Risk from Network Disruptions in an Aerospace Supply Chain

by

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Abstract

This thesis presents methods for determining the effects of risk from disruptions using an aerospace supply chain as the example, primarily through the use of a computer simulation model. Uncertainty in the current marketplace requires managers to be cognizant of the adverse impact of risk on their company's performance. However, managers who lack formal procedures for dealing with the potential impact of risk often are caught not knowing how much to invest in risk mitigation strategies.

A computer simulation model representing a supply chain for a space vehicle was used to test different disruption scenarios to determine their impact on total production duration time. Scenarios ranging from suppliers not providing parts on time to quality test failures to disease pandemics were all considered. Randomness was incorporated through use of a stochasticity factor that was applied uniformly throughout the model. Output of the model was used to develop confidence percentiles for the complete duration times.

Through testing of the various scenarios using the model we learned that most disruptions will add a deterministic time to the total estimated duration time of the system, regardless of the location of the disruption in the supply chain. In addition, we showed that a thorough review must be performed when choosing the stochasticity factor due to its large influence in determining total duration times and performance percentiles.

The creation of the confidence percentiles allows the aerospace company to use the model throughout the entire 3 to 4 year production process to continually update and evaluate their buffer times and likelihood of meeting target completion dates. This buffer time can then be turned into a key performance index to better manage this supply chain.

This model was created for a real supply chain, and it is currently being used by the aerospace company to help them plan and make appropriate decisions in regards to risk mitigation strategies in preparation for production of the space vehicle. They hope to expand the use of computer simulation models throughout the rest of their division to help drive down costs by increasing efficiencies in their planning.

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Chapter 1: Introduction

1.1 Motivation

1.1.1 Disruption Risk

Several major upheavals of the last decade have highlighted corporate risk due to supply chain disruptions. The September 11 terrorist attack on the United States, Hurricane Katrina's impact to the Gulf Coast in Louisiana and Mississippi, and the recent worldwide financial crisis have all made managers see the negative impact that unplanned disruptions can have on their company's supply chains. But despite this increased awareness of risk, there is still confusion on specific strategies for dealing with it. Upheavals of the magnitude of the three events mentioned above make it apparent that current risk mitigation policies do not offer adequate protection to managers.

Uncertainty in the marketplace makes it a requirement that managers be cognizant of the adverse impact of risk on their company's performance. However, managers who lack formal procedures for dealing with the potential impact of risk often are caught not knowing how much to invest in risk mitigation strategies. To create an objective way for the decision maker to compare the different trade-offs and associated short and long-term benefits, a comprehensive risk assessment is critical in every organization to provide data that leads to good, confident decisions.

1.1.2 Company Example for Thesis

The analysis in this thesis is based on an aerospace company's supply chain for a space vehicle. This system is representative of supply chains for single one-of-a-kind products produced over a multi-year period. This aerospace company is in a market that demands flawless execution of production and complete inclusion of all customer requirements. The company's supply chain also must deliver the highest quality possible for every individual product. This supply chain must be robust and resilient to disruptions but, interestingly, it is also of the type that significant control is surrendered to the other companies that supply the necessary components and sub-assemblies. Due to the integrated nature of these suppliers in the aerospace company's supply chain, many risks could have extensive, negative impacts to the program's performance. This multi-level supply chain presents many areas for potential disruptions. This increases the challenge of delivering the best quality product on time.

In addition to these challenges, the aerospace company is transitioning from a research and development mode to a production mode where they will produce 1-2 of these units per year. During the research and development phase the company did not have to worry as much about production schedules and ensuring sub-tier suppliers met shipment schedules. Ongoing quality was also less of a concern due to the made-to-order nature of development builds. Due to this transition from research and development to production, the risks to this product now originate primarily from the supply chain and steady-state production policies.

To help enhance how to identify and characterize supply chain risk, the research team for this project developed a computer simulation model of this specific supply chain that can analyze the impact of various disruptions. In particular, the goals set forth for this model were to:

1. Analyze the effects of randomness throughout the critical path.
2. See how quality test failures affect the overall duration time.
3. Analyze the impact of disruptions in various production phases or the non-availability of sub-tier components.

Simulation was deemed the best modeling approach for this project due to the complexity of the numerous interactions throughout the entire supply chain. Also, a computer simulation allows for stress testing of the supply chain to see how it performs under extreme conditions. Some of the scenarios described in this thesis are of an extreme nature, but it is through these extreme conditions that the resilience of the supply chain can be tested.

1.2 Supply Chain Background

1.2.1 Process Flow

The complete supply chain for the critical path of the space vehicle is summarized in Figure 1.1. The yellow boxes represent various production steps and quality tests, each with specific completion durations. When added up in series, these individual durations lead to an estimated total production duration of 4-5 years.

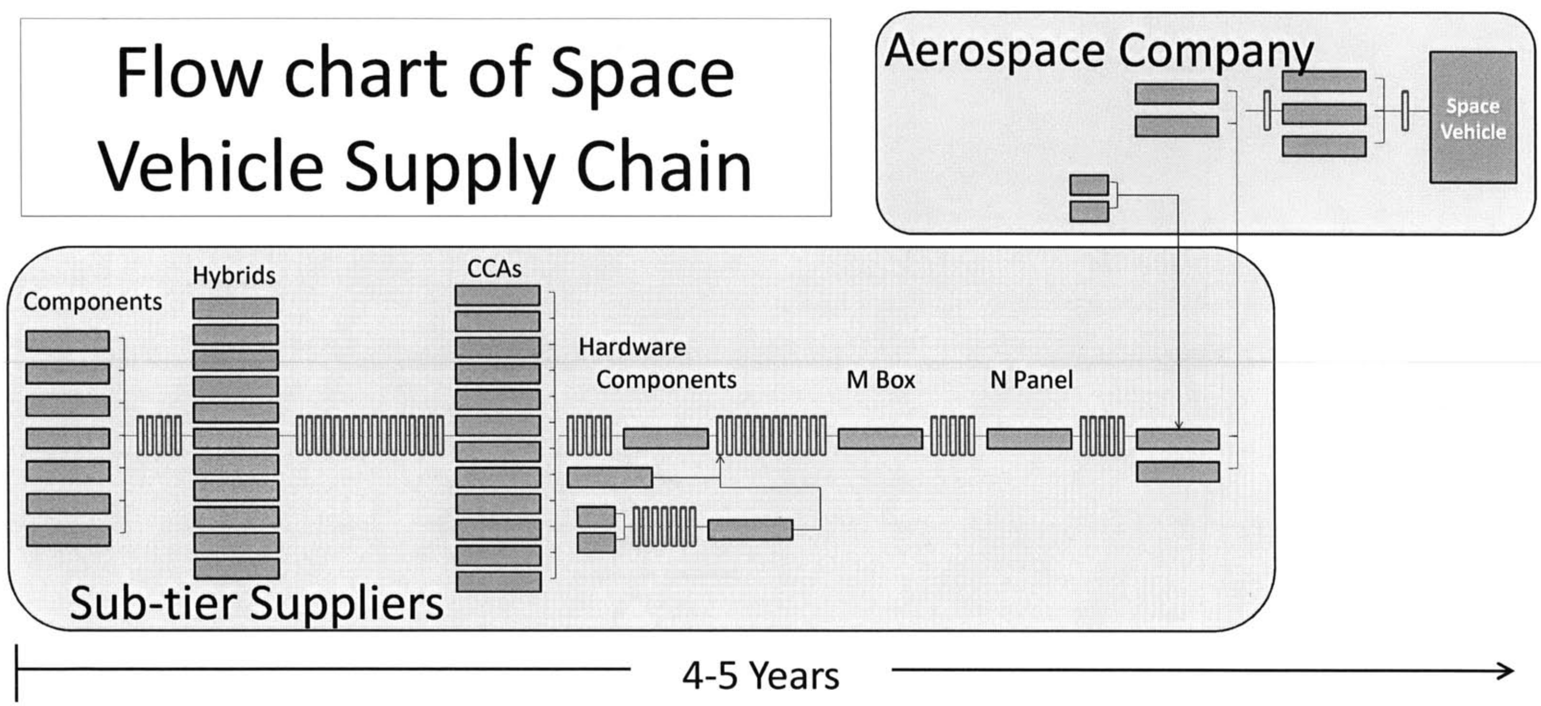

Figure 1.1. Complete Flowchart of Space Vehicle Supply Chain

The chain begins in Figure 1.1 with Component assembly, and then advances to 11 Hybrid assemblies. Each hybrid is created with the same steps as those shown in Figure 1.1, but only one is shown in order to fit the figure on one page. Following the hybrids, the Circuit Card Assemblies (CCAs) are produced, with the same omission of identical steps, and then everything comes together at the Hardware Components stage. From here the flow moves on to the last stages of assembly with the M Box, N Panel (specific assembly names are disguised for confidentiality), and finally the complete Space Vehicle. A non-critical path item called Stock is also included in the figure and joins the critical path at the completion of the Hardware Components. In addition, this figure highlights how this supply chain is controlled by sub-tier suppliers up until the end when total control is finally taken over by the aerospace company.

Each step for the supply chain, along with its duration, is listed in Table 1.1. The base unit for all durations is days. Using the aerospace company's 5-day work week, if all processes proceed according to this plan, the total duration from start to finish is 4.2 years.

Table 1.1. Duration Times (in days) for Each Process of Supply Chain

Process	Process Duration days
Process 1	270.00
Process 2	8.00
Process 3	8.00
Process 4	8.00
Process 5	8.00
Process 6	10.00
Process 7	1.00
Process 8	3.33
Process 9	3.33
Process 10	3.33
Process 11	3.33
Process 12	3.33
Process 13	3.33
Process 14	13.33
Process 15	13.33
Process 16	13.33
Process 17	0.50
Process 18	0.25
Process 19	0.50
Process 20	10.00
Process 21	27.00
Process 22	13.00
Process 23	5.00
Process 24	5.00
Process 25	5.00
Process 26	1.43
Process 27	1.43
Process 28	1.43
Process 29	1.43
Process 30	1.43
Process 31	1.43
Process 32	1.43
Process 33	2.00
Process 34	2.00
Process 35	2.00
Process 36	2.00
Process 37	2.00
Process 38	2.00
Process 39	2.00
Process 40	2.00
Process 41	2.00
Process 42	2.00
Process 43	15.00
Process 44	10.00
Process 45	15.00
Process 46	15.00
Process 47	25.00
Process 48	20.00
Process 49	10.00
Process 50	5.00
Process 51	5.00
Process 52	5.00
Process 53	5.00
Process 54	118.00
Process 55	0.00
Process 56	10.00
Process 57	13.00
Process 58	177.50
Process 59	177.50

This supply chain, as presented in Figure 1.1, represents the steady-state production and thus certain elements were ignored, such as software development. It is assumed that all software development and bug fixes will happen throughout the development phase of the first space vehicle and then the remaining space vehicles will essentially be replicas with the same hardware and software specifications. Thus this project and the associated model are applicable for the product assuming that all research and development work has been completed.

Another important consideration is that this study focuses only on the critical path of the space vehicle supply chain, that is, the production of the M Box. This keeps the scope of the project reasonable while still incorporating the majority of relevant risks and providing general insights of how this supply chain operates. Within the supply chain flow for the M Box, almost all steps follow each other one after the other (creating the M box critical path), with one exception: the Stock assembly. Stock acts as an input component for the M Box, as do the Hardware Component Assemblies (HCAs). Since the HCAs take longer to produce than the Stock, the HCAs are on the M Box critical path, but the Stock is not. By including the Stock in this study, we are able to include an example of non-critical path analysis in the results and why it might be useful to broaden the scope of the study to include even more non-critical paths of this supply chain.

The suppliers for this project are all located in the United States but are spread all around the country. Their locations range from up and down the east coast to California.

1.2.2 Supply Chain Risks

Due to the unique nature of this supply chain, several specific risks were identified that further enhanced the motivation for this study. Since the US government is involved with the contract for this space vehicle and for competitors' products, their power must not be overlooked. If, for example, a disruption were to occur at one of the sub-tier suppliers, the government could come in and reallocate the priorities of who was to receive that product, effectively extending the disruption the supply chain in this study if the government had other priorities at the time.

Also, due to the government's influence, all sub-tier suppliers must be based in the US, creating a situation that could make it difficult or even impossible to have a back-up source prepared to rescue a primary source. Much of the production of high-technology goods in the US has consolidated in recent years due to high labor costs and competition from Asian suppliers. Many of these suppliers are also providing unique parts for this space vehicle, meaning that even if a competitor was available, using their parts would require additional R&D capital and time. This could result in considerable delays in getting another location up and running.

Another unique consideration is the very low volume at which this supply chain will operate. With just 1 or 2 units a year, many sub-tier suppliers might consider this aerospace company to be of low importance and thus give priority to other customers if there was a supply disruption or if capacity became constrained. Without proactive mitigation, these sub-tier suppliers could also allow a product to become obsolete when they may still be needed by the aerospace company for future units, creating a significant problem for successful production of the space vehicle.

1.3 Analysis Structure

The process of researching the background structure of this supply chain and the subsequent development of a computer simulation to model this supply chain had been completed prior to the initiation of this thesis in the fall of 2009. The scope of work for this thesis included taking ownership of the model, performing any modifications that were needed to simulate specific scenarios that had already been developed, and performing all the simulations and data analysis for the predetermined scenarios that are presented in Section 3.2. The scope was expanded after thorough analysis of the generated data from those predetermined scenarios to include additional simulations that add to the understanding of how this supply chain handles disruptions and the importance the inputs to the model. These findings are presented in Section 4.3.

To present the material and research conducted for this study, this thesis is organized as follows. Chapter 2 presents a review of current literature that is applicable to mitigating risk in supply chains. Chapter 3 presents the methods used to obtain the necessary data to understand how this specific supply chain reacts to various scenarios and to conduct the analysis. Chapter 4 presents the actual results from simulating the various scenarios that are defined in Chapter 3. Finally, Chapter 5 summarizes the material by presenting managerial insights and additional research that could add additional understanding of how to mitigate risk from network disruptions.

