RESILIENT AIRCRAFT SUSTAINMENT:
Quantifying Resilience through Asset and Capacity Allocation

THESIS

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AFIT-ENS-MS-20-M-288

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AFIT-ENS-MS-20-M-288

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THESIS

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Logistics & Supply Chain Management

Zachary B. Shannon

March 2020

AFIT-ENS-MS-20-M-288

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AFIT-ENS-MS-20-M-288

Abstract

Decision makers lack a clear, generalizable method to quantify how additional investment in inventory and capacity equates to additional levels of resilience. This research facilitates a deeper understanding of the intricacies and complex interconnectedness of organizational supply chains by monetarily quantifying changes in network resilience. The developed Area under the Curve metric (AUC) is used to quantify the level of demand that each asset allocation can meet during a disruptive event. Due to its applicability across multiple domains, the USAF F-16 repair network in the Pacific theater (PACAF) is modeled utilizing discrete event simulation and used as the illustrating example. This research uses various levels of production capacity and response time as the primary resilience levers. However, it is essential to simultaneously invest in inventory and capacity to realize the greatest impacts on resilience. Real-world demand and cost data are incorporated to identify the inherent cost-resilience relationships, essential for evaluating the response and recovery capabilities across the developed scenarios. Results indicate that recovery capacity and response time are the greatest drivers of recovery after a disruption. Additionally, numerous network designs employing various levels of design flexibility are evaluated and recommended for future capacity expansion.

Acknowledgments

I would like to thank my advisor, Maj Breitbach, for his continuous support, guidance, and patience. He has truly been instrumental to my professional development. Additionally, I would like to thank my readers, Lt Col Cox and Dr. Steeneck, for donating a significant amount of their time to the development of this research. Lastly, I would like to thank Dr. Johnstone and Dr. Gaudette for their understanding of the academic rigor that is involved to complete this program. I truly would not be at this stage without the steadfast support of all of you.

Zachary B. Shannon

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RESILIENT AIRCRAFT SUSTAINMENT:
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I. Introduction

As the world continues to globalize, complexity amongst organizational supply chains continues to grow (Christopher & Peck, 2004; Pettit et al., 2010). Supply chains have lengthened, and the need to rely upon strategic partners has risen, creating an advanced interconnectedness among critical nodes (Christopher & Peck, 2004). This leads to a drastic increase in the operational vulnerabilities and uncertainties that firms continuously face (Tang, 2006). Ultimately, this creates the need to investigate ways to become more efficient and competitive in an environment that is constantly changing. To sustain a competitive advantage, decision makers often attempt to achieve "fully integrated and efficient" supply chain operations usually at the cost of risk mitigation capabilities elsewhere (Christopher & Peck, 2004:1). This foundational tradeoff between efficiency and risk mitigation exists in many respects of the supply chain and further adds to the narrative of an uncertain future (Pettit et al., 2010; de Neufville & Scholtes, 2011). Therefore, an organization's ability to mitigate the impact of network disruptions on network performance is critical to the short-term ability to meet demand, but more importantly, to an organization's long-term survival.

This research facilitates a deeper understanding of the complex interconnectedness of organizational supply chains by using the example of the F-16 repair network located in the Pacific Air Force (PACAF) theater. This research helps to further develop a generalizable tool and methodology to quantify network resilience. It analyzes incremental changes in resilience from the simultaneous investment in resilience levers.

Additionally, foundational cost-resilience relationships are identified, providing essential insight into the response and recovery capabilities of various network designs. PACAF was strategically chosen because of its immense geographic area, as well as the continual rise in operational and strategic capabilities of US adversarial threats located in theater. This research posits the use of the Area under the Curve (AUC) metric, which identifies the number of mission-capable days the network can support over time (Femano et al., 2019). The AUC provides decision makers the ability to forecast network performance levels resulting from predetermined asset allocations and corresponding investment while facing a network disruption.

1.1 Background & Motivation

Supply chains are extremely complex networks consisting of critical nodes that are essential for the achievement of operational and strategic initiatives (Blackhurst et al., 2005; Bakshi & Kleindorfer, 2009; Pettit et al., 2010; Tukamuhabwa et al., 2015). They are critical to the ability to meet demand and drive earnings, all the while playing an instrumental role in the ability to develop advantages that set organizations apart from competitors. Effective supply chains are a major driving factor of customer satisfaction, and the inability to proactively mitigate and respond to an increasingly uncertain future could have lasting and grave effects on the ability to sustain strategic operations and meet customer demand (de Neufville & Scholtes, 2011).

