Building a Framework for Determining the Optimal Supplier Shipping Performance

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Most companies aim for perfect on-time delivery from suppliers, since late deliveries can cause supply disruptions and raise the cost of inventory, transportation and coordination. But this assumes that companies do not incur expenses in increasing or maintaining supplier performance. Our thesis looks at the problem faced by those companies that do invest in suppliers to help them achieve a desired performance level. In these special cases, a perfect target may no longer yield the minimum cost incurred over a performance spectrum. Our thesis provides a framework that companies can use to determine an optimal target for timely deliveries by comparing the cost implications of different supplier performance levels. We pursue an empirical approach, using the data and metrics of an industrial equipment manufacturer that uses a hit-or-miss performance measure to evaluate on-time supplier deliveries. Within the scope of this performance management system, we determine the relevant cost categories. Using regression analysis, we create models projecting each category's expected behavior based on data we collect. Combining the models allows us to calculate a system optimal point at which the incremental cost of supplier development towards an improved performance target matches the benefit derived from avoided supply disruption. This performance target minimizes the total cost of the performance management system. While our framework is calibrated to a specific company, the models we create are general enough to be adapted by companies facing similar problems. By laying out our treatment of costs, we hope to make it feasible for other companies to calculate a target that makes sense: one that suppliers can achieve and purchasers can afford.

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We dedicate this work to Julia and Oriana – our companions and inspiration for so much in our lives.

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1. Background and Motivation

When setting performance targets for suppliers, most companies aim for nothing less than 100% on-time deliveries from suppliers, since late deliveries cause supply disruptions and associated costs. But this conclusion assumes that companies do not incur expenses in increasing or maintaining (nearly) perfect supplier deliveries. Select few companies, however, invest in suppliers to help them achieve a desired performance target. In these special cases, the minimum cost incurred over a supplier on-time delivery performance spectrum may no longer lie at 100%. But how much lower does it lie?

This thesis aims to provide a framework that companies can use to determine a performance target for timely supplier deliveries that minimizes their total cost. Applying our framework, companies can project and compare costs at different levels of supplier performance and determine the level at which total costs are minimal. We pursued an empirical approach, using the data and metrics of an industrial equipment manufacturer we refer to as MiCo. Over the course of several months, we evaluated MiCo's performance measure of incoming supplier deliveries and analyzed ordering and sales data specifically related to MiCo's service parts business segment. Within the scope of MiCo's existing performance management system, we determined the cost categories relevant to an optimization-oriented analysis and collected and analyzed data for each category. Finally, we created cost models projecting each category's expected cost behavior based on observations from our data collections. Since our thesis employed an empirical approach rather than a theoretical one, the scope of our work was closely framed with representatives from MiCo. The data, decisions and policies we review in our work represent actual observations taken from MiCo's service parts business. For the purpose of anonymity, terms and values have been modified without impacting the interpretative value of the data.

Our decision to pursue an empirical approach also reflects an absence of applicable literature. Our search for solutions and approaches came up with few theoretical, let alone empirical, treatments of the problem that MiCo faces. Although on-time delivery of suppliers is carefully tracked by most companies, the way in which firms gauge performance and adherence to targets can differ significantly. Possibly for this reason, we did not find any conclusive works that outlined a practical solution readily applicable to MiCo.

1.1 The Problem: Setting On-Time Delivery Targets

To understand the difficulty behind setting delivery targets requires capturing the implicit cost of imperfect deliveries and the cost of a supplier improvement policy. Unplanned delays cause interruptions in downstream processes and require remedial efforts of reactive or proactive nature. Reactive measures include efforts aimed at compensating for delays from late deliveries by speeding up other processes or changing overall conditions. Proactive measures include modifications to planning procedures, such as increasing inventory by adjusting order sizes or frequencies. Such measures cause unnecessary inefficiencies in operations and create costs, many of which we address in subsequent chapters. The costs of attaining and maintaining higher on-time delivery performance targets are less straightforward: a supplier may absorb the full burden of increased risk and cost, or pass it on to downstream customers through indirect means such as increased lead times or product pricing.

While MiCo experiences a multitude of costs from running supplier performance management, not all are easily measurable. The cost of vendor management and source selection, for example, might increase with higher performance expectations, as higher targets can lead to a rise in underperformers. To capture this type of burden, one would need to collect data on order conditions (e.g. lead times, prices) for equivalent vendors, time frames and products, and compare workforce requirements on purchasing departments at different target levels. MiCo's direct supplier development program, on the other hand, offers a more quantifiable approach to relating costs to targets.

1.2 An Overview of MiCo and its Performance Measurement of On-Time Delivery

The setting for our thesis is the service parts business segment administered by MiCo, a leading industrial equipment manufacturer. Like many firms, MiCo uses on-time delivery as a measure to gauge the effectiveness of its supply channels and sources. Due to differences in shipping transit times and the shipping terms negotiated with each supplier, MiCo actually measures the date of shipment rather than the actual date of delivery for incoming supplier orders. This feature benefits suppliers, ensuring that any delay caused by the transportation carrier is not attributed to suppliers. Since much of the literature focuses on supplier on-time deliveries rather than on-time shipments, we frequently use the two terms interchangeably: unless highlighted, we treat the terms as equivalent throughout this work.

MiCo implemented a Supplier Shipping Performance (SSP) measurement system following a Six Sigma project aimed at increasing supplier effectiveness. Capturing the SSP ratio is fairly simple: a supplier meeting a time window for shipment stipulated in an order receives credit, while a supplier failing to ship within this window does not. Supplier deliveries are aggregated on a monthly basis to determine each supplier's monthly SSP ratio. A three month running average determines each supplier's current SSP ratio, which MiCo uses for decision making and communications with suppliers.

Monitoring SSP rests on the assumption that SSP decreases lead to increased burdens. For MiCo to meet customer demands for service parts in a timely manner, late parts must be expedited at higher transportation rates from the supplier to MiCo, or between warehouses and distribution centers. While this is happening, MiCo's overall inventory levels may be depleting because of late or missing stock replenishments. The risk of inventory stock-outs from uncertain deliveries is often mitigated through an implementation of higher inventory buffers. A low SSP can therefore drive up inventory, transportation, and coordination costs. To avoid this scenario from pervading everyday business, MiCo also attacks the problem from another end by assigning a team of in-house employees to assist its most important suppliers in boosting their performance, in some cases by sending them out to the supplier's site.

MiCo began this policy by setting a 95% SSP target for suppliers. However, it appears that MiCo had based this target more on principal than calculations: a 95% target seemed reasonably close to (whilst just shy of) perfection, while leaving room for upward mobility. After observations showed that reaching the high SSP target of 95% would require excessive resources for supplier management, MiCo lowered the targets slightly. MiCo's quest for an empirical approach towards finding an optimal target through quantifiable and reproducible means presents the motivation for our thesis.

1.3 A Framework for Calculating Optimal On Time Delivery Targets – Specific, yet General

Although metrics for on-time delivery are commonly used across companies, many firms may pick targets without quantifying the true effect of setting them. Our thesis presents a way to assess the costs without the need to change targets on suppliers in order to observe reactions. We refer to data readily available to many firms, though it may take time to find, transform and correctly interpret the data. While the treatment of our framework is limited to the availability and accuracy of data provided by MiCo, the models we create are general enough to be adapted by companies facing similar problems.

A review of relevant literature in the next section is followed by an overview of the steps taken in building our framework: data collection, clean up, aggregation, conversion and regression. During the data analysis we apply this framework to actual data and model the cost functions which we finally combine into one in order to calculate the system optimal point. By laying out our approach to capture costs, we hope to make it feasible for companies to calculate a target that makes sense; one that suppliers can achieve and purchasers can afford.

2. Literature Review

2.1 Background and Scope

Although supplier delivery performance management is not a new concept (Guiffrida 2006), the business literature offers little material on the level of targets or the methodology that should be used in setting and enforcing them. This may come as a surprise, since most firms understand the importance of correctly applying Key Performance Indicators (KPIs) such as supplier on-time delivery performance (Chenhall 2003). Delving deeper into the issue of target setting, we found some of the features underlying the problem. First, there are two cost categories that need to be considered when setting a target, each of which contains several elements that can vary across firms. On one hand we have performance maintenance costs connected to administering and maintaining a target. These include the costs of negotiating, implementing, coordinating, monitoring, adjusting, enforcing and terminating contracts (Carr 1999). On the other hand we have consequence management costs, incurred when performance drops below 100% of the target level. A common example is the increase of stock levels to cope with variability in deliveries (Guiffrida 2006). For performance maintenance costs, the sources we found widely use a logarithmic function (Porteus 1985, Leschke 1997). For consequence management costs, a downward diminishing return function is shown to be accurate (Guifridda 2008).

Our literature review begins with a brief exploration of KPIs. After a survey of supplier delivery performance benchmark statistics, we review features of the Supplier Shipping Performance (SSP) metric and contrast its strengths and weaknesses. This is followed by a description of performance management, supplier development efforts and frequent pitfalls that companies should avoid. Finally, we investigate whether companies generally understand the financial impacts associated with metrics and briefly discuss the state of methodologies available in setting performance targets.

2.2 Supplier focused KPIs

Before we can set a target for a supplier-focused KPI we must understand how the KPI is used and how it enables future success. According to Harrington (1991), "measurements are the key. If you cannot measure it, you cannot control it. If you cannot control it, you cannot manage it. If you cannot manage it, you cannot improve it." Choosing the appropriate measures and setting the right target therefore play a crucial role in the success of a company.

So how can we formally describe a KPI? A KPI is a tool used to make informed decisions to reach long term organizational goals, based on the interpretation of available information from internal or external sources (operations or markets, respectively). Regular, quantifiable events are measured to evaluate success from various operations (Xiong 2010). Measurement is part of a regular, iterative process of defining, measuring, analyzing and controlling that aims to effectively use KPIs (Niedritis 2011). While KPIs can be classified as financial or operational, the inherent feature of any KPI is that it impacts financials (Ittner 2003).

2.2.1 Industry Prevalence

The 2005 Institute of Management Accountants Report states that companies need to carefully measure the performance of their supplier base in order to protect themselves from the influence that vendors can have on rising costs (Thomas 2006). Suppliers influence the total cost incurred with more than just the purchase price. Additional expenses can follow from low delivery reliability and high rejection or defect rates (Thomas 2006). Purchasing firms therefore evaluate their suppliers on multiple criteria, including size, products, turnover and performance (Minahan and Vigoroso 2002). Simpson (2002) found that if companies had a formal supplier rating system (and only half of surveyed firms did) they typically focused on quality, price, service (including delivery) and, more recently, relationships.

According to a 2002 Benchmark Report by the Aberdeen Group, on-time delivery is the second-most common performance criterion firms measure when assessing suppliers. Approximately 90% of firms evaluate suppliers on this criterion, with only slightly more measured on quality. Service and price were the next criteria on the list, albeit at a distance to quality and on-time delivery. Previous studies found that over 70% of companies closely followed delivery compliance and service, making it one of the most prevailing metrics used to measure suppliers (Tan, Kannan, Handfield 1998, Simpson 2002).

More recent reports continue to indicate that the most successful companies look very closely at timely deliveries. Furthermore, company surveys seem to indicate that companies carefully manage their suppliers in this regard. According to a more recent Benchmarking Report by the Aberdeen Group (2011), the 30 most successful companies taken from a sample of 150 firms representing various industries and sectors displayed a supplier on-time delivery of nearly 90%. This standard is close to the revised target MiCo set for its supplier base. The 50 least successful companies in this group of 150 exhibited timely incoming orders below 50%. The study accredits much of the discrepancy in timely delivery between the top firms and the bottom ones to the practice of performance management and control on behalf of the purchasing firms (Limberakis 2011).

2.2.2 Elements of SSP

SSP is one of many approaches to measure timely deliveries, so why use SSP? We answer this question by discussing considerations during the development of an SSP metric. Before highlighting strengths and weaknesses of the SSP metric, we investigate the different elements of the measure. In describing precisely this type of delivery performance metric, Miller (1990) outlines four key elements.

1. **Denomination:** This consideration determines the basis for the measurement. Typical options include line items, orders, dollars and units. Line items prevent single entries from dominating the calculation (which can happen when measuring in value or units), while still offering more detail than orders.

2. **Time frames**: This aspect concerns the period over which measurements should be aggregated, and whether a time window should be used for evaluating timely deliveries. The frequency of deliveries influences the effectiveness of aggregation. Aggregating over timeframes during which few orders arrive can cause volatile observation patterns (spikes and troughs of 0% or 100%). Infrequent aggregations, however, can limit responsiveness. In terms of the window size, setting it too small can create unnecessary reaction, while choosing it too large reduces the possibility of identifying a problem.
3. **Historical orders (past and present):** Adding unfilled orders of a past month to the scheduled deliveries of a current month drastically impacts SSP measurement. Miller (1990) recommends including past unfilled orders, since all orders result from planning or demand decisions. If past orders are excluded, the emphasis on following up might go astray.
4. **Point of measure:** This regards choosing the point in time at which a supplier is evaluated, and the physical point or location where a measurement is taken. A supplier is typically measured on the date of shipment or delivery. A deciding factor can be the ownership of shipping. If the supplier is responsible for shipping, Miller advocates recording the delivery date. Determining the point at which a supplier is evaluated for credit is a separate problem. A logical selection is the point of transaction (where ownership changes). But the ability to capture information at this point must be considered as well. Having customers actively track outgoing shipments at vendor locations is not cost-effective if only for the sake of crediting a timely shipment. This can happen once the goods arrive, even if the point of accreditation does not match the point of measurement. In line with Miller's argument, MiCo uses the delivery date as point of crediting, but the shipment date as point of measurement.

In reviewing these basic considerations, some weaknesses become apparent.

- Since SSP is a binary measure (hit or miss), it does not capture magnitude in terms of lateness of delivery or partial order fills. A delivery that is one day late is credited in the same manner as a delivery that is two weeks late. Similarly, an order that is 90% filled may be treated equal to an order that is only 10% filled. In a very strict hit-or-miss metric, each of these four examples would be treated similarly even though their impact is different.

- Studies have shown that variance in delivery date is a stronger driver of cost within a purchasing firm than traditional average days late (Richardson & Zeimer 2008). This variance is not captured in an SSP metric.