Chapter 2: Literature Review

In this chapter we present literature relevant to our study. The chapter is organized as follows: in Section 2.1, we discuss literature focusing on project management strategies for dealing with risk and disruptions throughout a project's lifecycle, in Section 2.2, we discuss literature focusing on supply chain disruption risk and strategies, and in Section 2.3 we discuss literature focusing on simulation of supply chain disruptions.

2.1 Project Management

To understand how companies can best protect themselves from supply chain disruptions when producing a single product, we first look at specific project management techniques for skillfully handling risk. Royer (2000) argues that unmanaged or unmitigated risk is one of the primary causes of a project's failure because it is very often simply ignored by the project manager. Often, project managers will manage risk through denial, sidestepping, or shielding themselves by "padding" their estimates with unjustified contingency time, pointing fingers and placing blame elsewhere when something goes wrong. These behaviors are reactive and weaken the credibility of the project manager. Furthermore, according to Royer, today's workplace emphasizes the need to be positive, which leads to problems being seen as opportunities and risks being seen as challenges to be overcome. One who emphasizes risks in this kind of environment is labeled as a negative thinker and a detriment to team unity. However, by not planning for risks the manager cannot minimize their impact. Royer divides risks into two categories: recognizable risks and unmanaged assumptions. Both are to be treated in similar fashion by first identifying and then coming up with a mitigation strategy for each one. At the close of the project, this list should be captured and used to assist new project managers as a starting point for their risk identification.

Swartz (2008) continues with this theme and expands on the importance of a project's stability, defined as the ability of a project to absorb disruption as a result of an unplanned event, using the aviation systems arena as the foundation for his research. The less stable a project is, the higher the likelihood of having deviations spread throughout the entire project network resulting in a loss of synchronization of activities and resources. Swartz argues that project stability is just as important to a project manager as the traditional measures of cost, schedule, and performance. By designing and monitoring specific buffers that are intentionally designed to resist or absorb unplanned variance or events, project managers can best protect themselves from supply chain disruptions.

2.2 Supply Chain Disruption Risk and Strategies

The importance of managing and quantifying risks of disruption throughout a supply chain has recently been given increased attention due to several highly-publicized events of the previous decade. Beginning with the September 11 terrorist attacks and continuing with Hurricane Katrina, media attention has created an unprecedented coverage of large scale service disruptions. Combining these events with new business strategies that strive for lower inventory carrying costs by moving to just-in-time production methods, supply chain managers now have numerous risks to manage in order to keep their operations running smoothly. Sheffi (2007) introduces numerous wide-ranging examples of problems that can occur at any point along a supply chain. Examples include when terrorists bombed four commuter trains in Madrid in 2004 killing 191 people and wounding another 1800, or something as simple as a small fire that was quickly contained in a Philips production facility in 2000, yet led to a disruption of semi-conductor chip manufacturing for weeks. He then presents four methods that companies can follow to reduce vulnerability, including reducing the likelihood of intentional disruptions, collaborating to enhance security, increasing the ability to quickly detect a disruption, and building resiliency through redundancy. By reducing its vulnerability a company can be at a competitive advantage to take market share and build its brand.

In terms of specific strategies in a single product setting, Tomlin (2006) looks at three supply-side tactics to mitigate risk from an unreliable supplier: sourcing mitigation, inventory mitigation, and contingent rerouting. Sourcing mitigation allows a firm to either dual source or have a reliable supplier ready to quickly ramp up production in case an unreliable supplier fails to satisfy orders. Inventory mitigation is basically the building up of excess inventory to cover some unforeseen future shortage. These mitigation strategies require an upfront investment and thus proper planning must be conducted in order for them to be effective. On the other hand, contingent rerouting can be utilized after a disruption occurs as it is shifting either production or transportation methods to minimize a disruption's impact. Schmitt and Tomlin (2009) further explore the sourcing mitigation strategy by examining the tradeoffs between diversification, emergency backup, acceptance, and stockpiling inventory. Diversification is using multiple suppliers to provide the same product on an ongoing basis. While this can be very effective for mitigating disruptions, increased infrastructure costs are necessary to manage the multiple supplier relationships and logistics. Emergency backup eliminates this ongoing investment that diversification requires as it is only used if a disruption occurs, but the per-unit cost will likely be higher and response times may be unpredictable. In addition to these two sourcing strategies, a company can simply choose to accept the disruption or they can build up inventory for use in such a situation.

2.3 Simulation of Supply Chain Disruptions

With the risk mitigation strategies presented in the previous two sections forming a foundation of best protection techniques, we now examine how to quantify scheduling risk using computer simulation. Jain and Leong (2005) demonstrate the value of simulating a supply chain by using the example of a defense contractor sourcing a part from a small company. They found that supply chain simulation can reduce the perceived risk of sourcing from such a small company by performing extreme scenarios (stress testing) and then developing and evaluating strategic changes to mitigate those risks. This simulation analysis provided the confidence necessary to use this small company as a supplier. Deleris and Erhun (2005) also present the benefits of simulation by arguing that such a tool enables managers to evaluate their risk exposure and increase the robustness and resilience of their respective networks.

With a computer simulation model developed, real world solutions can be created, tested, and implemented to make a supply chain more resilient to risk. Schmitt and Singh (2009a) develop risk profiles for locations and transportation connections in a consumer-packaged goods supply chain using Monte Carlo simulation. They test the effects of the profiles using discrete-event simulation in order to have a clear view of the impact disruptions have on a system. Like the project conducted for this thesis, they used Arena software to construct their discrete-event simulation. As an extension of that work, Schmitt and Singh (2009b) present examples using simulation to quantitatively analyze system resilience in a multi-level supply chain. This work is focused on high throughput systems with numerous options for dealing with disruptions, whereas in our work, a low volume production environment produces a single unit after a four to five year period and the options for dealing with disruptions are limited.

Snyder and Shen (2006) also look at multi-level supply chains using simulation. They analyze supply disruptions versus demand uncertainty and compare the effects of both in various environments. Their analysis finds that building resiliency to disruptions is often inexpensive and large improvements in service level can be achieved with only small increases in cost. To make the results of simulation actionable, Schmitt (2009) explains how managers, utilizing a simulation model, can see how various disruptions play out in real time and then test the effectiveness of various strategies. This exercise allows the most cost effective mitigation approaches to be selected. This method will be used in our analysis of the space vehicle supply chain.

To actually conduct a successful simulation, we look to Law (2003), who presents a seven-step approach. To begin, the problem must be stated, performance measures defined, and the scope of the model outlined. By having this foundation, data can then be collected and a conceptual model built. This conceptual model is useful in order to have all stakeholders ensure any assumptions are correct and to iron out any conflicts before the actual programming happens.

Once everyone approves, the actual programming can begin. After programming, the computer model must be verified and validated again by all stakeholders. Verification of a simulation model confirms the model performs as intended while validation confirms the model realistically depicts the system. This process creates credibility for the model. Rabe et al. (2008) present an approach to perform such verification and validation with single, directly usable sub-tasks to perform such verification and validation. After the computer model passes through the stakeholders, simulation experiments are designed, conducted, and analyzed. Finally, the results are documented and presented.

Chapter 3: Methodology

This chapter presents the methods used to obtain meaningful data from our computer model of the supply chain. The chapter is organized as follows: in Section 3.1, we discuss the actual development of the model, in Section 3.2, we discuss several specific disruption scenarios created jointly by the aerospace company and MIT research team, and in Section 3.3 we discuss three additional research extensions that build upon the developed scenarios and further investigate system performance.

3.1 Arena Model

As explained in Section 1.3, the computer simulation that models this specific supply chain was developed outside the scope of this thesis, but it is presented here anyway to provide insight on how this overall project developed. The model was designed using the Arena discrete-event simulation software package from Rockwell Automation Technologies, Inc. This simulation model allows the impact of risks caused by supplier non-availability, variability in the process times, test failures, and various other types of disruptions to be analyzed and interpreted. By performing numerous replications of the model (simulating building numerous space vehicles) a high level of confidence is gained in predicting duration times for each step of the supply chain.

3.1.1 Modeling Approach

The structure of the model is taken from Figure 1.1 with all numeric inputs being inserted into an Excel spreadsheet prior to the start of a simulation run. The various input parameters (e.g., duration times, quality test passing rates and rework times, component availability, and disruptions) can be adjusted via the Excel input worksheet. Figure 3.1 shows a screen shot of the complete Arena model. The colored boxes indicate various checkpoints throughout the supply chain such as hybrids, CCAs, M Box, etc. The vertical boxes in the bottom portion of the figure create the disruption logic, such as a supplier being unavailable.

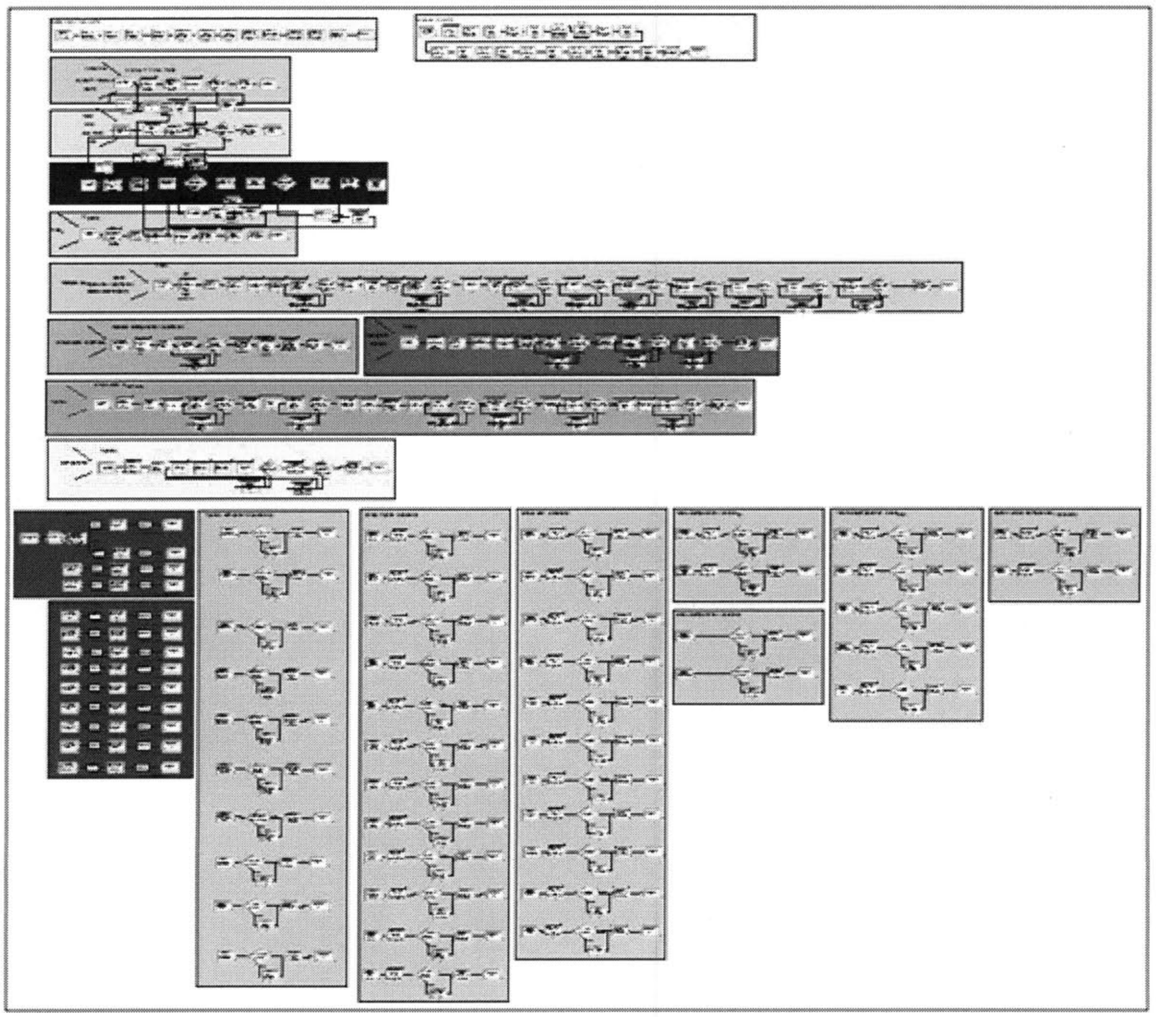

Figure 3.1. Complete Arena Model

To incorporate the natural variation that occurs in real life into the durations for each step of the supply chain, a randomness rate called the stochasticity factor is applied to the entire model. This factor was developed by first assuming that each of the individual processing steps is normally distributed with a mean that is equal to its estimated duration and a standard deviation equal to a fraction of that mean. We define that fraction as the *stochasticity factor*. In other words, the stochasticity factor is the coefficient of variance for all process steps in the model. To illustrate, assume the duration time for the first process in this supply chain was 30 days. If the stochasticity factor is set equal to 20%, then this first process would have a mean duration time of 30 days with a standard deviation of $30 \times 0.2 = 6$ days. With this information, the model randomly selects a unique duration from that distribution for each replication. This stochasticity factor is applied uniformly to the entire supply chain in order to allow for sensitivity testing of its general impact.

Once the specified number of replications is complete, Arena outputs duration times for each process segment from each replication into an Excel spreadsheet. That data can then be used to analyze the performance of that simulation run.

3.1.2 Verification and Validation

As described in Section 2.3, verification of a model involves debugging to the model actually runs as intended while validation involves comparing the actual performance and flow of a system to that of the model's. This section presents the steps conduced to verify and validate the model.

In addition to general modeling collaboration (careful examination of the model by multiple MIT team members) and debugging, to specifically verify the model's output a true deterministic run was performed. This run had no stochasticity for process times and a 100% passing rate for every quality test. This was done to ensure the duration for each replication was the same and added up to the duration that was read into the model through the Excel Input Sheet. The model accurately output a completion time for the space vehicle that matched the sum of individual processing times for the independent steps in the supply chain.

To validate flow of the model, the MIT modeling team confirmed that the entire flow of material in the simulation matches the flow shown in Figure 1.1. The actual model flow was demonstrated to members of the aerospace company for their input, and they felt it to be valid. Additionally, the flow and output was shared with representatives from their main sub-tier supplier and subsequently received their confirmation.