The importance of organizational resilience cannot be overstated. The ability to recognize an uncertain future facilitates a greater level of preparedness needed to hedge against downside risk (de Neufville & Scholtes, 2011). Take, for example, the recent outbreaks of the coronavirus. Similar to the SARS outbreaks in 2003, the virus has quickly spread to parts outside of Wuhan, China, impacting countries across the globe (Otani, 2020). News of the outbreak hit financial markets especially hard. For instance, the S&P 500 reacted accordingly by yielding the worst trading session in months (Otani, 2020). A rather optimistic view of 2020 global economic growth has been severely dampened by the unknown economic impacts of the virus, further exacerbating the need for proactively safeguarding organizational resources.

The ability of an organization to withstand the impact of a disruption has been explored extensively in the literature. Resiliency tactics, such as the capability factors presented by Pettit et al. (2010) and mitigation strategies proposed by Chopra and Sodhi (2004), provide foundational insight as to the wide range of response options organizations have at their disposal. Much of the developed research on supply chain resiliency is qualitative in nature (Tukamuhabwa et al., 2015). Much of the quantitative analysis is limited and provides minimal usefulness. A generalizable tool that measures the practicality of qualitative strategies and can be implemented to gauge resiliency is greatly lacking from a supply chain resiliency perspective.

In a military context, specifically the USAF’s F-16 repair network located in the Pacific (PACAF), the level of vulnerabilities that exist due to environmental factors and adversarial capabilities, create the continuous need to safeguard mission critical assets to maintain operations. PACAF provides an ideal test case for the applicability of this tool. For instance, PACAF features inherent flexibility due to the implementation of the repair network integration (RNI) construct. Implemented to supplement local maintenance capabilities, the RNI construct is meant to provide a holistic Air Force view of “off-equipment repair capabilities” and “integrated, agile support” to the warfighter by enhancing design and capability allocations across the repair network (RNIO et al., 2016). Moreover, the RNI construct is aimed at eliminating repair of Intermediate-level (I-level) and Depot-level (D-level) discrepancies in isolation to create a more robust and flexible repair capability for USAF operations (RNIO et al., 2016).

PACAF currently features a relatively high level of repair flexibility regarding I-level discrepancies for Avionics, Hydraulics, and Electrical & Environmental (E/E) at all four operating locations. However, centralization exists for the I-level overhauls of the F110-GE-129 engine. For instance, if a propulsion I-level discrepancy is identified at Osan AFB, the entire engine is packed, wrapped, and shipped to the propulsion centralized repair facility (CRF) located at Misawa AFB. Although centralization provides enormous benefits from efficiency and economies of scale, it simultaneously increases the vulnerabilities of the network (Tripp et al., 2010; Forbes & Wilson, 2018). Hence, if Misawa experiences a disruption, the impacts and subsequent ability to perform F110-GE-129 engine overhauls could be catastrophic.

1.2 Problem Statement

Decision makers must strike a balance between supply chain vulnerabilities and supply chain capabilities (Pettit et al., 2010). Network outages due to disruptions are often exacerbated due to the lack of visibility, connectedness among nodes, redundant capability or just flat out underestimation (Tang, 2006). Hence, many of the tangible losses organizations incur would be greatly diminished with a cost-effective, easily adaptable tool that provides decision makers the ability to quantify, analyze, and evaluate the impact of predetermined asset allocations on disruption performance.

1.3 Research Questions

This research explores the following research questions to better understand how the investment in resiliency impacts an organization's ability to perform during a disruption. Specifically, this research asks:

1. How do different investments in inventory and production capacity equate to different levels of resilience across the sustainment network?
2. How should the investments in inventory and production capacity be allocated across the sustainment network?

1.4 Research Overview

The research questions are answered through the analysis of a discrete-event simulation (DES) model that quantifies the level of resilience resulting from various levels of resilience investment. An extensive literature review draws upon the following literature streams: general resilience strategies, investments in resilience, production capacity and inventory tradeoff, and resilient design flexibility. The developed model is then applied to PACAF. Subsequently, sustainment data and results are analyzed over the different investment scenarios and network designs to identify resilience-cost relationships. Lastly, findings, future research opportunities, and limitations are presented to further facilitate a deeper understanding of resilience incorporation.

II. Literature Review

The following chapter provides an overview of the relevant research on supply chain resiliency. Existing literature lacks a clear, generalizable way to quantify incremental changes in network resilience due to the manipulation of resilience levers. Specifically, USAF decision makers lack the ability to quantify how additional investments in resilience equates to additional resilience. Much of the relevant literature streams have focused on a reactive approach to mitigate supply chain disruptions. However, this research provides decision makers insight into how network performance changes after a disruption based on a predetermined asset allocation. The relevant literature streams explored to address this gap include: general resilience strategies, investment in resilience, production capacity and inventory tradeoff, and resilient design flexibility.