However, an SSP metric does offer several benefits as well.

- It is a quick and easy measure of supplier delivery performance independent of order frequency.
- It is easily understood and therefor easily communicated.
- No single entry can distort the measurement (e.g. value, unit count, tardiness). The binary measurement gives each observation the same weight.

2.3 Performance Management

In an increasingly global economic environment, where products and services are outsourced daily as firms focus on respective competitive advantages, the selection and monitoring of suppliers is pivotal to the survival of businesses. Performance management provides the framework businesses use to gauge the achievements of their business partners. Unless specified, performance management refers to assessing suppliers, not a firm evaluating its own operations. According to the Aberdeen Group (2002), performance management is a "process of measuring, analyzing, and managing suppliers for the purpose of reducing costs, mitigating risk and driving continuous improvements in values and operations." Throughout our discussion of performance management, we will draw comparisons to the system in place at MiCo.

KPIs serve as principal analytical tools in administering performance management. Usually, firms focus on several KPIs to gain an understanding of business partners' performance over several functional dimensions. Regardless of which KPIs are selected by a firm, the performance management process frequently follows the four step model outlined by Forslund and Jonsson (2010). Given our focus on delivery performance, our description of the four steps is oriented towards supplier delivery.

1. **Defining Metrics:** This forms the foundation of a functioning performance management system. The result is a stipulated, clear, measurable set of criteria that can include "name, objective, scope, target, definition, unit of measure, frequency, data source, owner, and drivers" (Lohman, Fortuin and Wouters 2004).
2. **Target Setting:** Ideally this occurs after ample communication between suppliers and customers. Frequently, however, targets are set unilaterally by the party holding a stronger negotiation position resulting from size, importance or market share.
3. **Measurement:** To avoid redundant measurements, the responsibility for collecting measurements is usually assigned to one party. Nevertheless, all parties will likely capture some measurements to validate each other's findings, therefore some redundancy remains. Forslund (2007) found that 88% of customers measured their suppliers' delivery service times.
4. **Analysis:** The collected measurements are shared between parties, compared and validated with locally captured measurements. The gap between the measured performance and the target is then addressed. Ideally, addressing the gap is followed by a mitigation plan.

There are three options available when suppliers fail to meet performance standards (Wagner 2009). They can discontinue partnerships and re-source, attempt to in-source products or services currently furnished unsatisfactorily by the suppliers, or incentivize suppliers to improve performance. The following sections outline the two main methods typically used to improve supplier performance.

2.3.1 Indirect and Direct Supplier Development

The goal of supplier development is increased supplier performance. This can take the shape of increased capacity, efficiency, speed, flexibility or improvements to product/service quality and delivery (Wagner 2009). According to Wagner, supplier development has two dimensions: indirect or direct.

Indirect supplier development (also referred to as "externalized" development) is based on a goal-setting framework that includes the communication of a precise, understandable and measurable target that the supplier must achieve. The communication between parties using the indirect approach can range from informal information exchanges to contractual agreements (Frazier and Summers 1984). The purchasing firm creates a scheme that either incentivizes performance by promising increased future business relations or performance rewards, or by threatening to discontinue relations or levy penalties. Beyond the administrative cost of running an indirect development program (e.g. some staff and operating overhead), the purchasing firm does not incur significant cost.

Direct supplier development entails a customer's provision of personnel, knowledge, or material (including financial) assets. Williamson (1983) outlines four available asset classes: distribution and warehouse infrastructure, tools and mechanics (including software), physical plant capacity, and human capital. With regard to human capital, the customer attempts to improve supplier operations by leveraging its own staff or hiring third party resources such as trainers and consultants (Krause, Scannel and Calantone 2000). In doing so, the customer assumes a direct stake in the supplier's operations. Since the effort and investment of direct supplier development generally exceed those of the indirect approach, companies usually pursue indirect approaches first (Krause, Scannel and Calantone 2000). Furthermore, because of the comparably larger scope of direct supplier development initiatives (e.g. reducing manufacturing cost or speeding up lead times) and the risk of ambiguous goals, the success of direct efforts is more difficult to assess, particularly in the short term.

The success of supplier development programs, regardless of dimension, depends heavily on the customer's commitment to a dedicated team of professionals whose sole purpose is performance management. MiCo has had such a team in place for several years. According to recent benchmarking figures from a 2011 Aberdeen Report, they are in good company; the most successful firms are nearly six times more likely to have dedicated supplier compliance teams than the bottom performers. Furthermore, the internal investment that these compliance groups experience through training and supplier-facing skill development is ten times more present in successful firms than in those at the lower end of the spectrum (Limberakis 2011).

2.3.2 Danger of Mixed Strategies

Although each form of supplier development generally improves supplier performance in quality or delivery, a mix of both strategies risks mutually offsetting each other's effectiveness (Wagner 2009). This occurs particularly with direct investments in which the customer dispatches its workforce to the supplier in an attempt to analyze possible causes of deficiencies, or even modify the supplier's operations. When this happens, the incentive behind *indirect* supplier development can be rendered ineffective because the target-setting customer injects itself into the problem. This can lead to the perception that the responsibility for successful improvement initiatives no longer rests with the supplier, but is actually shared with the customer, or worse yet, transferred to the customer entirely. A flawed project implementation could be blamed on the customer at whose request the improvement effort was pursued. Even under favorable circumstances, an inconsistency in the level of focus between targets for direct and indirect initiatives makes combined programs difficult to control. Wagner (2009) argues against a joint initiation of indirect/direct programs. Furthermore, he discourages any direct development in cases where customers seek quick improvements in the quality or delivery of goods or services. Consistent with previous findings, Wagner advocates a consecutively structured approach from indirect to direct management when customers seek to develop long term business relationships and are committed to pursuing of an indirect development platform from the beginning.

MiCo uses SSP as a principal decision input when moving suppliers from indirect to direct supplier development. The sheer volume of suppliers forces MiCo to focus most of its direct supplier development program on suppliers with the highest order volumes or values. Most of the suppliers undergoing supplier development fall within the top 5% of MiCo's supplier base. While MiCo does communicate delivery performance targets to its entire supply base, its indirect supplier development program is less clearly defined.

2.4 Shortcomings of Performance Management Efforts

The discussion of direct and indirect supplier development programs already mentions mutual exclusivity as a barrier to successfully implementing performance management. Other disruptions occur when suppliers and customers are not sufficiently integrated and misunderstand each other in aspects critical to their supply chain interactions. According to Forslund and Jonsson (2010), customers and suppliers often fail to clearly specify the subjects and terms of measurement and consequently arrive at different conclusions upon observing the same data. In the context of on-time delivery measurements, such differences can result from the definition of order level, timeframe and frequency, and rules that specify when a transaction is counted as successful (Forslund and Jonsson 2007). Consider partial order fills, a problem frequently encountered by MiCo: depending on the terms specified for counting orders as successful, the rating could range anywhere from zero (failure) to one (success), or be pro-rated corresponding to the relative amount of the order filled on time.

Conflicting customer expectations can also cause friction. A firm that carefully monitors on-time deliveries should not lay an equivalent emphasis on competing performance metrics such as delivery flexibility and price. The more volatile a customer's ordering behavior, the harder it is for a supplier to react in a timely manner without increasing inventory, which in turn could raise prices. In prioritizing measures, customers must be aware of offsetting consequences. (Forslund and Jonsson 2010)

Oversimplification can also introduce problems. While the use of averages in determining a target performance level for all suppliers can simplify the process, it can be counterproductive if the supplier base is not sufficiently homogenous. With very few exceptions, MiCo uses a standard target for all of its suppliers. We came across no apparent reason in the literature that advocates such an approach, aside from simplifying target setting. In fact, it appears that customized targets can enhance the effectiveness of performance management initiatives, because they signal to suppliers that the customer is actively engaged in building a relationship with the supplier (Forslund and Jonsson 2010).

Manual processes during measurement and analysis also present a common barrier. The manipulation of information extracted from ERP and data storage systems may not only limit data conformity and consistency of report formats, but also introduces the possibility of human error during the manipulation of numbers and figures. A 2010 study by Forslund and Jonsson showed that 80% of firms reverted to manual means of collecting, analyzing and reporting data. Automated measurement and analysis output can greatly improve efficiency and accuracy. Beyond automation, some successful firms even use third party or outside regulatory parties to authenticate their data (Limberakis 2011).

General recommendations towards improving the effectiveness of performance management (Minahan and Vigoroso 2002, Forslund and Jonsson 2010) are briefly listed below.

1. ***Standardize performance measurement throughout the entire organization.*** If a firm is not streamlined internally, it should not expect integration with suppliers. Different departments might not only measure KPIs differently, but also apply information in different contexts and for different decisions. Precise definitions within the firm are of obvious importance.
2. ***Once internal standardization is complete, collaborate with suppliers to design the performance management system***. This includes precise definitions of metrics and stipulated procedures for targets, data collection and validation.

3. ***Propose profit sharing schemes for supplier actions that financially benefit customer and supplier.*** Doing so shares future success among all parties, thereby creating a common goal.
4. ***Use historical performance data as indicators for future performance.*** Too frequently, their use is limited to evaluating historical achievement of goals.

2.5 Connecting Measures, Operations and Financials

Although research indicates a correlation between non-financial, operational performance measures and future financial success (Ittner and Larcker, 1998; Hughes, 2000), this causal relationship is rarely drawn explicitly. Kelly (2010) argues that many companies intuitively assume that specific cause-and-effect relationships exist. They perceive the benefit of validating such assumptions as small relative to the amount of time and effort required to validate their nature. He found that over half of the companies neither test the implications of their measurements on financial outcomes nor verify the causality between their KPIs and future financial success (Kelly 2010). MiCo, to our knowledge, have conducted no previous study on the causality between improved SSP and financial success, or drawn a correlation between SSP and individual cost categories. The only KPI causality study we identified was between MiCo's outgoing service level and long term sales. Since the setting of targets ideally follows the establishment of causality or correlation, this thesis attempts to fill some of the potential gap.

Financial metrics directly reflect an organization's financial performance. Operational performance measures, on the other hand, are more difficult to relate financial impact. Since operational KPIs and financial KPIs are measured and derived differently, it becomes difficult to trace the connection between them (Chenhall 2003). Therefore, operational targets are frequently not based on their impact on the organization (neither short-term nor long-term). Chenhall argues that if studies are limited to investigating financial KPIs without considering the context on which control and management decisions are based, companies can draw incorrect conclusions. It is therefore important to not only follow the money trail, but to also understand what information was used to make decisions that influence daily operations.

2.6 Conclusion

Our literature review covered the importance of supplier performance KPIs for the success of companies, with a particular focus on the use of measurements such as those used by MiCo. Furthermore, it highlighted the importance of setting an appropriate performance target in coordination with suppliers and outlined the approaches companies take in engaging suppliers. Throughout our literature search, however, we found no determinate framework that offers an empirical approach towards finding an optimal level of performance targets. Nevertheless, the insights from our literature review helped us qualify some of the performance management approaches of MiCo, and thereby assisted us in building the framework we propose towards calculating an optimal target for supplier shipping performance.

3. METHODOLOGY

This section reviews MiCo's supplier on-time delivery performance metric (referred to as Supplier Shipping Performance, SSP) and how we can associate it with cost. We dissect specific costs expected to be impacted by SSP and offer a hypothesis on the behavior of these costs. We then outline the theoretical approach for building the cost models used in our data analysis. Lastly, we explain how to aggregate the separate cost models into one complete model that calculates the total effect of supplier shipping performance targets.

3.1 LINKING METRIC AND REALITY: UNDERSTANDING SSP

To answer MiCo's question of how to determine an optimal SSP target, we must understand how SSP is measured. MiCo's method for capturing SSP is fairly simple: a supplier meeting a timeframe stipulated in an order receives credit, while a supplier failing to ship within this window does not. To accommodate suppliers, MiCo positively credits all deliveries with a line item fill above 90%. For both criteria (timeliness and quantity), success is measured on a hit-or-miss basis. Supplier deliveries are aggregated monthly to determine each supplier's SSP ratio, dividing successful deliveries by the amount scheduled for the month. A supplier's current SSP is based on a running average of the last 3 months.

An order is evaluated when it arrives at MiCo. The date at which an order was shipped from the supplier's site determines whether or not a delivery counts as on-time. In this manner, any variability in the carrier or freight forwarder's performance is not attributed to the supplier. To provide additional flexibility to suppliers, the actual shipment date is compared to a time window spanning several days before and after the due date derived from the contractual lead time with the supplier. To illustrate: if a supplier offers a production lead time until shipment of 30 days on a parts order, MiCo will record any delivery to be on time if it ships fully in the interval $(t + 30 - x, t + 30 + x)$, with t representing the order date and x half of the window length. Both of these approaches make it easier on suppliers to achieve a higher performance level.

Our thesis splits costs associated with supplier delivery performance into two categories: performance maintenance, which includes the cost of supplier development programs, and consequence management, which groups the costs of reacting to or preparing for deficient supplier performance. Put in different terms, performance maintenance initiatives aim to change supplier delivery performance, while consequence management activities do not.

The task of setting an optimal performance target rests on the assumption that a tradeoff exists between these two cost categories, e.g. that a decrease in performance maintenance activities will result in an increase in the cost of consequence management. It then makes intuitive sense that there is an optimal point at which the two costs offset each other perfectly and the total cost (the sum of both categories) is at a minimum. When the supplier base performs below the optimal target point, investment in additional performance maintenance capacity to help reach the higher target is justified by the comparatively larger cost reductions witnessed in consequence management. Any additional investment beyond the optimal target, however, no longer yields an equally large or larger reduction in consequence management, so additional investment should be abandoned. A company's ability to calculate a target point dictates its movement towards this target, ensuring that the target becomes a (theoretical) steady state over the long term. Figure 1 below plots the relationship between the two costs over a span of suppler performance targets. The performance maintenance cost grows as the target moves towards the maximum level of 100%, while the consequence management cost increases as one moves the target away from 100%. In this simplified depiction, the optimal point is the target level at which both distances represent the same incremental cost.

