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Quantitative models for supply chain risk analysis from a firm's perspective

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Quantitative models for supply chain risk analysis from a firm's perspective

by

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DEDICATION

I dedicate this thesis to my mother and my father for their patience and support while I was away from them to complete my studies. I also dedicate this thesis to my sister for encouraging me to succeed since we were kids.

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ACKNOWLEDGMENTS

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ABSTRACT

Supply chain risk analysis garnered increased attention, both in academia and in practice, since the early 2000s. Modern production methodologies such as just-in-time and lean manufacturing, globalized supply chains, shorter product life cycle, and the emphasis on efficiency have increased the risk faced by many supply chains. Managing such risks that is faced by a supply chain is vital to the success of any company. Currently employed methods lack consideration of market reaction and incorporation of decision maker preferences in managing supply chain risk. In this thesis, these two factors are taken into consideration to develop quantitative methods to analyze supply chain risk.

The first study is focused on supply chain risk from the market side in case of a major disruption. A probabilistic model based on different types of customer behaviors is developed to identify the impact on the firm's revenue by forecasting the lost revenue in case of a production shut down from a disruption event. Results from a simulation of the developed model is analyzed to draw useful insights to manage the risk of such an event.

The second study is centered on supplier selection. It presents a 5-step framework based on KPIs derived from the performance metrics of the SCOR (Supply Chain Operations Reference) model. The framework can be used for supplier selection as well as for supplier performance monitoring as the firm continues to work with the selected supplier. Decision makers from a firm can incorporate their own preference within the presented framework to determine the most preferred supplier and assess the cost effectiveness to select a supplier in different scenarios to minimize supply side risk.

CHAPTER 1. GENERAL INTRODUCTION AND REVIEW OF LITERATURE

Risk analysis is a critical process and is widely adopted in many sectors ranging from manufacturing and retail to logistics and military (Bedford and Cooke, 2001). According to Kaplan and Garrick (1981), risk is associated with both uncertainty and damage and analyzing risk consists of answering three questions: 1) What can go wrong? 2) How likely is it that will happen? and 3) If it does happen, what are the consequences? Getting answers to these questions by identifying risk factors, their chances of occurrence, and their consequences, enables a decision maker to devise a plan to manage the risk (Chavas, 2004).

Risk analysis can be conducted through both qualitative and quantitative techniques and a mix of two, ranging from simple brainstorming to more technical computer stimulation (Modarres, 2006). The quantitative techniques for risk analysis use estimation method to find the probability of loss caused by a certain event and the magnitude of the loss (Modarres, 2006). In comparison, qualitative techniques are more flexible and instead of using probability, they usually use more diverse methods to decide the likelihood and impact of risks. The qualitative techniques are useful in the prioritization of the risk in accordance with their likelihood and magnitude of impact (Burtonshaw-Gunn, 2009). The mix of qualitative and quantitative technique use one of the techniques for measuring chances of loss and another one for amount of loss (Modarres, 2006).

Among different quantitative techniques for risk analysis, probabilistic method is most commonly used for studying complex technical systems (Käki, Salo & Talluri, 2013). The basic technique according to Käki et al. (2013) is to develop a structural model of the system under study, identify the key risk factors and measure their probability of occurrence, and finally conduct a probabilistic analysis to identify the most-risky segments of systems.

With the onset of global supply chains and outsourcing of suppliers, supply chains have become more complex in the 21st century. Although the cost can be reduced through outsourcing suppliers from different parts of the world, it increases the probability of risk as well as magnitude of loss (Choi and Krause 2006). In addition, the regulations have become diversified and more complex for a manufacturer to handle without conducting a proper risk analysis (Sadgrove, 1996). There is also shift in the attitude of clients who have become more demanding and critical (Sadgrove, 1996). As a result, companies have become more concerned about risk management than cost management when it comes to supply chain (Simchi-Levi 2010).

According to Waters (2011), each member of the supply chain is subject to some specified risks from his own activities, from activities of other members of supply chain and from the factors external to the supply chain. From a manufacturer or firm's perspective, the losses can range from delay in supplying finished good to market to their total inability to continue business. Firms face multiple decision problems where more than one factor influences the decision maker's preferences over the best possible outcome. When faced with such complex problems, decision makers often use simplified mental strategies, or heuristics due to limited information-processing capacity (Paul & George, 2004). Jüttner (2005) found that while there is growing awareness among manufacturers on the growing risk associated with supply chain, they still lack proper understanding of what entailed supply chain risk management. Improvement of this understanding and introduction of proper supply risk analysis practices in manufacturing firm is a critical need of the day.

Research Motivation

The motivation of this research derives from the need for clear and quantitative methods to express supply chain risk from the perspective of a firm or a manufacturer so that in a decision-making process, the firm can weigh risks along with all other costs and benefits. The objectives of this research are as follows:

1. To develop a method to quantify the risk faced by a firm or a manufacturer from a severe supply chain disruption with an explicit focus on customer demand.
2. To evaluate the extent to which a firm can be penalized from a supplier default leading to a temporary production shut-down.
3. To develop an effective framework for supplier selection and evaluation.
4. To derive risk management insights using the developed method and framework.

Thesis Organization

This thesis contains two research papers that constitutes chapters 2-3. The first paper in chapter 2 attempts to model downstream risk in a supply chain from a firm's perspective while the second paper in chapter 3 considers the upstream supply chain and presents a framework for supplier selection and evaluation. Both the chapters consist of an abstract, introduction, literature review, methodology, illustrative example, and conclusions. References that correspond to the in-chapter citations are provided at the end of each chapter. All the images and tables are first labeled with the chapter they reside followed by the number of the graphic within the chapter for clarity. The final chapter consist of general conclusions and future work.

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CHAPTER 2. A QUANTITATIVE MODEL FOR ANALYZING MARKET RESPONSE DURING SUPPLY CHAIN DISRUPTIONS

A book chapter accepted for publication in the Springer book *Supply Chain Risk Management: Advanced Tools, Models, and Developments*

Arun Vinayak, Cameron A. MacKenzie

Abstract

Supply chain disruptions can lead to firms losing customers and consequently losing profit. We consider a firm facing a supply chain disruption due to which it is unable to deliver products for a certain period of time. When the firm is restored, each customer may choose to return to the firm immediately, with or without backorders, or may purchase from other firms. This chapter develops a quantitative model of the different customer behaviors in such a scenario and analytically interprets the impact of these behaviors on the firm's post-disruption performance. The model is applied to an illustrative example.

Keywords - Supply Chain Risk Management; Supply Chain Disruption; Preparedness; Response; Customer Demand

Introduction

Supply chain disruptions have garnered increased attention, both in academia and in practice, since the early 2000s. Modern production methodologies, globalized supply chains, shorter product life cycle, and the emphasis on efficiency have increased the risk faced by many supply chains. Managing the risk facing a supply chain is vital to the success of any company.

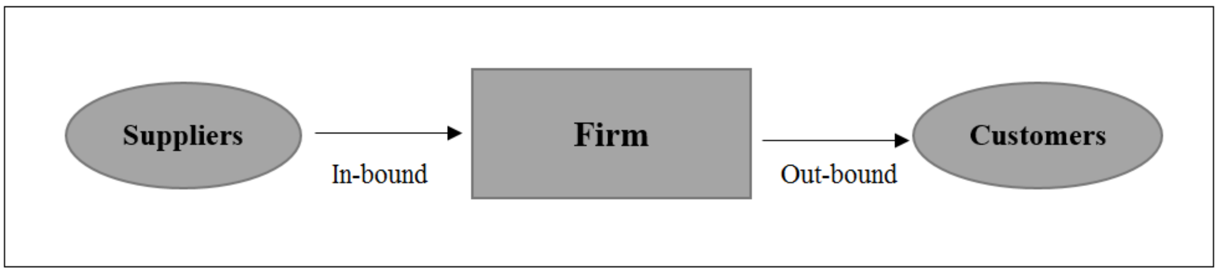

Fig. 2.1. A simple supply chain model

A supply chain is an integrated system of companies involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer (Mentzer et al. 2001). Fig. 2.1 presents a basic supply chain model from the firm's perspective. A supply chain is characterized by the flow of resources—typically material, information, and money—with the primary purpose of satisfying the needs of a customer, who are the source of revenue for a firm. A supply chain will ideally maximize the total value generated from customers and minimize the cost of meeting consumer demand.

Major disruptions, such as those that occur from natural disasters, terrorist acts, and labor strikes, can interrupt the flow of materials for several firms. Sodhi and Tang (2012) categorized supply chain risk into supply risks, process risks, demand risks, and corporate-level risks. These risks often materialize all together during a major supply chain disruption, and decision makers need to consider all of these risks. Kilubi and Haasis (2015) conducted a systematic literature review on supply chain risk management (SCRM) and identified ten different definitions of SCRM. Lavastre et al. (p. 839, 2012) defined SCRM as "the management of risk that implies both strategic and operational horizons for long-term and short-term assessment." As implied by this definition, decision makers need to consider both the long-term and short-term impacts from a supply chain disruption.

The marketplace or customers can play a significant role in the long-term impacts as their needs, values, and opinions will affect the firm's decisions during the disruption. The volatility of consumer demand is a major form of risk (Jüttner et al. 2003). Firms face a risk of being penalized by their customers if their suppliers default and firms are unable to deliver on their obligations. Assessing how consumers react to such disruptions helps to forecast the long-term profits for the firm and can help it make sound risk management decisions. Modeling consumer behavior is useful not only when a disaster occurs but also to build flexibility within the supply chain as a proactive measure to anticipate such threats and quickly respond.

This chapter presents a probabilistic model to quantify the risk from a severe supply chain disruption with an explicit focus on how consumers or the marketplace's demand for a product should influence a firm's risk management strategies. Many supply chain disruption models assume some type of demand function, which may be constant or random. However, that demand function does not usually change when the disruption occurs, or simple assumptions are made about whether or not customers are willing to wait for a final product. Less research has focused on how the final customers should influence how a firm determines what risk management strategies are appropriate. This chapter models the demand function using a probabilistic approach to customer behavior in a post-disruption scenario. The model assumes that a disruption causes a supplier to default, and a firm is unable to deliver its product to consumers. The market responds with defined probabilities and time delays. The model attempts to measure the extent to which a firm can be penalized due to a default from its supplier and recommends strategies or practices to build resilience to such disruptions.

This chapter is organized as follows: a literature review is given in Section 2. Section 3 presents the mathematical model framework, and Section 4 describes an illustrative example and performs sensitivity analysis. Section 5 concludes the chapter with recommendations, insights, and conclusions drawn from the study.

Literature Review

Supply chain management has seen a variety of trends, including Just-in-Time, global sourcing, and outsourcing. These methods are aimed at cutting costs in a firm's supply chain and enabling the firm to compete more effectively. Increasing supply chain efficiency can also make supply chains more vulnerable to disruptions (Christopher 2005). In the race to increase their market share, firms may ignore that their supply chains are susceptible to disruptions.

A wide variety of events can disrupt a supply chain, including supply-side difficulties, demand-side variability, operational problems, and large-scale disruptions such as natural disasters (Manuj et al. 2007). Qualitative studies to manage these disruptions recommend excess inventory, additional capacity, redundant suppliers, flexible production and transportation, and dynamic pricing (Sheffi and Rice 2005; Stecke and Kumar 2009). Managing one type of risk may exacerbate another risk, and identifying the best strategy relies on the manager's ability to identify the most crucial risk and understand the trade-offs in SCRM (Chopra and Sodhi 2004). Quantitative studies in SCRM generally model the trade-off between purchasing from alternate suppliers and holding inventory (Tomlin and Wang 2005), or they model the interaction between suppliers and customers (Babich et al. 2007; Xia et al. 2011). MacKenzie et al. (2014) used simulation to model the interactions among supply chain entities where each entity can take different actions such as holding inventory or purchasing from alternate suppliers. Interested readers should refer to Snyder et al. (2016) for an in-depth review of the recent models of supply chain disruptions and disruption management strategies.

Although research has focused on the impacts of supply chain disruptions based on stock returns (Hendricks and Singhal 2005) or based on the economic linkages (MacKenzie et al. 2012), less research has focused on how customers behave during and after a supply chain disruption. Nagurney et al. (2005) examined the impact of unforeseen customer demands on the supply chain, but this research assumes the customer behavior causes the disruption. Ellis et al. (2010) surveyed managers and buyers of materials to study how customers may perceive supply chain risk. Modern supply chain management is very sensitive to customer demand (Nishat Faisal et al. 2006), but examining the relationship between customer demand sensitivity and a manufacturer or retailer during a disruption has not been fully explored. An important exception to this lack of research is the modeling and analysis of consumer behavior following a food contamination (Beach et al. 2008; Arnade et al. 2009).

This chapter seeks to fill the gap in the existing literature by probabilistically modeling customer behavior following a supply chain disruption. Whereas much of the current literature focuses on the interaction between the supplier and the firm, the focus of this chapter is the market response to the disruption and its impact on the firm. The model examines the decisions customers make after the interruption of a firm's service due to a supply chain disruption. Possible customer behaviors are fused within a probabilistic model to assess the expected lost revenue of the firm. A firm can use this forecasted measure of average lost revenue to decide what it should do to prepare and respond to such a disruption in its supply chain.

Model

This section presents an overall profile of a supply chain disruption and develops a probabilistic model to focus on the market response to the disruption. A supply chain disruption occurs when a firm's supplier defaults. A major disruption impacts a firm in distinct phases (Sheffi and Rice, 2005). It may take time for the final consumer to be impacted by the supply disruption. If the firm does not have enough inventory or cannot purchase from alternate suppliers, it will not be able to satisfy demand for its goods. Consequently, consumers may choose to purchase from other firms. The consumers' loyalty depends on a number of factors such as their relationship to the product. To get back to standard performance levels, a firm may adopt various response actions such as working at over-capacity levels. If the firm is prepared for such a disruption (e.g., having multiple suppliers or having more inventory), it should be able to respond more effectively (Yu et al. 2009).

3.1 Model Framework

We develop a probabilistic model to quantify the reaction of customers following a supply chain disruption that causes a temporary production shut down. Before the disruption, there are n customers (they could also be retailers) who purchase from a firm in each time period before a disruption. In the base model, we assume the demand equals the number of customers. In other words, every customer buys exactly one product. This assumption is relaxed in Subsection 4.3, which considers varying demands from each customer. An unexpected disruptive event causes one or more of the firm's suppliers to default, and the firm is unable to satisfy any demand beginning at time period $t = 1$. The disruption continues for M time periods, and the firm does not deliver to its n customers for $t = 1, 2, .., M$. The firm recovers from the disruption at $t = M + 1$ and will be able to deliver at its full capacity C orders per time period, where $C \geq n$.

In the post-disruption time period beginning at $t = M + 1$, each customer decides whether or not to return to the firm in each time period $t = M + i$. Note that $i = 1, 2, \ldots$ since the customer cannot buy from the firm during time periods $t = 1, 2, .., M$. Each customer comes back to the firm with a constant probability p in each time period. The value of p depends upon the type of product as well as the firm's response actions such as qualifying alternate suppliers and making up for lost production by running at maximum capacity. If a customer decides not to return to the firm at a particular time period, the model assumes that it will return to the firm in the next period with the same probability p. Once a customer returns to the firm, it will continue to purchase from the firm in all future time periods.

If a customer buys from the firm at time $t = M + i$, it will return with one of the following behaviors:

1. Customers can return right away without backorders at time *t*. This category of customers might have used inventory from safety stock, not used the product, or purchased the product from other firms during the time periods 1 through M.
2. Customers who come back immediately and have backorders.
3. Customers who do not return immediately but return later to the firm with no backorders.