3.1.3 Determining the Stochasticity Factor

After verifying and validating the deterministic model, simulations using various stochasticity factors were performed with the output being analyzed and verified by both the aerospace company and their main sub-tier supplier in order to validate the data itself. Personnel from both companies provided input on what stochastic values would yield the most valid output for the best stochasticity factor. The main sub-tier supplier examined their historical performance and provided data on the stochasticity of the three main steps that it performs. Once these three separate estimates were obtained, the steps were weighted according to the percent of total hours of the work performed at that sub-tier supplier, which are given in Table 3.1. With this information, the data was combined to calculate a stochasticity factor estimate for the entire space vehicle as a whole.

Table 3.1. Breakdown of the Stochasticity Factor

Commodity	% of Total Hours	Stochasticity
Panel	0.22	0.4
Box	0.26	0.3
CCA	0.52	0.2

This leads to a weighted stochasticity factor of $0.22 \times 0.4 + 0.26 \times 0.3 + 0.52 \times 0.2 = 0.27$. Validation of this stochasticity factor came from sharing the output from Arena again with the aerospace company for confirmation.

3.2 Scenario Development

Six different scenarios were developed by both the aerospace company and MIT team in order to see their impact to the various duration times and begin to learn how to leverage this model. The 27% stochasticity factor (as explained in Section 3.1.3) is applied in every simulation. Each scenario is listed below, along with how it is implemented in the model.

3.2.1 Component-, Hybrid-, & CCA-Level Disruptions

The first three scenarios are very similar to each other as they each test a deterministic disruption of a specific supplier. The component-level disruption uses a diode contractor as the supplier and is modeled using three different durations: 20 days, 60 days, and 120 days representing 1 month, 3 months, and 6 months, respectively. Using these three durations, many possible supply chain disruption scenarios can be captured. For example, consider the 60-day duration. Suppose there is actually only a 20-day disruption at the diode supplier, but after the disruption the government regulates the destination of the diodes produced following the disruption; this could, for example, extend the disruption for another 40 days. The 60-day duration also captures a situation where the diode supplier could be down for 120 days but an alternate supplier is brought online within 60 days. Finally, it is not only disruptions of the actual supplier that this scenario captures; any kind of engineering design changes or even a physical change in location that causes a significant delay in production is captured in this scenario.

These same disruption durations are also tested on the hybrid and CCA levels of this supply chain. Each of these scenarios tests the effects of such a disruption that happens progressively later in the overall process of producing the space vehicle.

3.2.2 Pandemic

If a pandemic outbreak was to impact the aerospace company, the company estimated that 60-80% of their workforce could be unavailable for a period of 4 to 12 weeks. This scenario calculates the impact such a pandemic would have at one of the two facilities directly controlled by the aerospace company assuming a worst-case 12-week impact.

The standard duration of the stage of production conducted at either of the aerospace company's facilities is 177.5 days. Since a 12-week disruption is 60 days (assuming a 5-day work week), a pandemic would only affect a portion of this duration. To calculate the effect, we break the 177.5 days into two parts: production time not affected by the pandemic (PT_{NA}) and production time affected by the pandemic (PT_A), and then add them together to determine the new total duration time. PT_A is derived assuming that the effected duration of production would take 100%

of the original time (while only a portion of the workforce is working) plus the proportion that still had to be performed once the workforce was back. The formulations are detailed below:

.

$$PT_{NA} = Original\ Total\ Duration - Duration\ of\ Pandemic \qquad eq. 3.1$$

$$PT_{A} = Duration\ of\ Pandemic \times (1 + Percent\ of\ Workforce\ Affected) \qquad eq. 3.2$$

$$Total\ Duration\ with\ Pandemic\ Outbreak = PT_{NA} + PT_{A} \qquad eq. 3.3$$

For a 12-week, 60% pandemic outbreak:

$$PT_{NA} = 177.5 - 60 = 117.5\ days \qquad eq. 3.4$$

$$PT_{A} = 60\ \times\ (1 + 0.6) =\ 96\ days \qquad eq. 3.5$$

$$Total\ Duration\ with\ Pandemic\ Outbreak = 117.5 + 96 = 213.5\ days \qquad eq. 3.6$$

3.2.3 Smart Sparing

One risk mitigation idea for a supply chain that produces only one unit every year or so is to build two units at the same time instead of only one. This would mean that a quality failure of one of the units would not affect the delivery time of the promised unit. To simulate this risk mitigation approach, the first quality failure of any replication should not result in any rework time and instead the system should continue onwards without any delay.

This scenario required a slight modification to the Arena model. For the base input values, only three quality tests have less than a 100% passing rate. At the first instance of a quality test failure, the model will continue on as if the test was actually successful. However, any subsequent quality test failure will result in the normal rework time. To track whether a quality test failure had occurred, a new variable was created in Arena with an initialized value of 0. When the simulation had a quality test failure, it checked this variable to see if the value was still 0. If so, the simulation changed the value of the variable to 1 and continued moving forward without doing the rework for the failed test. If the variable already had 1 as its value, then the rework time would be applied since there is no longer a good spare that the production line could continue with.

3.2.4 N Panel Failure

The last scenario simulates a test failure at the point right before the aerospace company would take complete ownership of the nearly-complete space vehicle. Once the N Panel is completely assembled it goes through the "Complete Functionality Test". If it fails, it must be totally disassembled, repaired, and then reassembled. A failure at such a late stage in the entire process would be rare, but due to the complexity of its rework, the impact on the total completion time could be dramatic.

Here, as with the Smart Sparing scenario, a modification to the Arena model was necessary because we want the Complete Functionality Test to fail once and only once. To accomplish this, we hardcoded a 0% pass rate for this test and added a new step in the model immediately following this test. This new step reassigned the pass rate from 0% to 100%, ensuring that 1 and only 1 failure of this test would occur. As data to determine how long it would take to disassemble and repair the N Panel was not available, the modeling team assumed it would take the same number of days for it to be assembled, which is 20 days, before reassembly could occur.

3.3 Research Extensions

Section 3.2 contains all of the testing that was proposed by the aerospace company for the scope of the original sponsored project. For this thesis, we have used this validated model to further investigate system performance in regards to three specific areas: the stochasticity factor, quality test failure rates, and using different probability functions when defining disruption duration. This investigation into these extensions is an independent study to determine whether or not they are directly relevant to the aerospace company and to see what additional insights into this type of supply chain can be made.

3.3.1 Stochasticity Factor

For this research extension we look at what impact different stochasticity factors have on the overall results. As described in Section 3.1.3, the stochasticity value determined to be the most appropriate for this model was 0.27. However, we wanted to understand what happens when this value is changed. We look at the output for values of 0%, 20%, 27%, 40%, and 100%. These results are compared and the importance of an accurate stochasticity factor is discussed in Section 4.3.1.

3.3.2 Test Failure Rates

As with the stochasticity factor, the test failure rates are predetermined inputs into the model, and they play an integral role in determining the accuracy of the output of the model. As determined by the aerospace company, only 3 of the 25 quality tests in the model have a passing rate of less than 100%. By altering these rates we will better understand their effect on schedule risk and the importance of accurately capturing and modeling the rates. For this research extension we assume that every quality test has the same passing rates in order to keep everything uniform so there is no unintended bias towards any quality test. We simulate rates of 100%, 99%, 98%, 95%, 90%, and 85%. Since rework times were not provided for the majority of the tests, we assume that they are the same duration as the previous process step since it would have to be repeated for the rework. Those times are shown in Table 3.2, with the test passing rate is listed a 99% as an example.

Table 3.2. Rework Times for Quality Tests

Test	Test Passing Rate %	Rework Time in days
Quality Test 1	99	24
Quality Test 2	99	8
Quality Test 3	99	1
Quality Test 4	99	3.33
Quality Test 5	99	13.33
Quality Test 6	99	13.33
Quality Test 7	99	0.25
Quality Test 8	99	27
Quality Test 9	99	13
Quality Test 10	99	1.43
Quality Test 11	99	1.43
Quality Test 12	99	1.43
Quality Test 13	99	2
Quality Test 14	99	2
Quality Test 15	99	15
Quality Test 16	99	10
Quality Test 17	99	15
Quality Test 18	99	15
Quality Test 19	99	25
Quality Test 20	99	20
Quality Test 21	99	10
Quality Test 22	99	118
Quality Test 23	99	10
Quality Test 24	99	177.5
Quality Test 25	99	177.5

3.3.3 Probability Distributions

In all of the scenarios described in Section 3.2, a deterministic time was used to define the duration of the disruption. However, this model allows for a random value to be used by defining a statistical distribution. In this test, both exponential and triangular distributions will be used. As the data from Schmitt and Singh (2009a) shows, most distribution fits for disruption durations have long tails for their probability density function curves. Thus we assume the exponential distribution is a good fit, and we use it as the baseline for evaluation. For this study, the component-level disruption will serve as the scenario example. Implementing the use of an exponential distribution is straightforward; the deterministic duration previously used simply becomes the mean for the exponential distribution, which the model then uses to randomly select the new duration. Using an exponential distribution would also be simple to implement in the data gathering phase as it only requires a user to know the average time for disruptions.

The exponential distribution is normally used for events that are of extremely random durations by nature and thus it may not be the best choice for every type of disruption in this supply chain, such as if a dual-sourced part has a quality problem and the lead-time for switching between the two suppliers is well known. For this reason, we also investigate using a triangular distribution when defining the length of disruption durations. This distribution keeps the data gathering process simple by only requiring two additional data points: the absolute minimum and maximum disruption times. For instance, in Section 3.2.1 we describe testing what happens when there is a 60 day disruption at the component level of the supply chain. Instead of a deterministic time of 60 days, we can use a triangular distribution with a minimum duration of 20 days, a maximum duration as high as 120 days, and a most likely duration of 60 days.

The actual testing was performed as follows. First, to establish a baseline, we simulated what happens when a component-level disruption occurs with an exponentially-distributed duration with a 60-day mean. Next, we used a triangular with the values discussed in the paragraph above, which retains 60-days as the most likely observation. Finally, we used the minimum and maximum observations from the output of the exponentially-distributed disruption simulation to determine a minimum and maximum for a new triangular distribution. With these three sets of results we make a comparison between the deterministic model versus using probability distributions. We also evaluate whether the exponential can generally be used or whether the additional work to collect the extra data for the triangular inputs should to be carried out.

Chapter 4: Results

This chapter presents the results from simulating the various scenarios and research extensions outlined in Chapter 3. The chapter is organized as follows: in Section 4.1 we present the baseline data which will offer a foundation from which we can understand the true effect of changing the inputs to the model, in Section 4.2 we present the results from the specific scenarios defined by the aerospace company, and in Section 4.3 we present the results from the three research extensions that attempt to create further understanding of this supply chain.

All data presented throughout this chapter is based on 1000 replications. One replication is a single simulation of this supply chain using the Arena model. Using random number generation, multiple replications help a user see all of the different possible outcomes of a certain set of input conditions. By always running 1000 replications in this study the confidence intervals around the mean are sufficiently tight while ample extreme values of behavior are also provided.

4.1 Baseline Data

As described in Section 3.1.4, a stochasticity factor of 27% is believed to give the most accurate representation of this supply chain. As such, this is the baseline that we use when testing the impact of each differing scenario presented in this section. The importance of choosing the correct stochasticity factor is explored in Section 4.3.

With a 27% stochasticity factor, the overall completion time for production of a single space vehicle ranges from 729 days to 1419 days. At the suggestion of the aerospace company, days are the base unit for all inputs and outputs to the model. As the aerospace company conducts a 5 day work week, these numbers can be converted to weeks and years, as shown in Table 4.1. Going forward, all data will be presented in years, although disruption times will still be given in days since those are the units actually used in the simulation.

Table 4.1. Completion Time Conversion Table

Simulation Observations	Days	Weeks	Years
Minimum Completion Time	$729\ days$	$\frac{729}{5} = 146\ weeks$	$\frac{146}{52} = 2.8\ years$
Maximum Completion Time	$1419\ days$	$\frac{1419}{5} = 284\ weeks$	$\frac{284}{52} = 5.5\ years$

Due to the large difference between these numbers, we have consolidated all 1000 replications into what we refer to as confidence percentiles. Table 4.2 shows the confidence percentiles for our baseline test. A confidence percentile indicates the likelihood the actual production of the space vehicle will be complete prior to the number of days listed. That is to say, we are 95% confident the space vehicle will take less than or equal to 4.8 years to produce, given that the stochasticity factor is 27%.

Table 4.2. Confidence Percentiles for Baseline Test

Confidence Percentile (%)	Baseline (in years)
10	3.6
20	3.8
25	3.9
30	4.0
40	4.1
50	4.2
60	4.3
70	4.4
75	4.5
80	4.5
90	4.7
95	4.8
98	5.0
99	5.2

These numbers can also be shown graphically to help visualize the rise in the number of days as the confidence percentile increases (see Figure 4.1). This is helpful when comparing different scenarios as they can be placed on the same graph and the differences are quickly seen.