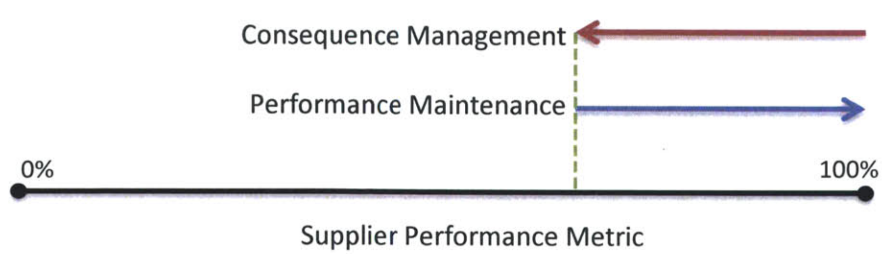

FIGURE 1: COST CATEGORIES

While the problem is easily explained and graphed in principle, it turns out that accumulating real data to feed such a model can be difficult. The complexity lies not only in collecting the correct data to determine empirical relationships, but also in fitting the separate costs of performance and consequence management onto a common scale that allows for direct comparison. Furthermore, one needs to carefully consider interdependencies between individual cost components.

Since the causal effects in cost behavior are influenced by the operating principles of a company, we used MiCo's operating principles as our reference and did not investigate other reactive measures (and their costs) potentially available to other firms. Though the nature and availability of data differ across companies, our thesis provides a framework that can be used to compare cost categories, thereby allowing companies tracking supplier performance in a similar fashion to empirically set an optimal on-time delivery performance target for their supplier base.

3.2 Capturing Cost of Supplier Shipping Performance

During a site visit to MiCo, we identified influences and consequences of the SSP metric and determined the cost categories needed to express the effect of SSP in financial terms. We grouped the costs between consequence management (an issue for every company) and performance maintenance (a real concern to MiCo, as they perform direct supplier development). The following subsections discuss and illustrate the different cost elements we considered.

3.2.1 Consequence Management Costs

1. **Service Loss:** Forgone revenue resulting from MiCo's short term inability to fill a customer order for service parts. If the receipt of replenishments is sufficiently delayed to cause stock outs, downstream customers may not be willing to wait for delayed delivery from MiCo. MiCo then loses the revenue that would have resulted from a partial or complete sale.

2. **Expedites:** The incremental cost of rushing an order for a service part into, within, or out of MiCo's network (e.g. to or from distribution centers and warehouses).

3. **Inventory Increase:** Late orders affect inventories either through lead time extensions or through lead time variability. Habitually late orders are equivalent to an extension of lead time. Regardless of the inventory model used by a company, growing lead times increase the average inventory levels. In a traditional Economic Ordering Quantity (EOQ) model, increasing lead time raises the reordering point, which triggers more frequent orders. In a periodic review model (the basis of MiCo's inventory policy), the order up to level increases with rising lead time, causing larger ordering quantities (Silver, Pyke, Peterson 1998). Variability in order deliveries affects inventories through the creation of safety stock. Sporadic delays can therefore also affect inventory levels. According to the basic safety stock calculation (Silver, Pyke, Peterson 1998), the level of additional inventory is determined by historical demand, lead time information and the desired outgoing service level. In general terms, the safety stock is given by

$$Safety\ Stock = k \times \sigma_D^L \text{ [1]},$$

where k equals the outgoing customer service level and σ_D^L the standard deviation of demand over lead time. Assuming demand patterns remain unchanged, the increased variability in lead time increases σ_D^L, and therefore the amount of safety stock. Notice that increases in lead time or lead time variability can both lead to higher inventory levels. Our cost model does not distinguish between types of inventory increase, which is consistent with the availability of inventory data we received from MiCo.

[1] Since our thesis scope does not concern itself with different types of inventory, we will not go into further detail on safety stock theory. For completeness, we add the formula for σ_D^L below and refer to Silver, Pyke, Peterson (1998) for a detailed discussion of inventory models and safety stock calculations.

$$\sigma_D^L = \sqrt{E(L) \times \sigma_D{}^2 + E(D)^2 \times \sigma_L{}^2}$$

4. **Long Term Lost Sales:** Finally, we considered the inclusion of long term sales through permanent loss of a customer, which differ from the immediate lost sales described above. An avoidable permanent loss generally occurs only after a pattern of multiple, consecutive lost sales. While much of MiCo's revenue is generated from the sale of equipment, the continuous purchase of service parts can represent a big portion of the lifetime value of a customer. Because the after-market sales for service parts can influence new equipment sales (e.g. new product generations), it is difficult to separate the two segments for this category. Additionally, since long term sales lagged observations of missed service levels by an estimate of multiple years, a causal relationship cannot be clearly inferred from historical order information on suppliers and customers. Lastly, there were too many unknown factors that could play into a customer's decision to abandon MiCo on a long term basis. Following our intuition and MiCo's recommendation, we finally decided that attempting to model the cost of long term lost sales in any sort of accurate manner would not be possible within the scope of our thesis project.

Figure 2 below plots the expected behavior of the three consequent management cost elements considered and the total cost curve that represents the sum of all elements. We expect each curve to follow a similar pattern of exponential decay, as costs run extremely high towards low values of SSP and converge towards a fixed value as supplier performance nears perfection. The flattening slopes indicate expected diminishing returns of SSP improvements. Each consecutive move towards a higher SSP target reduces cost by a smaller amount.

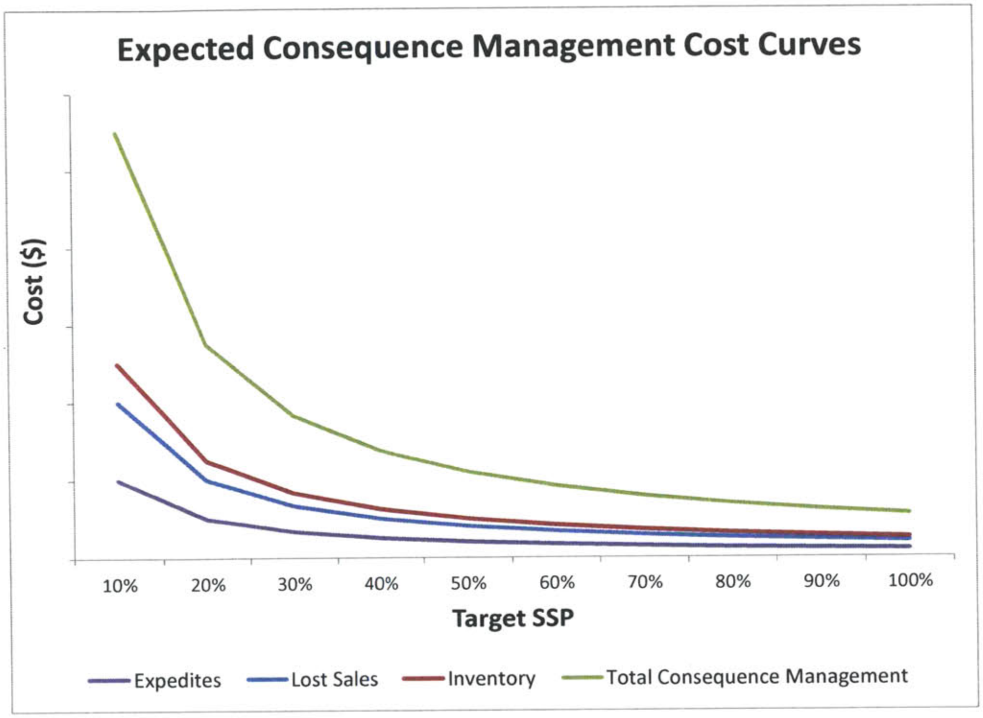

FIGURE 2: EXPECTED CONSEQUENCE MANAGEMENT COSTS

During our deliberations with MiCo, we learned that MiCo successfully maintains a very high service level to its customers regardless of supplier performance. Its reactive measures therefore seemed sufficient to cope with overall supplier base performance. This observation, however, convinced us that the costs incurred in the categories listed above were material, since consistently high service levels can only be maintained if poor supplier performance is sufficiently compensated.

3.2.2 Performance Maintenance Costs

1. **Direct Labor:** Labor hours and benefits of personnel working actively on supplier development, to include field assignments at supplier sites as needed. At MiCo, a team of Supplier Account Managers (SAM) works exclusively on performance management issues. Typically, an account manager will be assigned to up to 10 suppliers simultaneously.
2. **Administrative Overhead:** The cost of running a group dedicated solely to supplier development initiatives. This broad category includes HR services, payroll administration, travel, professional training and licenses, as well as supervisory positions (e.g. line managers) not directly involved in

performance management projects. Note that most overhead cost do not differ significantly with incremental increases in staff size (i.e. additions of single team members). For this reason, we decided with MiCo to consider administrative overhead a fixed cost.

3. **Clerical Overhead:** The cost of office space and supplies, to include office furniture, computers and communication equipment, and clerical items such as desk materials and paper. Similar to administrative overhead, we considered the cost fixed over incremental staff size increases.

The literature sources we reviewed widely used a logarithmic function to model the improvement in cost due to investments (Porteus 1985, Leschke 1997). This means that the incremental improvement achieved diminishes if the rate of invested effort stays constant. Inverting this, we find that a consistent performance improvement causes a company to expend increasingly more effort. Figure 3 illustrates the expected exponentially growing cost of performance maintenance graphed over supplier performance targets. As the increasing slope shows, a constant improvement in SSP (x-axis) requires an increasing financial investment (y-axis). In this manner, the behavior of consequence management cost relates inversely to that of performance maintenance.

Since we derive supplier management cost from the differences between two target levels, we only require knowledge of the variable cost to plot the behavior of the curve. Any fixed cost will simply shift this curve upwards, without affecting the slopes at any given position on the x-axis. In line with our discussion above, we focused our data collection on the cost of direct labor, since this determines the shape of the curve. Given the assumption of (near) fixed cost for overhead, we agreed with MiCo to not spend significant time deriving this cost.

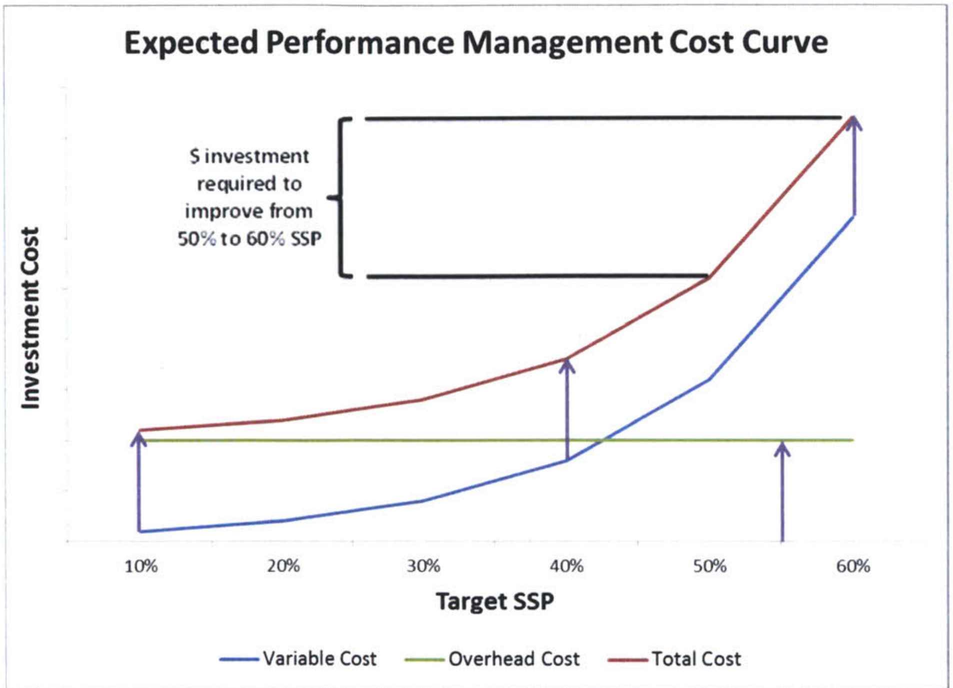

FIGURE 3: EXPECTED PERFORMANCE MAINTENANCE COST

3.3 Building the Framework

In modeling the cost behavior of the individual categories outlined above, we followed a series of 5 steps. This section reviews the methods, assumptions and procedures behind our approach, while the data analysis section goes over the details of each step as applied to MiCo's data.

3.3.1 Data Collection

The first step following our brainstorming with MiCo consisted of data collection. We went through multiple iterations of data requests, as each round revealed the nature of available information and significantly increased our understanding of MiCo's operations. We generally focused on data from the last two years of MiCo's operations, primarily because this was the timeframe for which MiCo stored historical SSP records on individual suppliers. We asked for minimally modified data so that we could aggregate records ourselves in a way that would enable comparison across different costs. Because of the sheer size of MiCo's supplier base and the high annual order volumes, we collected line item-level summaries per supplier and at monthly intervals.

3.3.2 Ensuring Data Integrity

Upon receipt of new data, we scanned the records for outliers and anomalies. We relied on statistical analysis to pinpoint outliers that might skew distributions. Overall, the amount of records removed was very small (it never exceeded 2% of total records). It is important to emphasize that we performed these activities throughout the data collection, aggregation and analysis phase. Some common cleanup targets included:

1. **Outliers:** For samples of continuous data, we calculated summary statistics and removed any record or observation located more than 3 standard deviations away from the mean. This step inherently assumes that the distribution of values (especially after aggregation) is normally distributed, so that a range of 3 standard deviations around the sample mean contains approximately 99.1% of expected data observations. We performed this step only when the count of observations was sufficiently large (at least several hundred records) or when the sample shape resembled a normal distribution.
2. **Duplicates:** We searched all received data for duplicate entries. While rare, we found and deleted some duplicates in source files. Since data alteration and aggregation sometimes introduced duplication, this activity represented an important, continuous check during the entire data analysis.
3. **Erroneous Entries:** When data recording depends on manual data entry, errors inevitably follow. These errors were usually quickly identified and deleted upon confirmation with MiCo.