2.1 General Resilience Strategies

Supply chain resilience "is the ability of a system to return to its original state or move to a new, more desirable state after being disturbed" (Christopher & Peck, 2004:2). However, it has never been more elusive or necessary for supply chain decision makers (Christopher & Peck, 2004; Forbes & Wilson, 2018). First and foremost, the concept of supply chain resilience is relatively unexplained (Christopher & Peck, 2004; Blackhurst et al., 2005; Wang & Ip, 2009). Furthermore, the rapid rise of globalization has led to "increased consumer expectations, more global competition, longer and more complex supply chains, and greater product variety with shorter product life cycles" (Sheffi & Rice Jr., 2005:41). Subsequently, increased organizational complexity in conjunction with a lack of known methods to tangibly implement and quantify resilience has given rapid rise to large-scale vulnerabilities that could drastically change the outlook of an organization's going concern (Blackhurst et al., 2005; Bakshi & Kleindorfer, 2009; Pettit et al., 2010; Tukamuhabwa et al., 2015). Although disaster and contingency planning have been widely explored, organizational contingency planning often exists in a silo, embedded away from the necessary cohesiveness that is required to build a resilient supply chain (Christopher & Peck, 2004). Carter and Rogers (2008) perform an extensive literature review to formulate a holistic framework to implement Sustainable Supply Chain Management (SSCM). Transparency and cohesiveness are greatly emphasized to ensure the successful implementation of such strategies (Carter & Rogers, 2008). Christopher and Peck (2004) assert that the lack of a foundational research base has created the inability to fully comprehend the importance and breadth of resilience incorporation in an organization's supply chain. Moreover, decision makers lack generalizable tools that can assist in gauging and implementing resilience into the supply chain (Christopher & Peck, 2004). This research will provide a tangible method to illustrate the importance of supply chain resilience incorporation and assist decision makers in gauging current levels of resilience due to a predetermined allocation of production capacity and inventory assets.

Craighead et al. (2007) argue that disruptions are inherently unavoidable; therefore, risk is constant in supply chains. Direct correlations are drawn from the disruption severity to the supply chain characteristics of density, node criticality, complexity, recovery and warning (Craighead et al., 2007). Specific to recovery, the ability of an organization to proactively and reactively allocate capacity in the event of a disruption greatly mitigates the impact of a disruption on performance (Craighead et al., 2007).

Ivanov et al. (2014) and Ivanov (2018) introduce the propagation effect that may occur without the proper recovery implementation. Although both proactive capacity and reactive capacity allocations work best in unison, proactive recovery capacity is more effective at limiting the propagation of the disruption throughout the entire supply chain. The literature presents copious amounts of varying definitions for the numerous resilience levers at the decision maker's authority. Using the definitions set forth in the literature, this research creates a method to add practicality to the many definitions that have been created.

Sheffi and Rice Jr. (2005) equate supply chain resilience to the reduction in probability of a disruption occurrence, thus, reducing overall system vulnerabilities. Specifically, resilience is created with the addition of inherent system flexibility and built in redundancy (Sheffi & Rice Jr., 2005). Melnyk et al. (2013) build upon this basic resilient structure by attributing the resilience of an organization's supply chain to the utilization of capacity to resist and recover from a disruption. Additionally, they recommend analyzing the system's transient states when measuring the impact of a disruption, and ultimately the network's cumulative resilience. Figure 1 illustrates the time periods associated with Melynk et al. (2013) concept of resistance and recovery capacity. An organization's ability to resist the impact of a disruption can be characterized by taking the integral above the curve for the time period TO – TP, while the ability to recover from a disruption can be characterized by taking the integral above the time period TP – TR (Melnyk et al., 2013). The smaller this integral, the greater the ability of an organization to resist and recover from a disruption (Melnyk et al., 2013).

