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ON THE APPLICABILITY OF ANALYTICAL SUPPLY CHAIN DISRUPTION MODELS FOR SELECTING THE OPTIMUM CONTENGENCY STRATEGIES FOR ELECTRONIC SUPPLY CHAIN DISRUPTION MANAGEMENT: A COMPARISON WITH SIMULATION

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ABSTRACT

Due to the nature of the manufacturing and support activities associated with long life cycle products, the parts that products required need to be dependably and consistently available. However, the parts that comprise long lifetime products are susceptible to a variety of supply chain disruptions. In order to minimize the impact of these unavoidable disruptions to production, manufacturers can implement proactive mitigation strategies. Two mitigation strategies in particular have been proven to decrease the penalty costs associated with disruptions: second sourcing and buffering. Second sourcing involves selecting two distinct suppliers from which to purchase parts over the life of the part's use within a product or organization. Second sourcing reduces the probability of part unavailability (and its associated penalties), but at the expense of qualification and support costs for multiple suppliers. An alternative disruption mitigation strategy is buffering (also referred to as hoarding). Buffering involves stocking enough parts in inventory to satisfy the forecasted part demand (for both manufacturing and maintenance requirements) for a fixed future time period so as to offset the impact of disruptions. Careful selection of the mitigation strategy (second sourcing, buffering, or a combination of the two) is key, as it can dramatically impact a part's total cost of ownership.

This paper studies the effectiveness of traditional analytical models compared to a simulation-based approach for the selection of an optimal disruption mitigation strategy. A verification case study was performed to check the accuracy and applicability of the simulation-based model. The case study results show that the simulation model is capable of replicating results from operations research models, and overcomes significant scenario restrictions that limit the usefulness of analytical models as decision-making tools. Four assumptions, in particular, severely limit the realism of most analytical models but do not constrain the simulation-based model. These limiting assumptions are: 1) no fixed costs associated with part orders, 2) infinite-horizon, 3) perfectly reliable backup supplier, and 4) disruptions lasting full ordering periods (as opposed to fractional periods).

Keywords: Total cost of ownership, buffering, part sourcing, supply chain, disruptions, electronic parts, life-cycle cost

NOMENCLATURE

λ_{du}	Probability of a disruption ending in the subsequent period
λ_U	Probability of system *remaining* undisrupted in the subsequent period
C_{ASYj}	Assembly Cost for a part in year j
C_{FFj}	Field Use Cost for a part in year j
C_{INVj}	Holding (Inventory) Cost without Disruptions for a part in year j
C_{PROCj}	Procurement Cost for a part in year j
C_{SUPj}	Cost to Support a Source for a part in year j
C_{TCO}	Cumulative Total Cost of Ownership of a part
CTCO	Cumulative Total Cost of Ownership
h	Holding Cost (per part per year)
I_{Ej}	Excess Inventory (positive values of I) in year j
K	Ratio of $\Delta C_{TCO} / C_{SUP}$
M	Number of state spaces representing the minimum disrupted periods
N	Number of state spaces representing the possible remaining disrupted periods
P_{BOj}	Backorder Penalty Cost for a part in year j
r	Weighted Average Cost of Capital (WACC) per year
TCO	Total Cost of Ownership

1 INTRODUCTION

The selection of optimal sourcing strategies for parts is a prevalent issue within the business management and operations research literature; however, the focus of existing analyses is typically on minimizing part procurement price. For example, lean manufacturing emphasizes the reduction of inventory size in order to cut costs. While this approach is largely effective for high-volume parts, it assumes that suppliers can provide parts for the manufacturing process without interruption [1], which is often not the case with electronic parts over long time periods (e.g., 10+ years or more).[1]

Several high-profile disruption events have caused shockwaves within the electronics industry in recent years. For example, in March of 2000 a fire at a major Phillips Electronics plant shut down production and damaged millions of existing microchips. Ericsson, one of their largest customers, was faced with a shortage of parts that lasted for months. As a result, Ericsson lost an estimated $400 million in sales [2]. Similarly, a Japanese earthquake disrupted the supply of parts to Kelly Micro Systems in 1994 [2]. Another Japanese earthquake (in 2011) led to a tsunami that forced the shut down of several plants that “supply much of the world’s silicon wafers, auto parts, flash memory, and other components” [3].

The simulation model presented in this paper provides a platform for effectively employing proactive mitigation strategies in order to minimize the effect of disruptions events, especially supplier-specific disruptions. This paper studies the applicability of this simulation-based approach when compared to traditional analytical models for the selection of an optimal disruption mitigation strategy.

1.1 DISRUPTION TAXONOMY

A supply chain disruption is a mismatch between supply and demand that would result in backordered parts if there were no mitigating factors such as buffered parts or second sources. While the primary effect of a disruption is the same, the source/cause of each event varies. Four disruption categories are discussed below: part-specific, supplier-specific, customer-specific, and external.[2]

1) <u>Part-specific</u>: Situations related to individual parts (not suppliers) can impact the ability of a customer to obtain the part from any supplier. The most common part-specific disruptions are part obsolescence and counterfeit part risk.

2) <u>Supplier-specific</u>: The two broad causes of supplier-specific disruptions are suppliers exiting the market and delivery delays.

3) <u>Customer-specific</u>: Poor estimation of part demand by the customer is the primary source of customer-specific disruption. Estimation issues are typically a result of unforeseen surges in demand and allocation issues.

4) <u>External</u>: Events that are beyond the control of the suppliers or customers may directly affect the efficient production of parts and subsequent delivery to customers. Common causes of external disruption include political/legislative events, transportation mishaps, and “Black Swan”[3] events.

Manufacturers periodically negotiate supplier contracts that define the price, lead times, and volumes of selected part shipments. These contracts are deciding factors in the manufacturer’s overall production schedule and as such variations from these contractual terms can be the basis for production disruption, whatever the cause.