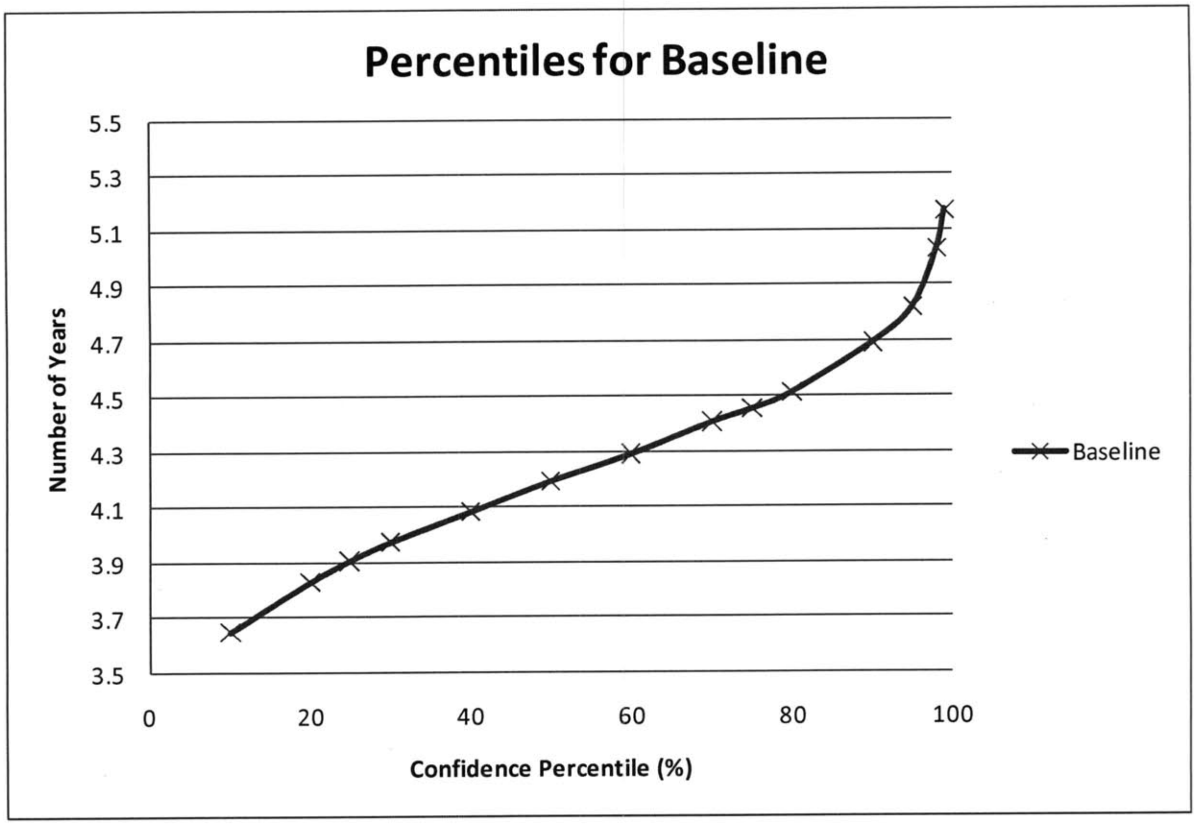

Figure 4.1. Graph of Confidence Percentiles for Baseline Test

While this graph is helpful for a quick understanding of the differences, the easiest way to compare testing results is to pick a certain confidence percentile as a goal and use that number in all comparisons; for example, we will focus on the 95th percentile in discussing the results throughout this chapter. In order to view the impact of each scenario and research extension, the curve in Figure 4.1 will be included in most of the results that follow.

4.2 Scenario Data

This subsection presents the data for the six scenarios that were developed jointly between MIT and the aerospace company as discussed in Section 3.2. Graphs will be provided for each scenario and the numerical outputs can be found in the Appendix.

4.2.1 Component-, Hybrid-, and CCA-Level Disruptions

Figure 4.2 shows the overall duration time to complete the space vehicle if a component-level supplier is disrupted for 20, 60, or 120 days, as compared to the baseline curve that was given in Figure 4.1. It shows how a deterministic disruption length will simply translate into a deterministic addition to the overall duration time (an upwards shift of the curve). For instance, the 95th percentile (indicated by the red vertical line in Figure 4.2) for a 60-day disruption would increase from 4.8 years to 5.1 years, a difference of 60 production days. This assumption that we know exactly how long a disruption will last is challenged in Section 4.3 where the duration is instead modeled using a probability distribution.

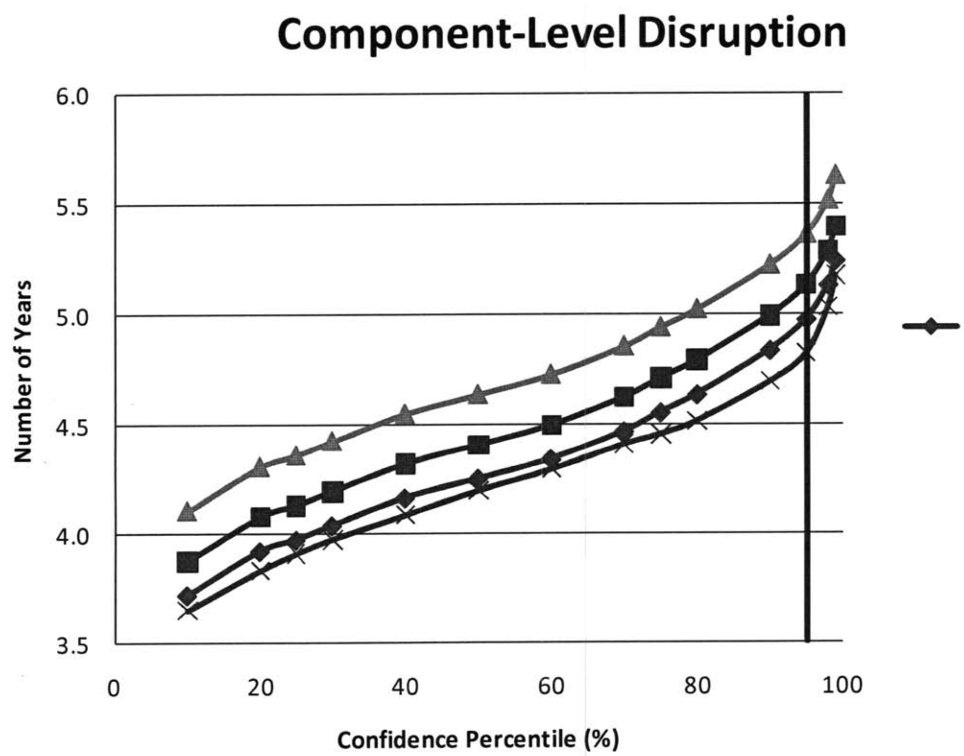

Figure 4.2. Component-Level Disruption Results

As the component-level suppliers are used very early in the supply chain, a disruption at this level may not necessarily require immediate expediting. This deterministic shift means that the original target date can now be reevaluated with a new confidence level for whether it will be met. For example, if the original committed target duration was 5.1 years, which provides a confidence level of 95% under the baseline scenario, and a 120-day disruption were to occur, this confidence level drops to 60%. Immediate expediting may not be required if 60% is a comfortable confidence for the organization. Thus the information output by the simulation can be used to evaluate the current risk of missing the scheduled target date in real time and operations management can make informed decisions and react accordingly.

As with the component-level disruption, a 20, 60, or 120 days disruption at the hybrid- or CCA-level in the supply chain leads to a deterministic addition of 20, 60, or 120 days to the overall duration curve for each. These figures are omitted since they match Figure 4.2, but they are included in Section A.1 in the Appendix for completeness. However, since those disruptions occur earlier in the supply chain, management will need to carefully assess the impact this will have on downstream operations and whether changes need to be made to the schedule for issues. For example, changes might be required to adjust the correct time to place orders for components.

4.2.2 Pandemic Results

The blue line in Figure 4.5 shows what impact a pandemic will have that affects 60% of the aerospace company's workforce for a duration of 12 weeks. The red line shows what happens when 80% of the workforce is affected. This company has two locations but their output curves are identical so only one is shown.

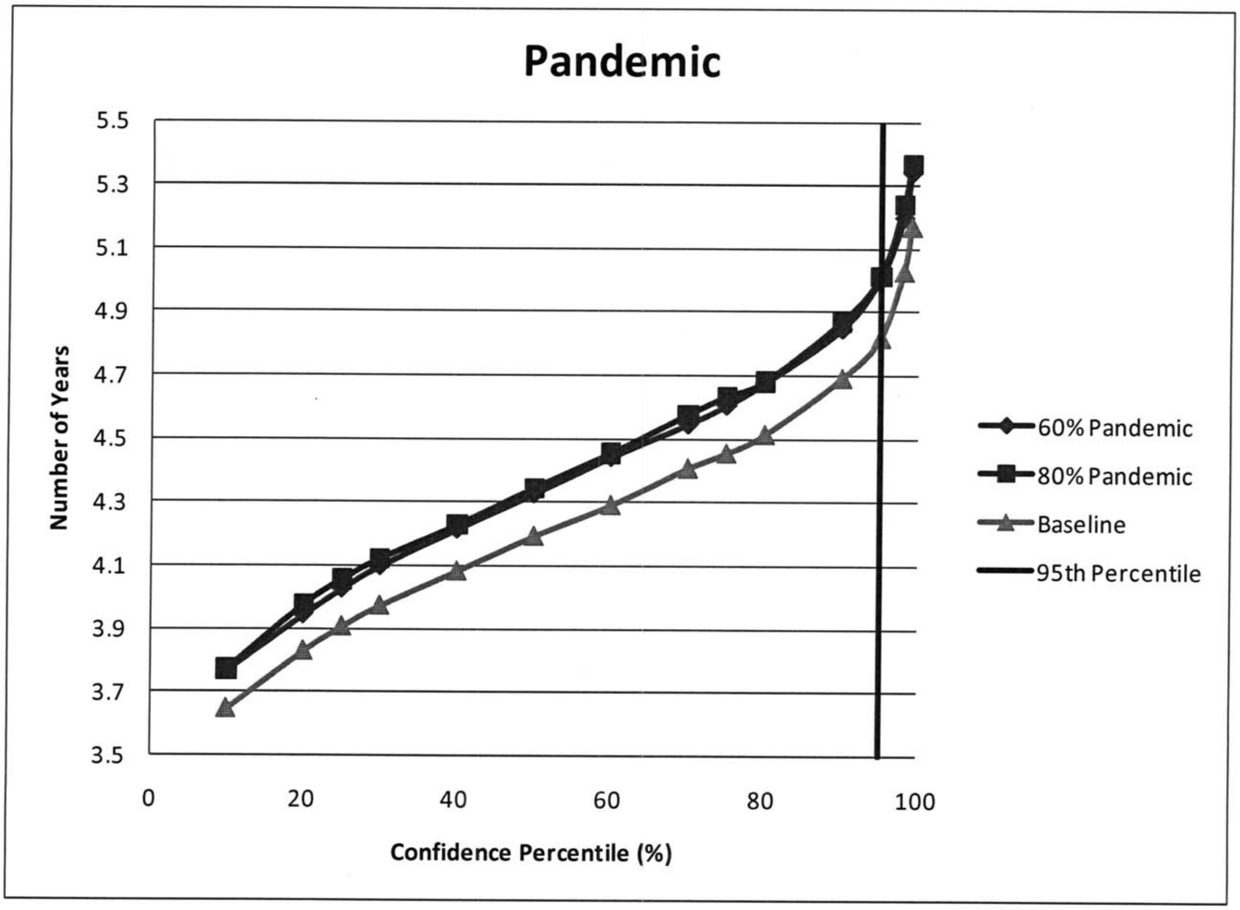

Figure 4.3. Pandemic Disruption Results

At the 95th Percentile, both a 60% pandemic and an 80% pandemic increase the total duration from 4.8 to 5.0 years. These curves are so close because there is only a 12 day difference in the disruption times between the two measurements. Since there is very little difference between the 60% and 80% levels, decision making should be based on the 80% line as it represents the worst case.

This scenario assumes that work is still being performed even with such a large percentage of employees unable to perform their duties, which may be too optimistic to truly consider it the worst case. While the aerospace company will undoubtedly do everything in its power to keep production going, without 80% of their workforce this could be very hard to do due to the potential lack of key, skilled labor. Instead of progressing at a slower rate, production could actually stop completely until enough employees were able to return to work. Thus pandemic impacts could be even worse than those observed here, and the company should spend time exploring what the most realistic duration and impact scenarios are.

4.2.5 Smart Sparing Results

Figure 4.4 shows what improvements could be obtained by using the Smart Sparing technique discussed in Section 3.2.5. However, as the graph shows, this idea has very little positive impact. The limited impact is due to the fact that there are only a few tests that have any failure rates in the model and to the small rework times for those few tests. According to the input data, only three quality tests can fail and the first test has a rework time of only 0.5 days. So, even if this test were to fail, the spare would only improve the performance by half a day. The second test has a rework time of 3 days and the third test a rework time of 15 days. At the 95^{th} percentile, the total duration time stays at 4.8 years, even with the spare unit.

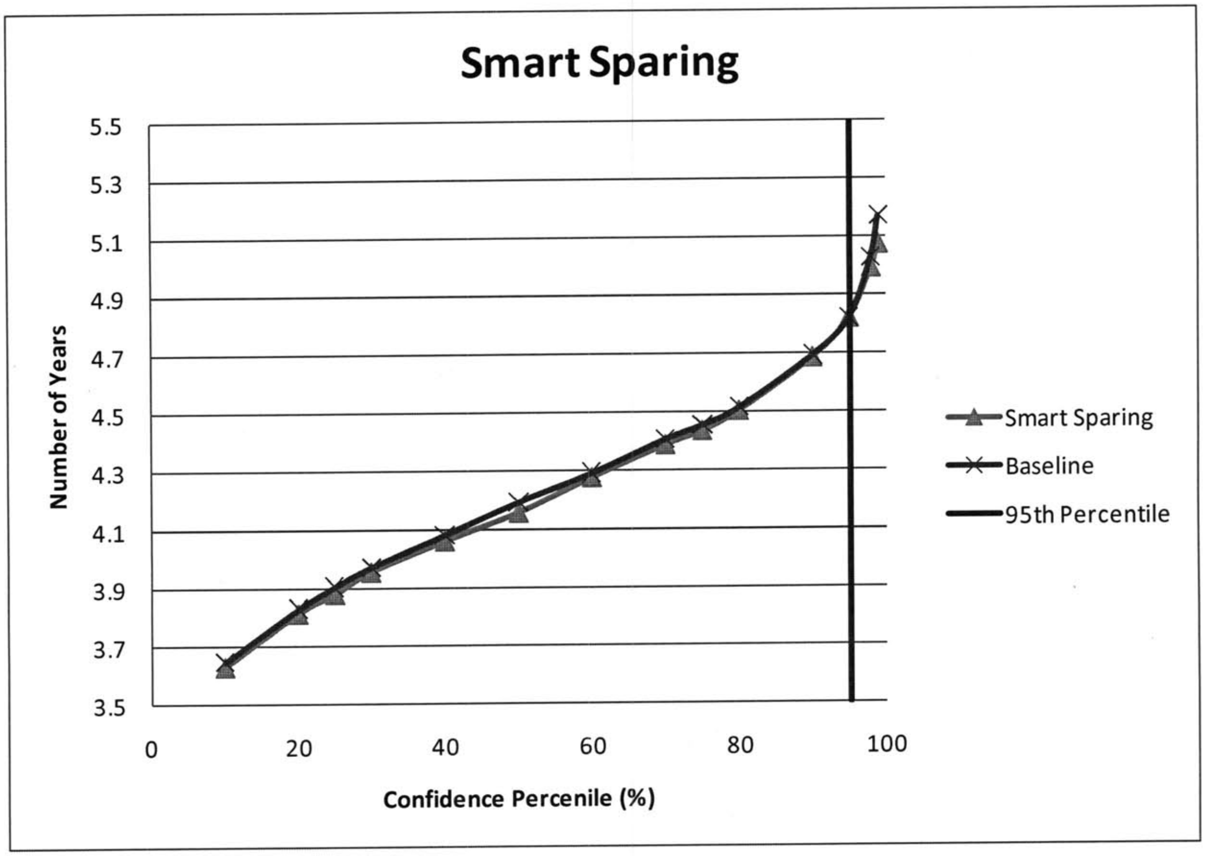

Figure 4.4. Smart Sparing Results

One potential strategy that could increase the benefit of this tactic would be to hold the spare (rework both pieces as needed) until the last test since it has the highest rework time. This strategy should be examined carefully based on this insight; if a smart sparing plan is implemented, the spare should be reserved for use when it is likely to do the most good (i.e. provide the largest time savings).