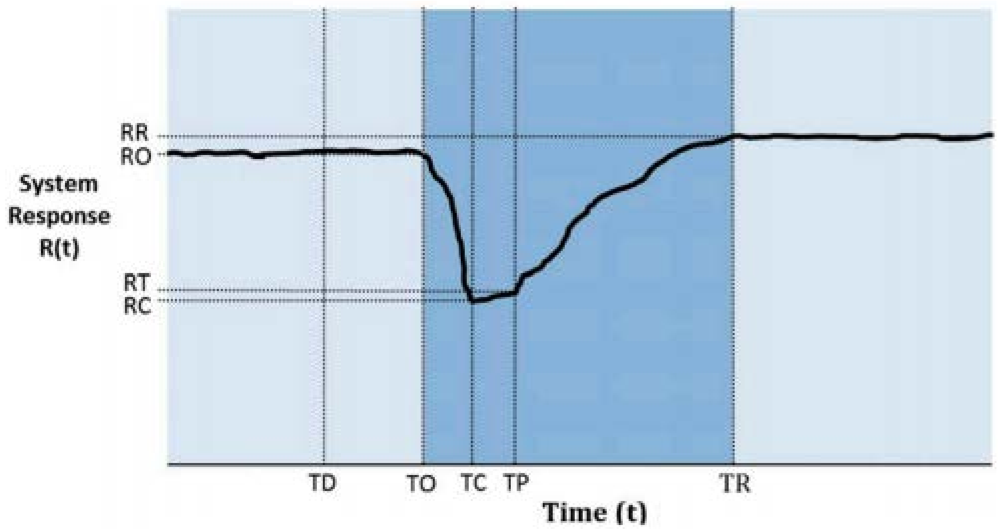


Figure 1: Disruption Time Periods (Melnyk et al., 2013)

This research also emphasizes the need of an organization to resist and recover from a disruption. However, and contrary to Melnyk et al. (2013), this research integrates the area under the curve (AUC) which provides a more accurate measure of cumulative network performance over the specified disruption time period (Femano et al., 2019). Additionally, the AUC provides a greater ability to analyze the impacts of resilience investments on network performance because it provides a forecast of the level of demand that can be met resulting from predetermined assets in the event of a disruption (Femano et al., 2019).

Blackhurst et al. (2005) recognize the need for resilience stemming from larger supply chains and increased dispersion. More specifically, the rise of global sourcing and transition to efficient operations, such as the incorporation of agility and lower inventory levels, further emphasizes the need for built-in resilience (Blackhurst et al., 2005; Kleindorfer & Saad, 2005; Tang & Tomlin, 2008; Bakshi & Kleindorfer, 2009; Pettit et al., 2010; Schmitt & Singh, 2012). Blackhurst et al. (2005) offer insightful analyses on disruption discovery, disruption recovery, and network redesign by conducting a “major multi-industry, multi-methodology, empirical study” which highlights general disruption behavior from an extremely broad perspective (Blackhurst et al., 2005:4078). However, the research is strictly qualitative and offers no quantification of various network redesigns or recovery strategies. Therefore, this research seeks to add to the largely conceptual nature of supply chain resilience literature by quantifying incremental changes in resilience.

2.2 Investment in Resilience

One of the issues with designing the supply chain for resilience is that much of the literature on resilience incorporation is conceptual in nature. Hence, a quantifiable method and tool that tests different resilience strategies will pay dividends for USAF decision makers when making resource allocation decisions.

Sheffi (2001) focuses primarily on the probability of a deliberate attack on a firm’s supply chain. Sheffi (2001) asserts that three main investment strategies exist that will maximize an organization’s resilience: (1) supplier relationships, (2) inventory management, and (3) knowledge and process backup. Sheffi identifies the cost tradeoff that exists between using local suppliers versus offshore suppliers. Although the use of local suppliers is more expensive, they offer quicker lead times. The use of offshore suppliers is often less expensive; however, the lead time is much longer (Sheffi, 2001). The concept of “Strategic Safety Stock,” which describes bolstered inventory levels used in the event of a disruption, is a useful way to help smooth out system performance level during disruption impact (Sheffi, 2001; Chopra & Sodhi, 2004; Tang, 2006; Liu et al., 2016). Tang (2006) echoes similar sentiment when recommending robust supply chain strategies. In particular, the use of "strategic stock" aids firms in responding to a wide range of demand when a disruption occurs (Tang, 2006). The use of redundant resources to increase network resiliency is not a new concept. Wang and Ip (2009) illustrate the impact of redundant, flexible, and decentralized resources on an aircraft servicing supply chain by modeling various levels of resilience. However, managerial insight into the different cost relationships between the various resilient concepts is not offered.

Christopher and Peck (2004) develop four main concepts for creating supply chain resilience: (1) resilience should be inherent to the system, (2) a high level of organizational cohesiveness is needed if risk is going to be managed, (3) the ability to lower response time is critical, and (4) risk management culture must be embedded in the identity of an organization. Additionally, Christopher and Peck (2004) identify the importance of the inherent tradeoff between expanded capacity and increased inventory, which provides added flexibility when coping with the impacts of unforeseen disruptions or demand surges (Chopra & Sodhi, 2004; Christopher & Peck, 2004; Tomlin, 2006; Lücker et al., 2019).