The probability q represents the conditional probability that the customer who comes back immediately at $t = M + 1$ will require backorders for $t = 1, 2, .., M$. In other words, given the customer has returned to the firm, the probability that he or she will have backorders is q. The revenue from backorders is accounted for at $t = M + 1$ since backorders are taken only in that time period. We assume that customers who wait longer to return do not have backorders (behavior number 3). The initial model assumes the firm can satisfy all the backorders. This could be because the firm is able to monitor activity and make plans to increase capacity to satisfy backorders. If q is small, the firm can be reasonably confident the backorders will not exceed its capacity. Since this assumption may not be realistic, Subsection 3.3 discusses how the model might change if a capacity constraint limits the number of backorders the firm can accept. Even if the lack of a capacity constraint may not be realistic, modeling the situation without this constraint generates useful insights into the potential benefits of increasing capacity after reopening.

3.2 Calculating the Firm's Post-Impact Revenue

The revenue at time periods $t = 1, 2, .., M$ is zero since the firm is not delivering any product to its customers. The total expected revenue after the firm reopens is calculated by estimating the number of customers who decide to buy from the firm at each period after it reopens at $t = M + 1$. Let X_t be the number of customers who decide to come back and purchase from the firm at time t. $X_t = 0$ for $t = 1,2,..,M$

For $t = M + 1, M + 2, \ldots$ each of the n customers returns with a constant probability p and X_t follows a binomial distribution.

At $t = M + 1$, $\quad X_{M+1} \sim Binom(n, p)$

$$with\ E[X_{M+1}] = np$$

At $t = M + 2$, $\quad X_{M+2} \sim Binom(n - X_{M+1}, p)$

$$with\ E[X_{M+2}] = np(1 - p)$$

At $t = M + 3$, $\quad X_{M+3} \sim Binom(n - X_{M+1} - X_{M+2}, p)$

$$with\ E[X_{M+3}] = np(1 - p)^2$$

……………………………………

At $t = M + i$, $\quad X_{M+i} \sim Binom\left(n - \sum_{j=1}^{i-1} X_{M+j}\ , p\right)$

$$\text{with } E[X_{M+i}] = np(1 - p)^{i-1}$$

Since the model assumes that a customer who returns to the firm will continue to purchase from the firm in subsequent periods, the expected number of customers who purchase from the firm at $t = M + i$ is:

$$np\left(1 + (1 - p) + (1 - p)^2 + (1 - p)^3 + \cdots + (1 - p)^{(i-1)}\right)$$

$$= np\left(\frac{1 - (1 - p)^i}{1 - (1 - p)}\right)$$

$$= n\left(1 - (1 - p)^i\right)$$

Since customers that return at $t = M + 1$ may return with backorders, the number of orders for the firm may exceed the number of customers X_{M+1}. The number of customers who return with backorders is represented by the random variable Z. The model assumes that backorders are placed only once at time $t = M + 1$ and $Z \sim Binom(X_{M+1}, q)$.

Although it makes intuitive sense to assume that customers who did not return to the firm immediately satisfied their demand during the shutdown period, $t = 1, 2, .., M$, from another firm, a further extension to this model may consider situations where customers who do not return immediately but return later to the firm also places backorders. In that case Z would need to be indexed by time *t*.

Since each customer orders exactly 1 product in each time period, a customer who returns with backorders is assumed to have M backorders (one backorder for each period that the firm was closed). Thus, the total number of orders at time $M + 1$ is $M * Z + X_{M+1}$. Using the expected number of customers from the above results and the conditional probability of placing a backorder, we calculate the expected number of orders at $t = M + 1$:

$$= \begin{pmatrix} \text{Expected number of} \\ \text{customers who return} \\ \text{with backorders} \end{pmatrix} * \begin{pmatrix} \text{Backorder} \\ \text{quantity} \\ \text{per customer} \\ + \\ \text{Regular order} \\ \text{quantity per} \\ \text{customer} \end{pmatrix} + \begin{pmatrix} \text{Expected number of} \\ \text{customers who return} \\ \text{without backorders} \end{pmatrix}$$

$$* \begin{pmatrix} \text{Regular order} \\ \text{quantity per} \\ \text{customer} \end{pmatrix}$$

$$= (np * q) * (M + 1) + \ np * (1 - q) * 1$$

$$= \ np(qM + q + 1 - q)$$

$$= \ np(qM + 1)$$

The expected cumulative orders at time $t = M + i$ for $i > 1$ equals $n\,(1 - (1-p)^{i})$, which is equivalent to the expected cumulative number of customers who have returned by time $t = M + i$.

If the firm's per-unit selling price is c, we calculate R_t the lost revenue at time t:

$$R_t = \begin{cases} cn & \text{if } t = 1,2,..,M \\ c(n - X_{M+1} - Z) & \text{if } t = M+1 \\ c\left(n - \sum_{i=1}^{t} X_{M+i}\right) & \text{if } t = M+2, M+3, \ldots \end{cases}$$

The expected lost revenue at time t is denoted as $\bar{R}_t$.

3.3 Production Capacity Considerations

In the proposed model, it is important to look at the production capacity of the firm, especially at time $t = M + 1$, when backorders may be received. The number of orders $M * Z + X_{M+1}$ must not exceed the available capacity C. If $M * Z + X_{M+1} > C$, the excess orders will be carried forward to the next time period, $t = M + 2$, but capacity restrictions require that $M * Z + X_{M+1} + X_{M+2} \leq 2C$.

Similarly, the firm can estimate and forecast the production capacity levels for future time periods. Depending on the willingness of customers to wait for the backorder delivery, the firm needs to prioritize production with the goal of meeting customer needs. If customers are likely to be lost in case of a late delivery, the firm will have to consider whether it can temporarily increase its production capacity or other alternatives to meet the spike in demand due to backorders.

Illustrative Example

This model can be applied to several situations. For example, a consumer-product manufacturing firm could face a supply chain disruption forcing it to shut down production. The firm's customers could react in different ways. One, a retailer who uses inventory during this period may come back to the firm immediately with backorders to replace its inventory. Two, a retailer who temporarily switches to another supplier may decide to come back when the firm starts producing again. Three, a retailer who switches to another supplier may decide not to come back when the firm starts producing again. The latter retailer may come back at a later stage depending on the firm's performance. By estimating the probability that the retailer takes any of these actions, the model can account for each of these scenarios.

4.1 Lost revenue with backorders

We illustrate the application of this model to a scenario in which a firm experiences a supply disruption and must stop production for $M = 4$ periods. Table 2.1 provides values for the parameters in this example.

Table 2.1. Parameters

	Symbol	Value
Number of customers or demand per period	n	100
Per unit selling price in dollars	c	1000
Probability with which customers return in each period	p	0.15
Conditional probability of backorder requirement	q	0.50
Duration of the disruption in periods	M	4

The average value and standard deviation of lost revenue at each time period were obtained via 10,000 simulations of the supply chain disruption model for customer reactions using the parameters in Table 2.1. Since the firm is unable to produce during $t = 1,2,..,M$, the lost revenue at each time period equals the total revenue per period at undisrupted production rates. Because some of the lost revenue in the first M periods may be recaptured via backorders, the lost revenue may not actually be completely lost. In the model, this is accounted for at $t = M + 1$.

Since the binomial distribution can be approximated by the normal distribution, we calculate 90% probability intervals for the lost revenue $\bar{R}_t \pm 1.64 S_t$, where $\bar{R}_t$ is the average lost revenue and S_t is the standard deviation for time period t. The results are illustrated in Fig. 2.2. The expected lost revenue reduces to less than 1% of the total pre-disruption revenue after $t = 34$, and the revenue from sales is almost completely restored to pre-disruption levels. If each time period is a week, the firm returns to its full performance in approximately 8 months.

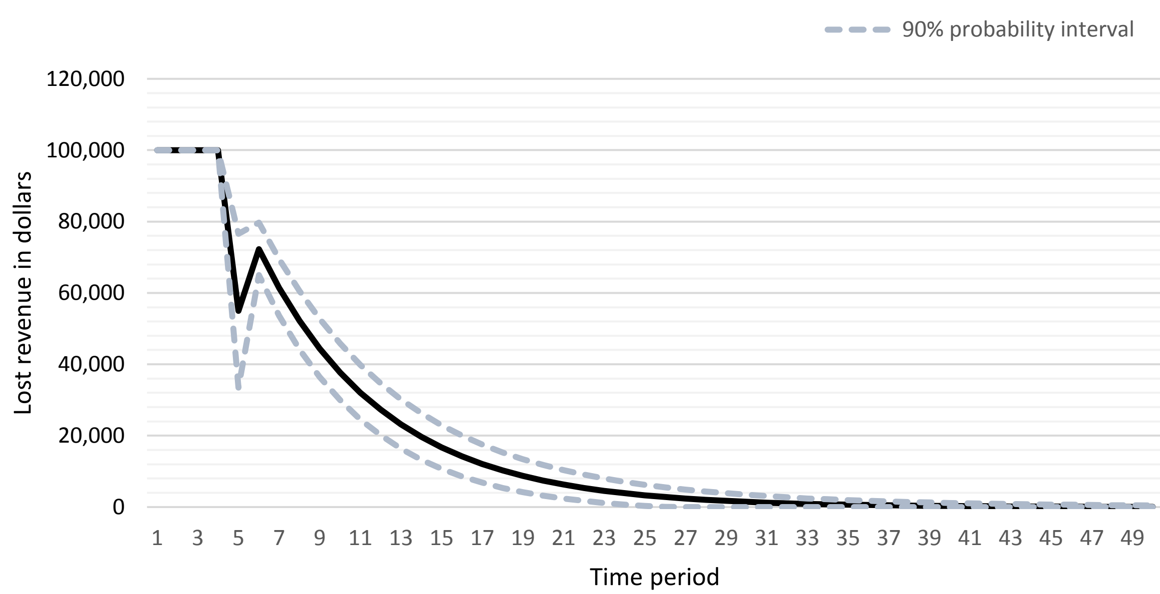

Fig. 2.2. The firm's expected lost revenue per period from the supply chain disruption.

As depicted by the probability interval, there is a 5% probability the lost revenue will be less than $1,000 within 24 periods and a 5% probability the lost revenue will be greater than $1,000 for at least 42 time periods. The expected lost revenue is at its maximum value for the first four periods, which is equal to the total pre-disruption revenue per period and then drops from $100,000 to $55,000. The downward spike in the expected lost revenue is due to the backorders. The lost revenue at $t = 5$ has a 5% probability of being as low as $33,444, which would occur if many customers return with backorders. If very few customers return with backorders, the lost revenue could be $76,556, which is the 95% upper bound for lost revenue in that time period. At time $t = 6$, the expected lost revenue increases to $72,250 and then gradually decreases over time as the firm recovers from the disruption.

4.2 Lost revenue without backorders

Certain disruptions may not allow for backorders. For instance, a restaurant could be closed for a period of time because of food poisoning, and when it reopens, backorders are not realistic because the delivered product is a service that cannot be backordered. We can assign $q = 0$ in the simulation model to reflect such a situation. Fig. 2.3 illustrates this scenario without backorders. Here, the expected cumulative lost revenue is higher because of the lack of backorders.

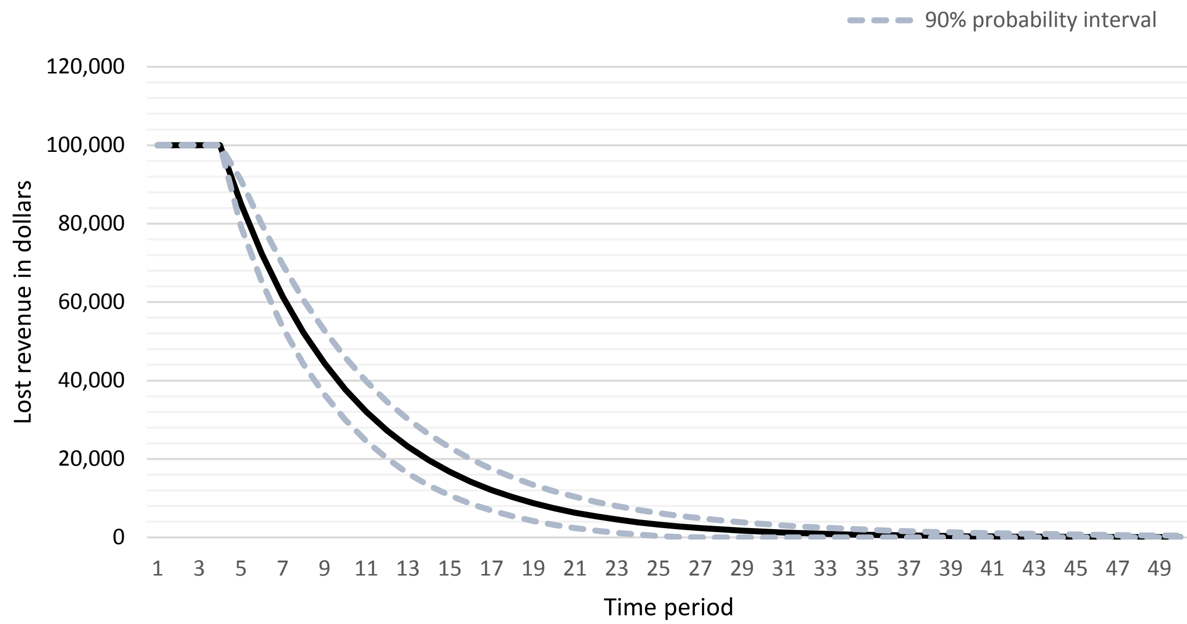

Fig. 2.3. The firm's expected lost revenue without backorders.

4.3 Customers with varying demand

The assumption that each customer buys exactly one product may not be valid. This sub-section extends the simulation model to accommodate varying demands from the firm's customers. The demand from customer l is n_l where $l = 1, 2, \dots, n$. We assume each n_l follows a discrete uniform distribution between 1 and 5, i.e., $n_l \sim U(1, 5)$. Backorders are ignored for simplicity. Parameters from Table 2.1 along with a simulation of $n_l \sim U(1, 5)$ were used in the model with varying demand from different customers to run 1,000 simulations. The results are illustrated in Fig. 2.4.

The maximum total expected lost revenue is much higher than the previous cases because the total initial demand is more than in the previous cases. The shape of recovery is very similar to the model in section 4.1 because each customer returns with the same probability. The expected lost revenue reduces to less than 1% of the total pre-disruption revenue after time period 25. This is comparable to the results from the model in sections 4.1 and 4.2. The results might look different if customers returned with different probabilities. For example, perhaps customers with more demand from the firm might be more likely to return because it may be more difficult for these customers to get all of their demand satisfied from the firm's competitors.