4.2.6 N Panel Failure Results

Figure 4.5 shows the impact of having the N Panel fail its quality test, assuming a 20 day disassembly time. The impact of such a failure is large, since not only does the failure require a disassembly, but all the steps of assembly must be performed again. To illustrate the impact numerically, suppose the overall production schedule is based on the 95th percentile of the baseline (4.8 years). A quality test failure would reduce the confidence of an on-time delivery down to nearly 50%.

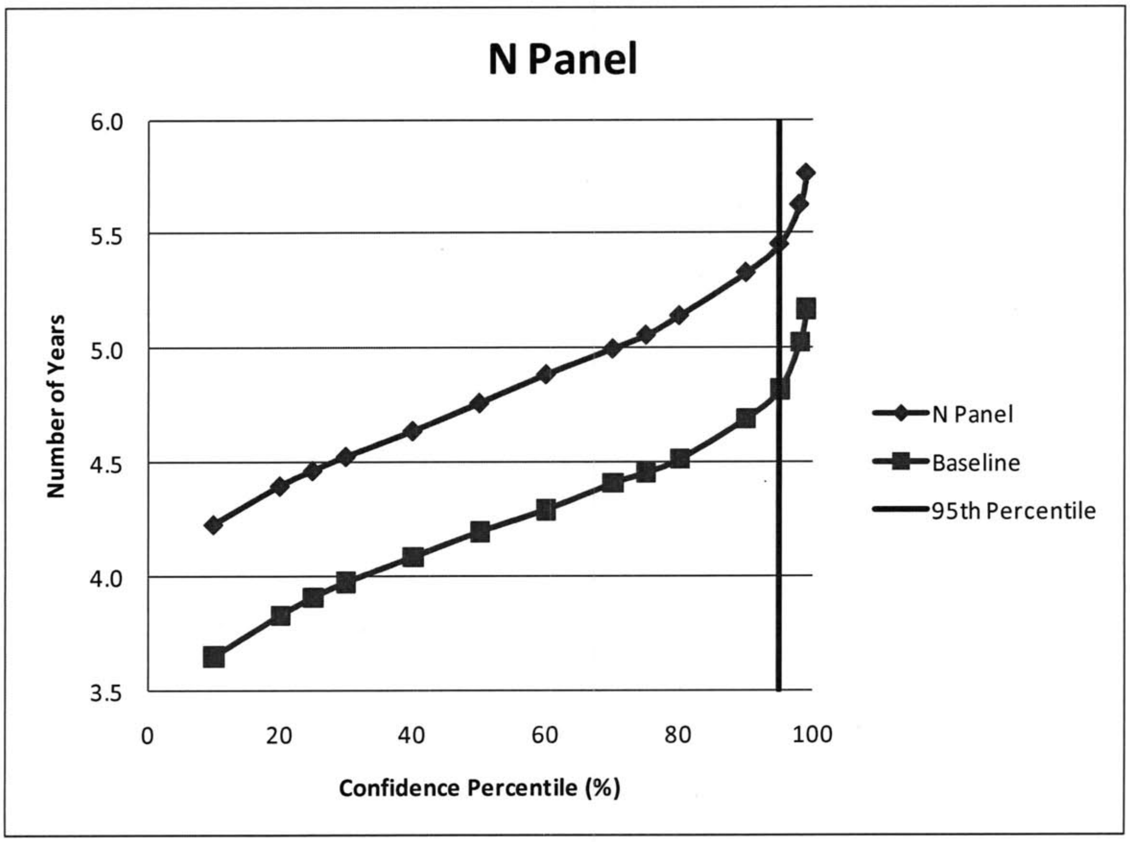

Figure 4.5. N Panel Failure Results

It is very important to have strong quality tests up to this point in order to ensure the N Panel passes this test and avoid having to perform a complete disassembly. Adding earlier tests as the panel is assembled could help reduce this risk.

4.3 Results from Research Extensions

This section presents the results from the research extensions that were developed after analyzing the results from each of the predefined disruption scenarios described above.

4.3.1 Stochasticity Factor Results

To determine the impact the selected stochasticity factor has on the results of our computer model, we first looked at what happens when the stochasticity factor is reduced all the way to 0%. This means there is no variability in any of the process times, so we consider the output from this scenario deterministic. However, there is some small variation because quality test failures can still occur, although as described in Section 3.3.2 only 3 of the 25 quality tests in the model have a passing rate of less that 100% and even those have low fail rates. Due to these conditions, the output is very stable and precisely predicts how long the entire production time would be if every process took exactly as long as predicted. The graph in Figure 4.1 shows how long the 1000 replications took to complete the space vehicle production, with the jumps showing replications where test failures occurred. Also note that the total duration only ranges between 4.2 and 4.5 years.

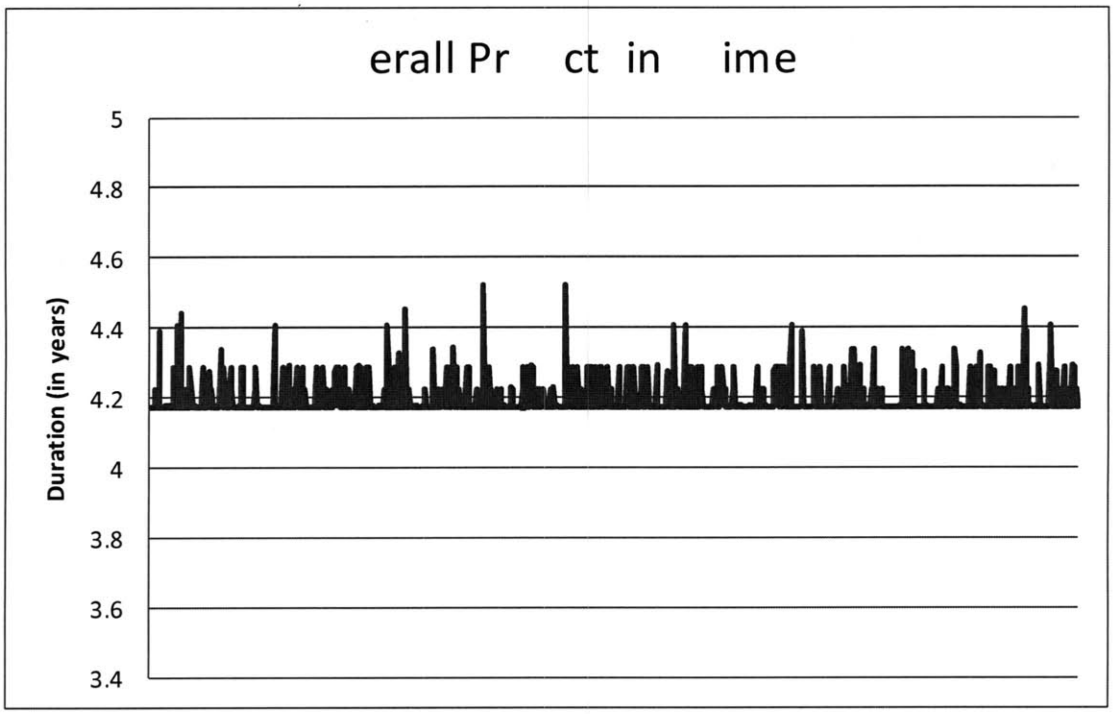

Figure 4.6. Deterministic Overall Production Time

Since the overall production is essentially flat for this deterministic scenario, the confidence percentile graph, shown in Figure 4.7, is predictably nearly a straight line, with the quality test failures providing a small rise as the curve approaches 100% confidence.

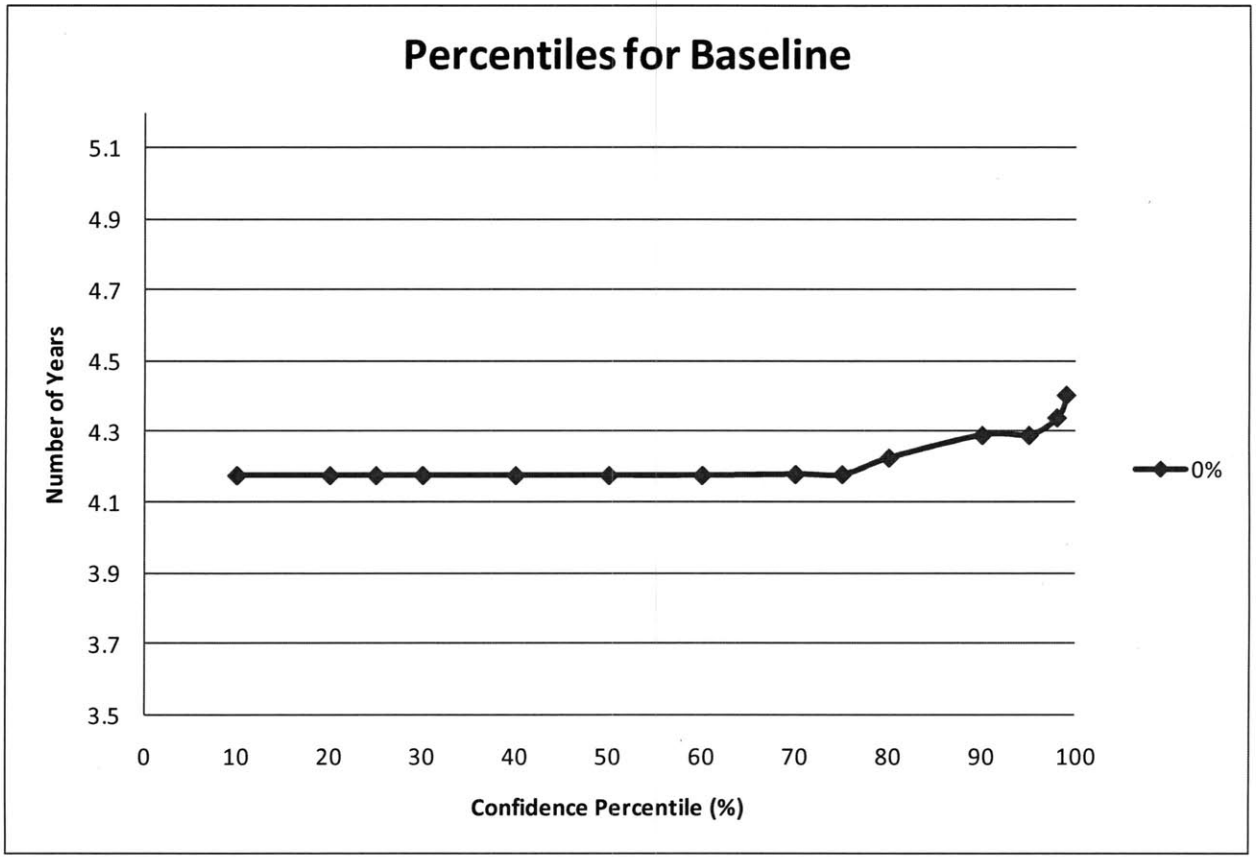

Figure 4.7. Confidence Percentiles for 0% Stochasticity

We now add variability to the duration times for each process by increasing the stochasticity factor. This is a vital study since the factor that we assign to the model has major consequences in determining the total duration time and confidence intervals for the production of a space vehicle, as shown in Figure 4.8.