Pettit et al. (2010) introduce three propositions that identify the sought after "zone of resilience." This equilibrium balances an organization's capabilities with the organization's vulnerabilities (Pettit et al., 2010). They assert that if a supply chain does not sufficiently invest to develop capabilities to offset the negative impacts of its vulnerabilities, excessive risk will occur. Conversely, excessive investment into risk mitigation capabilities will eventually begin to consume profitability (Pettit et al., 2010).

Additionally, Pettit et al. (2010) identify 14 mitigation capabilities that aim to address system vulnerabilities. In other words, networks that are prone to disruptions with limited resilience capabilities often place themselves in situations with excessive risk. Networks that invest heavily in the ability to mitigate vulnerabilities may be over investing and experience diminishing returns on those capabilities (Pettit et al., 2010). This research seeks to provide a method for striking a balance between network capabilities and network vulnerabilities.

In the time leading up to a disruption, whether anticipated or unforeseen, firms have numerous options at their disposal to help mitigate or respond to the event of a disruption (Kleindorfer & Saad, 2005; Tomlin, 2006; Yang et al., 2009). Yang et al. (2009) examine how the numerous risk management strategies change when one entity is faced with asymmetric information (Yang et al., 2009). Specifically, Yang et al. (2009) examine the necessary adoption of mitigation tactics and associated costs for organizations when facing asymmetric information. Tomlin (2006) and Ivanov et al. (2014) assert that mitigation tactics are proactive in nature, thus, if the firm decides to proceed, a cost will be incurred even if a disruption does not occur. For instance, if a firm builds excess inventory in anticipation of a disruption, the acquisition cost and holding costs are incurred even if the disruption does not occur (Chopra & Sodhi, 2004). A firm may also want to proceed with a contingency tactic, which is inherently reactive in the sense that the firm only enacts this strategy if a disruption has occurred (Tomlin, 2006; Ivanov et al., 2014). For instance, in the event of a disruption, a firm may be able to shift production from one supplier to another (Tomlin, 2006). Tomlin (2006) highlights that the firm need not proceed with only one of these tactics, and that the greatest benefit in added resiliency comes from an investment in simultaneous resilience tactics. Investing in isolation leads to inefficiencies within the system (Femano et al., 2019). This research applies this insight when balancing production capacity and inventory investments.

Schmitt and Singh (2012) build upon the mitigation and contingency tactic strategies of Tomlin (2006) by utilizing discrete-event simulation (DES) to illustrate the impacts of inventory placement and other methods. Using a real-world example of a consumer-packaged goods company, Schmitt and Singh (2012) and Snyder et al. (2012) emphasize the importance of capacity to mitigate a disruption impact shown by varying the level of capacity and response time. Although the use of disruption capacity is extremely important in a firm's ability to recover, the reaction time of the disruption capacity is often more important than the capacity itself (Schmitt & Singh, 2012; Femano et al., 2019). For instance, following a disruption, a 20% increase in capacity with a 1-week reaction time better mitigated the disruption impact than a 50% capacity increase with a 4-week reaction time (Schmitt & Singh, 2012). The speed at which a firm reacts to a disruption can often have the greatest impact on mitigation and recovery (Schmitt & Singh, 2012; Femano et al., 2019).

2.3 Production Capacity and Inventory Tradeoff

Decision makers are continuously challenged to maximize specific outputs given a finite level of resources to do so. Both in a commercial and military context, maximizing the availability of parts, equipment, and systems are of the highest priority (Sleptchenko et al., 2003). Given the inherent nature of network vulnerabilities, disruptions, and finite resources, the investment tradeoff between resilience levers is an integral part of any supply chain.

Maximizing the availability of any system entails two primary methods: increasing inventory or reducing throughput times (Sleptchenko et al., 2003). Increasing system inventory to buffer against longer than usual throughput times and increasing capacity to shorten throughput times leaves decision makers with an interesting paradox (Sleptchenko et al., 2003). As Tomlin (2006) highlights, the isolated investment in a single capability will be limited without the simultaneous investment in multiple capabilities. In other words, if capacity is proactively and reactively increased without supplementing inventory, the full potential of the capacity will not be realized, and vice versa (Femano et al., 2019). Hence, decision makers are faced with an extremely challenging dilemma: how does a firm simultaneously invest in resilience capabilities to maximize the availability of a given system?