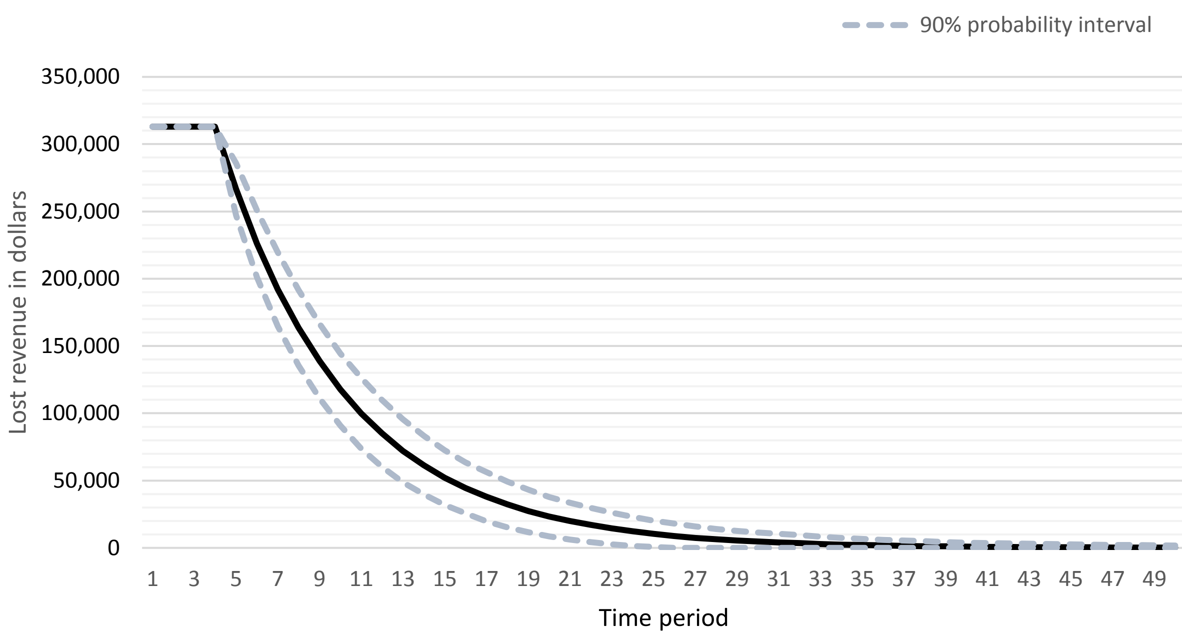

Fig. 2.4. The firm's expected lost revenue with varying demand from customers

4.4 Risk management insights

A firm can use this model to understand how parameters impact the firm's expected lost revenue. The results discussed are highly sensitive to the value of p. As illustrated in Fig. 2.5, the firm recovers more quickly when the probability with which customers are gained back in each period is larger. This makes intuitive sense since firms with loyal customers tend to recover faster. We observe that the downward spike at time $t = M + 1$ is directly correlated with p. At $t = M + 1$, the cumulative expected number of orders including the backorders is directly proportional to the probability of customers buying from the firm at a given time period after the disruption.

The expected lost revenue in time period $t = 5$ is negative when $p = 0.4$. This negative value represents revenue greater than $100,000 in that period, a trend that continues as the value of p increases. Such situations may require the firm to work at overcapacity immediately after reopening to meet the sudden increase in demand, which is an integral part of the firm's recovery process (Sheffi and Rice 2005). This provides an important insight to the firm's management that in case of a production shut down, it may need to be prepared to temporarily increase its production capacity after reopening. The model also helps to estimate the maximum production the firm would need in order to meet the demand.

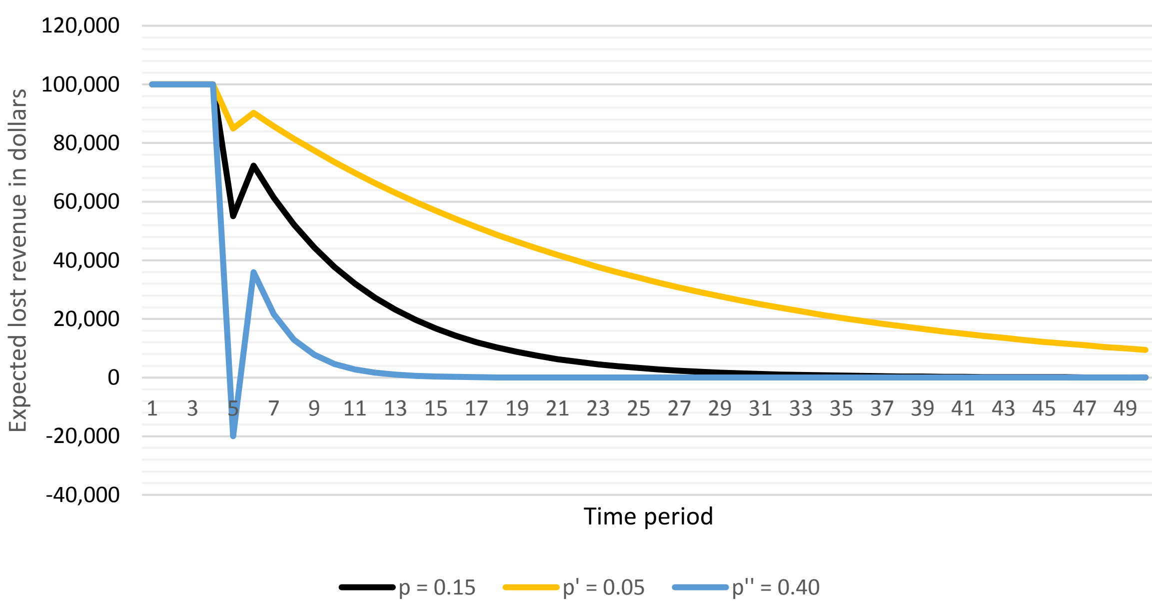

Fig. 2.5. Sensitivity of expected lost revenue to p.

A similar trend can be observed with the sensitivity analysis on q, as illustrated in Fig. 2.6. The time of recovery remains the same since p is constant. This is also an important insight since firms need to think about the likelihood that their customers will place backorders. Accordingly, they can devise suitable production plans.

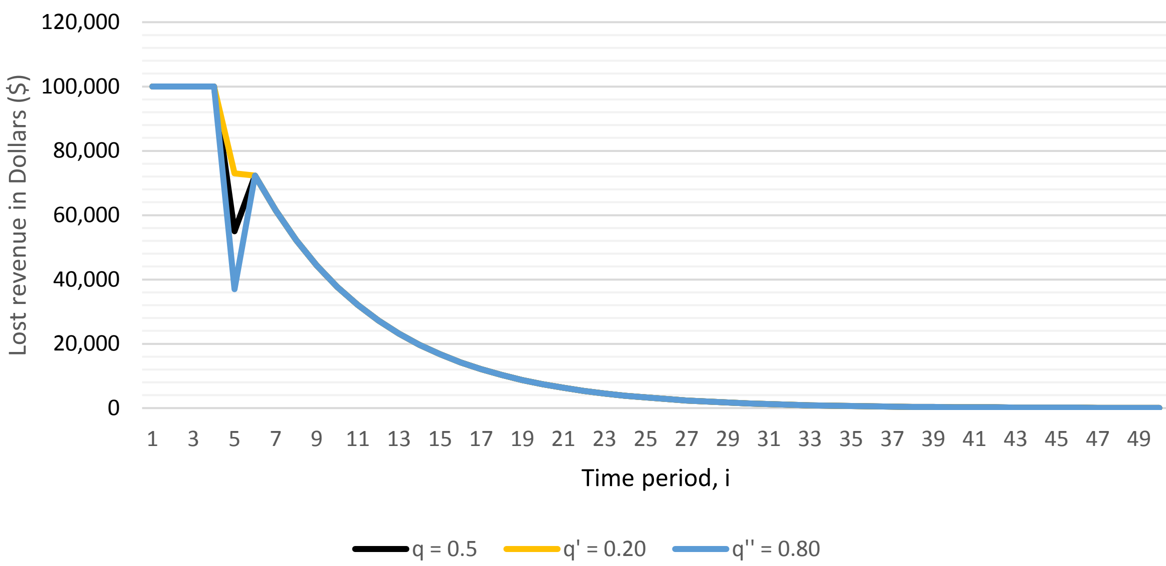

Fig. 2.6. Sensitivity of expected lost revenue to q.

Firms can prepare for disruptions by using this quantitative model to estimate the potential loss in revenue due to a shutdown of operations from a supply chain disruption. Moreover, the model can be used to evaluate whether preparation strategies are economical. Investments to reduce the chances of a supply chain disruption itself may not be practical or economically reasonable. In such cases, firms can use the expected lost revenue from the model to decide whether or not investments to reduce the risk of a disruption are cost effective. Preparedness measures can help reduce the probability of a disruption and/or allow the firm to regain more of its revenue following a disruption. Even if the disruption cannot be avoided, preparedness measures could reduce the shutdown length M. It is logical to assume that the probability of customers returning depends on M. Decision makers can make decisions about investing in preparedness measures based on understanding how much revenue will be lost if the disruption occurs as well as the chances of the disruption itself.

For example, the cumulative expected lost revenue in the illustrative example is \$536,667. A risk-neutral firm should spend at most \$536,667 in preparing for this type of disruption and should spend much less once the probability of a disruption is considered. Investing in risk reduction strategies such as inventory or an additional supplier could reduce the time the firm is closed. The chances of customers returning immediately to the firm are higher if the firm is not closed as long. This would increase the probability p and reduce the cumulative expected lost revenue. In the example, increasing the value of p from 0.15 to 0.2 decreases the total expected lost revenue from \$536,667 to \$360,000. Strategies that could reduce p from 0.15 to 0.2 are economically wise if these strategies cost less than \$176,667, assuming an extremely high probability of disruption.

Conclusions

This chapter proposes a model to quantitatively represent the way customers or the marketplace reacts to a supply chain disruption. The model is used to identify the impact of such an event on the firm's revenue. From the firm's perspective, the total expected lost revenue is a measure of the impact of the supply chain disruption and can be analyzed to draw useful insights to manage the risk of such an event.

The results obtained from applying the model serves as an illustration of the usefulness of the model. The simulation of the customer response model allows the firm to anticipate how customers might react to a supply chain disruption. The model can inform decision making to manage the risks of a supply chain disruption. Insights from the model can reveal how a disruption can affect the firm's revenue depending on the customers' decisions and the time a firm takes to recover to its pre-disruption revenue levels. Sensitivity analysis on the model parameters reveals how the probability at which customers return to the firm impacts the recovery time. Firms that expect most of its customers to return with backorders may need to temporarily increase production capacity. Management can use the cumulative expected lost revenue projections to evaluate investments aimed at increasing the firm's resilience to supply chain disruptions.

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CHAPTER 3. COST-EFFECTIVENESS ANALYSIS OF SUPPLIER PERFORMANCE BASED ON SCOR METRICS

Based on an abstract accepted for presentation at the 2017 IISE Annual Conference

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Abstract

A firm may use several metrics to assess a supplier's performance, including the quality of delivered products, the time it takes to deliver those products, and how quickly a supplier responds to changes in customer demand. Mapping these measures to what a firm ultimately cares about can help a firm select among suppliers. If a firm has little to no experience working with a supplier, a firm may have difficulty in objectively selecting a supplier. This paper presents a framework for supplier performance measurement based on supplier key performance indicators derived from the performance metrics of the Supply Chain Operations Reference model. The framework can be used for supplier selection as well as for supplier performance monitoring as the firm continues to work with the selected supplier. A decision maker in a firm can incorporate his or her own preferences within the presented framework to determine the most preferred supplier and assess the cost effectiveness.

Keywords: Supplier performance evaluation, SCOR model, Multi-objective decision making, Risk analysis, Supply chain.

Introduction

Selecting and evaluating a supplier is a multi-criteria problem that is growing in its scope and importance (Ho et al., 2010; Agarwal et al., 2011). With the availability of latest technology that can be used to monitor, measure, and compare various aspects of a supplier, organizations can benefit from a simple and effective framework for supplier selection using multi-criteria decision-making techniques. Emphasis on the firm's objectives and business requirements while selecting a supplier will play a critical role in the success of any firm as there is an increased dependency on suppliers due to business initiatives such as outsourcing, globalization, and lean manufacturing. While such focus on the firm's core values is vital, an effective supplier performance benchmarking framework must be simple and standardized for the use of multiple industries.

The Supply Chain Operations References (SCOR) model developed by the Supply Chain Council (SCC) with inputs from industry leaders presents a comprehensive hierarchical structure of a supply chain's performance metrics under five core performance attributes: reliability, responsiveness, agility, cost, and asset management efficiency. Fig. 3.1 presents the hierarchy of metrics of levels 1 and 2 for these five core attributes. To ensure balanced decision making in supply chain management, the SCC suggests that supply chain scorecards should contain at least one metric for each performance attribute. Although these five core performance attributes may be mutually exclusive, they are not directly measurable. There are 43 level-1 performance metrics that support these five attributes which would require extensive data gathering and is not practical. Moreover, these metrics in the SCOR model are designed to measure a supply chain's performance. While SCOR model serves as a comprehensive reference guide for supply chain performance measurement, there is a need for deriving a set of metrics that most effectively captures the performance of a supplier.

This paper presents a practical tool that simplifies and combines these attributes to account for their relative importance using a systematic process. Key Performance Indicators (KPIs) for the suppliers derived from the SCOR performance metrics enable us to compare different suppliers from a firm's perspective and understand the risk associated with them. A subset of the SCOR performance metrics are identified and then aggregated using a value-based approach to multi-criteria decision making. An Excel-based tool is presented for decision makers from a firm to incorporate their own preferences for carefully evaluating and identifying the best supplier in a rational mode. An illustrative case application of the proposed framework based on real world expertise is also presented that can be referred by analysts or decision makers from the industry to apply the framework in selecting new suppliers or evaluating existing suppliers.

The model adapts the SCOR metrics for reliability, responsiveness, agility, and asset management efficiency by focusing on the most important metrics and constructing a value function based on those metrics. The value function aggregates the attributes into a single measure of effectiveness. The cost of the supplier is separated from the effectiveness measure in order to make trade-offs between the cost and effectiveness of suppliers. Since several of the SCOR metrics concern evaluating activities for material flow, the proposed model is intended for manufacturing supply chains.

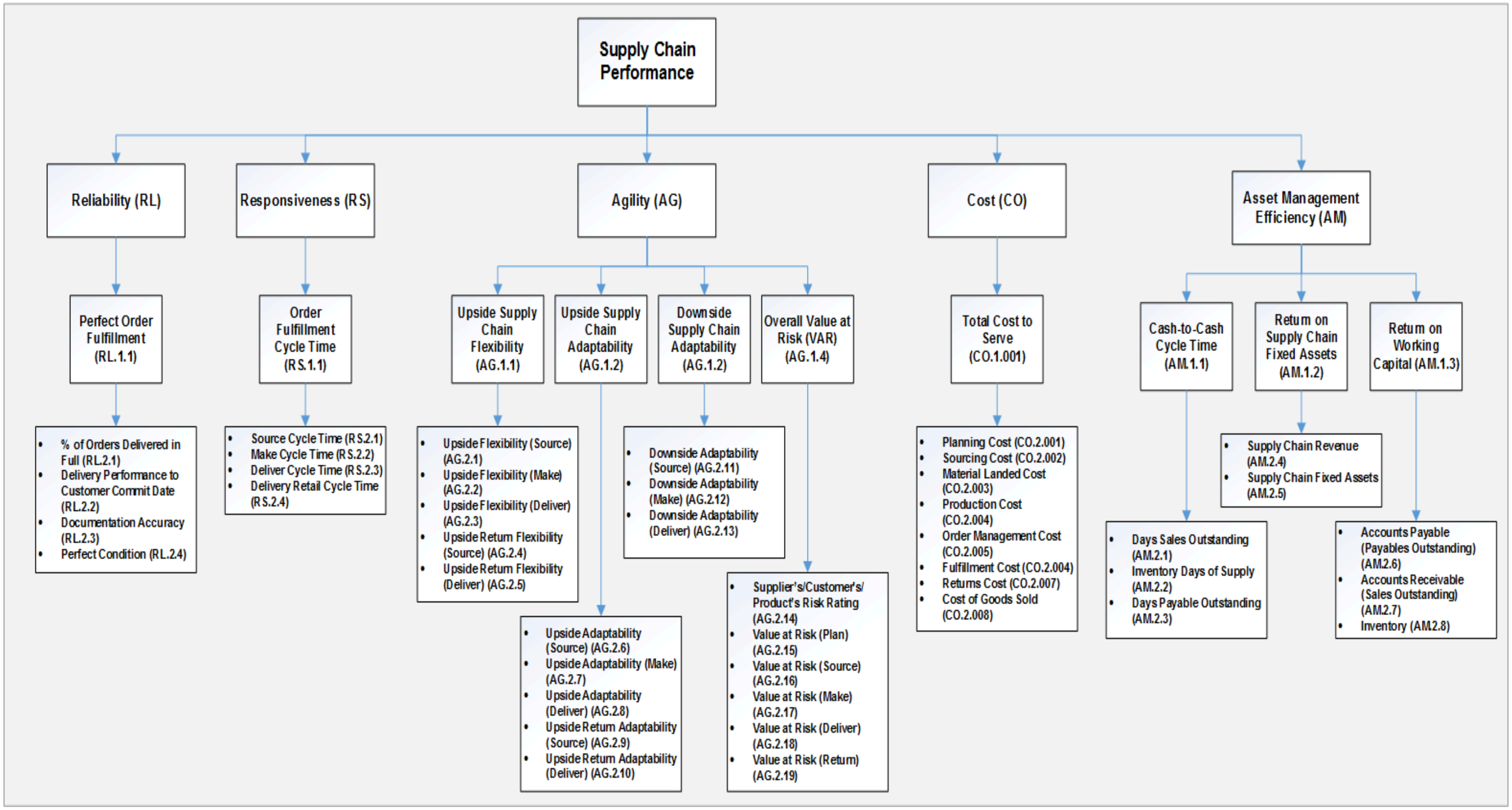

Figure 3.1: Performance attributes and metrics of the SCOR model (Council, 2012)

This paper is organized as follows: a literature review is given in Section 3.2. Section 3.3 presents the model framework along with an overview of the SCOR performance metrics that serve as the basis of the supplier KPIs presented in this paper. Section 3.4 describes an illustrative example. Section 3.5 concludes the paper with recommendations, insights, and conclusions drawn from the study.