3.3.3 Data Aggregation

Since SSP information was provided over monthly intervals, months became a general unit of aggregation. One purpose behind data aggregation was to summarize scattered individual observations to uncover hidden patterns. We usually grouped individual cost observations into "buckets" of SSP ranges to reduce the variability among the large data samples that we had accumulated. Whenever we performed aggregation, we statistically investigated the variability within the range. Aggregation was fundamental to build a regression model against observed data, since performing regressions against thousands of variable data points gave very low goodness of fit. Depending on the size of the data set, we chose SSP ranges of 5% or 10%, and analyzed the cost behavior from one group of to the next.

Depending on the data set, we also found instances where we had to aggregate to avoid distorting probability distributions. Customer orders, for example, were not always cancelled in a single event, but sometimes over multiple increments. These actions had to be merged into one cancelled order before we could associate the total cancelled items with a weighted SSP value from incoming deliveries. Not doing so would have inflated the probability of customer order cancellations, which would have affected calculations described in the following chapter.

3.3.4 Conversion to a Common SSP Scale

To compare and bring together all costs into a single model, we had to convert our observations to a consistent unit of measure. Cost over SSP target became the format into which we translated and plotted available data. This turned out particularly difficult since the time frame and context of the different cost drivers were not common between data sets. Furthermore, we had to account for delayed causal relationships between events and consequent costs incurred. For example, to associate SSP with lost sales, we considered delivery information for the period leading up to a cancelled order, rather than just the SSP at a given date.

We also applied concepts of probability theory to calculate the expected cost given certain drivers. Specifically, we applied Bayes' Theorem (Equation 1) which describes the relationship between conditional probabilities and allows us to transform one conditional probability into another.

EQUATION 1: BAYES' THEOREM, USED TO CONVERT CONDITIONAL PROBABILITY DISTRIBUTIONS

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

To illustrate its application: knowing the probability of a lost sale event and the distribution of SSP values across the entire population of suppliers, we were able to calculate the probability distribution of lost sales. Using Bayes' Theorem, we transformed the conditional probability distribution of SSPs for the sub-population of lost sales (which we derived from the data provided by MiCo) into conditional probabilities of lost sales at different SSP targets.

3.3.5 Regression Model

Depending on the size of our SSP ranges discussed in Section 3.3.3, we ended with up to 20 separate data points of accumulated cost over SSP. We used regression analysis programs to determine a cost function that would best fit the observations of our transformed data. The equation of each curve essentially modeled the relationship between SSP and the cost for each category. The regression models were either exponential or logarithmic, in line the results of our literature search.

3.4 Combine and Compare Regression Models

After completing the 5 step framework for each cost element, we consolidated individual cost curves through linear addition of performance maintenance and consequence management cost curves, respectively. This gave us the total cost functions for performance maintenance and consequence management listed below in Equation 3 and Equation 4. The simple addition was possible because of the common unit of measure we had ensured in building the models. The following notation describes the different curves and the steps performed in combining them.

EQUATION 2: CONSEQUENCE MANAGEMENT SUB-COST FUNCTION

$$f_i(SSP) \text{ from regression models}$$

EQUATION 3: TOTAL CONSEQUENCE MANAGEMENT COST FUNCTION

$$F(SSP) = \sum f_i(SSP)$$

EQUATION 4: TOTAL PERFORMANCE MAINTENANCE COST FUNCTION

$$G(SSP) = g(SSP) + overhead$$

The last step, formalized in Equation 5, brings together the total cost curves, whose first order derivative lets us determine the minimal cost of the total system (i.e. minimize $H(SSP)$). Since the performance maintenance cost aims to improve the SSP level, the average duration that a supplier stays at the improved level is important. The longer this duration, the more costs are averted. We capture this by considering the Net Present Cost of all future consequent management costs with the discount rate i and the duration of improvement n. Figure 4 shows the expected result of consolidating the costs, which we aim to reproduce in our data analysis. Note that our data analysis section will feature a pro-forma execution of this last step, since not all cost elements could be sufficiently modeled due to insufficient data.

EQUATION 5: TOTAL SYSTEM COST FUNCTION

$$H(SSP) = G(SSP) + \sum_{t=0}^{n} (1 + i)^{-t} \times F(SSP)$$

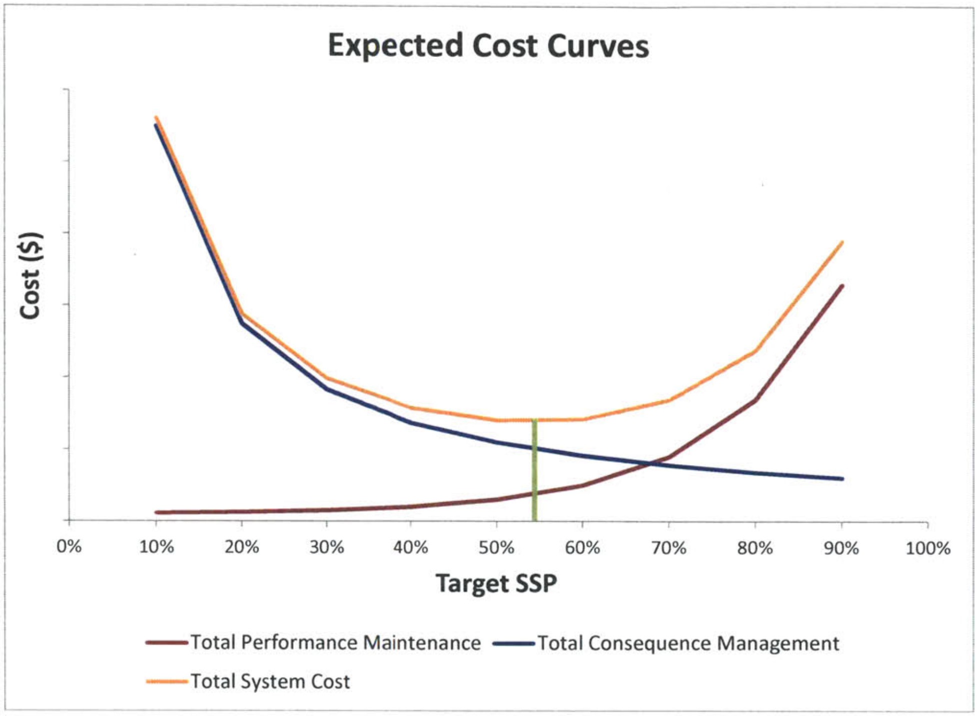

FIGURE 4: EXPECTED COMBINED COSTS WITH TARGET SSP

4. Data Analysis

The purpose of our data analysis was to search for relationships between actual Supplier Shipping Performance (SSP) data and the different types of costs observed by MiCo in order to construct a regression model with which to determine an optimal SSP target. The cost data we collected from MiCo were broken into two categories (performance maintenance and consequence management) and subordinate elements, according to the descriptions in the previous section. We began our analysis with consequence management costs, which were easier to grasp in concept and better recorded in MiCo's accounting systems. Over the course of discussions and site visits, we investigated which data were available, and after several iterations of data collection proceeded with a sequence of steps that were applied to each cost element.

1. ***Collect available data*** in multiple iterations.
2. ***Ensure data integrity*** by cleansing data of outliers and exceptions.
3. ***Aggregate data entries*** or sets and associate them with an SSP value, typically over a period.
4. ***Convert data*** to a common SSP scale, in part using transformation of conditional probabilities.
5. ***Build the regression model*** using SSP as input and the cost as output.

After completing these steps for each element, we combined the outputs of the individual regression models. The combined model projected total system cost, with which we could determine a theoretical optimal target level that minimizes cost implications of SSP. The following section provides a detailed description on all the steps for each of the cost elements.

4.1 Consequence Management Costs

The poor performance cost elements identified during our discussions with MiCo included:

1. **Service Loss** in the form of short-term, immediate sales forfeited
2. **Increased Inventory** to protect against stock out resulting from late deliveries or replenishments

3. **Unplanned Expedites** resulting from late deliveries that must be rushed in or out to customers
4. **Long Term Sales Decrease** from the long-term loss of a customer when poor SSP continuously keeps MiCo from meeting customer orders. As described in the methodology section, this cost element was dropped from consideration after data collection was determined infeasible.

The following sections provide a detailed overview of the unique characteristics of each cost element and a description of the form in which the data was captured, though we focus only on final iterations of data and on the specific content used. We discuss exceptions, outliers, calculations and the assumptions we made to convert the data into a workable format. The regression for each cost is outlined at the end of each overview.

4.1.1 Service Loss: Short Term Lost Sales

The first cost element captured was service loss. Because service loss can be caused by various factors (unexpected demand, bad planning by MiCo and poor deliveries by their suppliers), we had to carefully select only those lost sales caused by supplier delivery performance. To ensure this, MiCo provided a list of service losses caused specifically by deliveries that had not been received on-time (past due). This list contained open customer orders not yet filled because of delayed supplier deliveries, as well as previously cancelled customer orders that had gone unfilled within the last year for this specific reason. For brevity, any mention of lost sales from here on refers to lost sales due to past due. Because of the chance that open, active orders could still be fulfilled, we only used orders that had been canceled. To test the assumed association of these lost sales with late deliveries, we collected more than one year's worth of monthly snapshots which recorded supplier orders that were past due on respective snapshot dates. The overlap of over 99% between these lost sales and late supplier deliveries established the validity of our assumption. Connecting lost sales due to past due with SSP proved more complicated, though logically related: an SSP of 100% corresponds to no deliveries past due, while an SSP of 0% means that all scheduled deliveries are past due.

The information we used from the lost sales data is shown in Table 1. The requisition number uniquely identifies a customer order, while Part and Supplier IDs uniquely identify the service part and its supplier. The difference between order date and cancel date corresponds to the active period during which MiCo failed to fill a customer order. The distribution of active period lengths is shown in Figure 5.

TABLE 1: EAMPLE OF LOST SALES DATA

Requisition Number	Part ID	Order Quantity	Order Date	Dealer	Cancel Date	Change in Demand	Cancelled	Supplier
5996	KXY5	2	01/06/11	MN4	01/25/11	-2	Y	FG690

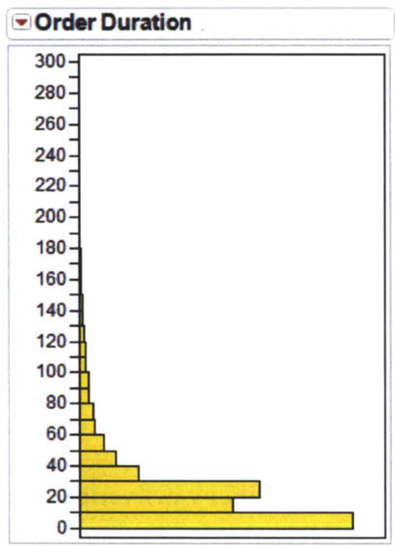

FIGURE 5: DISTRIBUTIONS OF LOST SALES DATA

After the data was collected and filtered on cancelled orders, we ensured data integrity. We removed duplicate entries and confirmed that canceled quantities per requisition number did not exceed ordered quantities (the opposite was possible because of partial cancellations). If canceled quantities exceeded those ordered, we checked whether any record reflected cumulative cancellations or whether an entry was simply erroneous. Based on our findings, we combined certain records or adjusted cancelled quantities.

With the data integrity ensured, we began joining the data sets to associate lost sales with SSP. Since SSP is measured on a monthly basis, we associated the lost sales records (consisting of unique combinations of order month, canceled month, Part ID and requisition number) with data on monthly deliveries from suppliers. Because a part delivered in a given month is not necessarily sold in the same month, we had to consider scheduled deliveries leading up to a customer order as well as those scheduled to ship during an order's active period. Since MiCo calculates a 3-month rolling SSP when evaluating suppliers, we included three months of orders prior to a given start date in our calculations of SSP. As the average order frequency over all parts amounted to less than one month, a 3-month time frame sufficiently captured general overall replenishment cycles. Depending on the length of an active customer order, the time frame over which we calculated SSP ranged from three months before a customer order up to the actual customer cancel date. Figure 6 illustrates this range graphically.

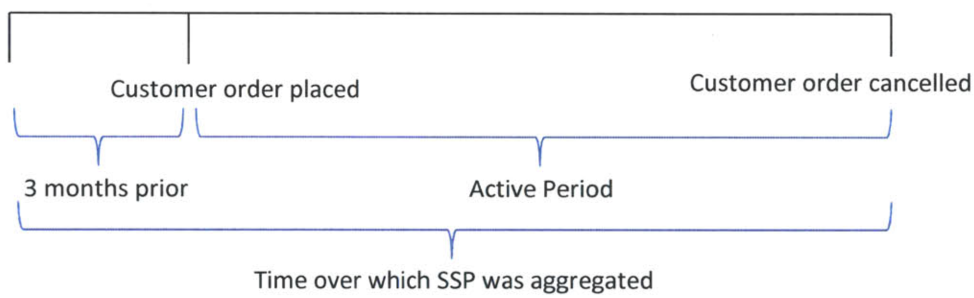

FIGURE 6: TIMEFRAME CONSIDERED FOR LOST SALES

Since MiCo sources many parts from more than one supplier, we included delivery information for all suppliers scheduled to ship individual parts to MiCo over this relevant range, thereby aggregating supplier-denominated SSP data into part-level SSP. After calculating SSP values for all records, we arranged the joined data according to Table 2. We also added the Net Sale values that MiCo provided.

TABLE 2: EXTRACT OF LOST SALES ASSOCIATED WITH SSP

Part ID	Requisition Number	Order Date	Cancel date	Scheduled Deliveries	Deliveries on Time	Net Sales	Cancelled Quantity	SSP
X5KL	84124305	06/01/2011	06/08/2011	2	1	[redacted]	1	50%

With the records in this table (several thousand in total), we built a probability distribution of SSP values by aggregating the number of observations over SSP ranges of 10%. Table 3 lists the counts from this aggregation. Its individual columns depict the cumulative observations and associated probabilities of lost sales, from which we calculated the corresponding non-cumulative counterparts.

TABLE 3: OBSERVATIONS OF LOST SALES OVER SSP RANGES

SSP Range	Lost Sales Observations	Probability of SSP within Range
0-10%	11834	81%
10-20%	1353	9%
20-30%	613	4%
30-40%	361	2%
40-50%	236	2%
50-60%	78	1%
60-70%	53	0%
70-80%	27	0%
80-90%	1	0%
90-100%	46	0%

The probability distribution depicted in Figure 7 reproduces the conditional probability that an observed SSP lies within a given range (delimited by the values on the x-axis) in the event of a lost sale. Written in equation form we find

EQUATION 6: PROBABILITY OF SSP GIVEN LOST SALE

$$P(X_{i-1} < SSP <= X_i | E = 1),$$

where E is a lost sale event and X refers to a given SSP value.