Sleptchenko et al. (2003) take a two-pronged approach to address this problem. Using the VARI-METRIC procedure for parts inventory within a repair network, Sleptchenko et al. (2003) model a similar multi-echelon repair network consisting of local and depot-level repair capabilities and illustrate the following: First, given a finite budget constraint, the goal is to maximize cumulative system availability. Second, given a specified availability target, an approach to minimize the investment costs is taken using the tradeoff of spare parts and production capacity (Sleptchenko et al., 2003). Although valuable insight into the cost relationships between spare inventory and capacity is provided, a resilience-building approach was not taken. This research incorporates a randomized disruption to measure the cost-resilience relationships between various levels of inventory and capacity and captures the overall impact on system performance over a specified time period.

Lücker et al. (2019) use the concept of reserve mitigation inventory (RMI) and reserve capacity to minimize the impact of an unforeseen disruption at a single location. Lücker et al. (2019) utilize RMI in a reactive manner contrary to the resistance concept developed by Melnyk et al. (2013). However, immediately following a disruption, the firm may use both measures instantaneously. Realistically, a time period will exist before an organization is able to respond. Under stochastic demand, Lücker et al. (2019) offer valuable insight into the optimal investment strategy of RMI and reserve capacity by evaluating the following risk strategies: inventory, reserve capacity, mixed, and passive (Lücker et al., 2019). This research quantifies resilience changes based on the investment in predetermined production capacity allocations, all the while emphasizing the need for the simultaneous increase in spare inventory.

2.4 Resilient Design Flexibility

Perhaps the single most important mitigation strategy an organization may utilize is in the flexibility design of its network. Process and design flexibility are essential in allowing organizations to vary their level of responsiveness while facing continuous uncertainties (Jordan & Graves, 1995). Flexibility is defined here as the ability to "restructure previously existing" production capacity to best mitigate and facilitate system recovery (Carvalho et al., 2012). Inventory is an excellent way to bolster resilience while facing continuous uncertainties (Sheffi, 2001; Chopra & Sodhi, 2004; Tang, 2006; Liu et al., 2016). Proactive mitigation techniques, particularly, the stockpiling of inventory can be extremely expensive (Tomlin, 2006). Therefore, Liu et al. (2016) introduce the concept of virtual stockpile pooling (VSP). Aimed at lowering the massive holding costs associated with higher inventory levels, VSP differentiates from the dedicated stockpile and integrated stockpile approach by “allocating the integrated stockpile amongst multiple locations” (Liu et al., 2016:1746). This approach enables transshipments to compensate for locations that are below their allocated stock levels (Liu et al., 2016). It does so by creating thresholds or “red lines” representing the amount that a location can go above or below its allocated threshold. Fluctuations beyond the allocated threshold are dependent upon the ability of another location to compensate by increasing or decreasing its allocated threshold (Liu et al., 2016). In theory, the implementation of VSP for an Air Force repair network could prove beneficial; however, the quantity and localized nature of less severe repairs does not create the need for VSP incorporation within the scope of this research. Although, used in a proactive and reactive manner, bolstered inventory levels drastically reduce the impact on performance levels of organizations following a disruption (Sheffi, 2001; Chopra & Sodhi, 2004; Tang, 2006; Liu et al., 2016; Femano et al., 2019).

Saghafian and Van Oyen (2011) highlight that a flexible design can be achieved by incorporating a backup supplier and gathering risk information through the use of primary suppliers. When facing the reality of finite budgets and the prospect of unreliable suppliers, a process is derived that assists in identifying which primary suppliers should be backed up (Saghafian & Van Oyen, 2011). This assumes that the achievement of full flexibility (backing up all primary suppliers) is not cost feasible (Saghafian & Van Oyen, 2016). This approach “backs up” or bolsters the investment in production capacity prior to the disruption occurring based on expected demand. In the context of a military repair network, strategic vulnerability assessments would occur to identify which nodes would benefit the most from redundant capabilities based on adversarial capabilities, location, and mission criticality.

Forbes and Wilson (2018) highlight the need for supply chain flexibility by introducing a case study on a wine distribution supply chain in Christ Church, New Zealand during the devastating earthquakes in 2010 and 2011. Although specific to the wine distribution industry, Forbes and Wilson (2018) examine organizational capabilities by comprehensively analyzing each entity's pre-event readiness, disruption response efforts, and long-term recovery efforts after a disruption occurred (Forbes & Wilson, 2018). Specifically, Forbes and Wilson (2018) identify the critical need for capital expenditure decentralization. Although decentralization can be costly, the inherent "geographical dispersion and flexibility" facilitated a greater performance level during the disruption than that of their competitors (Forbes & Wilson, 2018:486). However, not all organizations have the financial capability for such measures. Therefore, organizations should aim to strike the delicate balance between network capabilities and vulnerabilities (Pettit et al., 2010). This research examines the impacts on network performance by varying the level of flexibility that is inherent to the PACAF network design.