Literature Review

Supplier selection has received significant attention in the academia over the past few decades. Moore (2014) defines supplier selection as the process through which firms identify, evaluate and contract with suppliers. Lil (2007) argues that the sole purpose of selection is not to identify suppliers with the lowest prices and the materials at the right time. Rather, the process revolves around all strategic decisions aimed at meeting the company's long-term goals with less risk. This ensures that selecting the right suppliers dramatically minimizes purchasing costs while at the same time improving corporate competitiveness. Companies pay attention to the product life cycle, advanced manufacturing process, and the complexity of the design and manufacturing process when making supplier selection decisions (Mohammady & Martinez, 2006). Buyers are concerned with the supplier's willingness to deliver the right quality at the right time, mutual trust between buyer and seller, and the seller's technical and financial capabilities (Lima-Junior & Carpinetti. 2016).

Based on literature review on multi-criteria decision making techniques in 78 journal papers for supplier evaluation and selection from 2000 to 2008, Ho et al. (2010) identifies Data Envelopment Analysis (DEA) as the most popular approach. Agarwal et al. (2011) also identifies DEA as the most widely applied methodology for supplier selection based on 60 articles from various journals and conferences from 2000 to 2011. DEA is robust approach that mainly focuses on system efficiency and considers suppliers and processes as a system. In DEA, optimal weights to maximize the efficiency or performance rating of a supplier is calculated using the outputs (e.g. delivery performance, quality, etc.) and inputs (costs). Researchers (Weber, 1996; Braglia & Petroni, 2000; Songhori et al., 2011) conclude that significant benefits to a firm such as reductions in costs, time, and quality can be achieved if inefficient vendors can become DEA efficient. Moreover, supplier selection itself can be carried out based on DEA efficiency of available suppliers. Ho et al. (2010) argue that suppliers can easily get confused by its input and output criteria. The linear programming nature of DEA also assumes that the most effective suppliers are those that are able generate more outputs by using less inputs (Murkherjee, 2017). This is one of the main disadvantages of using DEA (Ho et al., 2010).

On the other hand, based on a review of multi-criteria decision making approaches for green supplier selection in literature from 1997 to 2011, Govindan et al., (2013) concludes that Analytical Hierarchy Process (AHP), a less data intensive and structured method for multi-objective decisions, is the most widely used approach. Basnet (2002) points that unlike other methods, AHP is easy to use, highly flexible and can be used in a wide range of fields. Furthermore, the method can be used to make a consistent decision with respect to multiple qualitative and quantitative criteria (Huan, Sheoran &Wang, 2004). Suppliers could use the combined approach of AHP and Quality Function Deployment (QFD), a management tool that provides a visual connective process to help teams focus on the needs of the customers throughout the total development cycle of a product or process (Moore, 2014; Bouchereau & Rowlands, 2000). When using this combination, the best supplier is assumed to be one that can efficiently meet most of the buyer requirements (Basnet, 2002). The QFD model is similar to the Simple Multi-attribute Rating Technique (SMART) which helps major decision-makers in the purchasing company to account for factors that are both qualitative and quantitative (Ho et al. 2010). Unlike QFD, the SMART model can structure the supplier's system and the environment into components that interact with each other to measure and regulate various effects of system errors.

The SCOR model is one of the most promising models for supply chain strategic decision making (Ravindran, 2013). Established in 1996, the model is a re-engineering, benchmarking, process measurement and best practice analysis to be used in supply chain as an integral modelling. SCOR works on the principle of aligning supply chain management practices as well as filling the gaps in supply chain (Lima-Junior and Carpinetti, 2016). Also, the model strives to improve the use of network modelling tools to support management decision and can be integrated with multi-criteria decision-making techniques. Due to this reason researchers agree the SCOR model remains the most effective individualized approach of supplier chain performance measurement given that it can produce better results on its own, compared to other models (Huang & Keskar, 2007; Huan et al., 2004; Kocaoğlu et al., 2013; Lima-Junior et al., 2016).

Integrated and individualized supplier selection methods are significant as they aid suppliers to select the most suitable and efficient suppliers. Using supplier selection methods ensures that companies get to work with the best suppliers who can effectively meet their specific demands. Supplier efficiency not only focuses on cost and ability to deliver quality goods at the right time but also on other equally important factors such as trust, financial capability and supplier's past reputation. However, there is a lack of alignment in the existing literature between supplier selection and supply chain strategic decision making as researchers overly emphasized the use of quantitative optimization models in supplier selection (Huang & Keskar, 2007). Hence, there is a pressing need for researchers to fill this gap. Firms should evaluate the expected level of supplier performance along with cost before selecting the most suitable one.

Lastly, there is a need to introduce more models that use value-focused multi-criteria decision-making techniques to address the problem of supplier selection. This is because the technique can integrate the supplier's structure and capabilities with the requirement of a firm. In the existing literature in supplier selection, methods such as DEA are chosen over value-based techniques since the latter requires more involvement of the decision maker (Seydel 2006). But from a practical perspective, identifying the right objectives and KPIs with the involvement of the decision makers is most important to a firm when compared to computationally intelligent methods to optimize supplier selection. The objective of this chapter is to improve the quality of supplier selection process in the industry by presenting a framework, based on existing multi-criteria decision-making techniques, that provides insights on the trade-offs, increases confidence (or highlight the risk) in the decision, and document the process. The presented framework can be potentially used by firms to evaluate new suppliers using their supplier selection phase with the easy to use Excel tool.

Methodology

This section defines a framework to help a firm select a supplier. The framework is based on the SCOR model which proposes a set of 43 metrics. The SCOR model provides a framework from which to construct a multi-criteria value model that aggregates these metrics into a single number that describes the effectiveness of a supplier. This section reviews the SCOR performance metrics, translates the SCOR model to an objectives hierarchy, and describes the value functions and weights needed to quantify supplier effectiveness.

3.3.1 Overview of SCOR Performance Metrics

The SCOR model, first developed by the SCC in 1996, is a very promising model for supply chain strategic decision making (Huan et al., 2004). It allows firms to perform a very thorough fact-based analysis of all aspects of their supply chain by providing a complete set of process details, performance metrics, and industry best practices. SCOR identifies five core supply chain performance attributes with 10 level-1 or strategic metrics and 43 level-2 metrics as shown in Fig. 3.1. Below is a summary of the SCOR performance metrics as defined by the Supply Chain Council in SCOR model reference documentation revision 11.0:

- **Reliability:** Reliability describes the ability to perform tasks as expected. This attribute focuses on predicting the outcome of a process. The level-1 metric associated with reliability is perfect order fulfilment, which can be defined as the percentage of orders meeting delivery performance with complete and accurate documentation and no delivery damage. Perfect order fulfilment is further broken down into: percentage of orders delivered in full, delivery performance to customer commit date, documentation accuracy, and perfect condition.
- **Responsiveness:** Responsiveness describes the speed at which tasks are performed in a supply chain. This is measured by the order fulfillment cycle time, which is the average cycle time to fulfil customer orders. The order fulfillment cycle time is composed of cycle times for the source, make, deliver, and delivery retail.

- **Agility:** Agility describes the ability of a supply chain to respond to marketplace changes to gain or maintain competitive advantage. The three level-1 metrics associated with agility are: Upside supply chain flexibility is the amount of time it takes a supply chain to respond to an unplanned 20 percent increase in demand without service or cost penalty. Upside supply chain adaptability is the quantity of increased production a supply chain can achieve and sustain for 30 days. Downside supply chain adaptability is the reduction in order quantities sustainable at 30 days prior to delivery with no inventory or cost penalties. Value at risk is a popular risk metric widely used by the finance industry to understand the risk exposure of a trading portfolio based on historic volatility.
- **Cost:** In the context of supply chain performance measurement, SCOR model describes cost as the operational costs of various processes in a supply chain. This is an internally focused attribute that is measured by the total cost to serve in monetary unites as a sum of planning cost, sourcing cost, material landed cost, production cost, order management cost, fulfillment cost, and returns cost.
- **Asset Management Efficiency:** Asset management efficiency is the ability to efficiently utilize assets. It is associated with three level-1 metrics:
  - Cash-to-cash cycle time is the time it takes for a company to turn cash spent on raw materials to inventory and back into cash. It is widely used measure of how a company manages its working capital assets and is calculated as:

$$AM.1.1 = [Inventory\ Days\ of\ Supply] + [Days\ Sales\ Outstanding] - [Days\ Payable\ Outstanding]$$

$Inventory\ Days\ of\ Supply:$ The amount of inventory (stock) expressed in days of sales.

$Days\ Sales\ Outstanding:$ The length of time from when a sale is made until cash for it is received from customers. In other words, number of days needed to collect on sales, or accounts receivable expressed in days.

Days Payable Outstanding: The length of time from purchasing materials, labor and/or other resources until cash payments must be made. By maximizing this number, the company holds onto cash longer, increasing its investment potential.

- Return on supply chain fixed assets is the return an organization receives on its invested capital in supply chain fixed assets and is calculated as:

$$AM.1.2 = \frac{([Supply\ Chain\ Revenue]\ -\ [Total\ Cost\ to\ Serve])}{[Supply\ Chain\ Fixed\ Assets]}$$

Supply Chain Revenue is different from *Net Revenue* which could include revenue from sources other than the supply chain, such as investments, leasing real estate, court settlements.

- Return on working capital is a measurement of the magnitude of investment relative to a company's working capital position versus the revenue generated from a supply chain and is calculated as:

$$AM.1.3 = \frac{([Supply\ Chain\ Revenue]\ -\ [Total\ Cost\ to\ Serve])}{([Inventory] +\ [Accounts\ Receivable] -\ [Accounts\ Payable])}$$

3.3.2 Objectives Hierarchy and Attributes

An outline of the proposed approach to support the supplier performance evaluation is presented in Fig. 3.2. The approach detailed in Wall & MacKenzie (2013) for multi-criteria decision making and cost effectiveness analysis (CEA) is applied to supplier selection to generate a set of KPIs based on the SCOR performance metrics. The proposed methodology provides managers in a firm with an easy tool that can be used to incorporate their own preferences for carefully evaluating and identifying the best supplier.

STEP 1: Form the Objectives Hierarchy with KPIs derived from the SCOR Metrics that are relevant to the firm while evaluating a supplier.

STEP 2: Develop value functions

STEP 3: Assess trade-off weights

STEP 4: Develop overall measure

STEP 5: Perform cost-effectiveness analysis

Figure 3.2: The proposed approach

First, an objectives hierarchy is developed based on the KPIs derived from the SCOR performance metrics. As depicted in Fig. 3.3, the overall objective is to maximize supplier effectiveness, and this objective is divided into five sub-objectives: maximize reliability, maximize responsiveness, maximize agility, minimize cost, and maximize asset management efficiency.

Although the cost of a supplier is a very important factor in supplier selection, cost is separated from effectiveness in order to focus on the benefits of selecting a supplier and then comparing those benefits with the cost. This approach can also help alleviate the potential issue of a decision maker adjusting the supplier's effectiveness in order to justify a lower or higher cost (Williams & Thompson, 2004). Cost is defined as the total cost associated with doing business with a supplier. Cost is excluded from the objectives hierarchy and considered in the final step of the methodology for CEA.

We identify 13 attributes based on the SCOR performance metrics (Fig. 3.4). The presented methodology is generic and the objectives hierarchy can be modified with other KPIs derived from the SCOR model depending on the firm or the industry. The selected indicators for the framework presented in this paper are shown in Table 3.1. As for the definition of KPIs, the SCOR model has provided with complete definitions for references in the context of an overall supply chain. However, to suit the context of supplier selection as opposed to supply chain performance evaluation, new definitions for the metrics or KPIs are presented in Table 3.1. During the application of this framework, these definitions could be altered based on interviews and discussion with management and staff of the case company. During the process of supplier selection, the KPIs and their definitions (after any necessary alterations) must be sent to each of the suppliers under consideration so that they can submit their estimated KPI values based on their capabilities.