2 LITERATURE REVIEW

A variety of models have been developed to study the effect of disruption events within a supply chain. Disruption models in the operations research realm focus on the study of dynamic inventory policies, in particular the selection of optimal buffer stock quantities. In fact, early disruption-specific models, such as Song and Zipkin [5] and Parlar and Perry [6], focus exclusively on inventory control methods for accommodating disruption events. These models developed robust disruption definitions and mathematical models that continue to serve as the basis for more complex disruption models.

Tomlin [7], Schmitt and Snyder [8], and Chen, et al. [9] incorporate the concept second sourcing as an additional disruption-management technique. However, while these models clearly define the effect of various disruption mitigation strategies on cost, supplier qualification is not considered and the secondary supplier is assumed to be completely reliable (essentially an emergency/backup supplier). In addition, Tomlin, and Schmitt and Snyder present infinite horizon models[4] (which do not consider cost of money). Although the restrictions surrounding these models prevent them from being useful decision-making tools for most real applications, a fact that their authors acknowledge, they can still provide valuable insight into the effect of disruptions and they allowed us to limit the number of

[1] While disruptions are a problem when lean manufacturing approaches are used for high-volume products, in the case of high-volume products, disruptions are usually relatively short in duration (e.g., hours or days), whereas in the case of low-volume, long field life products, disruptions due to allocation issues and obsolescence may have durations of months or even years.

[2] In the context of this paper, a customer is anyone who needs the part for manufacturing and/or support.

[3] Disruption events that occur outside of reasonable or regular expectations, produce an extreme impact, and involve “retrospective predictability” [4]. Retrospective predictability indicates that the probability of occurrence can only be quantified after the event (or similar event) has taken place. Examples of black swan events impacting electronic parts include the 2011 Thailand flood and the 2011 Japanese earthquake.

[4] Infinite-horizon models assume that each ordering period takes place within an infinite part usage lifetime. The simplifications associated with this assumption (i.e., no discounting or termination/obsolescence activities) help to insure the formulation of convex optimization problems.

necessary disruption-based inputs for our simulation-based model.

Schmitt and Singh [10] presented a simulation-based approach of Tomlin's [7] model that studies the propagation of disruptions through infinite-horizon, multi-echelon supply chains and the resulting effect on inventory flow. The simulation utilized in this paper (as opposed to that of [10]) focuses on a single echelon of the electronics supply chain, more specifically the flow of parts from supplier(s) to the original equipment manufacturer. Any disruptions that occur before the parts reach the supplier(s) are assumed to be included in the aggregate supplier disruption distribution. While Schmitt and Singh's model serves to bridge the gap between analytical models and simulation models, it is still constrained to the limiting assumptions presented in [7] (infinite-horizon in particular).

None of the existing models discussed so far in this section focus on long life cycle, low-volume products (all are for short life cycle, high-volume situations); and none are specific to electronic parts. The mitigation strategy selection method utilized in this paper starts with an existing total cost of ownership (TCO) model developed by Prabhakar, et al. [11]. The model developed in [11] demonstrated the effect of second sourcing and buffering on the total cost of ownership of a part and provided an efficient tool for calculations. The model in [11] is extended to simulate combinations of contingency strategies to support optimum disruption management for long life cycle products. The contributions of this paper include the presentation of a unique compilation of actual disruption data and the assessment of the simulation model as a real-world decision making tool (compared to existing analytical disruption models).

3 PART TOTAL COST OF OWNERSHIP (TCO) WITH DISRUPTIONS

The model described in [11] determines the part total cost of ownership in the presence of disruptions. The model was built so as to efficiently determine the mitigation strategy (second sourcing, buffering, or a combination of the two) associated with the lowest part total cost of ownership.

The decision to second source a part (as opposed to single sourcing) is based on the tradeoff between the benefit of extending the effective procurement life of the part by second sourcing and the additional cost of qualifying and supporting the second source. When the qualification and support costs associated with maintaining multiple suppliers negate the benefits of second sourcing, other mitigation methods (such as buffering) can be considered. Part buffering involves stocking a number of parts in the inventory equal to the forecasted part demand of a fixed future time period (e.g., holding three months' worth of part demand). The forecasted demand represents the quantity needed for manufacturing and the quantity of spares needed to maintain fielded systems (or satisfy warranties). The excess inventory provides a buffer that decreases the impact of supply chain disruptions on the part total cost of ownership (TCO), but increases the inventory holding cost. The model developed in [11] takes the final output (the part TCO) from the model in [12] and incorporates uncertainties (part demand and supplier) and buffering. The final annual part TCO (Eq. 1) is estimated by adding the penalty cost (associated with the supplier disruptions) and the holding cost associated with excess inventory (due to the buffering policy selected and part demand uncertainty) to the baseline annual part TCO. Note that in years where holding cost (h) is charged, there are no parts on backorder (and vice versa).

$$C_{TCO_i} = \sum_{j=1}^{i} (C_{SUP_j} + C_{ASY_j} + C_{PROC_j} + C_{FF_j} + P_{BO_j} + hI_{E_j}) \quad \text{Eq.1}$$

For a detailed explanation of the terms in Eq. 1, see [13].

Supplier disruptions and part demand uncertainty incur penalty costs, which can significantly impact the TCO. The final model output is the sum of the original part TCO without penalty and the penalty costs. This final value is considered the part TCO. The simulation model described in Section 4 concurrently analyzes the effect of both second sourcing and buffering on the part TCO so that the users are able to select the most effective management strategy for their specific needs.

4 SIMULATION APPROACH

In order to model real-world disruption events, a simulation model was developed from the underlying formulation discussed in Section 3. The simulation model employs several loops to determine the near optimum disruption mitigation strategy, which is the strategy (sourcing and/or buffering) associated with the lowest expected cumulative total cost of ownership (CTCO) per part site. Figure 1 details the simulation process that is implemented within a Monte Carlo analysis in order to calculate the expected CTCO per part site for each sourcing and buffering strategy considered. The effective disruption mitigation strategy can either be determined manually (the user can perform a select number of Monte Carlo analyses for predetermined sourcing and buffering strategy combinations), or automatically within a brute force "optimizer" (which runs through a range of buffering and sourcing strategy combinations).

