21)$$
$$U\xi_t^r + L\xi_t^r \leq \theta_1^U * \left(R\Delta\xi_t^+ + R\Delta\xi_t^-\right) + M*(1-Y_t^1) \qquad \forall\ t \in T \quad (22)$$
$$U\xi_t^r + L\xi_t^r \geq \theta_1^L * \left(R\Delta\xi_t^+ + R\Delta\xi_t^-\right) - M*(1-Y_t^1) \qquad \forall\ t \in T \quad (23)$$
$$U\xi_t^r + L\xi_t^r \leq \theta_2^U * \left(R\Delta\xi_t^+ + R\Delta\xi_t^-\right) + M*(1-Y_t^2) \qquad \forall\ t \in T \quad (24)$$
$$U\xi_t^r + L\xi_t^r \geq \theta_2^L * (R\Delta\xi_t^+ + R\Delta\xi_t^-) - M*(1-Y_t^2) \qquad \forall\ t \in T \quad (25)$$
$$U\xi_t^r + L\xi_t^r \leq \theta_3^U * \left(R\Delta\xi_t^+ + R\Delta\xi_t^-\right) + M*(1-Y_t^3) \qquad \forall\ t \in T \quad (26)$$
$$U\xi_t^r + L\xi_t^r \geq \theta_3^L * \left(R\Delta\xi_t^+ + R\Delta\xi_t^-\right) - M*(1-Y_t^3) \qquad \forall\ t \in T \quad (27)$$
$$\left(R\Delta\xi_t^+ + R\Delta\xi_t^-\right) = C_{ml}^r * Y_t^1 + 2C_{ml}^r * Y_t^2 + 3C_{ml}^r * Y_t^3 \qquad \forall\ t \in T \quad (28)$$
$$R\Delta\xi_t^+ + U\xi_t^r \leq M * Y_t^{10} \qquad \forall\ t \in T \quad (29)$$
$$R\Delta\xi_t^- + L\xi_t^r \leq M*(1-Y_t^{10}) \qquad \forall\ t \in T \quad (30)$$
$$\sum_{i=0}^{3} Y_t^i = 1 \qquad \forall\ t \in T \quad (31)$$
$$R\Delta\xi_t^+ + U\xi_t^r \leq M * \sum_{i=1}^{3} Y_t^i \qquad \forall\ t \in T \quad (32)$$
$$R\Delta\xi_t^- + L\xi_t^r \leq M * \sum_{i=1}^{3} Y_t^i \qquad \forall\ t \in T \quad (33)$$

The actual capacity represents the amount of capacity that is available during the reconfiguration period (20). The maximum number of modules that could be added to a system determines the maximum RMS capacity (21).

In order to represent the gradual capacity change during a reconfiguration period, the available capacity of RMS is modeled as a fraction of the nominal capacity through the constraint set (22) to (27). For each capacity change, we assume that θ_i^L to θ_i^U percent of the added capacity is available during the reconfiguration period. In this scenario, we assume that the nominal capacity can be changed in predetermined module sizes, which are identified in constraint (28). In any reconfiguration period, the system can either ramp up or ramp down (29),(30).The reconfiguration period is also determined through a set of binary variables, in the case of no reconfiguration; no capacity could be added or removed (31)-(33).

In order to incorporate the effects of congestion in the proposed methodology, we model the suppliers as a single server system with Poisson arrivals having general service time distribution (M/G/1). The relationship developed using this model allows developing the clearing function, defining the relationship between the workload and throughput [11]. Based on this clearing function, the expected system throughput $E(X_t)$ in any period is a function of the expected work load $E(\omega_{t-1}+rm_t)$, available capacity (C) and the mean and the variance of the processing time:

$$E(X_t)=\frac{1}{2}\left[C+k+E(\omega_{t-1}+rm_t)-\sqrt{C^2+2Ck+k^2-2CE(\omega_{t-1}+rm_t)+2kE(\omega_{t-1}+rm_t)+E(\omega_{t-1}+rm_t)^2}\right] \quad (34)$$

$$k=\frac{\mu\sigma^2}{2}+\frac{1}{2\mu} \quad (35)$$

The clearing function represented in (34) is concave and nonlinear [11]. In order to eliminate the nonlinearity, an outer approximation approach has been used to replace the clearing function with a set of lines. The tangent points to the curve and the number of lines are determined by a subtractive clustering method. The clearing function states that the production by the DMS supplier could not be more than the expected throughput (36).