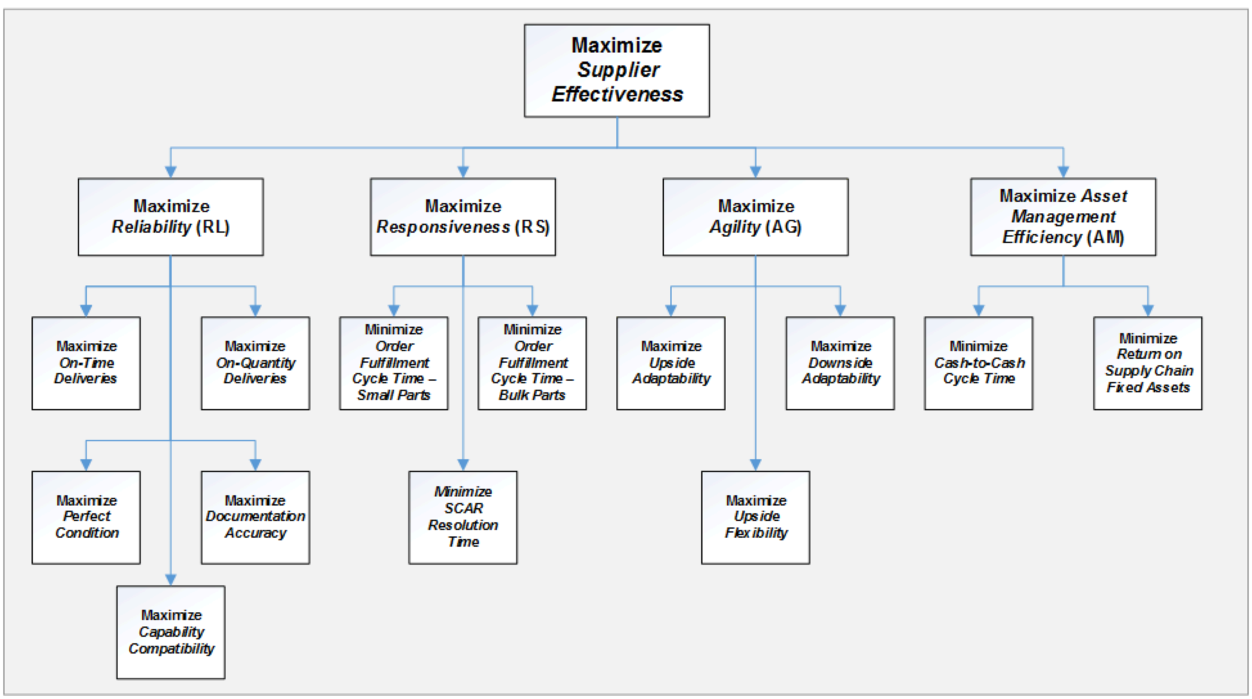

Figure 3.3: Objectives hierarchy for supplier effectiveness

Table 3.1. Supplier KPIs based on SCOR Performance Metrics

Attribute	KPI	Definition
Reliability – The ability of a supplier to perform tasks as expected.	*On-Time Deliveries*	Percentage of orders that are fulfilled on the originally committed date in complete or partial quantities.
	On-Quantity Deliveries	Percentage of orders which all the items are received by customer in the quantities committed.
	Perfect Condition	Measure of quality; Percentage of orders delivered in an undamaged state that meet specification, have the correct configuration, are faultlessly installed (as applicable) and accepted by the customer.
	Documentation Accuracy	Percentage of orders with on time and accurate documentation supporting the order, including packing slips, bills of lading, invoices, etc.
	Capability Compatibility	The ratio of a supplier's in-house capabilities to the capability required by the part being sourced.
Responsiveness – The speed at which a supplier can serve the customer needs*.	*Order Fulfillment Cycle Time – Small Parts*	The amount of time from customer authorization of a sales order for small parts to customer receipt of the product including minimum necessary dwell time.
	Order Fulfillment Cycle Time – Large Parts	The amount of time from customer authorization of a sales order for large parts to customer receipt of the product including minimum necessary dwell time.
	*SCAR** Resolution Time*	The number of days it takes a supplier to successfully resolve a SCAR from the date of issue of the SCAR.
Agility – The ability of a supplier to respond to changes in order quantities.	*Upside Flexibility*	The number of days it takes a supplier to respond to an unplanned 20% increase in demand without service or cost penalty.
	Upside Adaptability	The maximum percentage increase in production quantity relative to the current order requirements that a supplier can achieve & sustain in 30 days.
	Downside Adaptability	Percentage reduction in order quantities sustainable at 30 days prior to delivery with no inventory or cost penalties.
Asset Management Efficiency – The ability of a supplier to efficiently utilize assets	*Cash-To-Cash Cycle time*	The number of days it takes for a supplier to turn cash spent on raw materials to inventory and back into cash by selling its finished products.
	*Return on Supply Chain Fixed Assets****	A supplier’s profit (revenue minus cost) divided by its invested capital in supply chain fixed assets.

* Note that in this context, the firm is the customer.

**SCAR – Supplier Corrective Action Request / Report

****Supply Chain Fixed Assets* is different from *Total Assets*, which could include assets from sources other than the supply chain, such as investments, leasing real estate, court settlements etc.

3.3.2.1 Reliability

The Reliability hierarchy for supplier effectiveness is depicted in Fig. 3.4

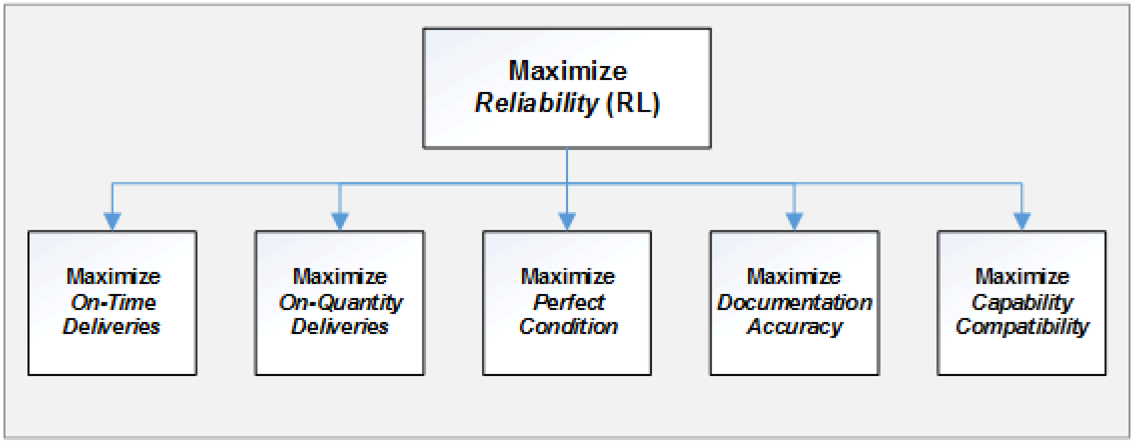

Figure 3.4: Supplier Reliability Hierarchy

Based on the SCOR metrics, we identify five KPIs for measuring the reliability of a supplier: on-time deliveries, on-quantity deliveries, perfect condition, documentation accuracy, and capability compatibility. The definitions all the five KPIs are provided in Table 3.1.

Note that suppliers are evaluated based on order delivery performance, and there needs to be a mutually agreed tolerance rate for KPI value calculation. This is particularly important while dealing with multiple orders. A firm and a supplier need to agree on the allowable percentage of damaged parts per order up to which an order would be marked to be in perfect condition. For instance, for a given supplier-firm relationship, delivering at least 99% of the order quantity on a particular order could be accepted by a firm as acceptable as on-quantity. Another tolerance is what should be the minimum order quantity that will be counted as on-time. Usually firms have a minimum quantity depending on how much is required to sustain production until they receive their next shipment to complete the order. Also, one might argue that the KPIs on-time and on-quantity measures the same. But with only one KPI for measuring on-time and on-quantity deliveries, suppliers will not have any incentive to deliver partial shipments when on-quantity deliveries are not possible. Failure to receive any orders on the committed date could affect the operations of a firm significantly and hence having a KPI for on-time delivery becomes important in such scenarios. In the context of a new supplier, a firm can ask a supplier to provide estimates based on their business capabilities and historic performance.

3.3.2.2 Responsiveness

Order fulfillment cycle time can be defined as the total cycle time from the order placement by the customer to the acceptance of the order by the customer. This includes all the time between these two events irrespective of whether the supplier was fulfilling the order. It could be the case that the customer placed the order in advance to reserve capacity or material. Hence, order fulfillment cycle time consist of two components: order fulfillment process time and dwell time. Note that the components of order fulfillment process time will depend on the supplier's business model. For instance, for a supplier with a make-to-stock business model, it would include only order processing and transportation time whereas for a supplier with make-to-order and it would also include the manufacturing time. Even though order fulfillment process time most accurately reflects the responsiveness of an organization, one can make the argument that if a supplier has too many customers lined up, the dwell time is significant to measuring the responsiveness of a supplier. But at the same time, a supplier's responsiveness should not be impacted by orders that are placed much earlier in time (where dwell time is much higher than the minimum associated with the supplier). Hence, we define order fulfillment cycle time as the amount of time from customer authorization of a sales order to customer receipt of the product including minimum necessary dwell time. Ultimately with order fulfillment cycle time, we are trying to measure how readily the product is available with a supplier.

Moreover, a firm's definition of responsiveness for a supplier can vary based on the type of product. In other words, for small parts that occupy less cubic volume per part, a firm may not require the supplier to be equally responsive compared to the case of large parts which would require relatively much higher volume per part for storage. For instance, 3 days could be an excellent order fulfillment time for small parts since inventory for 3 days can be stored easily at a factory, whereas the same firm may require 0.5 days of order fulfillment time for large parts due to lack of storage space. Hence, we have identified two KPIs for measuring the responsiveness of a supplier: order fulfillment cycle time – small parts & order fulfillment cycle time – bulk parts.

The third KPI to measure responsiveness is based on Supplier Corrective Action Requests (SCAR) which is a report that a firm can issue to a supplier based upon defects that corrective and/or preventive action on the supplier's part to eliminate future occurrences. The responsiveness hierarchy for supplier effectiveness is depicted in Fig. 3.5.

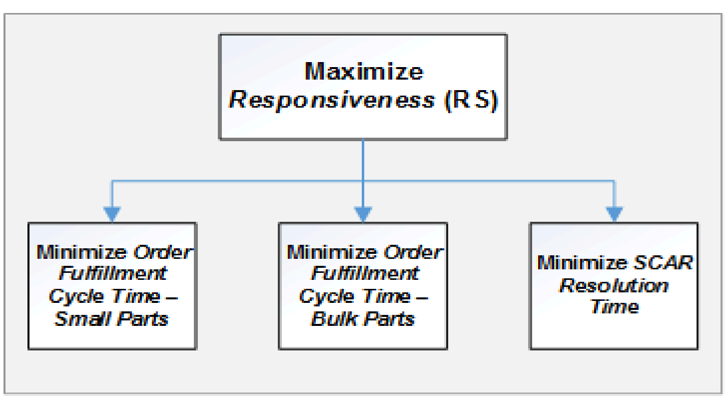

Figure 3.5: Supplier Responsiveness Hierarchy

3.3.2.3 Agility

In the context of supplier performance evaluation, the SCOR level-1 metrics for agility can be applied directly. We define upside flexibility, upside adaptability, and downside adaptability in Table 3.1. Upside flexibility and adaptability measures the capacity and speed of a supplier in case of increased demand from the customer and downside adaptability measures the reduction in order quantities that is acceptable to a supplier without penalizing the firm. The authors believe that value-at-risk, which is a measure of risk exposure, should not be one of the input parameters of this model since the ultimate objective of the model is to evaluate the risk of a supplier through the measurement of supplier effectiveness. The agility hierarchy for supplier effectiveness is depicted in Fig. 3.6.

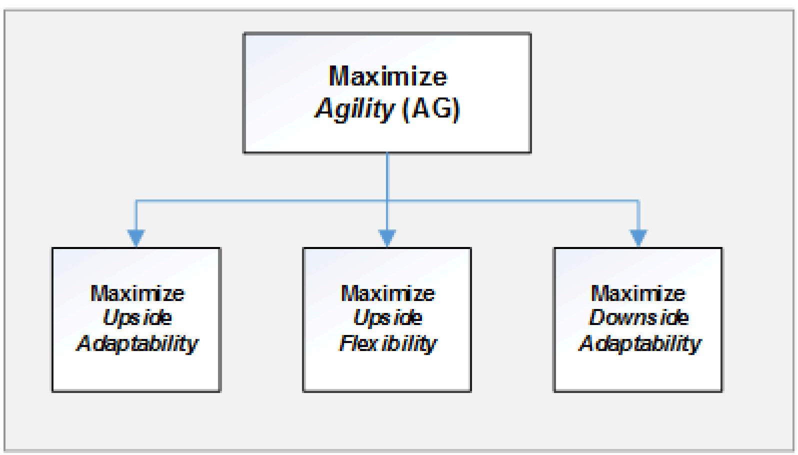

Figure 3.6: Supplier Agility Hierarchy

3.3.2.4 Asset Management Efficiency

The financial status of a supplier is often a key concern of firms in many industries as it helps to think about the risk from a supplier during disruptive events. Three critical elements in measuring asset management efficiency of a supplier namely sales outstanding, inventory, and payables outstanding forms the basis of the level-1 SCOR metrics cash-to-cash cycle time

(AM.1.1) and return on working capital (AM.1.3). In AM.1.1, these three elements are measured in terms of days whereas in AM.1.3 they are measured in monetary units.

For managers from a manufacturing firm who are not experts in financial ratios, it makes more sense to assess these three elements in days rather than in monetary units and hence we only consider cash cycle time. One might argue that we miss out on considering the profitability of a supplier by not considering return on working capital. But Return on Supply Chain Fixed Assets (AM.1.2) considers how efficiently the company is converting the money it has to net income by considering profits and assets. One can say a higher AM.1.2 number, the better, because the company is earning more money on less investment. The definitions for the two KPIs are provided in Table 3.1 and the Asset Management Efficiency hierarchy for supplier effectiveness is depicted in Fig. 3.7.

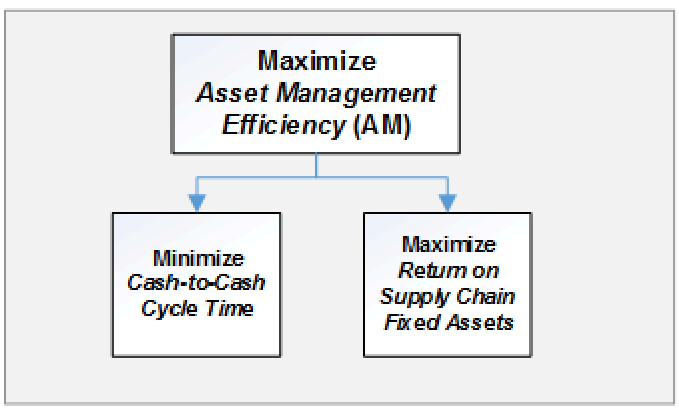

Figure 3.7: Supplier Asset Management Efficiency Hierarchy

With the measurable KPIs that form the bottom level of the objectives hierarchy, an additive value function can be used to measure the effectiveness of a supplier (Kirkwood 1997). This framework assumes preferential independence of the KPIs. The additive value function is comprised of an individual value function for each KPI and swing weights that describe the trade-offs between the KPIs and objectives.

3.3.3 Value Functions: Marginal Preferences in KPI values

The second step of the proposed framework uses value functions to convert a decision maker's preferences to real number under conditions of certainty. Value functions are most appropriate when there are multiple and conflicting objectives, and the attributes do not have any uncertainty. We consider a deterministic case in which no uncertainty is associated with the supplier KPIs. Assessing value functions require interpersonal communication between an analyst and a decision maker and can be done using several methods. The direct rating method directly assigns values to various levels of a criterion and is most useful when the metric has a few discrete levels. In the mid-value splitting technique, a value function is developed based on the indifference of the decision maker between changes in levels of the metric. Regression analysis can be used if data reflecting direct ratings from decision makers is available.

In this paper, since we are dealing with KPIs that can take infinitely many levels and is dealing with one or small number of decision makers, the mid-value splitting technique presented by Keeney & Raiffa (1993) is most appropriate. An Excel tool is presented based on Wall & MacKenzie (2013) and serves as a guide for the interaction between an analyst and the decision maker to assess a value function for each of the KPIs. The numerical parameters assessed from the decision makers are shown in Fig. 3.8. The steps are summarized as follows:

1. Determine the range and direction of preference. Estimate the minimum (MIN) point at which the decision maker get some value and the maximum (MAX) point which if

exceeded do not give any value in the given context. Set V(MIN) = 0 and V(MAX) = 100.

2. Split the range of KPI performance on the horizontal axis so that the value of the change from the MIN to the split is the same as the value from the split to the MAX. Here the indifference between changes in levels of the KPI value is measured. The decision maker is asked to indicate the value X50 such that he or she is equally satisfied between a change of the KPI value from MIN to X50 and a change of KPI value from X50 to MAX.
3. This process is then repeated for X25 and X75, shown on the vertical axis of Fig. 3.8, thus the subject is estimating a value function that transforms performance levels on the attribute to value levels. The decision maker is asked to indicate the value X25 such that he or she is equally satisfied between a change of KPI value from MIN to X25 and a change of KPI from X25 to X50. Similarly, the decision maker is asked to indicate the value X75 such that he or she is equally satisfied between a change of KPI value from X50 to X75 and a change of KPI from X75 to MAX.
4. Consistency check: Determine whether there is equal satisfaction with the KPI value change from X25 to X50 as with a change from X50 to X75. If the answer is affirmative, the value function can be considered consistent. Otherwise, the decision maker is asked to revise his or her responses (i.e., steps 1 to 3 are repeated).