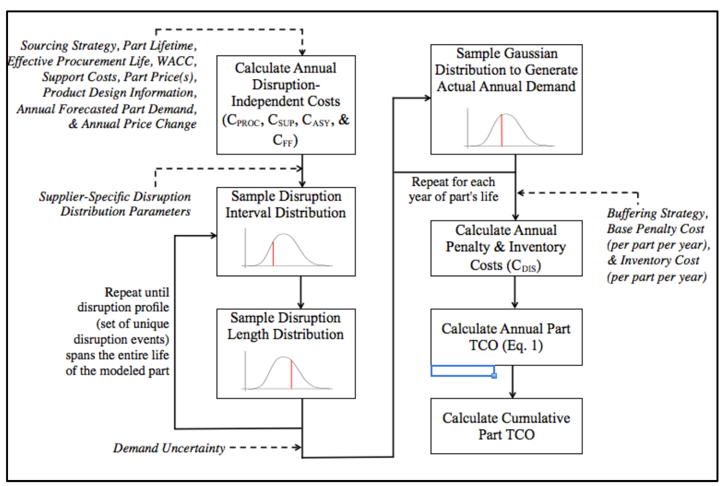

Figure 1: Simulation model process and inputs used to determine the cumulative TCO per part site for a unique set of disruption events.

The model described in [11], and shown in Figure 1, concurrently analyzes the effect of both second sourcing and buffering on the part TCO so that companies are able to select the most effective management strategy for their specific needs. The model utilizes Eq. 1 to calculate the part total cost of ownership from the following inputs: part price, part demand (forecasted and actual), support costs, penalty costs, supplier (sourcing) information, and historical/expected disruption distributions.

Uncertainty is introduced into the model through the generation of random supplier disruption events. The disruptions are modeled using a three-parameter Weibull distribution (which was selected for generality, but other distributions could be used). In addition to the generation of disruption events, the simulation model incorporates the effect of demand uncertainty. For each year in the part's life cycle, the simulation model samples a random value from a Gaussian distribution (with the forecasted part demand acting as the mean and a user-supplied value acting as the standard deviation) and sets that value as the actual annual part demand. The penalty and inventory costs associated with these disruptions are then calculated using the method developed in [11]. The final output of the model is a distribution of the likely cumulative TCO per part site[5] (generated by implementing the process shown in Figure 1 into a Monte Carlo analysis) over the support life of the product (or family of products) for the mitigation strategies in question.

Figure 2 shows example electronic part distributor delivery data from 2007 to 2013. This data not only serves to highlight the size and frequency of part orders as seen by the distributor, it also allowed us to isolate any discrepancies between scheduled and actually delivery dates. The graph in Figure 2 shows how long it took delayed parts to reach the distributor.

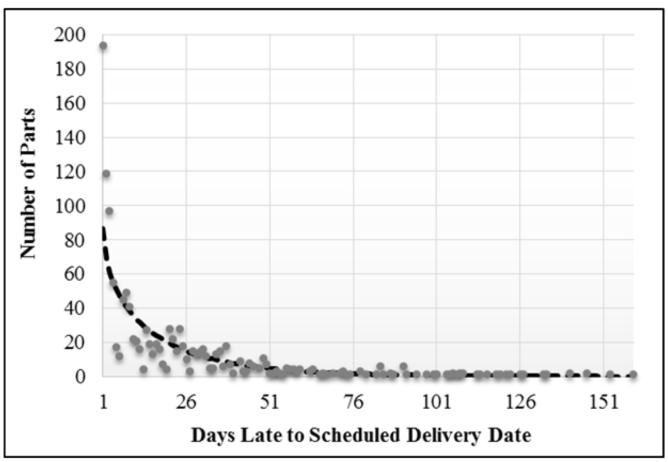

Figure 2: 2007-2013 Distributor delivery data for a sampling of integrated circuits and transformers.

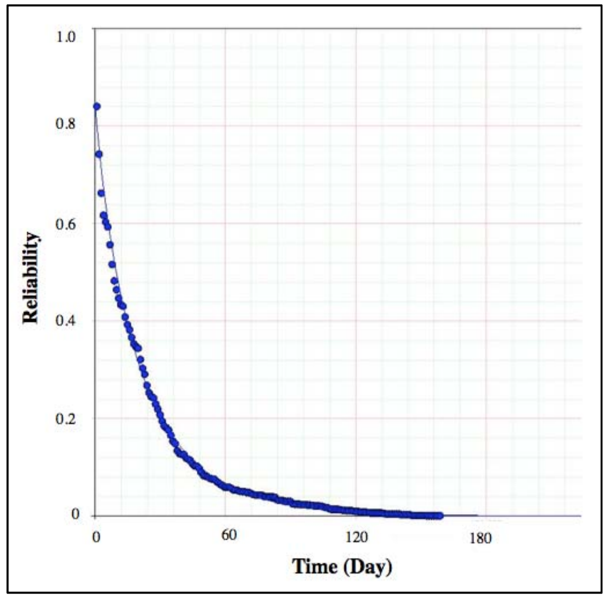

Figure 3: Weibull curve fit of the distributor data in Figure 2. The curve parameters are automatically calculated by the software and listed beside the output (beta: 0.834, eta: 18.726 days, gamma: -2.358 days).

While the data in Figure 2 does not fit into a traditional Markovian format (a common input for analytical models), it can be transformed into a useful input for the disruption model where its effect on the total cost of ownership can then be quantified and studied. While the data in Figure 2 is directly connected to disruptions at the distributor level, an additional offset factor can be applied to the parameters in order to modify the data for use by original equipment manufacturers (essentially left-censoring the data to accommodate distributor mitigation activities). Ideally, disruption models could be applied on a part, product, or supplier specific basis.

The raw delivery data (such as the data shown in Figure 2) was organized into frequency bins according to disruption length, i.e., 20 parts experienced a one-week delay, ten parts experienced a two-week delay, etc. This binned data can then be used to generate a disruption probability distribution. In our study, we utilized Weibull++ software to fit the data to a three parameter Weibull distribution. The parameters used to describe this distribution (shape, scale, and location) are direct inputs for the model. Figure 3, shows the curve that was generated using the delivery data and Weibull++.