$$D\lambda_t \le \psi_\eta^d*(\omega_{t-1}^d+rm_t^d)+\lambda_\eta^d \qquad \forall\ \eta \in \mathrm{N}^d \quad \forall\ \mathrm{t} \in \mathrm{T} \quad (36)$$

$$IR\xi_t = C_{ml}^r*Y_t^{100}+2C_{ml}^r*Y_t^{200}+3C_{ml}^r*Y_t^{300}+4C_{ml}^r*Y_t^{400} \qquad \forall\ \mathrm{t} \in \mathrm{T} \quad (37)$$

$$\sum_{j\in\{100,200,300,400\}} Y_t^j = 1 \qquad \forall\ \mathrm{t} \in \mathrm{T} \quad (38)$$

$$R\lambda_t \le \psi_\eta^r*(\omega_{t-1}^r+rm_t^r)+\lambda_\eta^r+M*(2-Y_t^0-Y_t^j) \qquad \forall\ \eta \in \mathrm{N}_{0,j}^r \quad \forall\ \mathrm{t} \in \mathrm{T} \quad (39)$$

$$R\lambda_t \le \psi_\upsilon^r*(\omega_{t-1}^r+rm_t^r)+\lambda_\upsilon^r*(R\xi_t)-\Upsilon_\upsilon+M*(2-Y_t^i-Y_t^j) \qquad \forall\ \upsilon \in \mathrm{V}_{i,j}^r \quad \forall\ \mathrm{t} \in \mathrm{T} \quad (40)$$

Since the RMS has varying capacity levels within the planning horizon, a set of binary variables are presented in (28),(37),(38) to activate the appropriate clearing function. The same type of constraint as in (36) can be utilized to represent the RMS clearing function for periods with fixed capacity levels (39). During the periods where capacity of RMS is changed, the clearing function can be represented as a function of two variables: workload and service rate. In this situation, the clearing function is generated as a set of hyper planes (40).

The presented MIP model generates the supply configurations under normal operational condition of DMS. In order to represent the contingency capacity plan once DMS fails, the following changes are incorporated to the MIP. The binary variable Y_t^{DMS} indicates the DMS failure.

$$Y_t^{DMS} = \begin{cases} 1 & \text{If DMS is available} \\ 0 & Else \end{cases} \qquad \forall\ t \in T \qquad (41)$$

$$I_t^d = I_{t-1}^d + (Y_t^{DMS} * D\lambda_t) - D_t^d \qquad \forall\ t \in T \qquad (42)$$

$$D\lambda_t + E\xi_t^d = (Y_t^{DMS} * D\xi_t) \qquad \forall\ t \in T \qquad (43)$$

$$rm_t^r \le M * Y_t^{DMS} \qquad \forall\ t \in T \qquad (44)$$

$$\omega_t^d = \omega_{t-1}^d + Y_t^{DMS} * (rm_t^d - D\lambda_t) \qquad \forall\ t \in T \qquad (45)$$

$$D\lambda_t \le Y_t^{DMS} * f^d(\omega_{t-1}^d + rm_t^d) \qquad \forall\ t \in T \qquad (46)$$

$$I_t^d = I_t^{d,ini} \qquad \forall\ t \in \{1,...,t_D - 1\} \qquad (47)$$

$$I_t^r = I_t^{r,ini} \qquad \forall\ t \in \{1,...,t_D - 1\} \qquad (48)$$

$$Y_t^i = Y_t^{i,ini} \qquad \forall\ t \in \{1,...,t_D - 1\} \qquad (49)$$

Once the DMS supplier is disrupted, the demand could be satisfied through current inventory and/or RMS production (42). Furthermore, there is no production and material release in DMS supplier (43),(44). The DMS WIP level during the disrupted periods remains equal to the last period before the disruption (45). The clearing function of DMS is inactive during the disruption (46). In order to avoid for the model to build inventory to cover the disrupted periods, the inventory levels and the capacity planning of DMS and RMS for the periods before the disruption are set to the values obtained in the initial capacity planning model (47)-(49).