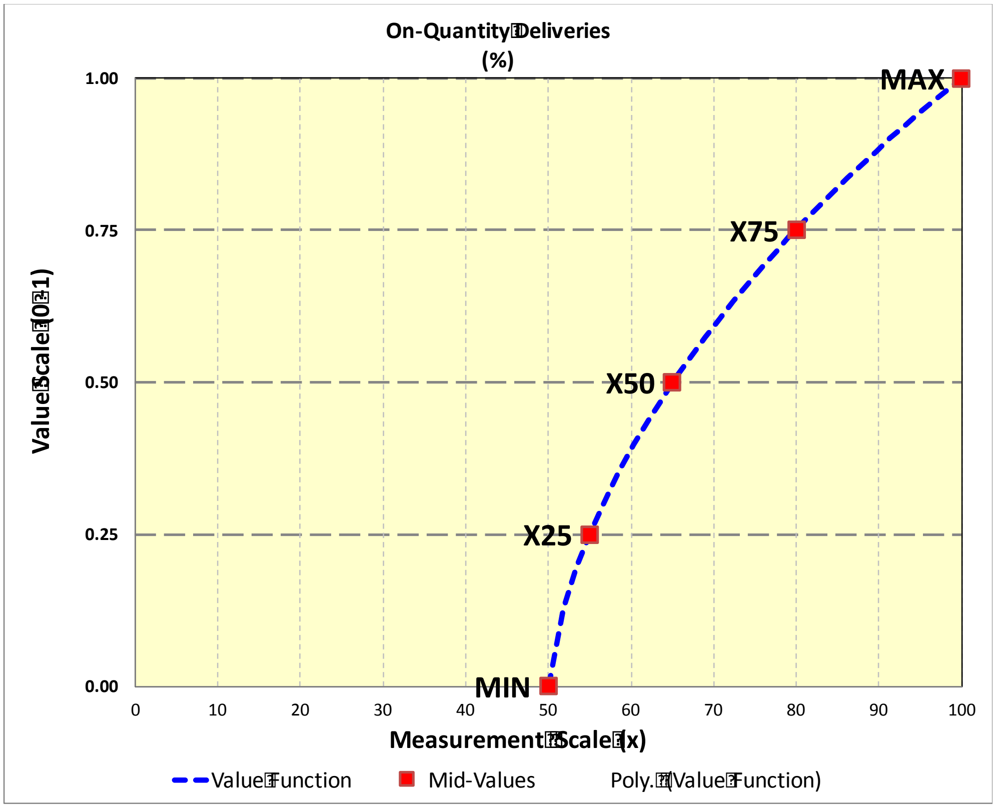

Figure 3.8: Mid-value splitting

Using the values obtained, the value functions for each of the KPIs in the objectives hierarchy can be constructed using the Excel tool as explained in Appendix A.

3.3.4 Weights: Making trade-offs between KPIs

A firm with four fundamental objectives may not be able to maximize all four without making some trade-offs. This framework provides a systematic method for a decision maker to articulate his or her preference for one objective versus another objective. If the attributes have uncertainty, the problem becomes more complex because the decision maker needs to trade-off between objectives under uncertainty.

The weights serve as the decision maker's reflection of the relative importance of various criteria. Trade-offs in multi-objective decision making problems are dependent on the subjective judgement of the decision maker and can vary from one decision maker to the other. These weights can be assessed using many techniques such as direct assessment, equal importance, rank sum, rank reciprocal, pairwise comparison, and swing weighting (Wall & MacKenzie, 2013). In the proposed methodology, the swing weight procedure is used to assess local trade-off weights. It incorporates ordinal, relative importance, and range of variation of individual KPIs and involves four major assessment steps as summarized below:

1. A decision maker is presented with a hypothetical supplier in which all the KPI values within one of the four attributes at their worst or least-preferred values.
2. The KPI for which it is most preferred to change (or swing) from its worst or least-preferred value to its best or most-preferred value, all other KPIs remaining at their worst values, is determined.
3. After the first KPI is selected, the decision maker is asked to select the second KPI that he or she would next choose to move to its best level. The process is repeated for all KPIs under the selected attribute and the KPIs are ranked from most important to least important according to the user's preference.
4. A weight of 100 is assigned to the most preferred KPI. Weights to the remaining KPIs are determined in proportion to their rank of importance.

It is more effective to perform the swing weight method to each objective separately. That is measure the swing weights for each KPI under reliability first and then repeat the process for responsiveness, agility, and asset management efficiency. Finally, the trade-off weights between the four objectives can be determined using the same swing weighing procedure and global trade-off weights are determined by multiplying the local swing weights of the KPIs by the local swing weights of the respective parent attribute or objective. Finally, all the weights are normalized so that each weight is between 0 and 1 and the sum of the weights equals 1. The Excel tool serves as a visual guide for the decision maker to assess the weights and helps the user maker refinements, if necessary.

3.3.5 Overall Measure of Supplier Effectiveness

Supplier effectiveness combines all the KPIs into a single measure of the overall effectiveness for each supplier using the value functions and weights. A well-defined logical method for combining the performance scores into one overall number was developed by Keeney and Raiffa (1993).

The product of each value function and its corresponding importance is added together as depicted in the formula below to obtain supplier effectiveness of the *j*th supplier:

$$v(j) = \sum_{i=1}^{M} w_i v_i(x_i(j)) \tag{3.1}$$

where w_i is the global trade-off weight for KPI i, $v(.)$ is a value function for KPI i, $x_i(j)$ is the level of KPI i for alternative j, and M is the total number of KPIs ($M = 11$ in the objectives hierarchy presented in Fig. 3.4)

3.3.6 Cost-Effectiveness Analysis

The first four steps of this methodology produces a supplier effectiveness score corresponding to each potential supplier with which a decision maker can easily order the suppliers in the order of preference. As we discussed earlier in the paper, most of the literature in supplier selection considers many attributes other than cost. But when it comes to practice, many organizations care too much about cost in supplier selection and hence this step becomes very critical. Here, we simply integrate the supplier effectiveness with the cost of doing business to engage the decision maker in cost-effectiveness analysis.

CEA is a two-objective problem in which a decision maker chooses an alternative with the goal of (i) maximize effectiveness and (ii) minimize cost. The measure of effectiveness is calculated for each supplier from Eq. (3.1) and each supplier has an associated cost. Often, no single supplier will be the most effective and the cheapest. The firm needs to consider the benefits or incremental effectiveness gained by sourcing from a more expensive supplier and consider the trade-off between cost and effectiveness. Plotting the cost and effectiveness of each supplier on a graph can help visualize this trade-off and identify an efficient solution set. The efficient set is composed of suppliers that are not dominated by another alternative. Here dominance is achieved if a supplier is more effect and cheaper than another supplier.

Illustrative example and analysis

The methodology presented in the previous section is applied in an illustrative example based on real world expertise for a typical case of an automotive manufacturer. All the four steps in the supplier cost-effectiveness analysis is demonstrated along with the Excel tool. In this illustrative case, the aim is to evaluate the performance of eight suppliers. One decision maker from the supply chain area and other from manufacturing were interviewed and walked through the methodology for the selection and definition of the KPIs, development of value functions, and trade-off weight assessment. Although, this is illustrative in nature, based on the author and industry experts' experience, the numbers closely align with what an automotive manufacturer would encounter.

The first step is to select the appropriate supplier KPIs from the SCOR performance metrics through interviews with the staff in the company. Here, during the interview, the objectives hierarchy in Fig. 3.4 and the KPI definitions in Table 3.1 were presented to the decision makers and it was ensured that all the components of the objectives hierarchy and the KPI definitions are applicable for the firm. Since this illustrative example deals with suppliers for low-tech automotive parts, the KPI capability compatibility was excluded from the objectives hierarchy. For this illustrative case, the estimation of KPI values for all 8 suppliers were obtained based on estimates from the two decision makers (Table 3.2). However, during the application of this model in a real supplier selection scenario, the firm entering a supplier relationship must obtain these KPI values along with the cost quotations when the suppliers put together their bids. In some firms, employees from supply chain area visit suppliers' facilities and verify or obtain the KPIs that are identified as critical from suppliers' ERP system etc. Another useful source of data is the SCORmark, which is a manufacturing benchmarking tool with data on KPIs which can be obtained by APICS SCC affiliation (SCORmark Manufacturing, APICS).

Table 3.2. KPI values for the 8 suppliers

Key Performance Indicator (KPI)	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Supplier 6	Supplier 7	Supplier 8
On-Time Deliveries (%)	78	73	85	81	92	95	90	85
On-Quantity Deliveries (%)	77	53	71	59	100	81	58	83
Perfect Condition (%)	93	94	100	99	95	97	90	96
Documentation Accuracy (%)	96	75	87	72	71	90	74	67
Order Fulfillment Cycle Time – Small Parts (Days)	5	3	2	2	2	4	4	1
Order Fulfillment Cycle Time – Large Parts (Days)	0.5	2.8	1.5	2.5	2.5	2.0	2.6	3.0
SCAR Resolution Time (Days)	19.0	17.0	14.0	8.0	25.0	21.0	27.0	11.0
Upside Flexibility (Days)	30	64	8	55	77	0	7	8
Upside Adaptability (%)	24	31	24	105	152	121	203	122
Downside Adaptability (%)	48	50	43	4	47	42	11	3
Cash-To-Cash Cycle time (Days)	126	140	99	47	92	112	77	119
Return on Supply Chain Fixed Assets	0.41	0.63	0.68	0.08	0.81	0.51	0.54	0.73
Cost ($)	$11,869	$22,122	$19,643	$12,563	$21,801	$18,360	$23,999	$11,572

As the second step, which is the assessment of value functions, the decision makers were taken through the mid-value splitting technique explained in section 3.2. Fig. 3.9 details the assessed value functions for each of the 12 KPIs. A detailed step-by-step assessment of the value function evaluation method using the excel tool is presented in Appendix A for interested readers.

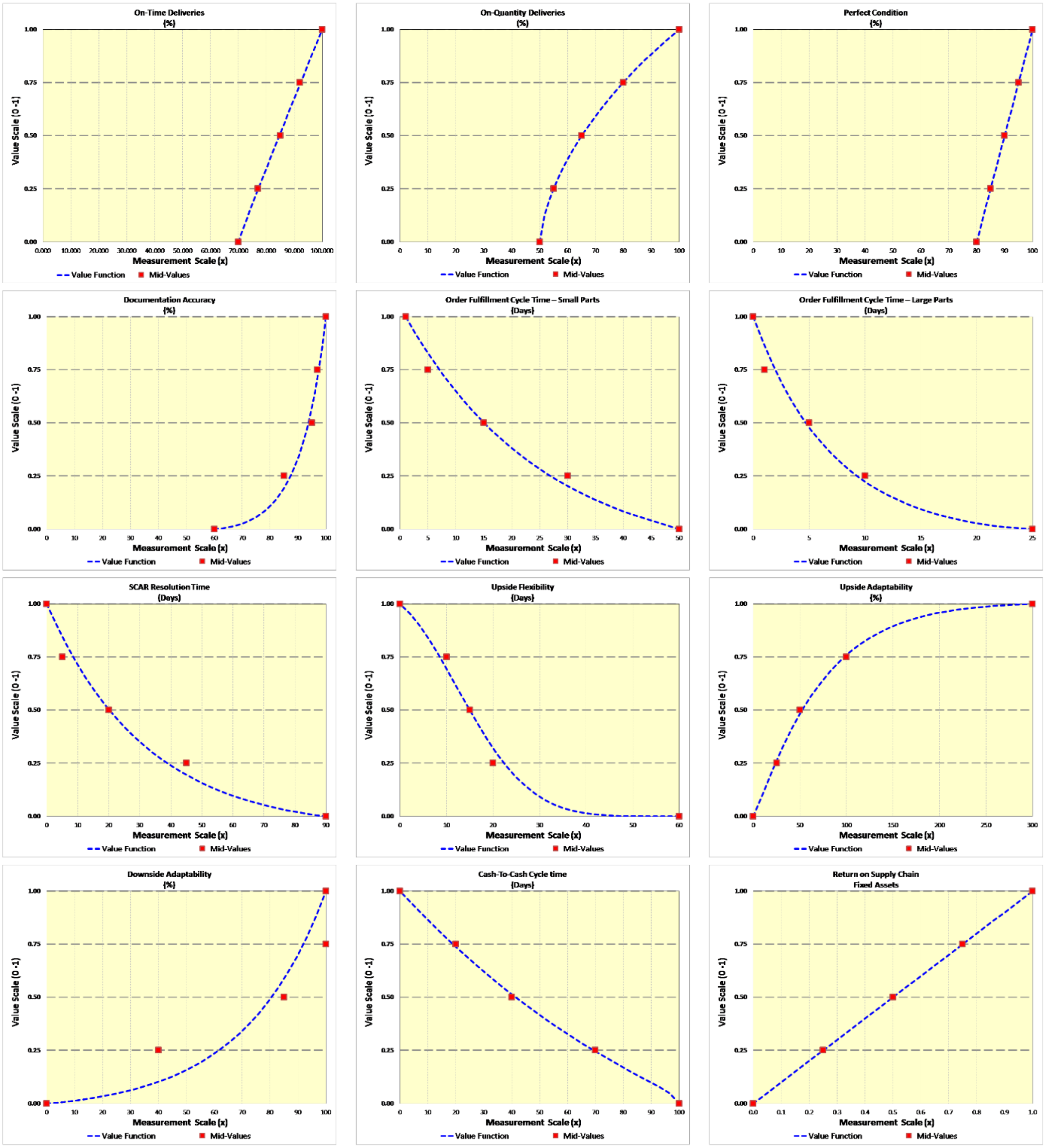

Figure 3.9: Value functions for the 12 supplier KPIs

As the third step, the trade-off weights are assessed based on the decision makers' preferences using the swing weights technique explained in section 3.3. Improving the reliability from the worst to best level is most important and has a local trade-off weight of 0.35. Improving responsiveness is almost as important, and the decision makers assign a local weight of 0.30. This is followed by asset management efficiency with a local weight of 0.20. Finally, improving agility is least important, and its local weight equals 0.15. Within the reliability objective, we assess that on-time deliveries is the most important KPI, followed by perfect condition, on-quantity deliveries, and documentation accuracy. Similarly, the swing weight method is applied to the KPIs under responsiveness, agility, and asset management efficiency. Finally, we use the rank-sum method to calculate the local trade-off weights for all the 12 KPIs. Fig. 3.10 details the assessed local trade-off weights and the calculated global trade-off weights.

Attribute	Weight	Key Performance Indicator (KPI)	Local Weight	Global Weight
Reliability	*0.35*	*On-Time Deliveries*	0.4	0.14
		On-Quantity Deliveries	0.25	0.0875
		Perfect Condition	0.3	0.105
		Documentation Accuracy	0.05	0.0175
Responsiveness	*0.3*	*Order Fulfillment Cycle Time – Small Parts*	0.4	0.12
		Order Fulfillment Cycle Time – Large Parts	0.4	0.12
		SCAR Resolution Time	0.2	0.06
Agility	*0.15*	*Upside Flexibility*	0.4	0.06
		Upside Adaptability	0.3	0.045
		Downside Adaptability	0.3	0.045
Asset Management Efficiency	*0.2*	*Cash-To-Cash Cycle time*	0.7	0.14
		Return on Supply Chain Fixed Assets	0.3	0.06

***Supply Chain Fixed Assets* is different from *Total Assets,* which could include assets from sources other than the supply chain, such as investments, leasing real estate, court settlements etc.