Once the parameters are input into the model, a Weibull probability distribution is generated. Each time a disruption begins (intervals between disruptions are governed by a second Weibull distribution) a random value is selected from this probability distribution and set as the length of the disruption event. The penalty costs associated with these events are then calculated for each year of the parts life (according to the methods discussed in [11]) and added to the base part TCO. Figure 4 shows an example of the cumulative TCO per part site (including penalty) for a 13-year part life cycle and a disruption profile based on the delivery delay data presented in Figure 2. It should

[5] A "part site" is defined as the location of a single instance of a part in a single instance of a product. For example, if the product uses two instances of a particular part (two part sites), and 1 million instances of the product are manufactured, then a total of 2 million part sites for the particular part exist. The reason part sites are counted (instead of just parts) is that each part site could be occupied by one or more parts during its lifetime (e.g., if the original part fails and is replaced, then two or more parts occupy the part site during the part site's life). For consistency, all TCO calculations are presented in terms of either annual or cumulative cost per part site.

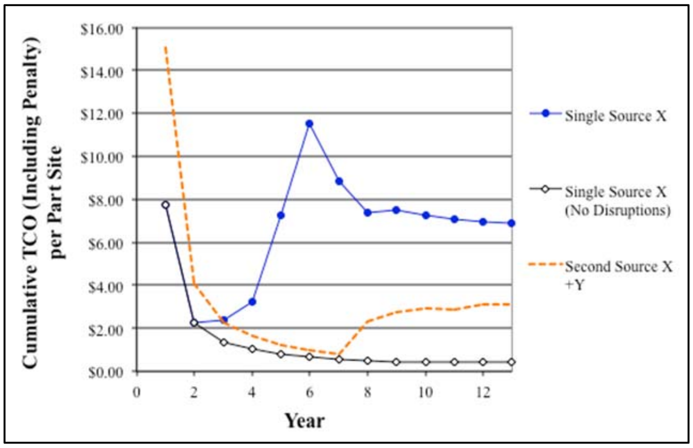

Figure 4: Cumulative part TCO (including penalty) over a 13 year period for a selection of sourcing strategies and a 10-week buffer.

be noted that the cumulative TCO per part site decreases over time in this example case because additional part sites are added to the total population each year (due to fluctuating annual part demand). The resulting effect of penalty costs and initial support costs on cumulative TCO is spread out amongst the additional part sites each year, reducing the per part cost.

The two steps described above are repeated for a series of Monte Carlo runs in order to produce a distribution for the expected part total cost of ownership. Figure 5 shows the result of a Monte Carlo analysis that was performed in order to account for the disruption uncertainty associated with the scenario shown in Figure 4. For the modeled scenario (based on low-volume electronic components), second sourcing and buffering is a more cost effective disruption mitigation strategy than single sourcing and buffering.

5 VERIFICATION CASE STUDY

In order to study the effectiveness of the simulation-based model described in Section 4, a verification case study was performed. Tomlin [7] presents a cost model for finding sourcing policies to minimize cost during disruptions. Tomlin's analytical model utilizes a constrained infinite-horizon, periodic-review inventory system. In Tomlin's model, all unmet demand is backlogged with instantaneous production and lead-time. The model allows for positive lead-time, assuming that lead-time is constant throughout the model. Tomlin's analytical model was selected as the verification case due to its similarity in approach and its widespread acceptance in the supply-chain community.

Tomlin presents the idea of flexible capacity as a defining characteristic for underlying model selection. The sub-model most applicable to the problem we are interested in solving has what Tomlin calls "Type II" flexibility. Type II flexibility implies that the emergency backup supplier can offer infinite and instantaneous capacity, essentially allowing for uninterrupted supply in the eyes of the consumer.

Tomlin employs a basic Markovian disruption model that designates each period as either disrupted/"down" or non-disrupted/"up". This model specifies the probability of the disruption ending each period (λ_{du}), and the total expected number

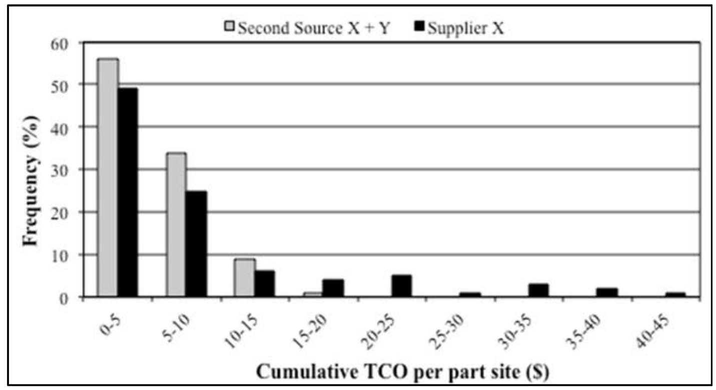

Figure 5: A comparison of the expected cumulative TCO for two sourcing strategies (a 10-week buffer assumed in both cases).

of disrupted periods. While Tomlin utilizes an infinite cumulative distribution function to calculate the resulting steady state uptime, he didn't provide detailed calculations. Consequently, the reimplementation of Tomlin's model (see Appendix) used in this paper employs a truncated transition state matrix. This matrix converges over time and specifies a steady-state probability of the system being "up". This "percent uptime" designates how many periods within the life of the part are not disrupted. Similarly, Tomlin developed equations utilizing this steady-state uptime and the resulting disruption probability distribution (along with a variety of other factors) to determine the optimal buffer quantity.