The impact of the RMS response speed is illustrated through the RMS' available capacity during the reconfiguration period. This is indicated through the coefficients of the upper and lower bounds in constraints (22)-(27). These coefficients are increased to represent the increasing response speed as indicated in Table 2.

Response speed	Slow			Medium			Fast		
Number of modules	1	2	3	1	2	3	1	2	3
θ_i^U	0.75	0.5	0.4	0.85	0.65	0.5	0.95	0.85	0.7
θ_i^L	0.5	0.4	0.2	0.65	0.5	0.3	0.85	0.7	0.55

Table 2.The coefficients of capacity boundaries corresponding to different speeds

4.2 Generation of disruption scenarios

In order to represent the low frequency of natural disasters, we limit the number of disruptions to one occurrence in each considered scenarios within the planning horizon (T). The Markov discrete time distribution is incorporated to identify the probability of each disruption scenario. The parameter α represents the failure probability and the parameter β defines the recovery probability. Based on these assumptions, the probability of a disruption at time m with the length of n is computed through the following formulas.

$$\text{P(No Disruption)} = (1-\alpha)^T \qquad (50)$$

$$\text{P}_{\text{Disruption}}\text{(m,n)}=\alpha\beta(1-\alpha)^{m-1}(1-\beta)^{n-1} \qquad n \in \{1,...,T-m\}, \forall m \le T \qquad (51)$$

$$P_{Disruption}(m,n)=\alpha(1-\alpha)^{m-1}(1-\beta)^{n-1} \qquad n \in \{T-m+1,...,T\}, \forall m \le T \qquad (52)$$

4.3 Decision tree analysis

Due to the stochastic nature of disruptions, an optimal response speed can be identified based on the expected cost of scenarios and the attitude of decision maker towards risk. In identifying the optimal response speed for backup supplier, a decision tree analysis is conducted. As indicated in Figure 1, the square nodes are decision options and circle nodes represent the chance events.

The decision set regarding response speeds (RS_k) includes Fast (RS_1), Medium (RS_2) and Slow (RS_3). For a set of plausible disruption scenarios (S), each of these speeds associated with backup supplier correspond to a total cost as a result of the contingency plan obtained from the MIP model. This allows computing the expected cost corresponding to each decision through the following formula:

$$E(RS_k) = \sum_{(m,n)\in S} P_{(m,n)} \times Z_{(RS_k,m,n)} \qquad \forall k \in \{1,2,3\} \qquad (53)$$