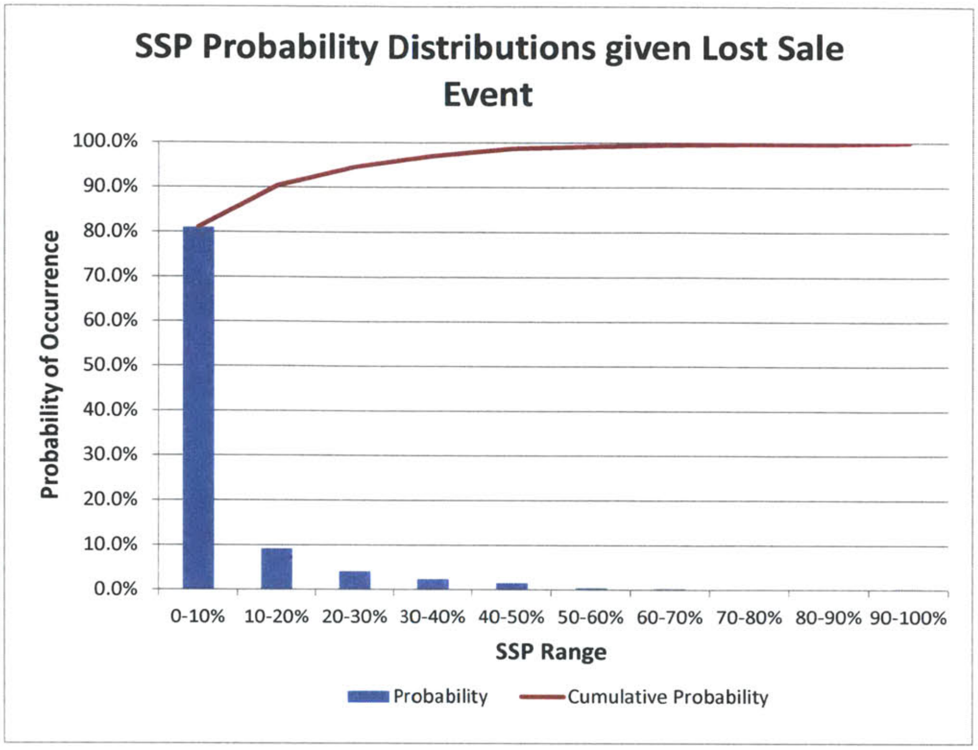

FIGURE 7: PROBABILITY OF SSP GIVEN A LOST SALE

Our goal, however, was to find the inverse conditional probability of a lost sale occurring given an SSP (target) range, which in equation form looks as follows.

EQUATION 7: PROBABILITY OF LOST SALE GIVEN SSP

$$P(E = 1 | X_{i-1} < SSP <= X_i)$$

Using Bayes' Theorem from Equation 8 we derived the second set of conditional probabilities from the first, given that we knew the overall probability of a lost sale due to past due, $P(E = 1)$, for the entire order population and the probability distribution of SSP values across all parts, $P(SSP <= X)$.

EQUATION 8: BAYES' THEOREM, APPLIED TO LOST SALES

$$P(E = 1 | X_{i-1} < SSP <= X_i) = \frac{P(X_{i-1} < SSP <= X_i | E = 1) \times P(E = 1)}{P(X_{i-1} < SSP <= X_i)}$$

The first probability was already known to MiCo, since it represents another important KPI tracked on a regular basis. But to get the overall SSP distribution across all parts we had to calculate SSP values over a 3-month period to get an approximation of the overall SSP distribution. This was done because month-on-month snapshots of SSP values by part and/or supplier varied significantly and were considered too erratic. Because we did not have sufficient order-level data on all parts, however, we had to use the regular, supplier-denominated SSP over the entire year as proxy for the overall part-level SSP that our described calculations use. This of course, assumes that the overall distribution of on-time shipments at the level of parts approximately matches that of suppliers. The non-cumulative and cumulative SSP probability distributions we calculated off of available data can be seen in Figure 8.

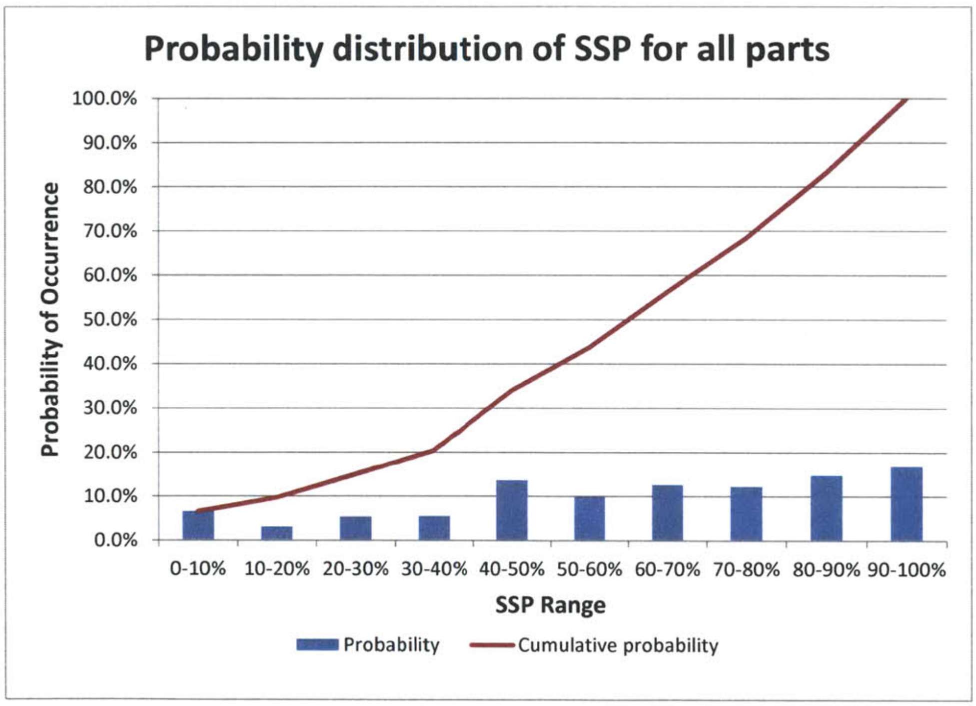

FIGURE 8: OVERALL PROBABILITY DISTRIBUTION OF SSP

With the probability distribution of SSP given a lost sale, the probability distribution of SSP for all parts and probability of lost sales (given by MiCo) we calculated the probabilities using Bayes' Theorem. The results of our calculations are shown in the last column of Table 4 and graphically in Figure 9.

TABLE 4: CONVERTING BETWEEN CONDITIONAL PROBABILITIES – LOST SALES

SSP Range	Prob. of SSP Range given Lost Sale	Prob. of SSP Range	Prob. of Lost Sale for Population	Prob. of Lost Sale given Part SSP
0-10%	81.0%	6.5%	0.4%	5.5%
10-20%	9.3%	3.1%	0.4%	1.3%
20-30%	4.2%	5.4%	0.4%	0.3%
30-40%	2.5%	5.5%	0.4%	0.2%
40-50%	1.6%	13.5%	0.4%	0.1%
50-60%	0.5%	9.8%	0.4%	0.0%
60-70%	0.4%	12.6%	0.4%	0.0%
70-80%	0.2%	12.2%	0.4%	0.0%
80-90%	0.0%	14.7%	0.4%	0.0%
90-100%	0.3%	16.8%	0.4%	0.0%

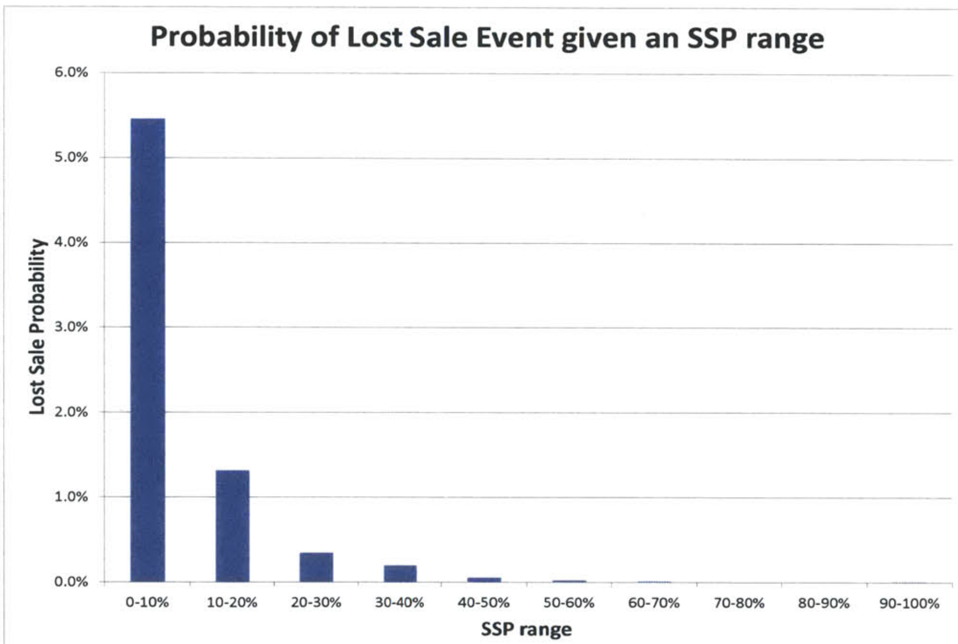

FIGURE 9: PROBABILITY OF LOST SALE GIVEN SSP

The histogram in Figure 9 shows the probability of a lost sale occurring if a part is delivered within a certain SSP range. For example, if a part experiences on-time shipping performance between 10% and 20%, an estimated 1.314% of customer orders for that part will not be fulfilled due to late supplier deliveries. Knowledge of these values, the average sales per supplier, and the average value per cancelled sale allowed us to calculate the expected annual cost per supplier for a given SSP target (Equation 9). The final graph from which the regression model is built is shown in Figure 10.

EQUATION 9: EXPECTED COST OF LOST SALES

$$E\$(X_i) = P(E = 1|X_{i-1} < SSP <= X_i) \times \mu_{nr\ of\ annual\ sales/supplier} \times \mu_{cancelled\ sale\ value}$$

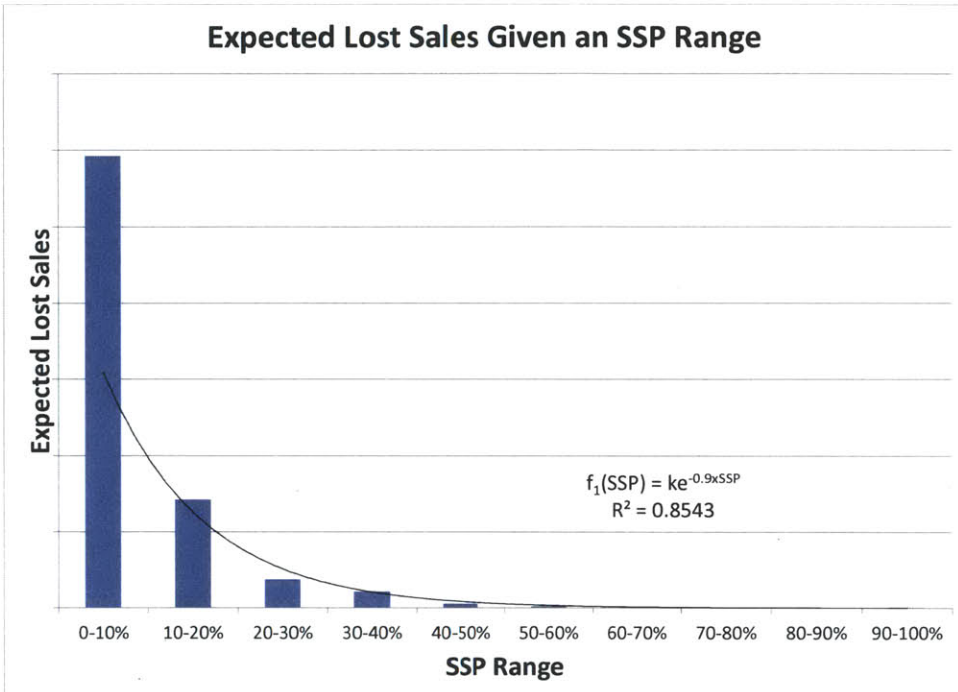

FIGURE 10: EXPECTED COST FROM LOST SALES GIVEN SSP

Having calculated the expected cost for each range, we performed a regression on the data. Since an exponential decline relationship was inferable from Figure 10 we used the natural logarithm of expected lost sales to build the regression model for SSP. The regression returned a R^2 of 85.43%.

TABLE 5: REGRESSION STATISTICS FOR LOST SALES

Regression Statistics	
Multiple R	92.43%
R Square	85.43%
Adjusted R Square	83.61%
Standard Error	1.194
Observations	10

From the regression model we can conclude the final equation for the expected cost of lost sales for a given SSP target is $E\$(SSP) = e^{-9 \times SSP+14.23}$.

4.1.2 Inventory Increase

According to the inventory theory briefly discussed in the methodology section, we expected increased delivery delays to cause additional inventory stock. Although SSP does not measure the extent of delays or the underlying variability, there is some relation between delivery variability and SSP: a high SSP limits the delivery variability, as most deliveries occur within the shipment window. As SSP decreases, more deliveries occur outside of the window and average delays increase. We therefore embarked on the data analysis expecting to see an increasing trend for inventory as SSP declined. To our surprise, however, our analysis of MiCo's inventory data implied the opposite. Inventory boosts moved in line with SSP values, rather than in opposite direction. In light of this unintuitive result we had to research the context of MiCo's inventory processes in more depth. Aside from describing our analysis of the data collected, this chapter outlines the origin and implications of MiCo's inventory policy.

Similar to the data on lost sales, MiCo provided a list of historical inventory boosts covering more than a full year. This list contained Part and Supplier ID, as well as start date, end date and quantity of each temporary inventory boost. An extract of the data is shown in Table 6. Some increases occur in multiple steps, since staggered start dates assist suppliers in coping with the bump in demand.