In order to make the simulation model match Tomlin's environment, several important model inputs were set to zero (support costs, cost of money, demand uncertainty, price-change, and termination costs). Removal of these effects, while necessary to reproduce Tomlin's result, severely impact the realism of the modeled system. The steady-state probability distribution (explained further in the Appendix) for each scenario (scenario: expected downtime, minimum downtime, % uptime) was utilized in the simulation model in conjunction with Tomlin's case study inputs and equations to calculate the average expected cost associated with each of his three main sourcing strategies: contingent rerouting (or acceptance, a subset where the rerouted production = 0), inventory management, and sourcing management.[6] The calculated costs were then compared, and the optimal sourcing strategy (the strategy associated with the smallest cost) was selected. This method was employed repeatedly to generate points on a graph that correlated to the output presented by Tomlin shown in Figure 6. The cases are organized according to overall supplier uptime and expected disruption length (the combination of which characterizes the frequency of disruption). Scenario-specific inputs and equations that result in the solid lines shown in the figure are given in

[6] While Tomlin utilizes different terms to describe disruption mitigation strategies, each strategy can be directly linked to second sourcing and/or buffering. The three mitigation strategies he describes are: contingent rerouting [pure second sourcing (no buffering), rerouting production to the second/backup supplier in the event of disruption.], inventory management [pure buffering, single sourcing.], and sourcing management [single sourcing from a reliable supplier, no buffering.].

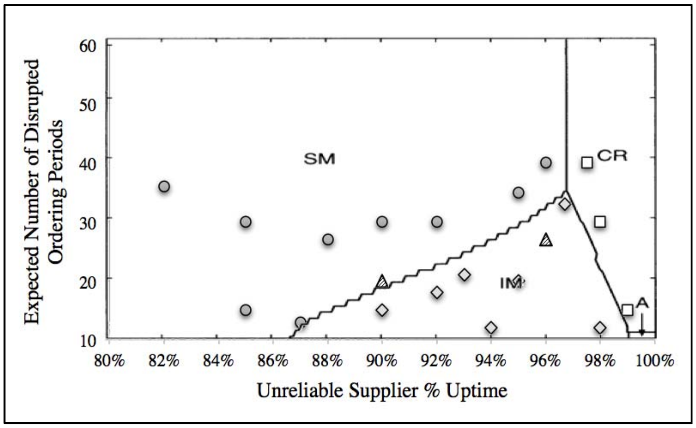

Figure 6: Optimal sourcing strategies for select disruption scenarios. The overlaid points show the mitigation strategy associated with *simulation* test points: Circles represent Sourcing Management, diamonds represent Inventory Management, squares represent Contingent Rerouting (CR), and the triangles represent equal cost for both Sourcing Management (SM) and Inventory Management (IM).

Tomlin [7]. With the exception of a few boundary points (which do not match due to numerical noise), the simulation results aligned closely with Tomlin's results. This correlation serves not only to verify the results produced by the simulation model, but also to highlight the utility of the simulation model as a decision-making tool.

6 LIMITATIONS OF ANALYTICAL MODELS

Figure 6 demonstrates that the simulation can be appropriately parameterized to generate the same solution as the analytical model of Tomlin [7]. While the model presented by Tomlin [7] effectively selects an optimal disruption mitigation strategy for a given set of inputs, it can only be applied to very restricted cases. The limitations that are inherent to the model are relatively common amongst analytical supply-chain models and are imposed by the models to insure that the formulation is convex (an optimum solution can be found). For the simulation-based model, no such limitations are necessary. In particular, there are four key restrictions that are problematic when applying the existing analytical models to low volume, long life cycle systems (where support costs and procurement lives are critical):

1) Fixed costs of ordering are ignored. This assumption limits the use of the model to cases where the order (demand) time scale is shorter than disruption time scale (i.e., order daily, disruptions last weeks). In addition, any fixed costs associated with supplier or part qualification (which were shown in [13] to have a direct effect on the total cost of ownership) cannot be considered. Tomlin notes that adding fixed/support costs and varying lead times might require simulation-based optimization.

2) Infinite-horizon model. This restriction, which works for an idealized high-volume, short life-cycle scenario, doesn't incorporate cost of money or price change over time, which are necessary components of long life-cycle products.

3) Disruptions last full ordering periods (i.e., disruptions are delivered in full or not at all). Tomlin, in particular, employs an idealized Markovian disruption model (discussed in Section 5).

4) Secondary (a.k.a., emergency/backup) supplier is completely reliable. This assumption indicates that second sourcing consistently allows for an uninterrupted supply of parts (as long as all the suppliers have enough notice and capacity). This restriction ignores overlapped supplier downtime (independent probability distributions), which is a more realistic scenario (especially when it comes to industry wide shortages).

7 RELAXING ANALYTICAL MODEL ASSUMPTIONS

Section 5 demonstrated that the simulation model described in this paper is capable of reproducing the results obtained by Tomlin [7]. However, the simulation model does not have the same core restrictions. A simulation-based approach, while not capable of guaranteeing a formal optimum, is able to produce a practical near-optimum value that incorporates both a greater amount of uncertainty and more complex parameters. This effective optimum can be calculated for realistic supply systems, and therefore can be more readily utilized as a decision-making tool.

In order to determine the impact of analytical model assumptions, several case studies were performed.

7.1 FRACTIONAL DISRUPTION PERIODS

One of the underlying assumptions within the verification case (Section 5) is the Markovian format of the disruption model. In Tomlin's [7] work, ordering periods (defined as a full rotation of orders and fulfillment) are either up or down (non-disrupted) as seen by the user. However, this generalized model, while appropriate for scenarios where disruptions always last at least several ordering periods, does not accommodate small-scale disruption events (such as delivery delays) or disruptions that start/stop within an ordering period (resulting in the delivery of a fractional order).

The simulation model presented in this paper employs user-controlled disruption distributions (non-Markovian), which allows fractional orders to be delivered due to downtime in the previous order cycle. In order to test the validity of Tomlin's model in these types of disruption events, a modified version of the verification case study was performed. The following model assumptions are important to note:

1) Disruptions in period i affect the order size delivered in period i+1. For example, if the disruption lasts 25% of year i [three months.], then 25% of year i+1's order will not be delivered on time.

2) Infinite-horizon assumptions are still in place (no cost of money or fixed costs are considered)

3) All of the inputs used in Section 5 were preserved for this case study, with the exception of the expected disruption lengths.