2.4.1 Long Chain Flexibility Approach

Effectively designing the network to efficiently allocate capacity in a proactive manner allows cumulative network performance to better withstand any impact that may arise due to a disruptive event (de Neufville & Scholtes, 2011). Building upon the added benefits of flexibility incorporation, the "long chain" or "one chain" strategy, introduced by Jordan and Graves (1995) describes a flexibility approach that connects all production plants and serviceable products by "product assignment decisions" (Jordan & Graves, 1995:577). For instance, two plants can service each product, and each plant only services two products (Graves & Tomlin, 2003). This concept is illustrated by using the example of ten production plants and ten products, each with their own individual demand. The "no flexibility" design highlights an instance where each plant produces only one product and yields a cumulative capacity utilization of only 85.3% (Jordan & Graves, 1995). Next, the "full flexibility" example provides each plant the ability to produce every product. This design yields a capacity utilization of 95.4%; however, the cost of doing so is not feasible (Jordan & Graves, 1995). Graves and Tomlin (2003) build upon this concept by developing a process flexibility framework. The stark differences in the various network design structures are illustrated in Figure 2, which uses the terms "long chain" and "one chain" interchangeably. Although the "three chain" and "one chain" strategies have an equal number of links, the ability to meet demand, as indicated by sales and capacity utilization greatly benefits the "one chain" design (Jordan & Graves, 1995). As mentioned, the "total flexibility" approach yields similar results to the "one chain" design. However, the cost of "total flexibility" greatly exceeds that of "one chain," or partial flexibility (Jordan & Graves, 1995). For the remainder of this research, this flexibility strategy will be referred to as the "long chain" structure.

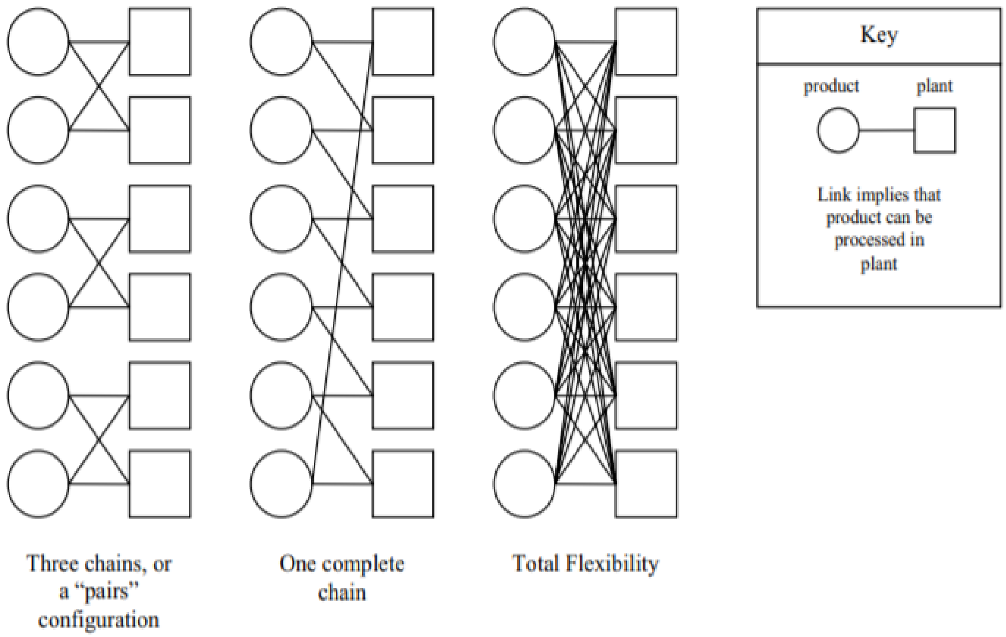


Figure 2: Various Flexibility Configurations (Graves & Tomlin, 2003)

The long chain structure allows the incorporation of flexibility into the system design, thereby, easing the shift of capacity to handle random fluctuations in demand from plant to plant, which facilitates a higher performance level (Graves & Tomlin, 2003). Additionally, flexibility incorporation allows quicker response times without sacrificing costs of buffer inventory and buffer capacity (Simchi-Levi & Wei, 2012). This research utilizes the long chain flexibility approach by illustrating the associated benefits when facing a disruption. Although the PACAF network design is inherently flexible, the cost of operational expansion would prove infeasible. The impacts on cumulative network performance resulting from the incorporation of the long chain structure and the resulting cost savings are illustrated in the methodology and results sections.