Figure 3.10: Local and global trade-off weights

Reliability is ranked most important because ensuring that the production runs according to the production plan with parts received from the suppliers as expected is critical to the business strategy of the firm. Responsiveness is considered the next best attribute for this case as it is the objective of the manufacturing firm to drive improvement projects and initiatives and with a delay in responses, valuable resources can be idled without direction on how to move forward.

Table 3.3 (also in Appendix A) shows the scaled KPI values corresponding to the KPI values from Table 3.1 for each of the 8 suppliers obtained using the assessed value functions show in Fig. 3.9. Supplier effectiveness score obtained was obtained for each supplier using Eq. 3.1. As can be seen from Figure 3.11, there is no dominant solution when maximizing supplier effectiveness and minimizing cost. The efficient solution set is comprised of supplier 8 and supplier 6 since neither of them are dominated by any of the others. Deciding among these two suppliers require further examination of the decision maker's preferences concerning supplier effectiveness and costs (Wall & MacKenzie, 2013).

KPI	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Supplier 6	Supplier 7	Supplier 8
On-Time Deliveries	0.0391	0.0153	0.0715	0.0531	0.1036	0.1173	0.0945	0.0715
On-Quantity Deliveries	0.0619	0.0158	0.0534	0.0318	0.0875	0.0670	0.0296	0.0694
Perfect Condition	0.0683	0.0735	0.1050	0.0998	0.0788	0.0893	0.0525	0.0840
Documentation Accuracy	0.0112	0.0010	0.0042	0.0006	0.0005	0.0005	0.0009	0.0002
Order Fulfillment Cycle Time – Small Parts	0.0994	0.1093	0.1145	0.1145	0.1145	0.1042	0.1042	0.1200
Order Fulfillment Cycle Time – Large Parts	0.1115	0.0795	0.0962	0.0830	0.0830	0.0894	0.0818	0.0771
SCAR Resolution Time	0.0312	0.0335	0.0372	0.0457	0.0252	0.0291	0.0235	0.0413
Upside Flexibility	0.0055	0.0000	0.0462	0.0000	0.0000	0.0600	0.0484	0.0462
Upside Adaptability	0.0114	0.0145	0.0114	0.0350	0.0405	0.0373	0.0433	0.0374
Downside Adaptability	0.0065	0.0071	0.0053	0.0002	0.0063	0.0050	0.0007	0.0001
Cash-To-Cash Cycle time	0.0000	0.0000	0.0034	0.0622	0.0116	0.0000	0.0268	0.0000
Return on Supply Chain Fixed Assets	0.0246	0.0378	0.0408	0.0048	0.0486	0.0306	0.0324	0.0438
Supplier Effectiveness	0.4705	0.3872	0.5891	0.5308	0.6001	0.6297	0.5384	0.5912
Cost ($ thousand)	11.8690	22.1220	19.6430	12.5630	21.8010	18.3600	23.9990	11.5720
Effectiveness by objective								
Reliability	0.18	0.11	0.23	0.19	0.27	0.27	0.18	0.23
Responsiveness	0.24	0.22	0.25	0.24	0.22	0.22	0.21	0.24
Agility	0.02	0.02	0.06	0.04	0.05	0.10	0.09	0.08
Asset Management Efficiency	0.02	0.04	0.04	0.07	0.06	0.03	0.06	0.04

Table 3.3: Scaled KPI values and overall measure for the 8 suppliers

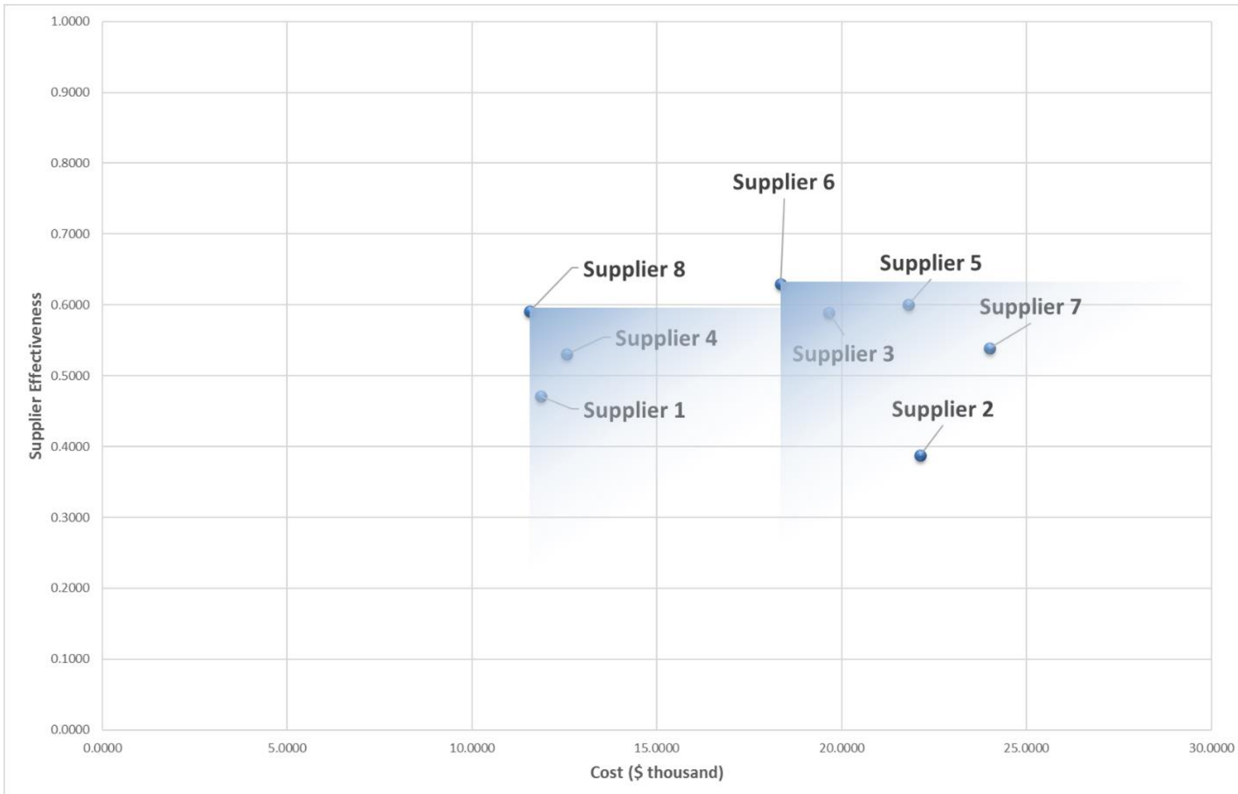

Figure 3.11: Cost-Effectiveness Analysis

The trade-off between supplier 6 and supplier 8 can be examined based on Figure 3.11 and Table 3.3 which reveals the effectiveness according to each objective. The firm or the decision maker must decide if an increase in supplier effectiveness of 0.0385 is worth the additional investment of $6,788 for supplier 6 compared to supplier 8. Supplier 6 is 22% better than supplier 8 in reliability and agility, but supplier 8 is 8% better than supplier 6 in responsiveness and asset management efficiency. The analysis can be extended to look at how the two suppliers compare at the KPI level. Supplier 6 has much better percentage of on-time deliveries, document accuracy, and downside adaptability than supplier 8. The decision maker needs to determine if doing better in these areas is worth $6,788.

Conclusion

This chapter demonstrates the use of multi-attribute decision making for supplier selection and evaluation using a five-step framework based on the SCOR performance attributes. The framework is used for an illustrative supplier selection problem based on inputs from an automotive company to analyze the cost-effectiveness of 8 suppliers.

Supplier effectiveness serves as a numerical score to identify the most preferred supplier after considering all of the firm's objectives and preference levels. CEA helps the decision maker understand the trade-offs that the firm will have to incur to gain better delivery of the preferred services from a supplier. Apart from the supplier effectiveness score and CEA, the process of going through the proposed framework for supplier selection presents significant benefits to the firm in terms of gaining valuable insights into what the firm ultimately cares about in a supplier and how much each of the supplier's KPI matter to the firm.

Even though supplier selection and supplier performance measurement has attracted a lot of research interest from as early as 1980s, few attempts to establish a simple framework for supplier selection that incorporates multi-attribute decision-making techniques. In this chapter, such a framework is presented. This chapter also identifies SCOR as the most comprehensive and efficient model for supply chain performance measurement from which supplier performance measurement metrics are derived to evaluate and compare suppliers from a firm's perspective. With an illustrative example of the framework's application, value functions and trade-off weights that change based upon a firm's requirements and preferences are derived. Our analysis demonstrates that the cost-effectiveness of a supplier depends on the decision maker's preferences, and the firm should continue to update or reevaluate its requirements, preferences, and trade-off weights.

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CHAPTER 4. GENERAL CONCLUSIONS

General Discussion

Supply chains have developed over time to meet the demand of delivering products and services faster and cheaper than before. However, these advances have come at the cost of expanded defenselessness of supply chains. Since the current global supply chains are highly connected, the negative impact of disturbances occurring due to new unknown variables can spread rapidly. To cope with this increased vulnerability, we argued in Chapter 2 that companies must actively work to manage the risk from its downstream supply chain by forecasting the impact of a temporary production shut down due to a disruption event. Further, with today's increased dependence on supply chain networks, firms are directly exposed to their suppliers' risk profiles. This, on the other hand, needs a systematic framework using effective supplier performance metrics and multi-objective decision making techniques to select most effective supplier and we demonstrated such a model in Chapter 3.

The focus of this thesis was to develop quantitative methods to analyze supply chain risk from a firm's perspective. First, we modeled the different types of customer behaviors as a probabilistic model to forecast the lost revenue from a production shut-down due to a supply chain disruption. Second, we presented a new framework for supplier selection and evaluation using the combination of multi-criteria decision making techniques and the SCOR model.

In the market response model presented in Chapter 2, lost revenue serves as a measure of risk and enables a firm to foresee the consequences of a production shut down. While the values of the uncertain parameters p, the probability with which each customer comes back to the firm, and q, conditional probability that the customer who comes back immediately will require backorders, are uncertain and beyond the scope of this thesis, we can use the model to derive important risk management insights that would lead to making better decisions increasing the supply chain resilience of a firm.

Using the framework presented in Chapter 3, decision makers from a firm can incorporate their own preference within the presented framework to determine the most preferred supplier and assess the cost effectiveness to select a supplier in different scenarios. Depending on specific cases such as whether the firm is in a position where it can make trade-offs on costs and demand higher supplier effectiveness or the firm has a maximum threshold on costs within which it requires most effective supplier, the COE can be used to select most cost-efficient supplier.

Recommendations for Future Research

The proposed market response model could be developed further by relaxing some of the assumptions. For instance, customers may return with different probabilities or probabilities that change over time. Further extensions to this research can include the development of a decision-making framework to utilize the mathematical model to determine the most effective risk management decisions during a supply chain disruption. Another extension is to model the probability of a supply chain disruption along with the total expected lost revenue to make sound management decisions regarding investments in preparedness measures. An optimization model that minimizes the lost revenue during the disruption periods can also serve as a future extension to this chapter.

Further studies on supplier selection can apply the proposed framework for supplier selection and evaluation in manufacturing supply chains with different strategies such as lean, agile, lean etc. Suggestions for future research include further development of objectives hierarchy to include other supplier KPIs that are not covered in the SCOR model. For instance, a firm may care about expedition capability of a supplier.

The major limitation of the proposed supplier selection framework is the certainty assumption of supplier KPIs. Hence, in case applications with deterministic metrics, sensitivity analysis must be carried out to assess the sensitivity of the results to the weights and preferences. Moreover, the proposed method can be developed further by considering non-deterministic case of supplier performance where each KPI can be represented by a probability distribution. Such models that accounts for the uncertainty with supplier performance can use Bayesian updating for updating supplier performance beyond the supplier selection process. A firm could update its belief about a supplier and reassess the supplier effectiveness using data from ERP systems as it continues to work with the supplier and observe the supplier's performance. Finally, the Excel tool for supporting supplier selection and evaluation can be further developed with feedback from practitioners through multiple case studies.

APPENDIX APPROXIMATING VALUE FUNCTIONS IN EXCEL

This section describes how decision maker can use the authors' Excel worksheets, otherwise known as Excel Tool, to fashion their own multi-objective, cost- effective analysis for supplier selection. The decision support tool is coded in Microsoft Excel and is customizable. It serves as a guide for the interaction between an analyst and the decision maker to assess a value functions and trade-off weights to measure suppliers' effectiveness. This appendix provides some detail into using the Excel tool to evaluate the cost-effectiveness of a supplier. A screenshot of excel tool with all the worksheets can be seen in Figure A.1.

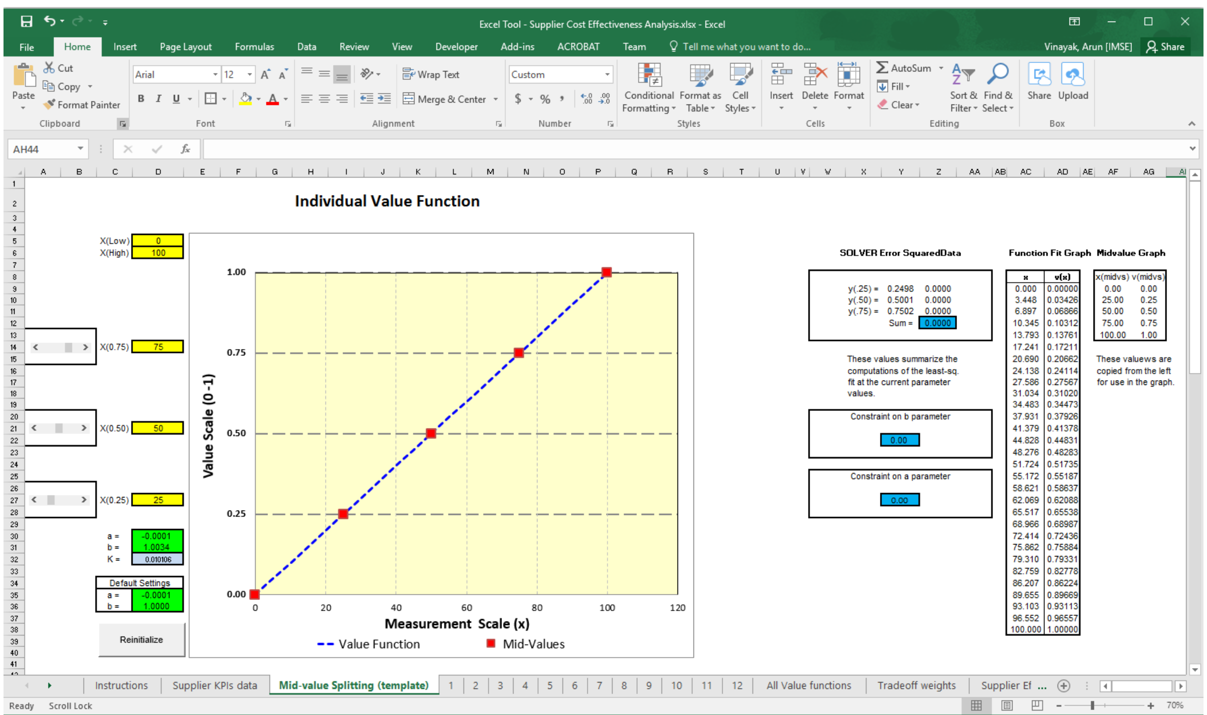


Figure A.1: Excel tool interface

The first worksheet named *Instructions* provide general guidelines for using the tool described in detail here. The second worksheet named, *Supplier KPIs data*, lists raw data used for the supplier selection. The current data is based on the illustrative example presented in the paper.