4) When implementing fractional disruption periods into Tomlin's formulas for identifying i_{crit} [7] and the optimal inventory level, the number of modeled periods was rounded up

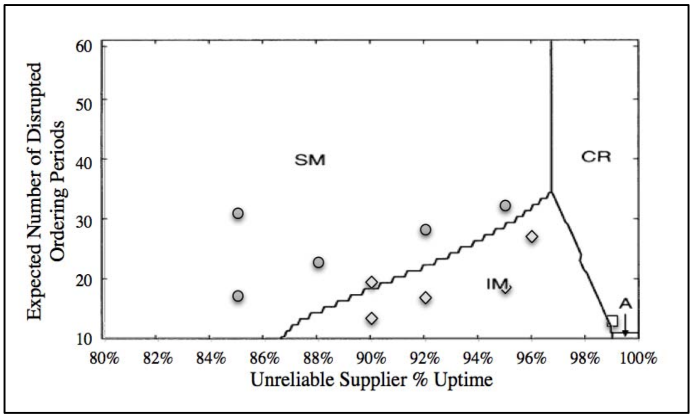

Figure 7: Optimal sourcing strategies for select disruption scenarios. The overlaid dots show the mitigation strategy associated with *fractional disruption* test points: Circles represent Sourcing Management, diamonds represent Inventory Management, and squares represent Contingent Rerouting.

to the nearest integer. The calculated values of i_{crit} are therefore a conservative estimate.

As seen in Figure 7, the inclusion of fractional disruption periods has minimal impact on the optimal mitigation strategy. The simulated points still follow the underlying pattern defined by Tomlin.

7.2 FINITE HORIZON (COST OF MONEY)

In order to study the impact of the infinite-horizon assumption within the verification case, cost of money (r = 2%) was incorporated into the case study outlined in Section 7.1.

Figure 8 shows that the optimal buffering strategy no longer aligns with the results from Tomlin's equations. Instead, the inclusion of cost of money shifts the optimal buffering strategies so that fewer buffered parts are needed in the optimal strategy. In addition, the optimal mitigation strategies no longer match up with Tomlin's overlaid infinite-horizon results (also shown in Figure 8). Instead, second sourcing (or a combination of second sourcing and buffering) becomes a much more prevalent option. Note, the 2% cost of money assumed in this example is significantly smaller than the WACC (weighted average cost of capital) of most electronic systems manufacturers, so the discrepancy is actually much greater than that shown in Figure 8. Tomlin utilizes very long life cycles (100-1300 periods) and minimal recurring costs, so a WACC of 2%/period was chosen (as opposed to a more common value of 10-12%/year) in order to maintain reasonable differences between the cumulative total cost of ownership (CTCO) per part site values. For example, in one of the most extreme cases (1250 modeled years and 98% supplier uptime) the CTCO per part site for second sourcing was found to be \$0.040799998 and the CTCO per part site for single sourcing from the unreliable supplier was found to be \$0.04080001 (a discrepancy of 10^{-8}). If the WACC was increased to a more standard rate, the CTCO per part site values would decrease even further (diverging even more from Tomlin's results).

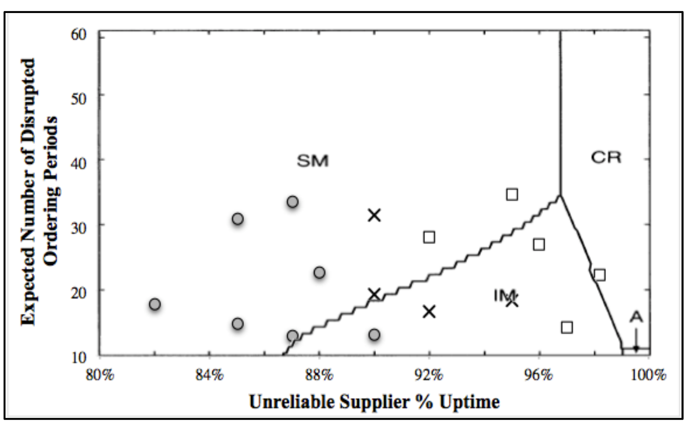

Figure 8: Optimal sourcing strategies for select disruption scenarios. The overlaid dots show the mitigation strategy associated with *cost of money* test points: Circles represent Sourcing Management, squares represent pure Contingent Rerouting, and X's represent a combination of both Contingent Rerouting and Inventory Management.

7.3 FIXED COSTS

Prabhakar et al. [12] noted the significant impact of fixed costs (support costs in particular) on the part total cost of ownership of low volume electronic parts and systems. Low volume, long life cycle products cannot spread the effect of fixed costs over a large part population, so elevated support costs directly impact the TCO per part site. The majority of analytical disruption models, however, focus on long run average costs due to the minimal impact of initial support costs on high volume consumer electronics. In order to study the effect of the fixed costs omission within the validation case, a \$1000 product specific approval cost was added to the case study outlined in Section 7.1. Similar to the reasoning behind the use of a small WACC in Section 7.2, a relatively small product specific approval cost was employed in this case study so as not to unduly offset the small CTCO per part site values accumulated in Tomlin's original case study. Product specific approval costs are a popular form of support costs that are incurred each year a product is introduced and charged for each contracted supplier.