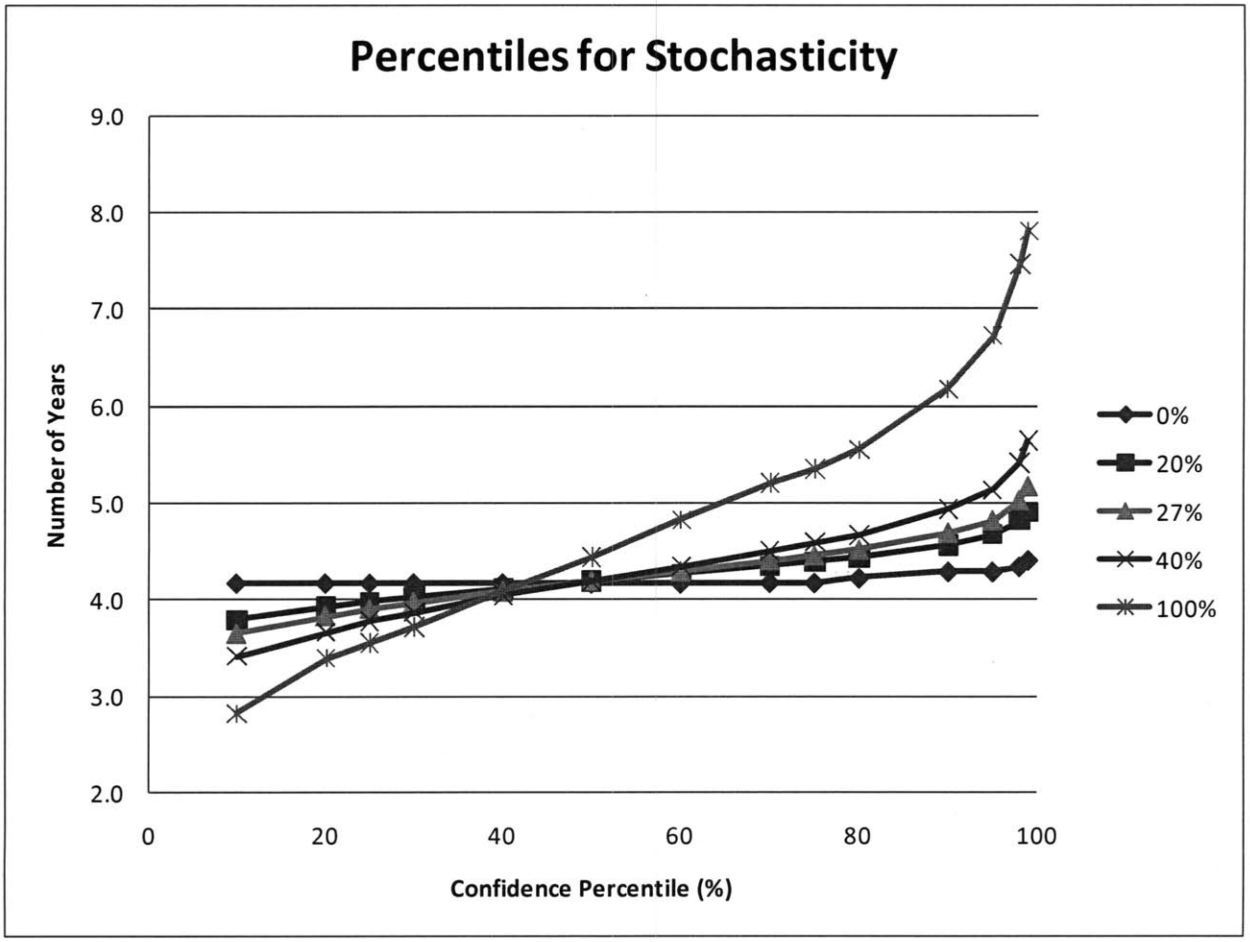

Figure 4.8. Stochasticity Factor Results

As is clearly shown, the chosen stochasticity factor has a very large impact when calculating the confidence percentiles. At a confidence percentile of 95%, the total maximum duration ranges from 4.3 to 6.7 years.

Mathematically, each curve in Figure 4.8 should have the same value at the 50th percentile point because a normal distribution ranges from negative infinity to positive infinity. However, the numbers do not exactly match since we cannot let the realization for processing times go negative (whereas true, non-truncated normal distributions do allow for negative realizations).

Instead, our lowest limit is 0 and our highest limit is positive infinity. Thus as stochasticity rises, so does the value at the 50th percentile point.

Another interesting observation is that below the 40th percentile the overall durations actually decrease for higher stochasticity factors. This happens because we do not define an absolute minimum for each process and thus with the higher standard deviations for each process, lower values can be randomly chosen by the simulation software.

To stress the importance of these results, the numeric data is reproduced in Table 4.3.

Table 4.3. Confidence Percentiles for Varying Rates of Stochasticity

Confidence Percentile (%)	0%	20%	27%	40%	100%
10	4.2	3.8	3.6	3.4	2.8
20	4.2	3.9	3.8	3.7	3.4
25	4.2	4.0	3.9	3.8	3.5
30	4.2	4.0	4.0	3.9	3.7
40	4.2	4.1	4.1	4.0	4.1
50	4.2	4.2	4.2	4.2	4.4
60	4.2	4.3	4.3	4.3	4.8
70	4.2	4.4	4.4	4.5	5.2
75	4.2	4.4	4.5	4.6	5.3
80	4.2	4.4	4.5	4.7	5.5
90	4.3	4.6	4.7	4.9	6.2
95	4.3	4.7	4.8	5.1	6.7
98	4.3	4.8	5.0	5.4	7.5
99	4.4	4.9	5.2	5.6	7.8

Even with no disruption to this supply chain, there is still a dramatic difference on the output of the model simply depending on the stochasticity factor. If a manager wants 95% confidence in the schedule, the numbers to set as the target range anywhere from 4.3 years to 6.7 years.

Taking these results one step further, we reexamined the component-level disruption of 60 days from Section 3.2.1 and changed the stochasticity from 27% to 40%. Recall that one of the production segments did have a 40% stochasticity factor according to the main sub-tier supplier, as shown in Table 3.2. Figure 4.9 further demonstrates the importance of choosing or calculating the correct stochasticity factor for this model of the supply chain since the completion time curve shifts considerably.

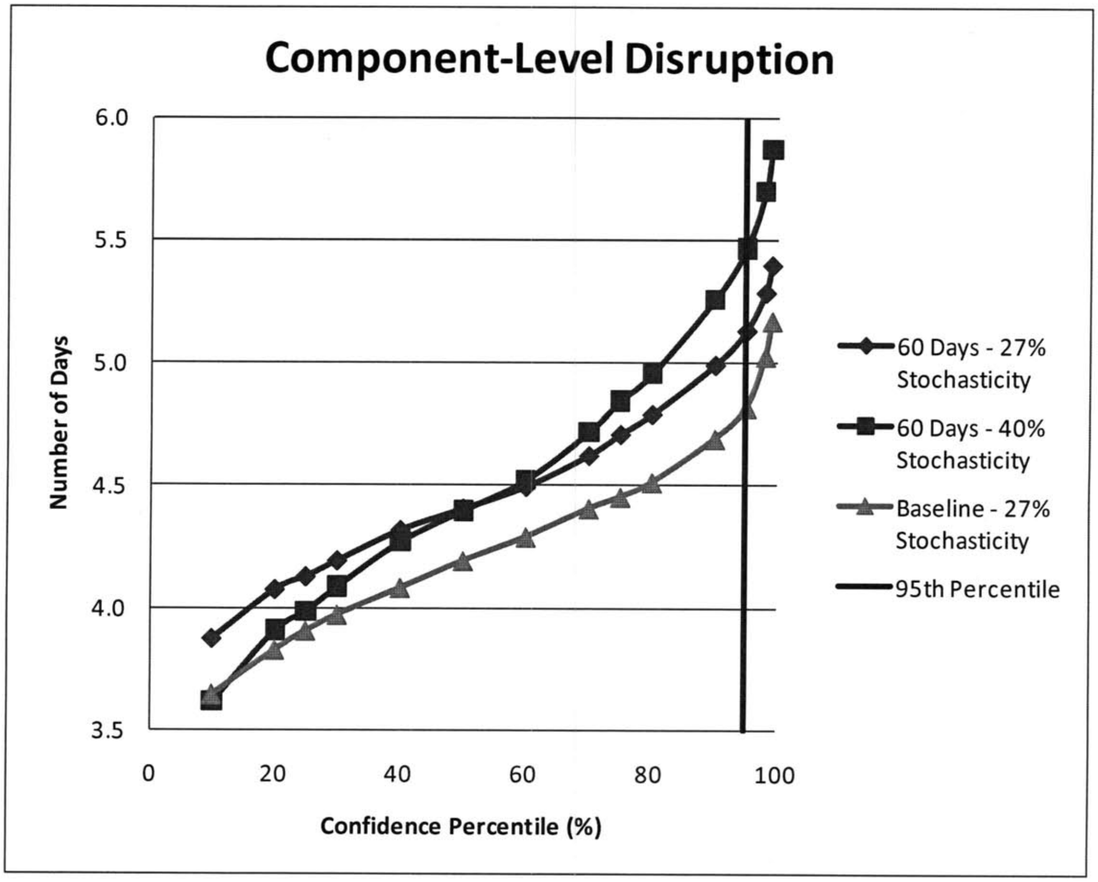

Figure 4.9. Confidence Percentiles for Component-Level Disruption (60 days) and varying Stochasticity Factors

Table 4.4 shows that varying the stochasticity factors causes the maximum completion time at the 95th confidence percentile to rise from 5.1 years to 5.5 years. Put another way, suppose the 40% stochastic is the most realistic but all decisions were made assuming a 27% stochasticity factor. Then instead of having a 95% confidence before the disruption, which would have been an 80% confidence after the disruption, in reality the company would only have a 70% confidence after this disruption.

Table 4.4. Comparison of Varying Stochasticity Factors at 95th Percentile

No Disruption	60 Day Component-Level Disruption	
Baseline – 27% Stochasticity	**27% Stochasticity**	**40% Stochasticity**
4.8 years	5.1 years	5.5 years

4.3.2 Test Failure Rates Results

Another assumption that was deemed appropriate to investigate was the very small number of quality tests that were predicted to fail. By systematically and uniformly reducing the passing rates, their importance can be observed. Figure 4.10 shows the results of having each quality test have passing rates of 85%, 90%, 95%, 98%, 99%, and 100%.

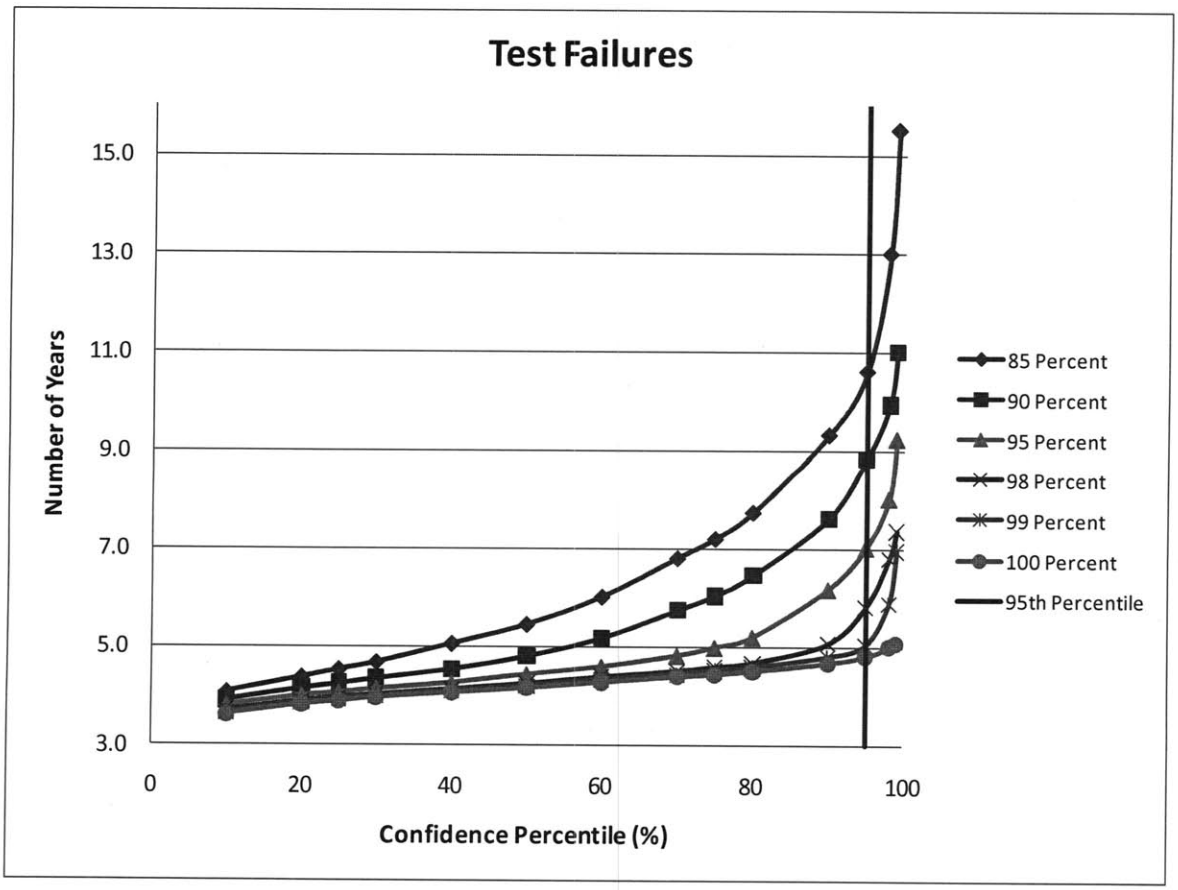

Figure 4.10. Confidence Percentiles for Various Test Failure Rates

These results are quite startling. For readability the numeric values are presented in Table 4.5. Again focusing on the 95% percentile, the data ranges from 4.8 years to an amazing 10.6 years. More importantly, the difference between a 100% pass rate and a 98% pass rate is significant, increasing the maximum duration time 21.2% from 4.8 years to 5.8 years. Table 4.6 shows the percent increase in the 95th percentile duration times when compared with the duration time for 100% pass rates (4.8 years).

Table 4.5. Confidence Percentiles for Various Test Failure Rates

Confidence Percentile (%)	85 Percent	90 Percent	95 Percent	98 Percent	99 Percent	100 Percent
10	4.1	3.9	3.8	3.7	3.6	3.6
20	4.4	4.1	4.0	3.9	3.8	3.8
25	4.5	4.2	4.1	4.0	3.9	3.9
30	4.7	4.3	4.1	4.0	4.0	3.9
40	5.1	4.5	4.3	4.1	4.1	4.1
50	5.4	4.8	4.4	4.2	4.2	4.1
60	6.0	5.2	4.6	4.4	4.3	4.3
70	6.8	5.7	4.8	4.5	4.4	4.4
75	7.2	6.0	5.0	4.6	4.5	4.4
80	7.7	6.5	5.2	4.7	4.6	4.5
90	9.3	7.6	6.2	5.1	4.8	4.7
95	10.6	8.9	7.0	5.8	5.0	4.8
98	13.0	10.0	8.0	6.8	5.9	5.0
99	15.5	11.0	9.3	7.4	7.0	5.1

Table 4.6. Percent Rise in Overall Duration Times

Confidence Percentile (%)	85 Percent	90 Percent	95 Percent	98 Percent	99 Percent	100 Percent
95	120.8%	84.1%	46.2%	21.2%	4.7%	0.0%

If the quality tests all pass with a 99% or higher rate, then it may be reasonable to ignore them if the company is comfortable with just 4.7% error being added. Any rates below 99%, however, should be taken into account in order to avoid significant additional error.