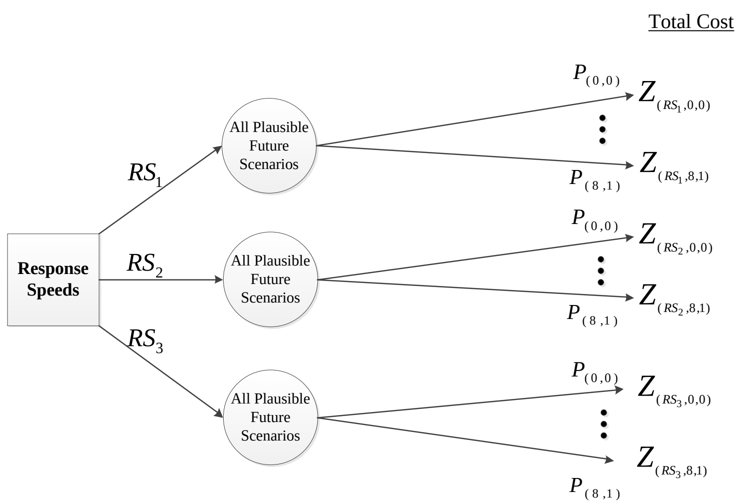

Figure 1.The decision tree for the optimal selection of the response speed

The term $P_{(m,n)}$ represents the probability of occurrence of scenario (m, n) and $Z_{(RS_k,m,n)}$ is the objective function of the MIP contingency capacity planning model associated with a response speed RS_k and the disruption scenario (m, n). The expected cost criteria can be used to identify the optimal response speed where the decision maker is risk neutral. The response speed which minimizes supply chain's cost under all plausible future scenarios is the optimal speed.

If the decision maker is risk averse, the risk of high losses as a result of disruptions is controlled by the confidence level γ. This means that there is a target cost of portfolio called value at risk (VaR) such that the costs for γ percent of the scenarios would be less than or equal to VaR. A risk aversive decision maker minimizes the expected cost of the worst case scenarios defined as conditional value at risk (CVaR) [12]:

$$CVaR_{RS_k} = VaR_{RS_k} + (1-\gamma)^{-1} \sum_{(u.v)\in S} P_{(u,v)} \Delta_{(u,v)} \quad (54)$$

$$\Delta_{(u,v)} = Z_{(RS_k,u,v)} - VaR_{RS_k} \quad (55)$$

Where (u,v) define the scenarios that cost more than VaR. The following section presents an example in order to illustrate the proposed methodology.

5. Numerical results

The response speed of RMS is determined through decision tree analysis. The impact of the different failure and recovery probabilities on decision making process is evaluated by a sensitivity analysis.

We consider the supply chain associated with a product whose lifecycle lasts for eight periods. The demand level follows a classical pattern over the lifecycle of the product. The following assumptions have been made regarding cost and capacity related input data.

Cost Parameters	Value	Cost Parameters	Value
DMS Raw Material Purchasing cost	2S	DMS Finished Good Holding cost	4S
RMS Raw Material Purchasing cost	2S	RMS Finished Good Holding cost	12S
DMS production cost	2S	RMS Reconfiguration Cost-Slow	2S
RMS production cost	10S	RMS Reconfiguration Cost-Medium	3S
DMS WIP Holding cost	3S	RMS Reconfiguration Cost-Fast	6S
RMS WIP Holding cost	10S		

Table 3.Supplier's costs parameters $/Unit

The production cost of RMS is higher than DMS [3]. Therefore WIP and the finished good inventory holding cost of RMS are higher than DMS. The RMS excess capacity costs and the product's shortage costs are presented in Table 4. The product's shortage costs are defined with respect to the demand pattern. The DMS supplier has a fixed capacity of 500 while the RMS supplier can vary its capacity level. The initial configuration of RMS is a base with 100 units of capacity. It can raise its capacity level by adding modules where each module has a capacity of 100.

Periods	1	2	3	4	5	6	7	8
RMS Excess capacity Costs	2S	2.5S	3S	3.5S	4S	5S	6S	7S
Product Shortage Cost	70S	70S	70S	65S	60S	55S	40S	30S

Table 4. Excess and shortage costs

In a risk neutral behavior, the optimal response speed is selected by comparing the expected cost of the supply chain under all plausible future scenarios. The expected cost of supply chain grows as the failure probability increases and/or the recovery probability decreases. Since the expected cost of the supply chain depends on the failure and recovery probabilities of DMS, the optimal response speed changes depending on these parameters (Figure 2).