As mentioned in section 3.4, the firm entering a supplier relationship must obtain these KPI data along with the cost quotations when the suppliers put together their bids. This sheet should not be modified unless the user has different data or would like to insert another supplier.

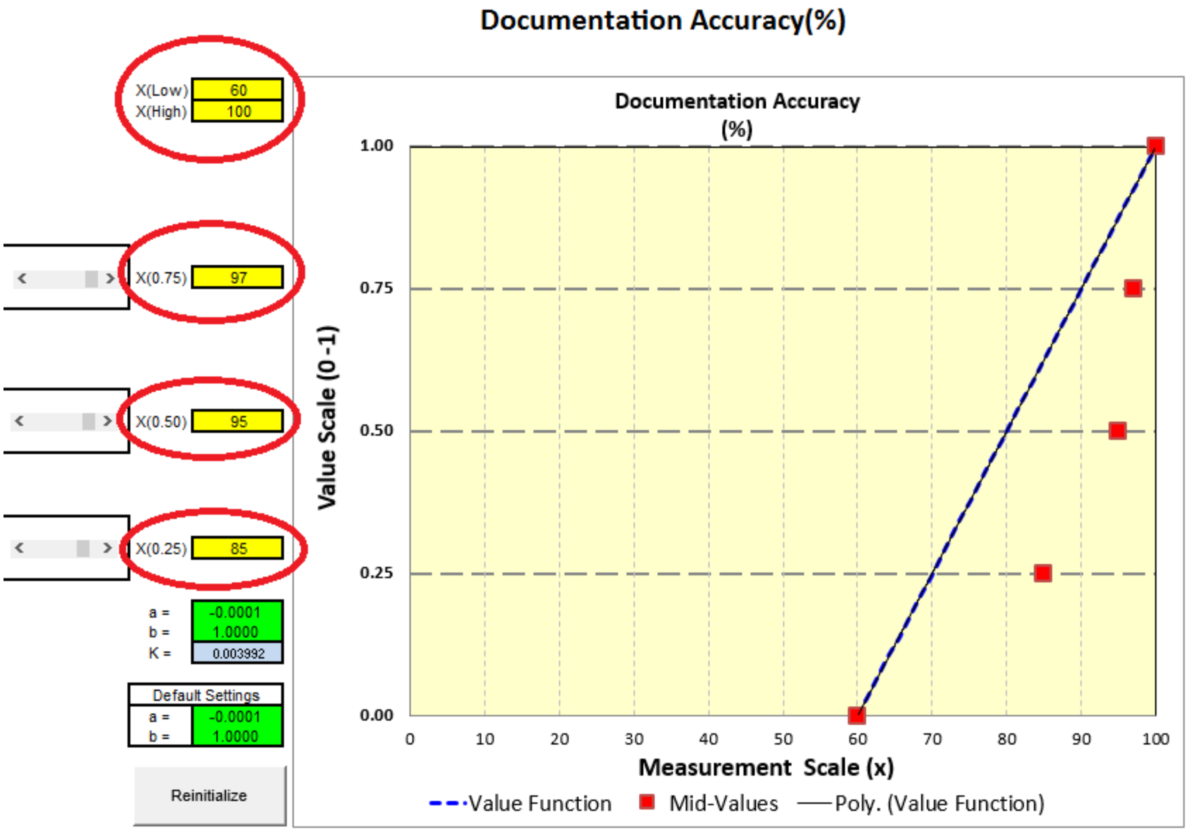


Figure A.2: Excel tool interface for assessing value function

The third worksheet named, *Mid-value Splitting (template)* is the general template that is used to create value functions for each of the KPIs selected by the decision maker. This worksheet is duplicated and fashioned for each of the KPI in the objectives hierarchy according to the decision maker's preferences using mid-value splitting technique. Worksheets 1 to 12 represent value functions corresponding to the 12 KPIs identified for the supplier selection problem in the illustrative example (Section 3.4). The first steps to approximating a value function are to plot the points of the value function using mid-value splitting technique. Here, the analyst can use the steps listed in section 3.32 to interact with the decision maker to obtain the required inputs (cells highlighted with yellow in Fig A.2) for creating the value function for the decision maker's marginal preference in KPI values.

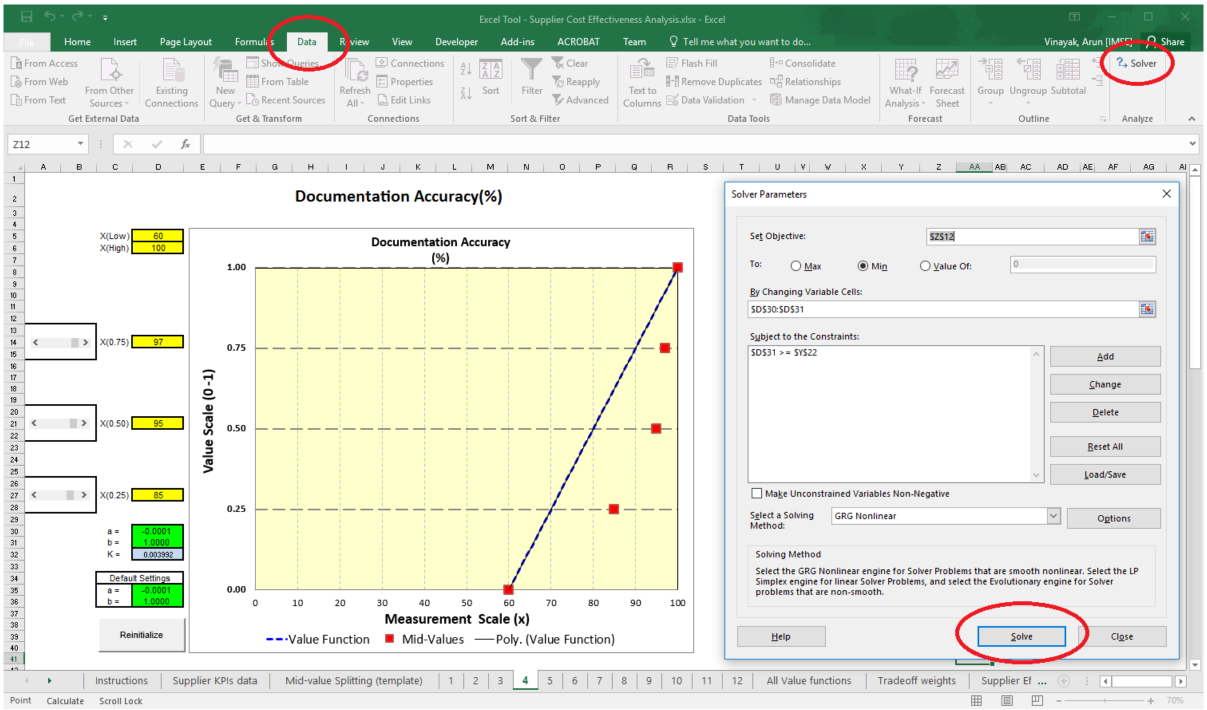
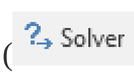


Figure A.3: Using Excel Solver to create value function

When the values are assessed, they can then be inputted and fit to the exponential value function by use of Excel solver. Clicking on the *Data* ribbon, and then "Solver" (

) should lead to a pop-up window on which the user can then click "Solve" in order to determine an equation for an exponential function which is a best fit line to the values assessed using mid-value splitting technique. This is done by minimizing the sum of the squared differences. When the user clicks "solve", the parameters that will change are in cells highlighted with a light green. The exponential functions used depends on whether the decision maker direction of preference for the KPI.

$$v_i(x_i) = \begin{cases} \dfrac{1-\exp\left(a\left[x_i - x_{\min}\right]^b\right)}{K} & \text{if more is preferred} \\ \dfrac{1-\exp\left(a\left[x_{\max} - x_i\right]^b\right)}{K} & \text{if less is preferred} \end{cases} \tag{A.1}$$

where $K = 1-\exp\left(a\left[x_{\max} - x_{\min}\right]^b\right)$ is a normalizing constant,

The function shown above consists of three parameters, these are: x_{min}, x_{max} , and a. While the first two are known due to the specification of the range of interest over which xi will (given as [$x_{min} \leq x_i \leq x_{max}$]), the last parameter, a, is obtained using a least-squares regression in the solver "add-in" tool in Excel. The best-fit line can be seen as the dotted blue line.

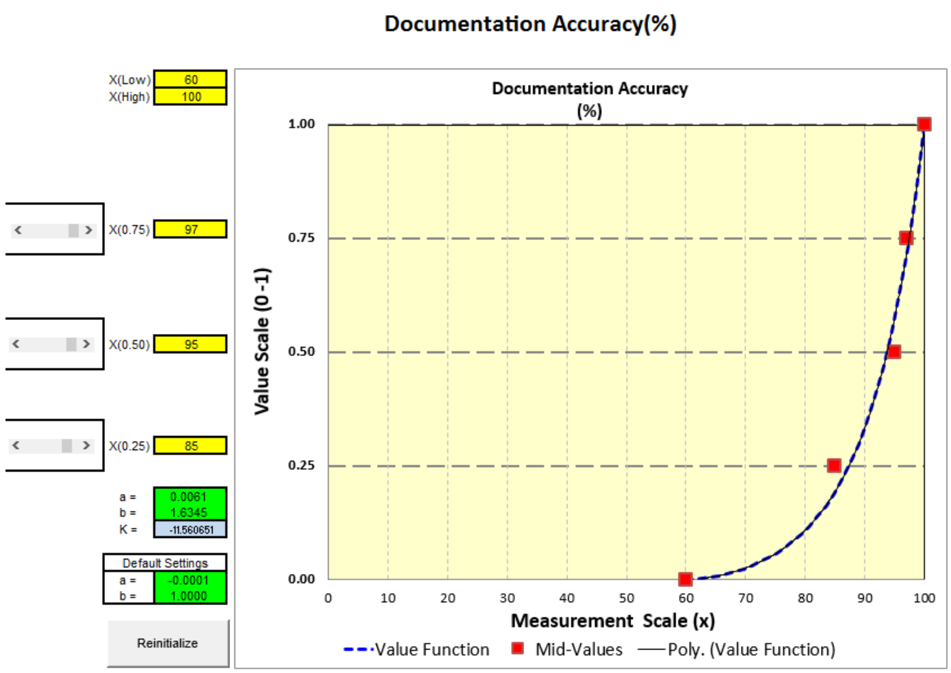
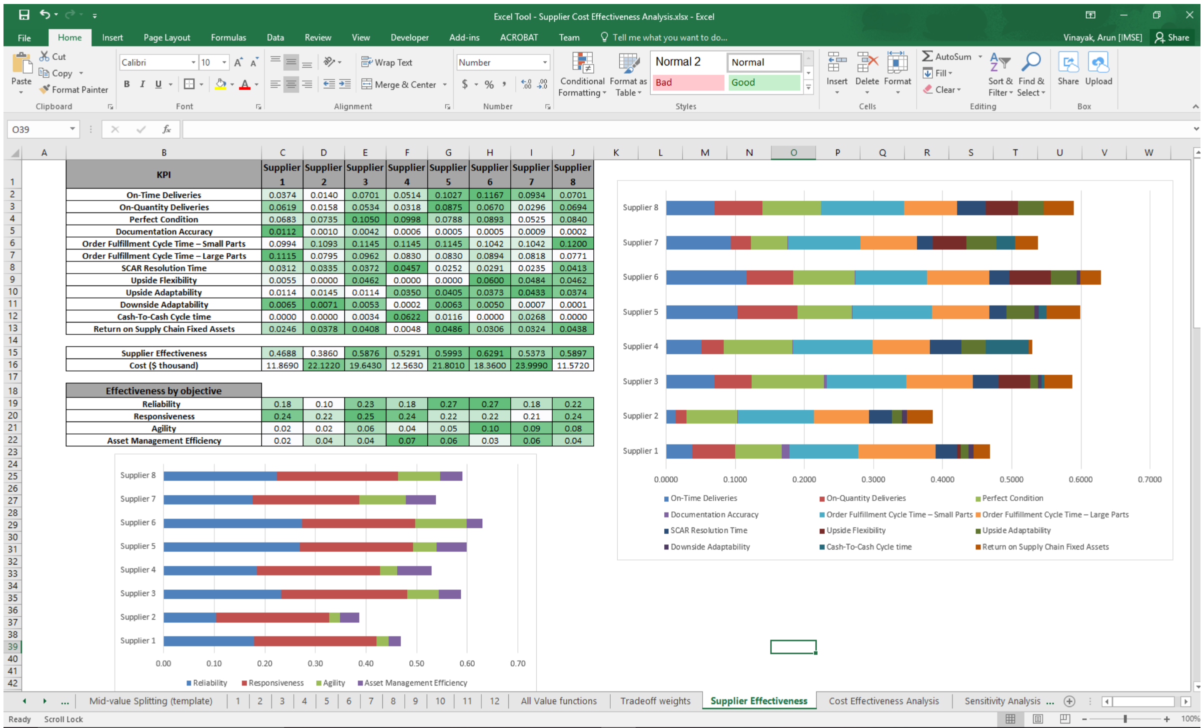


Figure A.4: Assessed value function for *Documentation Accuracy*

The worksheet tab supplier effectiveness depicts the overall effectiveness and effectiveness by objective for each supplier.



KPI	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Supplier 6	Supplier 7	Supplier 8
On-Time Deliveries	0.0374	0.0140	0.0701	0.0514	0.1027	0.1167	0.0934	0.0701
On-Quantity Deliveries	0.0619	0.0158	0.0534	0.0318	0.0875	0.0670	0.0296	0.0694
Perfect Condition	0.0683	0.0735	0.1050	0.0998	0.0788	0.0893	0.0525	0.0840
Documentation Accuracy	0.0112	0.0010	0.0042	0.0006	0.0005	0.0005	0.0009	0.0002
Order Fulfillment Cycle Time – Small Parts	0.0994	0.1093	0.1145	0.1145	0.1145	0.1042	0.1042	0.1200
Order Fulfillment Cycle Time – Large Parts	0.1115	0.0795	0.0962	0.0830	0.0830	0.0894	0.0818	0.0771
SCAR Resolution Time	0.0312	0.0335	0.0372	0.0457	0.0252	0.0291	0.0235	0.0413
Upside Flexibility	0.0055	0.0000	0.0462	0.0000	0.0000	0.0600	0.0484	0.0462
Upside Adaptability	0.0114	0.0145	0.0114	0.0350	0.0405	0.0373	0.0433	0.0374
Downside Adaptability	0.0065	0.0071	0.0053	0.0002	0.0063	0.0050	0.0007	0.0001
Cash-To-Cash Cycle time	0.0000	0.0000	0.0034	0.0622	0.0116	0.0000	0.0268	0.0000
Return on Supply Chain Fixed Assets	0.0246	0.0378	0.0408	0.0048	0.0486	0.0306	0.0324	0.0438

Supplier Effectiveness	0.4688	0.3860	0.5876	0.5291	0.5993	0.6291	0.5373	0.5897
Cost ($ thousand)	11.8690	22.1220	19.6430	12.5630	21.8010	18.3600	23.9990	11.5720

Effectiveness by objective								
Reliability	0.18	0.10	0.23	0.18	0.27	0.27	0.18	0.22
Responsiveness	0.24	0.22	0.25	0.24	0.22	0.22	0.21	0.24
Agility	0.02	0.02	0.06	0.04	0.05	0.10	0.09	0.08
Asset Management Efficiency	0.02	0.04	0.04	0.07	0.06	0.03	0.06	0.04

Figure A.5: Effectiveness scores for each supplier