TABLE 6: EXTRACT OF INVENTORY INCREASE DATA

Part ID	Start Date	Stop Date	Increased Quantity	Net Sales	Supplier
OS2KM	06/22/11	04/07/12	32	[redacted]	BX1262

Our first steps consisted in testing the assumption that late deliveries drive inventory increases. Using the snapshots of orders past due already used for our validation of lost sales, we found that only 35% of the parts receiving inventory increase had a delivery past due. Conversely, only 4% of the deliveries past due could be matched with an inventory increase. These tests indicated that factors other than past due impacted inventory boosts. Subsequent discussions with MiCo's inventory analysts who had helped design the inventory policy confirmed that average days late was the main driver for inventory increase, not deliveries past due or SSP. Furthermore, we learned that the average days late calculations did not include supplier deliveries that had not yet arrived.

While there is a logical relationship between average days late and SSP (single orders increasing average days late decrease SSP), it cannot be defined in absolute terms. Because average days late can be dominated by extreme observations, we cannot infer that an increase always relates to a decrease in SSP. Likewise, an SSP may suffer from consistently late deliveries of very low magnitude, which also results in relatively low average days late. There are differences in measurement as well; a supplier is credited for SSP when shipping within a window around the due date. Average days late are measured directly from the due date, with no consideration of delivery windows. Since measurement occurs at the delivery date, average days late includes carrier variability – unlike SSP.

With a better grasp on the inventory driver, we proceeded with our analysis. We combined the staggered increases to determine total inventory increases for a single part and analyzed data integrity. Since our final goal was to determine the expected cost of carrying additional inventory over an SSP range, we performed statistical tests on the total burden of the increase (factoring each part's quantity, duration and net sales value). Using summary statistics, we removed all records whose distance from the mean exceeded 3 standard deviations (226 out of 13,130 records), as not to not skew results.

Before we could match part-level SSP with inventory boosts, we had to decide on the range of SSP values we would consider. Inquiring further on the methodology of MiCo's inventory procedures, we learned that the average days late for each part were calculated using deliveries from the previous 13 months. If these deliveries exceeded 36 in total, only the most recent 36 were counted. We applied the same criteria in calculating SSP, using the previous 36 (or 13 months of) scheduled deliveries prior to the

TABLE 7: APPLICABLE INVENTORY INCREASE DATA WITH SSP

Part ID	Inventory Boost	Net Sale	Duration (days)	Holding Cost	SSP
WR81T	32	[redacted]	290	[redacted]	75%

Counting the number of entries within SSP ranges gave us the probability distribution of SSP values given the event of an inventory increase, depicted in Figure 11. The result is completely opposite to our expectations, since it shows that the probability of an inventory increase rises as the supplier improves in shipping performance. Given this clash with theoretical models, we returned to focus on MiCo's decision making process to understand the context from which such observations emerged.

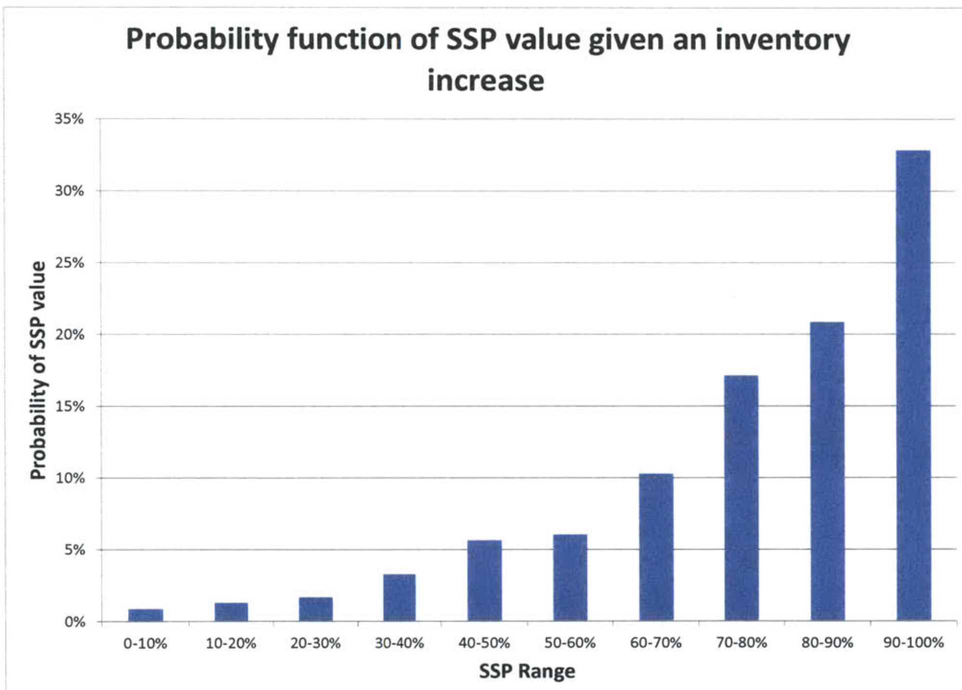

FIGURE 11: PROBABILITY OF SSP GIVEN AN INVENTORY INCREASE

In researching further, we found that MiCo runs two concurrent decision processes that lead to temporary inventory increases: one manual, one automatic. For the automatic, data-driven program, average days late represent the biggest driver of inventory increases. But before average days late over past deliveries are calculated, the individual Part IDs undergo numerous decision filters, which include

- Forecast filters (ensure demand to justify an increase),

- Part type filers (consider only certain part families and categories) and
- Delivery filters (ensure sufficient recent deliveries to have a statistical analysis).

After the filters disqualify certain records, the inventory program calculates summary statistics such as the number of deliveries, average days late, the 90-percentile and standard deviation of days late, as well as its coefficient of variation (CV, a measure of variation). These summary statistics enter the inventory decision process as follows.

1. If the 90-percentile value of days late amounts to less than 14 days, a corresponding amount of inventory is boosted to cover this period of up to two weeks.
2. If the 90-percentile value of days late amounts to between 14 and 45 days, a maximum of 14 days of inventory is boosted, provided that the CV does not exceed a threshold.
3. If the 90-percentile value of days late amounts to more than 45 days or the CV exceeds the threshold, no inventory is boosted.

The immediate consequence of these decision rules is that parts delivered excessively and habitually late will never be boosted. A habitually, excessively late supplier has a very low SSP – which helps explain our observation of the probability distribution. To complicate matters, the data-driven process can also be augmented by manual decisions taken by inventory specialists. These people consider a wide variety of strategic and operational factors in deciding which service parts may be crucial in the short term, or lack sufficient historical ordering patterns because of new product introductions. Because such decisions are uniquely structured by MiCo, we will not expand on them much further. We did, however, review the frequency of their occurrence, to provide additional perspective. Not that both the manual and data driven increases follow a similar trend.

TABLE 8: INVENTORY INCREASES FOR DIFFERENT DECISION CATEGORIES

SSP Range	**Manual Driven** Inventory Increases	**Data Driven** Inventory Increases
0-10%	19	96
10-20%	37	133
20-30%	36	183
30-40%	88	343
40-50%	122	619
50-60%	120	674
60-70%	237	1,114
70-80%	392	1,857
80-90%	517	2,222
90-100%	711	3,603

With the decision process understood, our focus shifted to the underlying reasons why MiCo used so many filters and why they create a counter-intuitive distribution. The root cause was identified not in a specific filter or statistical calculation, but in a principle that preceded them all. We learned that MiCo instituted a budget ceiling during the design of the current system. Setting such a cap required a process that governed selection of inventory increases, as not to exceed the cap and ensure that the inventory investment yielded high returns. Investing in inventory from predominantly stable suppliers followed an assessment of risk: suppliers with low average days late and low delivery variability are more predictable and more easily controlled. An inventory investment in poorly performing suppliers may be too cost intensive to really cover the risk. Furthermore, a supplier struggling to meet existing delivery requirements may simply not have the capacity to meet increased demands. Finally, variable deliveries can result from many factors: bad supplier practices, misalignments between customers and suppliers, or inherent variability in the processes throughout the value chain. Increasing inventory does not address the true cause, but rather the symptom

For the purpose of our thesis, the most important insight was the discovery of the budget cap. If the total inventory increase budget was dynamic, we would consider how it changed over time, which could then be correlated with average SSP. Under a firm budget cap it would not matter how SSP or delivery performance changed – the system would increase inventory through relaxation or tightening of filters or decision rules. After further consultation with the inventory experts, we found the latter to be true: total investment in inventory boosts stayed predominantly constant. We therefore accounted for the total annual holding cost as a constant, taking the average investment over a few years.

Nevertheless, we completed the 5-step framework using the original data set from Figure 11. In much the same way as with service loss, we converted the probabilities we had calculated using Bayes' theorem. We used the same SSP distribution over all service parts, but had to calculate the probability of an inventory increase occurring new. We divided the average number of items increased over a year with the total number of items available for sale. Table 9 shows the conversion of probabilities.

TABLE 9: CONVERTING BETWEEN CONDITIONAL PROBABILITIES – INVENTORY

SSP Range	SSP Prob. given Inventory Increase	Prob. of SSP over Population	Prob. of Inventory Increase	Prob. of Inventory Increase given SSP
0-10%	1%	6.5%	8%	1.1%
10-20%	1%	3.1%	8%	3.3%
20-30%	2%	5.4%	8%	2.5%
30-40%	3%	5.5%	8%	4.8%
40-50%	6%	13.5%	8%	3.3%
50-60%	6%	9.8%	8%	4.9%
60-70%	10%	12.6%	8%	6.5%
70-80%	17%	12.2%	8%	11.2%
80-90%	21%	14.7%	8%	11.3%
90-100%	33%	16.8%	8%	15.6%

The final step consisted in determining the average cost of an inventory increase, for which we needed to first calculate the average duration of inventory increases and the average value over all items increased. The equation for expected cost due to inventory increase over given SSP ranges is provided in Equation 10. Plotting the values and applying a regression model yields the final cost function as shown in Figure 12.

EQUATION 10: EXPECTED COST OF INVENTORY

$$E\$(SSP) = P(I = 1 | SSP = X_{i-1} < SSP <= X_i) \times \mu_{duration} \times \mu_{value} \times \%\ holding\ cost \times \#\ of\ parts$$

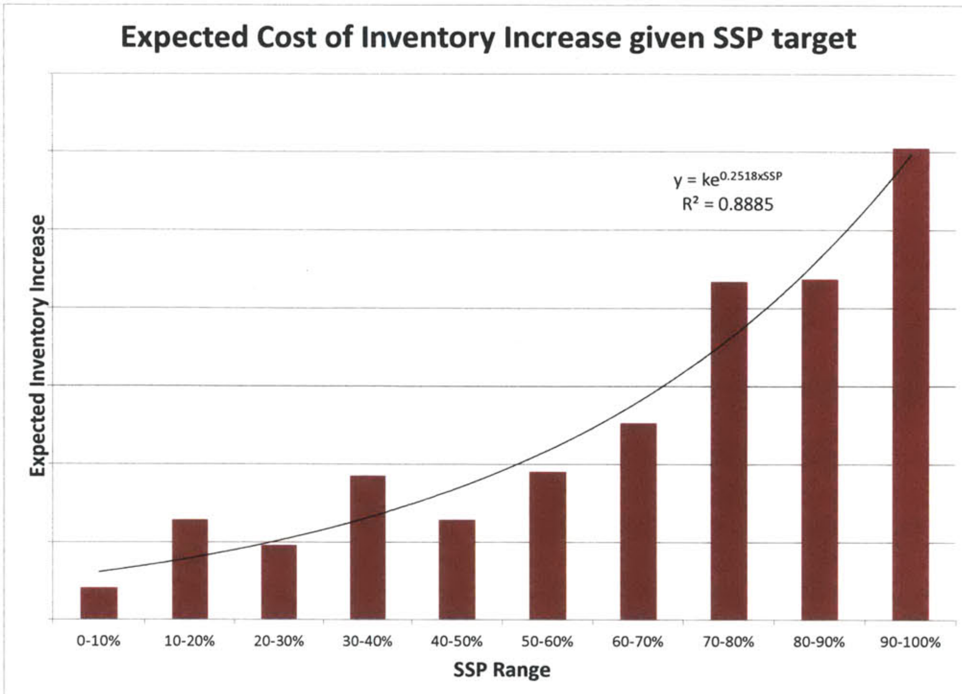

FIGURE 12: EXPECTED COST OF INVENTORY INCREASE

4.1.3 Expedited Costs

Since MiCo's network comprises several thousand suppliers and customers, we expected this cost to be significant. We also expected to find that the cost and frequency of expedites increase as supplier delivery performance decreases. We had learned early in our project that most of the data on rushed shipments would relate to expedites from suppliers to MiCo, and between the different warehouses of MiCo. Our data collection would therefore focus on capturing mostly inbound traffic.

Unfortunately, it turned out that MiCo's accounting systems did not sufficiently track expedited shipments, apparently lacking a function or coding procedure that distinguished rushed shipments from regular shipments. In a final attempt at collecting data, we received a file containing approximately two years of historical shipments that apparently represented rushed orders. While the records did consist of inbound shipments to MiCo, the count and value of the observations was too small to represent the entire transportation volume expedited in. Furthermore, there was no way to distinguish whether these orders were really expedited because suppliers had failed to ship on time. They could also have resulted from unexpected demand surges or flawed planning by MiCo. Establishing this link to late supplier deliveries formed a prerequisite to our ability to model the cost behavior.

As not to categorically refuse the data, we proceeded to analyze the limited list of shipments in a similar manner as inventory increases. We matched each record consisting of a shipping date, a supplier ID and a shipping cost to available SSP values. We then grouped these observations into SSP ranges and scanned each group for significant outliers. Although this aggregation allowed us to form a frequency distribution of shipments over SSP ranges, we could not proceed further. To perform the conversion described in the other sections, we needed the overall probability of a shipment being expedited, as well as some certainty that our observations indeed resulted from late suppliers. Establishing these facts, however, was not possible at the time.