4.3.3 Disruption Probability Distributions Results

For this research extension, we first ran the simulation using the exponential probability distribution (which we are assuming to be the most realistic) with the deterministic input for the duration as the mean, followed by a triangular probability distribution using logical inputs in relation to the given deterministic input. After these two simulations, we calculated parameters for the "new" triangular based on the output of the exponential and ran the simulation again.

To calculate these new parameters for the triangular distribution, we determined what the minimum and maximum disruption duration was by subtracting the results of the exponential run from the baseline and taking the minimum and maximum values. This data is presented in days instead of years in Table 4.7 due to the small differences between the two.

Table 4.7. Difference Between Exponential and Baseline

Confidence Percentile (%)	Exponential	Baseline	Exponential - Baseline
10	1006	948	57
20	1048	996	53
25	1066	1016	50
30	1082	1033	49
40	1113	1062	51
50	1141	1090	51
60	1176	1116	61
70	1212	1146	66
75	1231	1158	73
80	1259	1174	85
90	1305	1220	85
95	1356	1253	104
98	1410	1307	103
99	1453	1344	109

Based on this data, the new triangular distribution should have a minimum value of 49 days and a maximum value of 109 days, and we hold the mode at 60 days. The input parameters for the distributions are summarized in Table 4.8.

Table 4.8. Inputs for Probability Distributions for a 60-day Disruption at the Component Level

	Mean	Mode	Minimum	Maximum
Deterministic	60 days			
Exponential	60 days			
Triangular		60 days	20 days	120 days
"New" Triangular		60 days	49 days	109 days

With these inputs, Figure 4.11 was generated to show the resulting complete duration times for each of these structures for the disruption duration distributions along with the baseline for comparison.

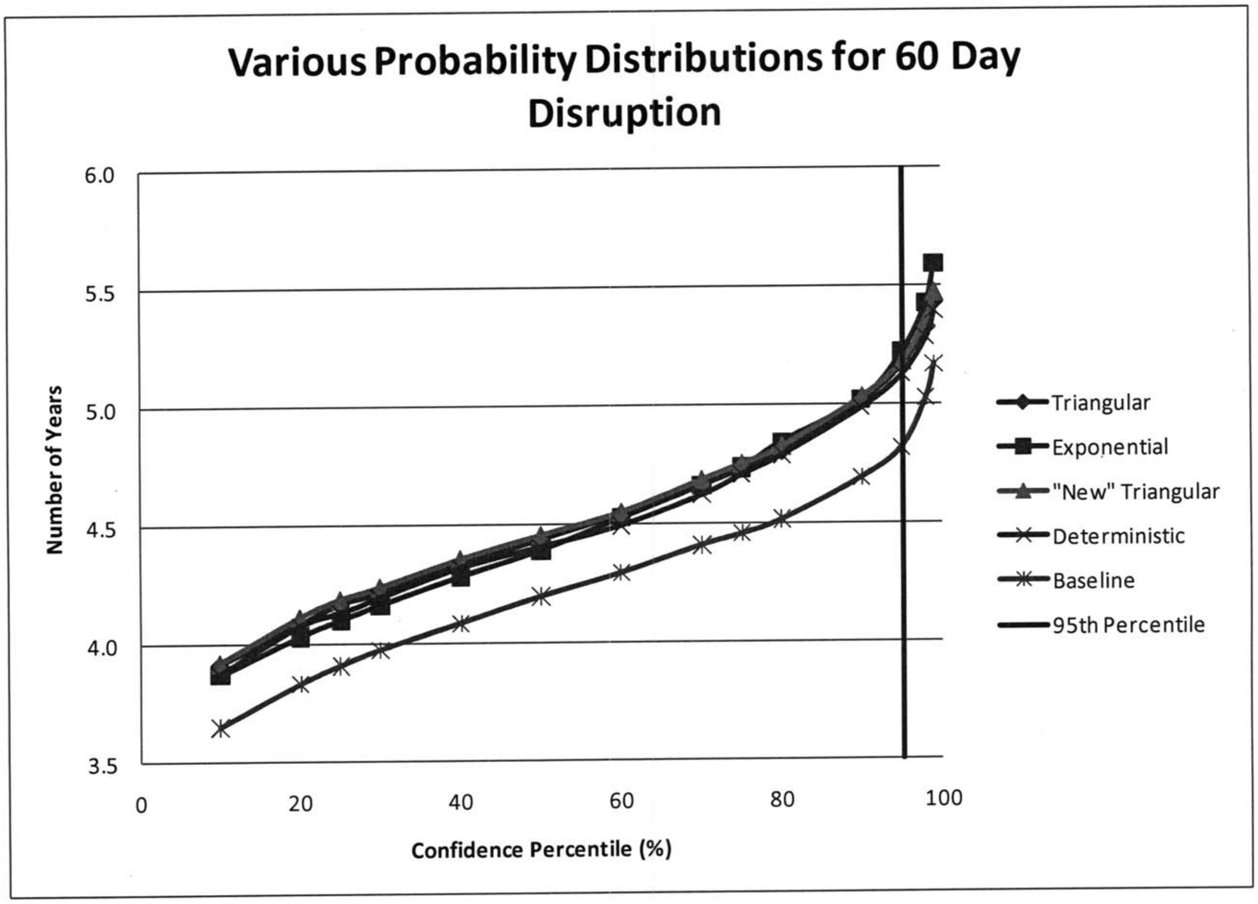

Figure 4.11. Confidence Percentiles for Various Probability Distributions for a Component-Level Disruption

Since these results are very similar and the differences are hard to see in Figure 4.11, Table 4.9 presents the actual numeric values.

Table 4.9. Confidence Percentiles for Various Probability Distributions for a 60-Day Component-Level Disruption

Confidence Percentile (%)	Triangular	Exponential	"New" Triangular	Deterministic	Baseline
10	3.9	3.9	3.9	3.9	3.6
20	4.1	4.0	4.1	4.1	3.8
25	4.2	4.1	4.2	4.1	3.9
30	4.2	4.2	4.2	4.2	4.0
40	4.3	4.3	4.4	4.3	4.1
50	4.4	4.4	4.5	4.4	4.2
60	4.5	4.5	4.5	4.5	4.3
70	4.7	4.7	4.7	4.6	4.4
75	4.7	4.7	4.7	4.7	4.5
80	4.8	4.8	4.8	4.8	4.5
90	5.0	5.0	5.0	5.0	4.7
95	5.2	5.2	5.2	5.1	4.8
98	5.3	5.4	5.4	5.3	5.0
99	5.4	5.6	5.5	5.4	5.2

As the 95th percentile indicates, there is very little difference between the three probability distributions and only a small difference between the deterministic. Table 4.10 shows the error percentage, assuming the exponential is the true distribution.

Table 4.10. Percent Error of Various Methods for Modeling Disruption Durations

Confidence Percentile (%)	Triangular	Exponential	"New" Triangular	Deterministic	Baseline
10	1.09%	0.00%	1.29%	0.08%	-5.70%
20	1.19%	0.00%	1.91%	1.03%	-5.02%
25	1.56%	0.00%	2.04%	0.66%	-4.68%
30	1.15%	0.00%	1.74%	0.70%	-4.53%
40	1.10%	0.00%	1.67%	0.83%	-4.60%
50	0.97%	0.00%	1.41%	0.30%	-4.47%
60	0.34%	0.00%	0.52%	-0.70%	-5.15%
70	0.04%	0.00%	0.50%	-0.85%	-5.44%
75	-0.14%	0.00%	0.34%	-0.58%	-5.91%
80	-0.85%	0.00%	-0.40%	-1.11%	-6.76%
90	-0.14%	0.00%	0.25%	-0.61%	-6.52%
95	-0.99%	0.00%	-0.71%	-1.73%	-7.64%
98	-1.82%	0.00%	-1.24%	-2.60%	-7.31%
99	-2.87%	0.00%	-2.15%	-3.51%	-7.52%

At the 95th percentile there is very little variation between the different methods for modeling disruption durations, even with the deterministic method. With this data, the aerospace company can be reasonably confident in using deterministic numbers when defining disruption durations. If, however, a confidence of 99% is needed, using an exponential distribution may be a better choice since the error begins to increase due to the large duration values that the exponential distribution can generate.

Chapter 5: Conclusions

This chapter presents the conclusions and insights developed throughout this thesis. It is organized as follows: in Section 5.1 we present the insights gained from developing and using the computer simulation model of this supply chain; in Section 5.2 we present future research that can be conducted for further insights in managing the risk from disruptions from the point of view of the aerospace company; in Section 5.3 we present future research of interest to the academic community; and finally, in Section 5.4 we summarize the results overall.

5.1 Insights

5.1.1 Model Development

One of the most significant benefits of conducting this study was to demonstrate the importance for a manager to completely and fully understand the supply chain which he or she supervises. To create the computer model, the research team had to first construct the entire supply chain map, which illustrates the entire process to build a space vehicle. To create such a map, the research team had to thoroughly gather information for each supplier of every component. This information included their physical location, their historical performance in regards to quality and delivery, and whether there was an alternate supplier available. Organizing all of this information ensured that the managers of this supply chain truly knew what it was they were controlling. By thoroughly defining the critical path, the key input-output relationships became clear. With this increased understanding of their supply chain, the aerospace company was able to comfortably validate the computer simulation model which further increased their confidence in its results.

5.1.2 Buffer Time Management

As is common practice whenever devising schedules, the aerospace company personnel intentionally built in buffer times when determining the duration times for each processes listed in Table 1.1 that allow for a measure of uncertainty. For example, if an engineer thinks it will take 6 weeks to qualify a part, it is likely he may tell his manager it will take 8 weeks to give himself some leeway in case something goes wrong.

Instead of using intuition alone to come up with these buffer times, the computer model provides a guide for determining what buffer times should be built into the committed completion date. By using the stochastic results from Section 4.3.1 for the chosen stochasticity factor, a manager can pick the confidence percentile she is comfortable with and use that result to calculate her buffer time. For example, with no randomness on the model, the completion time is 4.2 years. If the target confidence percentile is 95% and the stochasticity value is chosen to be 20%, the new maximum completion time is 4.7 years, which indicates the need of a half year of buffer time.

Using this method to set buffer times allows the target completion dates to be backed with a statistical confidence that is generated via the model. This statistical data is really what makes this model powerful for supply chain managers. While other scheduling methods are available, computer simulation combines the randomness of events and logic for rework or recovery with a schedule to generate confidence percentiles of completion times.

5.1.3 Real Time Model Usage

Throughout this entire study we have examined the effect of running the simulation at time zero. Instead of just using this model before this project begins, valuable data can be generated by continual and real time use of this model throughout the entire production cycle. The model can be rerun after completion of each major stage of the supply chain to update the forecasted completion date. Since these duration times are no longer uncertain, the stochasticity factor must be removed for those processes. This real time use will tighten the tolerance of the forecasted completion date.

The new forecasted completion date will also help with forecasting future procurement schedules by more accurately predicting when each stage of production will begin. These dates can be given to the purchasing department from which they can optimize their procurement plans. This optimization would reduce unnecessary inventory carrying charges since parts will be arriving closer to the time when they are actually needed.

If there is a disruption to the supply chain, an understanding of whether it impacts the final delivery date of the space vehicle can be gained much earlier in the production cycle through real time use of the model. Knowing how far the confidence level has fallen will aid in determining whether the duration times of future processes need to be shortened through increased investment. If it is not possible to reduce the durations of these future processes, advance notice of the delay can be given to the customer of the space vehicle, which may lessen the financial impact of missing the target.

Finally, the buffer time as explained in Section 5.1.2 can be managed and tracked in real time and thus can be a key performance index (KPI) of scheduling risk. For example, suppose 10 weeks of buffer time was built into the committed completion date. If production is advancing ahead of schedule, the manager will know the buffer time is increasing through real time use of the model. On the other hand, if production is advancing slower than anticipated, the manager will know how much buffer time is lost. Certain triggers can be established to signal if too much buffer time has been lost, for example, if the buffer dropped to 4 weeks remaining, and then again at 2 weeks remaining. Having such a meaningful KPI that managers can understand will be much more effective than relying on intuition or experience when determining overall schedule risk.

5.1.4 Human Reaction to Disruptions

Even with a thorough investigation of disruptions through testing numerous scenarios using the model, human reaction may differ from those predicted and produce a different outcome from what the model suggested. For example, disruptions that occur very early in the process may not generate much excitement as there are still years ahead to catch up. However, if the disruption happens much later in the process, it is likely the company will move into a crisis mode and do whatever necessary to get production back online. While this behavior seems logical, it can be very costly and inefficient if the confidence of the forecasted completion date does not decrease due to that particular disruption. While going into crisis mode can be very beneficial in getting the production line running again, it should only be employed when truly necessary. By using the model, human reaction can be better controlled to best fit the situation. New confidence percentiles can be generated through real time use of the model to help understand just how bad the disruption will impact the final delivery date.

Modifying such behavior will not be easy as the correct response to a disruption may not seem logical to the workers involved. Due to this, all employees should be aware of the KPIs that are developed to manage buffer times as described in Section 5.1.3. Using these KPIs to modify behavior will result in a better-managed production schedule.

5.1.5 Efficient Risk Management Plans

Since this model provides a tool for testing the impact of disruptions and their durations, efficient risk management plans can be devised by evaluating how certain mitigation strategies reduce the duration of a disruption. Investment should only be made in the strategies that deliver the best increase in the confidence percentile of the targeted completion date. Due to the large impact that stochasticity has on this system, the aerospace company should also investigate what methods will reduce process variability overall and include those in their risk management plan.

5.2 Aerospace Company Extensions

5.2.1 Review of Input Data

As with any model, the quality of the output data is only as good as the input data. The aerospace company should continue to investigate the process times of each of the durations listed in Table 1.1. The buffer times, as discussed above, should be identified and adjusted accordingly. It may be necessary for the aerospace company to identify any sub-tier suppliers of their sub-tier suppliers to best estimate the durations and variability of processing times and part availability for any processes they deem questionable.