As shown in Figure 9, the addition of fixed costs does not

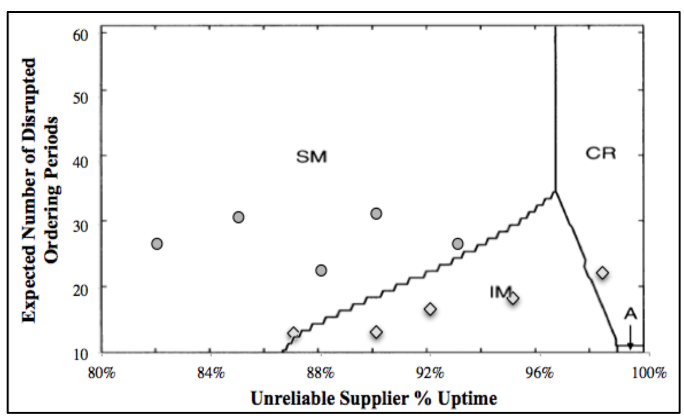

Figure 9: Optimal sourcing strategies for select disruption scenarios. The overlaid points show the mitigation strategy associated with fixed cost test points: Circles represent Sourcing Management and diamonds represent Inventory Management.

have a marked effect on Tomlin's original case study results for disruption scenarios with relatively small-moderate values of overall percent uptime. However, for scenarios with a higher percent uptime (less accumulated disruptions), the effective optimal disruption strategy switches from contingent rerouting to inventory management. This change in results is due to the fact that support costs are duplicated (*K* factor of 1) when the manufacturer contracts two suppliers. The combination of elevated support costs and a premium emergency part price ($2.63 per part from the backup supplier when acting in an secondary/emergency capacity) causes contingent rerouting to be less cost effective than inventory management.

7.4 UNRELIABLE BACKUP SUPPLIER

The case study performed in this section assesses the effect of maintaining a completely reliable backup supplier. This assumption gives manufacturers the option to pay a premium part price in order to ensure a consistently uninterrupted supply of parts. In realistic supply chains, however, supplier disruptions can never be completely prevented at any price and depending on the nature of the disruption, a backup supplier may be affected the same as the primary supplier.

An additional disruption profile was implemented in the simulation model in order to generate disruption events for the backup supplier. The parameters used to describe the disruption profile (Weibull distributions) are shown in Table 1. The parameters were selected to reflect significant disruption events (expected length: 1.6 ordering periods) that occur on average every 5.5 years. All of the other inputs used for this case study are discussed in Section 7.1 and detailed in the Appendix. Once again, the simulation model's internal optimization capabilities were utilized to identify the optimal inventory level instead of Tomlin's [7] formulas.

Table 1: Weibull parameters used to generate disruption events for the backup supplier (Y).

	Backup Supplier (Y)		
	gamma (years)	*beta*	*eta (years)*
Interval	5	1	0.5
Length	1	1	0.6

The unreliability of the backup supplier, while less significant than the unreliability of the primary supplier (i.e., less accumulated disruption) is further exacerbated in this case study by the higher backup part price. As detailed in the Appendix, the primary supplier has a set price of $1.00 and the backup supplier has a set price of $1.05 (unless acting in emergency/secondary backup capacity, in which case they charge $2.63 per part). In Tomlin's original case study, the accumulated penalty costs associated with the unreliable primary supplier outweighed the elevated price of the backup supplier because a continuous stream of parts was guaranteed when single sourcing from the backup supplier. However, as shown in Figure 10, the addition of disruption events at the backup supplier increases the total cost of ownership and makes single sourcing from the less expensive unreliable supplier generally more cost effective. In addition, in regions where single sourcing from the backup supplier is more cost effective (relatively low values for unreliable supplier percent uptime and high values for the expected number of disrupted ordering periods) a small buffer is necessary in order to offset disruption events and achieve the lowest expected cumulative part TCO.

8 DISCUSSION AND CONCLUSIONS

This paper demonstrates the effectiveness of a simulation-based approach when compared to traditional analytical models for the selection of an optimal disruption mitigation strategy. While Tomlin's model [7] and other infinite-horizon disruption mitigation models are generally effective for high-volume, short-ordering period part supply chains, several underlying assumptions prevent them from being applicable to low-volume, long life-cycle products and systems. Four assumptions, in particular, were found to limit the realism of most analytical models but do not constrain a simulation-based model. These limiting assumptions are: 1) no fixed costs associated with part orders, 2) infinite-horizon, 3) perfectly reliable backup supplier, and 4) disruptions lasting full ordering periods (as opposed to fractional periods). The final limiting assumption (disruptions lasting full ordering periods) was modeled in Section 7.1 and found to have minimal effect on the optimal disruption mitigation strategy. The remaining assumptions, however, were found to have a direct and significant impact on the optimal disruption mitigation strategy and therefore cannot be ignored in realistic case studies. By replicating the results of a widely accepted analytical model [7], the simulation model has proven not only its effectiveness as decision-making tool, but also its versatility.

The case studies presented in Section 7 show the effect of slight variations to Tomlin's [7] assumptions, however they do not capture the true potential of the simulator. As shown in the previous paper and Section 4, the simulator is capable of modeling highly specific and realistic cases. In particular, obsolescence-type disruptions and fixed support costs have been

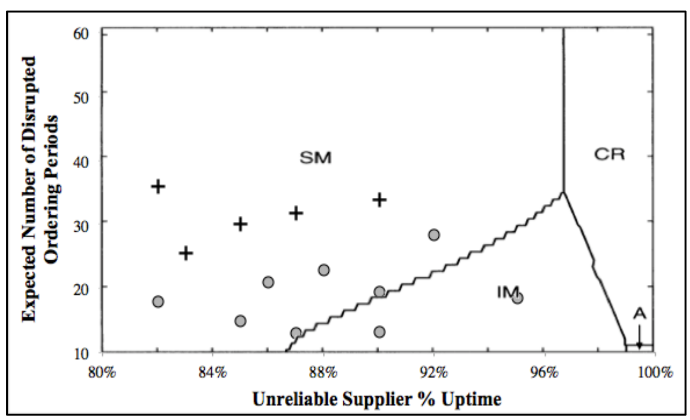

Figure 10: Optimal sourcing strategies for select disruption scenarios. The overlaid points show the mitigation strategy associated with unreliable backup supplier test points: Circles represent Sourcing Management and +'s represent a combination of both Sourcing Management and Inventory Management.

shown to greatly affect the total cost of ownership (and therefore the optimal mitigation strategy). The most effective disruption management plan may not be a single mitigating strategy. Instead, a combination of both second sourcing and buffering has been shown to decrease the mean cumulative TCO.

9 ACKNOWLEDGEMENTS

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APPENDIX

In Tomlin [7], steady-state uptime probabilities (which define the Markovian model) are calculated from cumulative distribution functions that deal with an infinite number of states. In order to efficiently reproduce Tomlin's work, a finite transition state matrix was built in Matlab. This matrix was used to quickly find the optimal buffer quantity associated with a set number of disrupted periods (percent uptime).