4.2 Performance Maintenance costs

The performance maintenance costs that MiCo carries relate to attempts at improving SSP. As depicted in Figure 3 of the methodology section, we expected to find that consistent performance improvements cause MiCo to expend increasingly more effort, mainly in the form of labor to directly assist suppliers in achieving or maintaining a target SSP. Naturally, there is also an overhead component for running an office of supplier maintenance personnel. Since the cost of non-personnel was not determined by our company, we focused on personnel cost. In the regression model, the supervisory staff members represent a fixed component to overall cost.

With the annual labor costs of personnel collected, we had to associate the effort and time they spent on particular suppliers. To analyze for a correlation between time spent and SSP improvement we needed information on the Supplier Account Manager (SAM), the assisted supplier, the timeframe and its impact. MiCo tracked this information in a historical assignment schedule that listed performance maintenance projects performed by SAMs over the last two years. An example is shown in Table 10.

TABLE 10: EXAMPLE OF HISTORICAL ASSIGNMENT RECORDS

Supplier Code	Responsible SAM	Status	Assigned Date	Assigned SSP%	Reassign/ Closed Date	Reassign/ Closed SSP%
AB1240	Doe	Monitor	03/01/09	11.5%	8/1/2010	12.5%
AB1240	Smith	SAM	06/08/11	55.7%		

Additionally, we requested the historical shipping performance of MiCo's top suppliers over the same time frame. We focused on the top suppliers because, with few exceptions, they represent the pool of suppliers to which a SAM can be assigned. An extract of the data is shown in Table 11. Considering that SSP is captured at month's end, the table provides starting and ending SSPs, and therefore the change in SSP for any given month. Note that compared to previous data analyses, the data for performance maintenance comprise three dimensions: time (which is converted into cost via salaries), starting SSP and change in SSP. Previous analyses had only featured cost and one SSP value. While this adds some complexity to the model for performance maintenance, we proceed in a similar manner as with the other costs. Fixing the time intervals between observations to one month, while ensuring the highest level of detail available, helped simplify the problem.

TABLE 11: HISTORICAL SSP PERFORMANCE

Supplier Code	Date	SSP	Change in SSP
AJ1360	10/1/2010	36%	
AJ1360	11/1/2010	38%	2%
AJ1360	12/1/2010	34%	-4%
AJ1360	1/1/2011	40%	6%
AJ1360	2/1/2011	39%	-1%
AJ1360	3/1/2011	39%	0%
AJ1360	4/1/2011	35%	-4%
AJ1360	5/1/2011	30%	-6%
AJ1360	6/1/2011	28%	-1%
AJ1360	7/1/2011	42%	14%

Since Table 10 has a start and end date of assignment we were able to append a logical value to Table 11 which indicated whether a SAM was assigned to a supplier during a month for which we had SSP (1 = assigned, 0 = not assigned). This distinction allowed us to calculate and aggregate the monthly change in SSP for records with and without SAM assignments. Given our goal to model the impact SAMs have on SSP, we filtered our analysis on the data points associated with SAMs and sorted them by starting SSP. We aggregated all observations into SSP ranges of 5% intervals and calculated the average and standard deviation of each range. To ensure data integrity within each range we removed outlying change in SSP values located more than three standard deviations away from the range mean. Table 12 shows the results of this aggregation. Of particular note are the average changes in SSP for all ranges above 80%: they are all negative. Along with the general trend of declining changes in SSPs, this observation supports the notion that it becomes increasingly difficult for SAMs to improve suppliers as the starting SSP moves high.

TABLE 12: AVERAGE CHANGE IN SSP CALCULATIONS

Start SSP Range	Average Change	Number of Observations	Max in Range	Min in Range	Standard Deviation
0-5%	25.5%	2	46%	6%	20.0%
5-10%	0.9%	11	6%	-3%	2.8%
10-15%	5.3%	3	13%	-1%	6.0%
15-20%	5.6%	8	10%	2%	3.2%
20-25%	9.7%	15	30%	-3%	10.1%
25-30%	7.6%	19	35%	-10%	12.1%
30-35%	5.4%	22	29%	-15%	10.3%
35-40%	4.1%	39	29%	-15%	8.4%
40-45%	2.6%	37	24%	-28%	12.0%
45-50%	5.1%	46	28%	-17%	12.0%
50-55%	6.3%	43	38%	-19%	14.4%
55-60%	1.4%	40	22%	-22%	11.4%
60-65%	1.5%	46	23%	-17%	10.2%
65-70%	-0.1%	57	19%	-26%	9.1%
70-75%	1.4%	52	26%	-17%	8.5%
75-80%	1.6%	57	19%	-26%	9.8%
80-85%	-0.3%	63	14%	-16%	7.0%
85-90%	-0.2%	60	11%	-12%	5.2%
90-95%	-0.7%	68	8%	-11%	4.0%
95-100%	-1.1%	37	3%	-8%	2.5%

The next step consisted in plotting the average changes in SSP over the ranges of starting SSPs. After our initial attempt at plotting the average changes in SSP (Figure 13), we reviewed and removed ranges that did not contain at least 15 separate data points, since the risk of outliers and skewed summary statistics was too high in these groups. We removed the ranges at low SSP (subject to fewer observations and potentially volatile behavior) and ended with a revised set of data depicted in Figure 14.

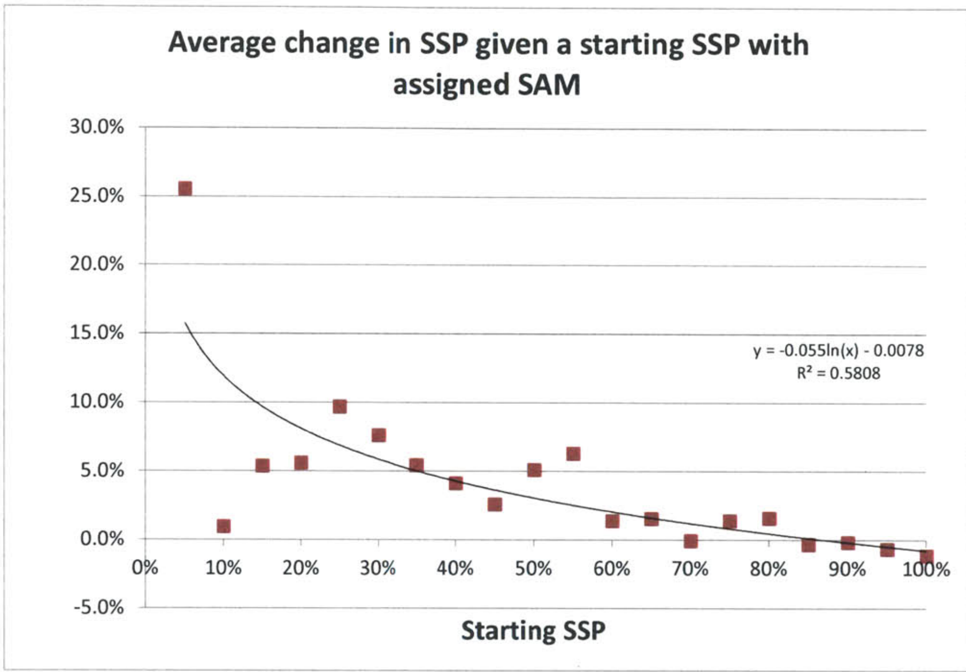

FIGURE 13: AVERAGE CHANGE IN SSP PER MONTH

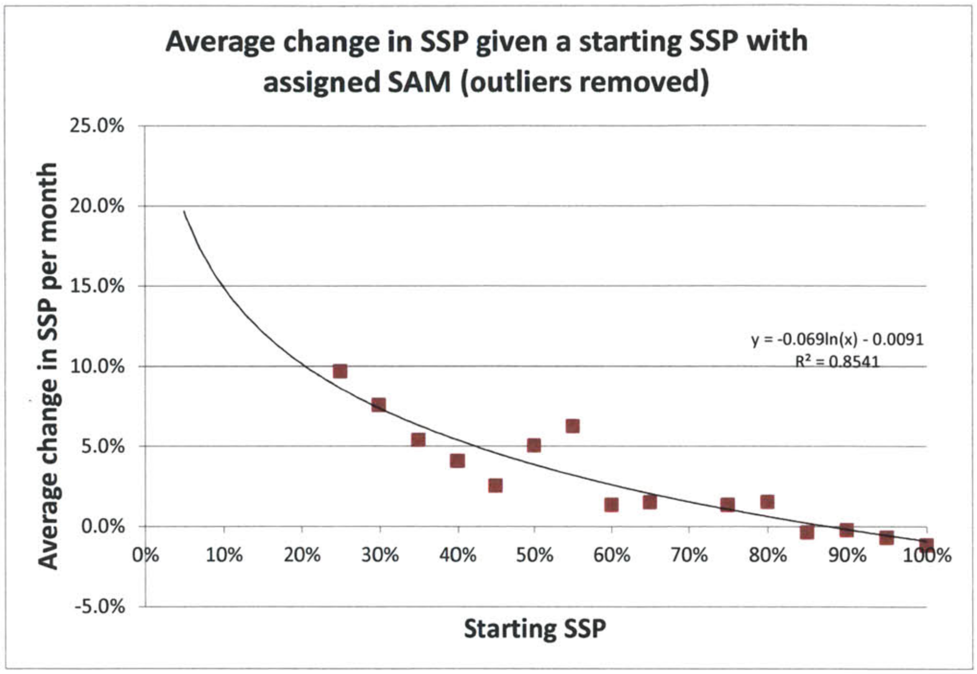

FIGURE 14: AVERAGE CHANGE IN SSP PER MONTH (OUTLIERS REMOVED)

As all SSP values derive from monthly measurements, the average changes in SSP represent one month's rate of change at different levels of starting SSP. To estimate the cost of SSP improvements we needed to convert this data. Assuming that the rate of improvement within each range behaves approximately linearly, we calculated the man-months required to move a single supplier from the lower bound of a range into the next range. Our knowledge of the interval size (5%) and the rate of change enabled this calculation, dividing the first by the latter to get required man-months. Since negative average changes in SSP implied (on average) no improvement, we did not use these cases in calculating man-months. The final graph of plotted man-months is depicted in Figure 15.

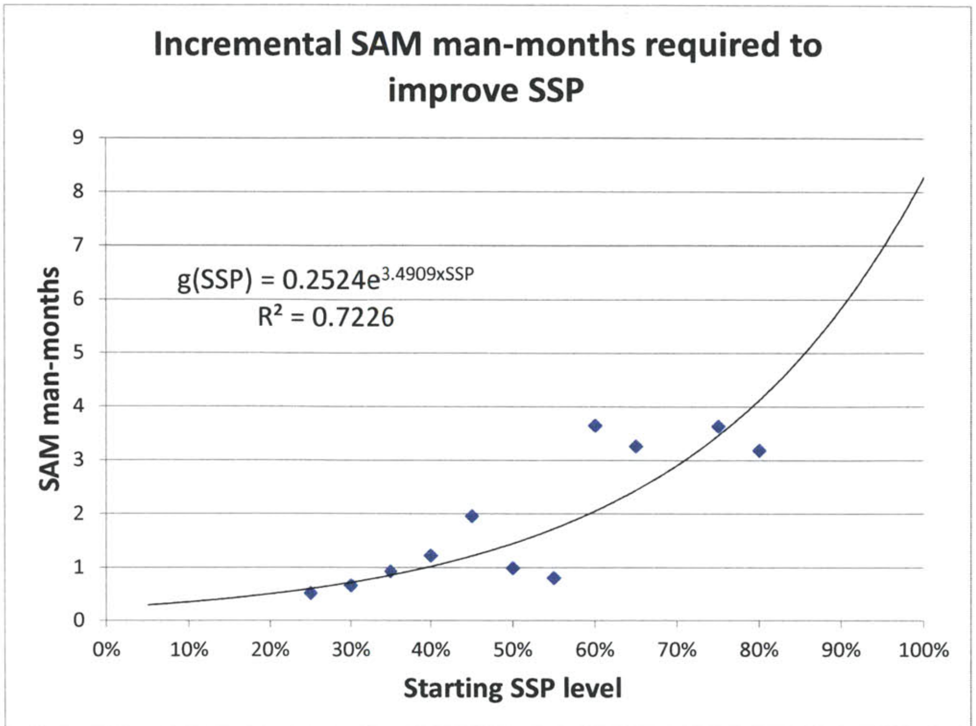

FIGURE 15: SAM EFFORT IN MONTHS

The final steps consisted in converting the man-months for single supplier improvements to an expected investment cost, and subsequently integrating the results. For illustration purposes, we assume throughout further discussion that the fully-burdened annual compensation (with benefits) amounts to \$120 000 per SAM. From the assignment schedule we deduced that SAMs typically work on 9 suppliers on average, so that the average spend on a single supplier is around \$1,111 per SAM per month. Very few suppliers had more than one SAM assigned simultaneously – such double counts could therefore be ignored. Multiplying the fitted curve's equation from Figure 15 with the cost of man-months of \$1,111, we get the equation $g(SSP) = 280.43 \times e^{3.4909 \times SSP}$. We used this function to determine the cumulative investment function for improving from one SSP range to the next. Figure 16 shows the graph of the investment function, which at any given point represents the total investment required to move a supplier from 0% to the desired SSP.