The passing rates of the quality tests must also be investigated as shown in Section 4.3.2. With only 3 of the 25 quality tests having a passing rate of less than 100%, the data seems a little suspect. Passing rates below 99% have a significant impact on determining the estimated completion date and thus should be accurately captured in the model. Alternately, if there really are only 3 of the 25 tests that have a passing rate less than 100%, then the current number of quality tests may not be needed in this supply chain. By removing unnecessary quality tests the company can save the time and money it takes to run so many tests.

5.2.2 Add Secondary and Tertiary Paths

Due to the time constraints and complexity involved with constructing and utilizing this model, only the critical path was included. The aerospace company, as time permits, could go back and add the secondary and tertiary paths of this supply chain to further build the foundation on which their output data and the associated confidence percentiles are generated. As this could be a very time-intensive project, these paths should be prioritized in terms of the potential risk they pose to interrupting the flow of the critical path. In addition to adding to the model, this process would add to the knowledge of potential risks that was generated by initially constructing this model, as described in Section 5.1.1.

5.2.3 Unique Stochasticity Factor

Since picking the correct stochasticity factor is vital to having accurate confidence percentiles, the aerospace company may want to divide the entire supply chain into smaller pieces and define a unique stochasticity factor for each piece. As it currently is designed, the stochasticity factor is applied evenly throughout the entire system, which might not accurately portray what is happening at each sub-tier's facilities.

5.3 Academic Extensions

5.3.1 Include Supply Chains of Sub-tier Suppliers

The computer model is currently designed from the perspective of a single company who contracts with sub-tier suppliers to produce much of their product. By not only modeling this supply chain but instead going one step deeper to model each of the sub-tier vendors' supply chains, increased visibility of risk will be gained. Accuracy of the confidence percentiles could increase with this additional information. A comparison between this more complex model should be made with the original model to determine whether the increase in accuracy of the confidence percentiles is worth all the additional work it would take to gather the new data.

5.3.2 Incorporate Cost Information into Model

No financial data was included with this model. An investigation could be undertaken to learn how to incorporate financial data in order to calculate the optimal cost tradeoffs when developing a risk mitigation plan. The impact on product quality should also be included in such a study to determine what investments in research and development would be needed to raise, for example, the passing rates of the quality tests from 99.0% to 99.5%. By incorporating cost, quality, and schedule into the model a manager will be best equipped to determine what tradeoffs need to be made to achieve the goals for each of those three categories.

5.4 Summary of Results

The three goals for this project, as stated in Section 1.1.2, are reproduced here for convenience:

1 Analyze the effects of randomness throughout the critical path.

2 See how quality test failures affect the overall duration time.

3 Analyze the impact of disruptions in various production phases or the non-availability of sub-tier components.

Through use of the computer simulation model all three goals were accomplished as presented throughout this chapter. But as with most studies, additional takeaways manifested themselves throughout the entire project.

Building and utilizing a computer model of a supply chain is one of the best ways a company can begin to understand their own supply chain's complex behavior and how best to plan for unforeseen circumstances. The process of assembling a model generates an increased understand of the system as it requires the builders to investigate every process, every quality test, and every supplier and then put all that information into a logical flow chart that maps every action that takes place. With the model in place a company can test a wide-ranging set of scenarios to see what impact they will have on the overall system. This data then allows for the development of proper risk mitigation strategies that can keep a project on schedule if a disruption were to occur. By using models in real time a company can impose proper control mechanisms, such as actively monitoring and managing the buffer time that is available to the system.

Using this specific model for a supply chain that is building 1-2 space vehicles a year, we were able to learn that most disruptions will add a deterministic time to the total estimated duration time of the system, regardless of the location of the disruption in the supply chain. Adding probability distributions to determine disruption durations did not add much value to the model's predictions. However, care must be taken to choose the correct stochasticity factor for processes themselves due to its large influence on the final results.

Smart sparing does not look to be a viable risk mitigation tactic due to the small number of tests that have passing rates below 100% and the very short rework times if a failure were to occur. The passing rates of the quality tests should be investigated further. Smart sparing would only prove to be useful if there is a concern of a failure at the N Panel level. A failure at that level resulted in the confidence percentile dropping from 95% all the way to 50%.

Since this model was created for a real supply chain, it is currently being used by the aerospace company to help them plan and make appropriate decisions in regards to risk mitigation strategies. Much of the research suggested in Section 5.2 is currently underway as they prepare to start to production processes at the end of this year. They hope to expand the use of computer simulation models throughout the rest of their division to help drive down costs and risks by increasing efficiencies in their planning. The success of this project is being shared among their executive team and it will be exciting to see the results of using this model in real time once production begins in December.

Appendix A: Numerical Data

This appendix contains the numerical output from the Arena model that is the basis for all the graphs presented in Section 4.2, unless the numerical output has already been included there. It also contains the two graphs for the Hybrid-Level Disruption and the CCA-Level Disruption.

A.1 Component-, Hybrid-, and CCA-Level Disruptions

Table A.1. Component-Level Disruption Completion Times

Confidence Percentile (%)	20 Days	60 Days	120 Days	Baseline
10	3.7	3.9	4.1	3.6
20	3.9	4.1	4.3	3.8
25	4.0	4.1	4.4	3.9
30	4.0	4.2	4.4	4.0
40	4.2	4.3	4.5	4.1
50	4.2	4.4	4.6	4.2
60	4.3	4.5	4.7	4.3
70	4.5	4.6	4.9	4.4
75	4.6	4.7	4.9	4.5
80	4.6	4.8	5.0	4.5
90	4.8	5.0	5.2	4.7
95	5.0	5.1	5.4	4.8
98	5.1	5.3	5.5	5.0
99	5.2	5.4	5.6	5.2

Table A.2. Hybrid-Level Disruption Completion Times

Confidence Percentile (%)	20 Days	60 Days	120 Days	Baseline
10	3.7	3.9	4.1	3.6
20	3.9	4.1	4.3	3.8
25	4.0	4.1	4.4	3.9
30	4.1	4.2	4.4	4.0
40	4.2	4.3	4.5	4.1
50	4.2	4.4	4.6	4.2
60	4.3	4.5	4.7	4.3
70	4.5	4.6	4.9	4.4
75	4.5	4.7	4.9	4.5
80	4.6	4.7	5.0	4.5
90	4.8	4.9	5.1	4.7
95	5.0	5.1	5.3	4.8
98	5.1	5.3	5.5	5.0
99	5.2	5.4	5.6	5.2

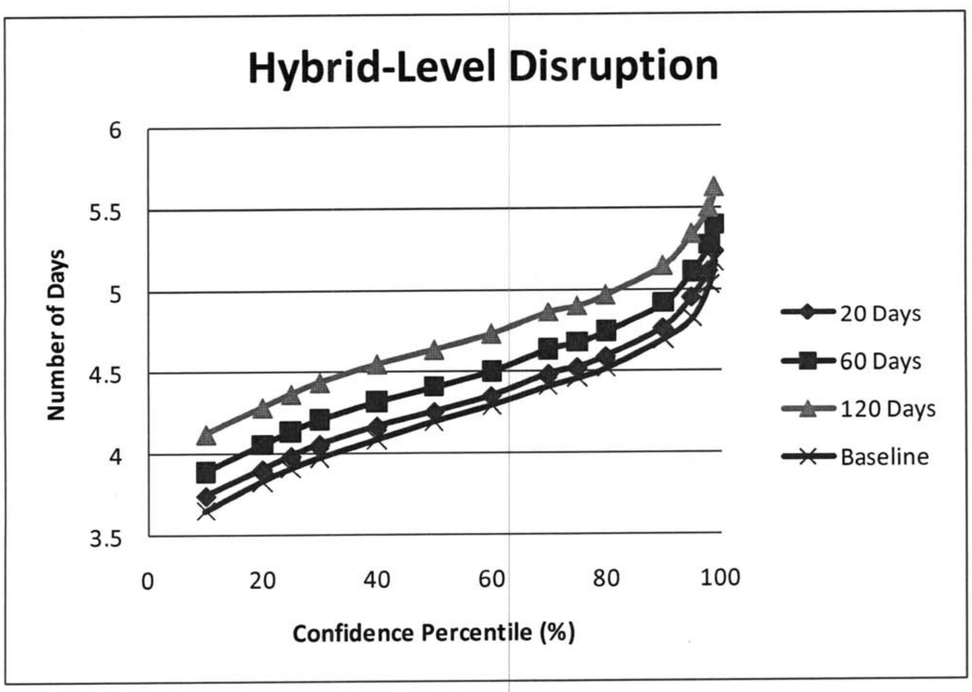

Figure A.1. Hybrid-Level Disruption

Table A.3. CCA-Level Disruption Completion Times

Confidence Percentile (%)	20 Days	60 Days	120 Days	Baseline
10	3.7	3.9	4.1	3.6
20	3.9	4.1	4.3	3.8
25	4.0	4.1	4.4	3.9
30	4.0	4.2	4.4	4.0
40	4.1	4.3	4.5	4.1
50	4.2	4.4	4.6	4.2
60	4.3	4.5	4.7	4.3
70	4.5	4.6	4.9	4.4
75	4.5	4.7	4.9	4.5
80	4.6	4.7	5.0	4.5
90	4.8	4.9	5.2	4.7
95	5.0	5.1	5.3	4.8
98	5.1	5.3	5.5	5.0
99	5.2	5.4	5.6	5.2

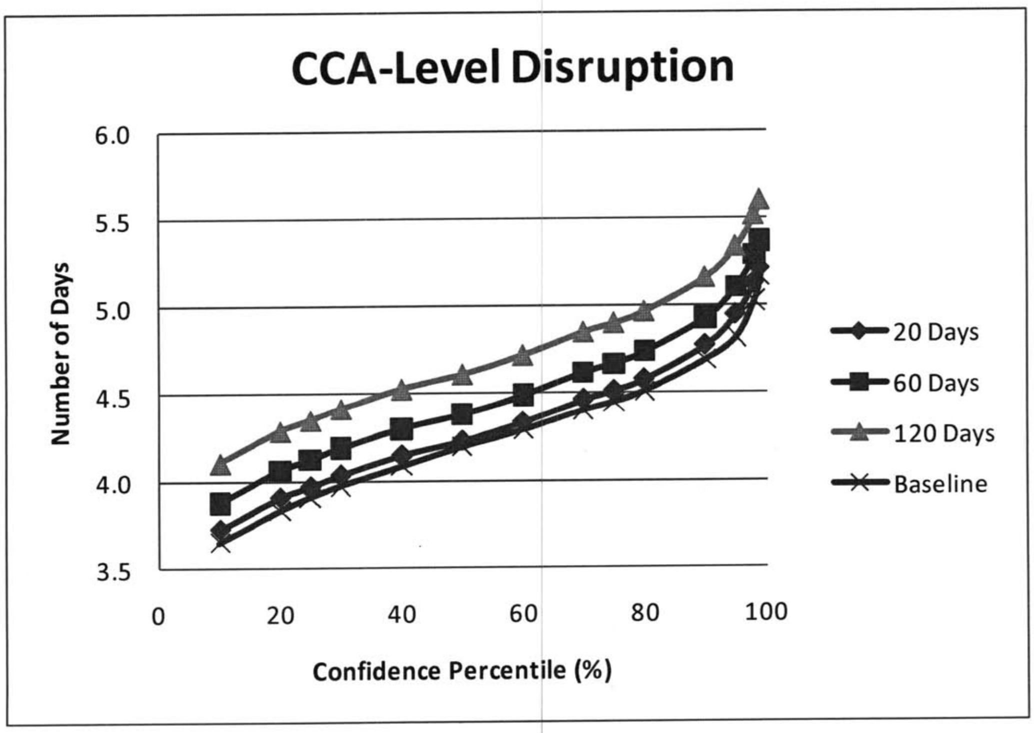

Figure A.2. CCA-Level Disruption

A.2 Pandemic Disruption

Table A.4. Pandemic Disruption Completion Times

Confidence Percentile (%)	60% Pandemic	80% Pandemic	Baseline
10	3.8	3.8	3.6
20	3.9	4.0	3.8
25	4.0	4.1	3.9
30	4.1	4.1	4.0
40	4.2	4.2	4.1
50	4.3	4.3	4.2
60	4.4	4.5	4.3
70	4.5	4.6	4.4
75	4.6	4.6	4.5
80	4.7	4.7	4.5
90	4.8	4.9	4.7
95	5.0	5.0	4.8
98	5.2	5.2	5.0
99	5.3	5.4	5.2

A.3 Smart Sparing

Table A.5. Smart Sparing Completion Times

Confidence Percentile (%)	Smart Sparing	Baseline
10	3.6	3.6
20	3.8	3.8
25	3.9	3.9
30	4.0	4.0
40	4.1	4.1
50	4.2	4.2
60	4.3	4.3
70	4.4	4.4
75	4.4	4.5
80	4.5	4.5
90	4.7	4.7
95	4.8	4.8
98	5.0	5.0
99	5.1	5.2

A.4 N Panel

Table A.6. N Panel Completion Times

Confidence Percentile (%)	N Panel	Baseline
10	4.2	3.6
20	4.4	3.8
25	4.5	3.9
30	4.5	4.0
40	4.6	4.1
50	4.8	4.2
60	4.9	4.3
70	5.0	4.4
75	5.1	4.5
80	5.1	4.5
90	5.3	4.7
95	5.5	4.8
98	5.6	5.0
99	5.8	5.2

A.5 Stochasticity

Table A.7. Stochasticity Completion Times

Confidence Percentile (%)	60 Days - 27% Stochasticity	60 Days - 40% Stochasticity	Baseline - 27% Stochasticity
10	3.9	3.6	3.6
20	4.1	3.9	3.8
25	4.1	4.0	3.9
30	4.2	4.1	4.0
40	4.3	4.3	4.1
50	4.4	4.4	4.2
60	4.5	4.5	4.3
70	4.6	4.7	4.4
75	4.7	4.8	4.5
80	4.8	5.0	4.5
90	5.0	5.3	4.7
95	5.1	5.5	4.8
98	5.3	5.7	5.0
99	5.4	5.9	5.2

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