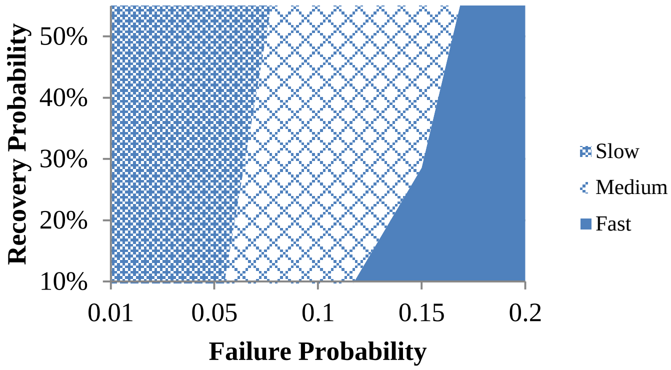

Figure 2.Optimal response speed-Risk Neutral

The slow speed is the optimal response speed for low probabilities of DMS failure since it is not economical to provide the RMS supplier with costly faster recovery speeds. When the failure probability increases and/or the recovery probability decreases, the available capacity within the response time becomes critical to minimize the shortages during the disrupted periods. Therefore, faster response speeds are appropriate.

In the case where the decision maker is risk averse, the response speed is selected to minimize the expected cost of the worst case scenarios. This is accomplished by minimizing the expected cost of the 80 percent of the worst scenarios; the optimal selection of the RMS response speed is presented in Figure 3.A.

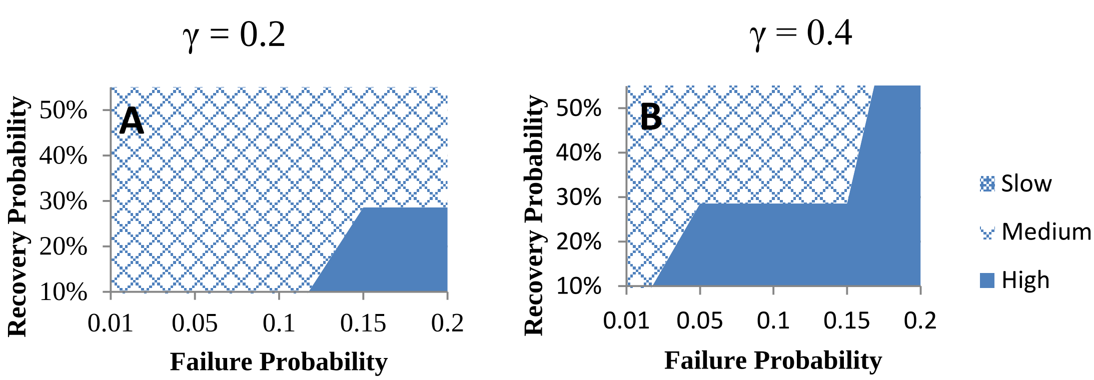

Figure 3.Optimal response speed- Risk averse

The worst case scenarios can be described by the disruptions during which high shortage costs and/or long disruptions occur. In both cases, the slow speed is not optimal since it provides a low capacity within the response time. The medium speed is optimal in most of the failure and recovery probability combinations except the region corresponding to high failure and long recovery period. Since a higher amount of the capacity is required within the response time for those situations, the fast speed is optimal.

Figure 3.B displays the optimal selection of the response speed with focus on 60 percent of the worst case scenarios. This means that the focus is on the smaller portion of the worst case scenarios albeit with higher impacts. Therefore, more capacity within response time is required

to minimize the impact of such disruptions. As result of this, the need for medium speed is reduced when the focus is on 60 percent of worst case scenarios compared to the previous case. In such situation, the tendency to select fast speed increases.

The results show that, a risk aversive decision maker would select faster response speed levels compared to the risk neutral counterpart. Furthermore, the more risk aversive decision maker would select the faster response speeds

6. Conclusion

In this paper, we evaluate the selection of the backup supplier's response speed with the purpose of increasing the supply chain responsiveness when the main supplier fails due to catastrophic events. The contribution of our methodology is the accurate estimation of available capacity within response period through employing the clearing function. Finally, a decision tree analysis determined the optimal response speed under all plausible future scenarios for a given failure and recovery probabilities. The results show the optimality of the faster response speed as the failure probability increases or recovery probability decreases. For a given failure and recovery probabilities of the main supplier, the proposed results would give a precise perspective to the supply chain management regarding the selection of the backup source's configuration.

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