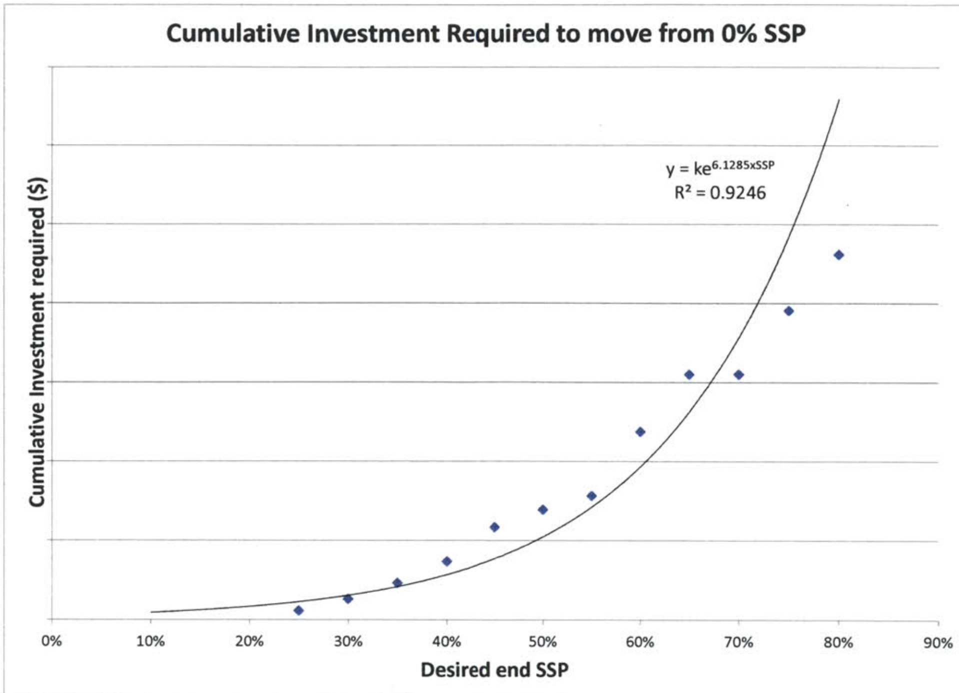

FIGURE 16: TOTAL INVESTMENT REQUIRED TO INCREASE SSP

4.3 Final Combined Model

Even though we could not derive all the equations of the cost elements identified at the onset (due to a lack of data or an integrated business processes aligned to SSP), we proceeded with using the information we had to determine the "optimal" SSP target that would minimize total (captured) cost. The various cost elements and their respective equations follow.

EQUATION 11: OBSERVED PERFORMANCE MAINTENANCE COST FUNCTION

$$G(SSP) = E\$(SSP) = e^{3.209 \times SSP + \mathrm{K}} + c$$

The fixed cost component of $G(SSP)$ represents the overhead cost we attributed from management and supervisory positions overseeing the Supplier Account Managers and their performance improvement efforts.

EQUATION 12: OBSERVED LOST SALES COST SUB-FUNCTION

$$f_1(SSP) = E\$(SSP) = e^{-9 \times SSP + k}$$

EQUATION 13: OBSERVED INVENTORY INCREASE COST SUB-FUNCTION

$$f_2(SSP) = E\$(SSP) = \ constant$$

EQUATION 14: OBSERVED EXPEDITES COST SUB-FUNCTION

$$f_3(SSP) = E\$(SSP) = \ unkown = 0$$

Since all consequence management costs have a common unit of measure, we can add them together to get the Total Consequence Management Cost:

EQUATION 15: OBSERVED TOTAL CONSEQUENCE MANAGEMENT COST FUNCTION

$$F(SSP) = \sum f_i(SSP) = e^{-9\times SSP+k} + c.$$

As $F(SSP)$ represents an annual cost per supplier, we had to make an assumption regarding the Performance Maintenance Cost, which was denominated in cost per suppler. To add the time dimension, we needed to know the duration over which the investment in the supplier returned improvements, i.e. the lifetime of a SAM project after completion. This lifetime would enable us to calculate the Net Present Cost (NPC) of the performance maintenance system per supplier in Equation 16.

EQUATION 16: OBSERVED TOTAL SYSTEM COST

$$H(SSP) = G(SSP) + \sum_{t=0}^{n}(1+i)^{-t} \times F(SSP),$$

where n represents the total years that the improvement in a supplier's SSP remains in effect. To determine whether a minimization of this cost function is achievable we determined the shape of $H(SSP)$ graphically. The graph in Figure 17 shows that a global minimum value exists. This represents the target SSP for the system, provided all system costs are captured. By taking the derivative of $H(SSP)$ and solving it for$h(SSP) = 0$, we can calculate this minimum point. Since the derivation of a constant is 0, overheads associated with any cost category do not influence the location of the optimal point, only the total cost at this point. Since we did not have sufficient data on which to base the lifetime of supplier improvement projects, we calculated the target levels for various possibilities of expected lifetimes. These can be found in Table 13.

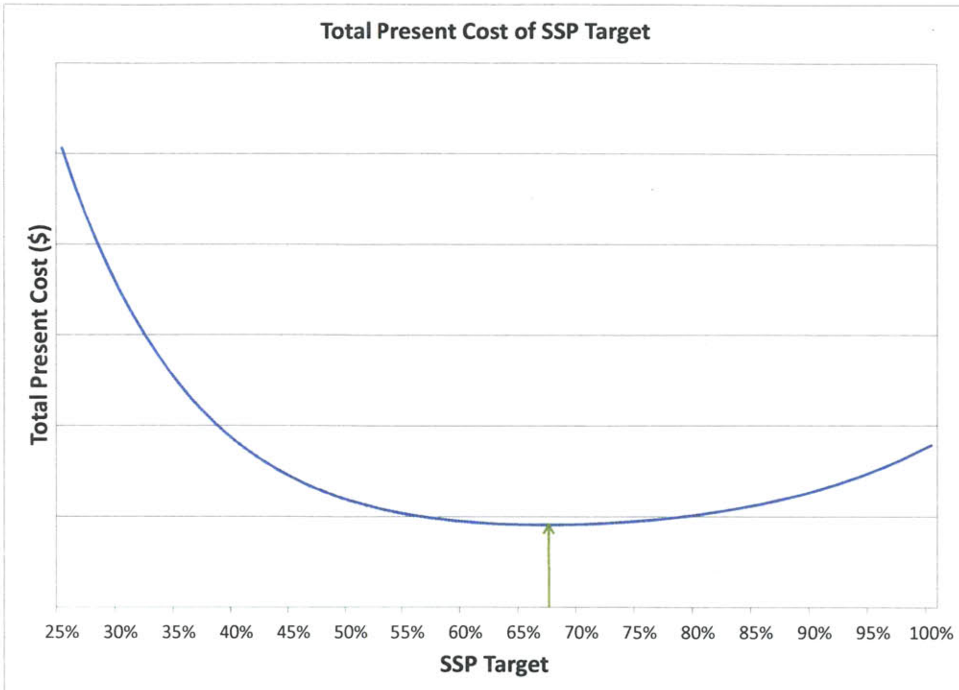

FIGURE 17: TOTAL OBSERVED SYSTEM COST FOR SSP TARGET

TABLE 13: SSP "TARGET"

Life of SSP Improvements (years)	"Target" SSP
1	60%
2	65%
3	67%
4	69%
5	70%

5. CONCLUSIONS

Through the process of associating various cost elements to SSP we developed a 5-step framework that can be applied to MiCo's SSP measure. The framework can also be applied to other supplier-focused metrics, provided a similar tradeoff between the costs exists. During our analysis we came across some counterintuitive results for certain cost elements that were not clearly tied to the supplier-focused metric – supplier performance changes may therefore not impact observed costs, at least not directly. On other cost elements, sufficient data was not available to build a reliable model. While our goal was not to determine the actual SSP target for MiCo, we did build the framework and test our model and its capability of finding an optimal solution. Though a final, reliable answer depends on filling gaps of missing data and determining a lifetime for supplier development projects, our approach shows that a target can be found. Depending on the investment horizon of improvement projects, the "optimal" target ranges from 60% (1 year lifetime) to 70% (5 years lifetime).

5.1 IMPLICATIONS TO MICO

- **Completing the Model:** Since MiCo faced constraints on data for expedited orders, we could not fully test our framework across this cost category. Future applications of this framework would ideally include expedited order data.

- **Communicating Targets:** As discussed in the literature review, performance targets are most successful when created in cooperation with suppliers. If MiCo determined that the optimal SSP for investing in suppliers were 80%, it is unlikely that it would communicate this target to suppliers. Our framework does not address the question of communicating a target, since this depends heavily on the nature of the industry and the relationship between customer and supplier.

- **Limits to Growth:** While the observations of SSP change were subject to significant variability (prompting us to aggregate the information to aid interpretation), the overall trend of diminishing returns to supplier improvement efforts were evident. To gain a better understanding of performance towards the extreme end of SSP, we looked in detail at the cases where SAMs had worked on suppliers with an SSP above 80%. Figure 18 illustrates the risk involved in assigning SAMs to suppliers with high SSPs. The probability of increasing performance is predominantly below 50%, and the average returns almost universally negative. Since the return on investment bears significant uncertainty when SSP exceeds 80%, MiCo should carefully consider the risk when investing in such suppliers.

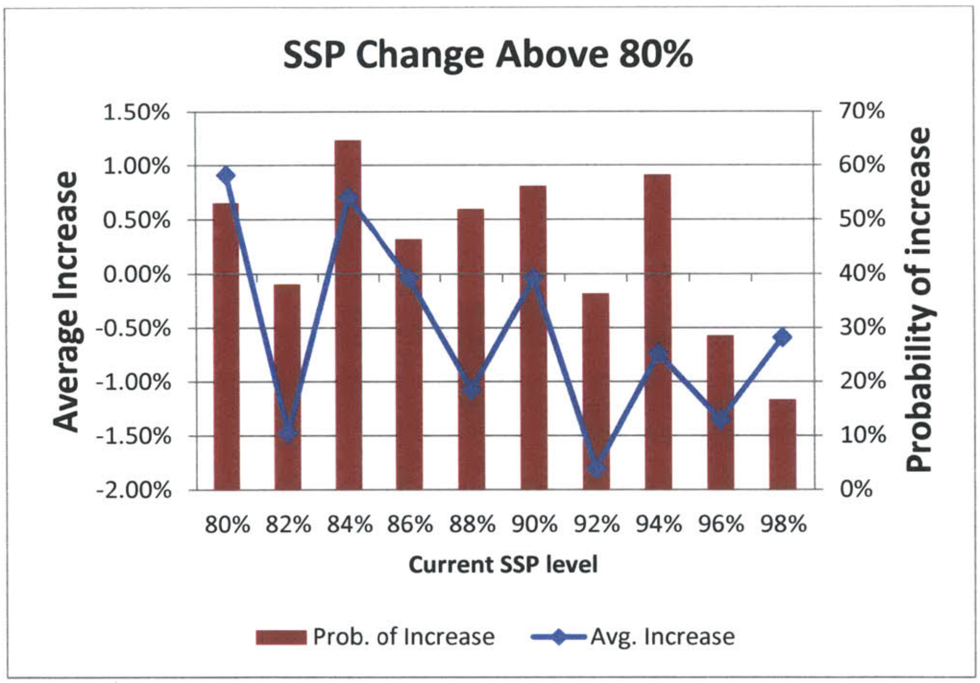

FIGURE 18: SSP CHANGE ABOVE 80%

5.2 IMPLICATIONS TO INDUSTRY

- **Adaptable Framework:** Based on our review of literature, very few attempts exist to empirically derive an optimal performance target for supplier delivery. Future studies can refine our approach by applying the framework developed in this thesis to other companies or to other metrics.

- **Making Connections:** While one assumes that companies understand their business processes, they may be understood in isolation. Investigating an optimal target provides an opportunity to realign metrics to business decisions and potentially discover hidden cost savings.

- **Investment Decision:** If all applicable data is available and the framework can be applied to all cost elements, an optimal target can be set. This target determines whether to invest in a specific supplier development or not.

5.3 Takeaways of the Empirical Approach

- **Data Availability:** A major limitation of any empirical approach is the availability of accurate, reliable data. While the problem and our approach were grasped early on, finding the applicable data turned out more difficult than anticipated. Repeated iterations of data collection improved our understanding of the breadth of available data, but could not offset a lack of appropriate information or a sufficiently large observational horizon. This problem can be systemic to any company or industry.

- **Data Usability:** The drivers behind dependent or related data must be clearly associated with observed data. When possible, this association must be tested before using the data.

5.4 Future Developments

The ideas listed below contain limitations and constraints we encountered, as well as suggested future research for MiCo or companies facing similar situations.

- **Shipping Metric:** MiCo's current hit-or-miss metric is simple to use and understand, but has limitations repeatedly highlighted. While our scope focused on examining the implications of SSP, our framework could be adapted to an alternate metric such as average/median days late or delivery variability, provided such data is available. The metrics could then be compared for relevance and fit to observed data. Since we learned that SSP is not the only measure of supplier on-time delivery performance used throughout MiCo, future projects should look into the standardization of a single on-time delivery metric used across all processes.

- **Dynamic Inventory Increase:** MiCo's decision process for boosting inventory in response to late deliveries is marked by a fairly constant investment cap and a proclivity for better performing suppliers according to the SSP metric. It may be prudent to set limits on procuring additional stock (currently at most 14 days of extra demand) and consider volatility of supplier deliveries. However, the system may yield a more optimal coverage of demand if focusing on suppliers further towards the middle of the performance spectrum, rather than singling out the top performers and categorically ignoring the poor.

- **Cost Interdependency:** The behavior of the consequence management cost categories may differ significantly between companies depending on inventory policies used. The first two consequence management categories (immediate lost sales and order expedites) are both reactive in nature; they occur as a result of (or in response to) late supplier deliveries. Inventory increases, on the other hand, aim to cancel out the need for such reactionary measures. Positioning more inventory stock should therefore reduce the frequency of lost sales and expedites, since late deliveries no longer cause stock outs. In this manner, the inventory policy can set limits on the costs of lost sales and order expedites. In a similar fashion, one could attempt to draw a dependency between expedited orders and lost sales, since an order is rushed to prevent a lost customer sale. We would therefore expect the observations of lost sales to be limited by expedited orders as well. The described interdependencies may allow for the construction of a model towards determining the frequency (and cost) of lost sales, dependent on both proactive inventory boosts and reactive order expedites.

- **Mixed Target Strategy:** Our current approach finds one target for a large supplier base. Companies may choose to limit the application of targets in practice, much as MiCo currently does when selecting which suppliers to develop. Additionally, companies may want to segment supplier groups for target setting, or even create individual targets in a more dynamic system.

- **Discounting Supplier Improvements:** As our data analysis shows, the assignment of SAMs to suppliers on average increases supplier performance across most of the performance spectrum (it does not at higher SSPs). However, suppliers that were not assigned to SAMs also improved slightly on average, a trend that would reduce the incremental value of active supplier development. Since non-assigned suppliers may still be influenced from previous SAM assignments, we did not attempt to discount SAM development efforts. Accumulating more observations over the near future will enable MiCo to investigate the continued influence of SAM assignments after closure.

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