Components of transition rate matrix (size of matrix: 1+M+N):

- 1: State space 0 (no disruption occurring)
- M: State spaces representing the minimum number of disruption periods
- N: State spaces representing the possible remaining disrupted periods (in excess of the minimum) with which there is a constant probability of the disruption ending. Ideally N=infinity, but steady state probabilities converge when N is a finite large number

Example: M=4, N=3

State	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
0	λ_U	1- λ_U	0	0	0	0	0	0
1	0	0	1	0	0	0	0	0
2	0	0	0	1	0	0	0	0
3	0	0	0	0	1	0	0	0
4	λ_{du}	0	0	0	0	1-λ_{du}	0	0
5	λ_{du}	0	0	0	0	0	1-λ_{du}	0
6	λ_{du}	0	0	0	0	0	0	1-λ_{du}
7*	1	0	0	0	0	0	0	0

Because the transition state matrix is truncated (after 1+M+N periods) in order to produce a practical model, the final possible state has a transition rate of 1 (returning the system to state 0, no disruptions).

In order to isolate an effective value for N (that allows the system to converge to steady-state), several case studies were performed. In Figure 11 for a steady-state probability of 90.07% and a minimum number of disrupted periods (M) equal to 20, the number of additional state spaces modeled (N) was varied from 0 to 300.

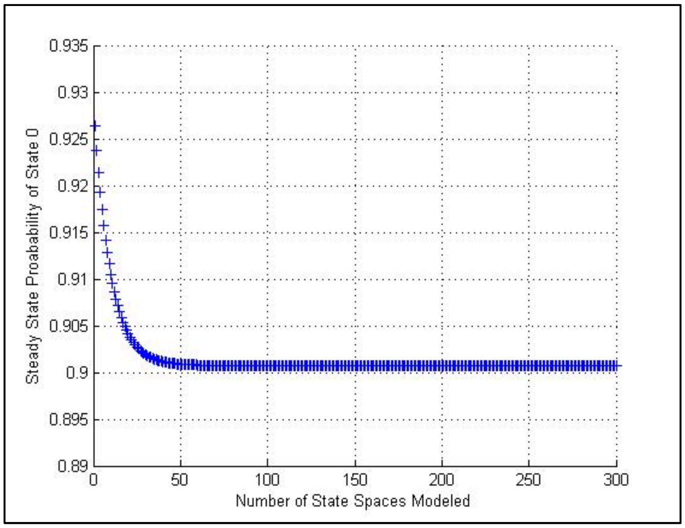

Figure 11: Number of state spaces required to converge to 90.07% steady state probability

The system converged to the expected steady-state value within 100 steps. Similarly, for a steady state probability of 80.01% and a minimum number of disrupted periods (*M*) equal to 40, the number of additional state spaces modeled (*N*) was varied from 0 to 300 as shown in Figure 12.

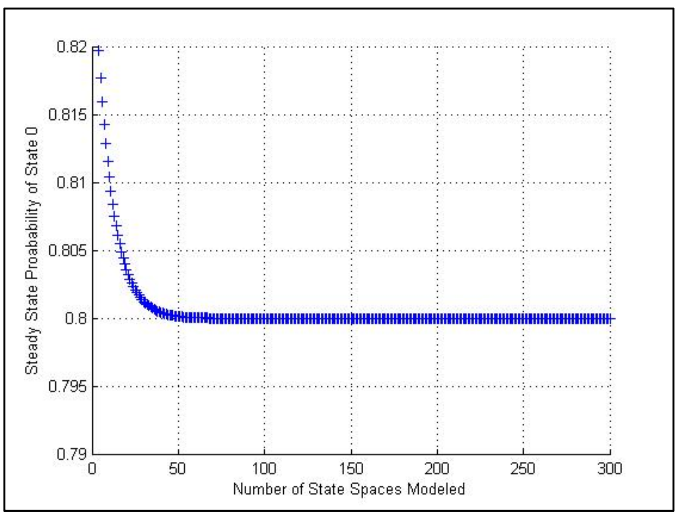

Figure 12: Number of state spaces required to converge to 80.01% steady state probability

Once again, the system converged to the expected steady-state value within 100 steps. Several more state spaces were modeled, and the expected steady-state value was consistently achieved within 100 steps. For this reason, a buffer value of 200 steps was set as *N* for all of the case studies discussed in this paper.

The remaining inputs utilized within the simulation model for the Tomlin-specific case studies in this paper are shown in Tables 2-4.

Table 2: General inputs used to re-implement Tomlin's methodology within the developed simulation model, see [13] for explanation of variables.

General Inputs	
Ratio, K	1.00
Cost of Money, r	0.00%/year
Base Year for Money	1
LTB overbuy	0.00%
Inventory Cost, h (per part)	$0.0015
Price change (per year)	0.00%
Supplier X Price (per part)	$1.00
Supplier Y Backup Price (per part)	$2.625
Supplier Y Base Price (per part)	$1.05
Product Designs	1
Annual Forecasted Part Demand	10
Demand Uncertainty	0
Backorder Penalty, P_{BO} (per part per year)	$0.15
Scrap Cost (per part)	$0

Table 3: Support costs modeled within the reimplementation Tomlin's methodology, see [13] for explanation of variables.

Support Costs ($)	
Product-Specific Approval	0
Initial Approval	0
Annual Part Data Management	0
Annual Production Support	0
Annual Purchasing	0
Obsolescence Case Resolution	0
PSL Qualification	0

Table 4: Supplier specific Weibull parameters used to generate disruption events that emulate Tomlin's methodology within the developed simulation model.

	Supplier X			Supplier Y		
	gamma (years)	*beta*	*eta (years)*	*gamma (years)*	*beta*	*eta (years)*
Interval (years)	100	5	1	3000	0	0
Length (years)	0	1	10	0	0	0
Analysis Run-In Time (years)	0	0	0			