2.5 Literature Conclusion

This research builds upon the supply chain resilience literature by measuring the impact of different resilience strategies. Specifically, this research addresses the identified literature gap by incorporating the outlined flexibility approaches in conjunction with the inherent tradeoff between inventory and production capacity to quantify how additional investment in the resilience levers equates to additional levels of resilience. More importantly, this tool builds upon the literature foundation by providing essential insight into the inherent cost-resilience relationships to better facilitate network performance in the event of a disruption.

III. Methodology

This research addresses the gap in the literature by developing a simulation model to incrementally quantify the impact of resilience investment. The PACAF F-16 repair network is modeled to demonstrate the degree to which resiliency is currently incorporated and to determine how varying the level of investment and network designs impact cumulative network resilience. The identified resilience levers are spare inventory, production capacity, and the speed at which a disruption response occurs. A comprehensive examination of resilience lever manipulation and its subsequent impact on the pre-disruption and post-disruption performance levels will provide key insight as to the optimal allocation of resources across the network. The examination of key variables on the system's ability to resist the occurrence of a disruption, mitigate the impact on performance level, and expedite recovery after a disruption has occurred will provide a system's approach to examining network resilience levels.

The adopted research methodology consists of the following steps:

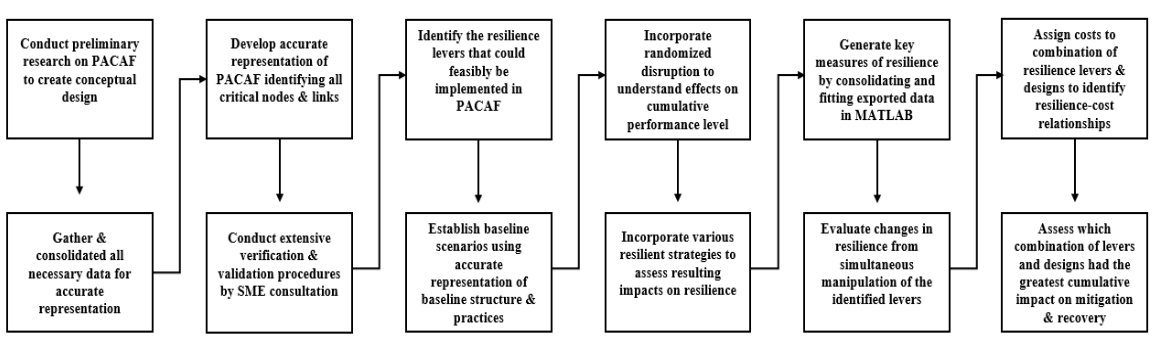


Figure 3: Adopted Research Methodology

3.1 Conceptual Design

This research models the impact of a network disruption on the PACAF F-16 repair network as it is currently structured. Furthermore, various network designs are proposed and tested using the numerous flexibility approaches outlined in the literature. Repair network operations located at Misawa AFB, Kunsan AFB, Osan AFB, and Eielson AFB are modeled by incorporating four individual Product Repair Groups (PRGs): Propulsion, Avionics, Hydraulics and Electrical & Environmental (E/E). The distribution of resources (capital fixtures necessary for repair) for each location are based off the quantity of resources for the F-16 C & D models located at Shaw AFB. For instance, identified quantities of production capacity at Shaw AFB are distributed to each location in PACAF in proportion to the amount of allocated aircraft located at each base. Table 1 illustrates the back shop capacity allocation for the initial baseline system.

Table 1: Baseline System Capacity Allocation

Back Shop	Eielson	Osan	Kunsan	Misawa	Total
Propulsion	2	2	4	4	**12**
Avionics	3	3	5	6	**17**
Hydraulics	1	2	3	3	**9**
E/E	1	1	2	2	**6**
Prop CRF				5	**5**
Total	**7**	**8**	**14**	**20**	**49**

3.2 Data Collection

The Air Force’s Logistics, Installations, and Mission Support-Enterprise View (LIMS-EV) was utilized as the primary source of data. LIMS-EV is the “single entry point” or consolidated warehouse of Air Force logistics data and was created to ensure "one version of the truth" for all logistics data exploitation (Petcoff, 2010). Therefore, this research relies heavily upon the accessibility and accuracy of the consolidated database. When identifying and gathering the necessary data, all results were filtered to contain the relevant metrics for the chosen network and chosen airframe. Sortie quantity, flying hours, total aircraft inventory (TAI), and break rates were gathered and incorporated from various dashboards located within LIMS-EV. Furthermore, specific line replaceable unit (LRU) data is gathered from the DLR Flying Dashboard. Additionally, small focus groups with each PRG back shop were held that facilitated discussion and validation of model assumptions. Conversations with subject matter experts (SMEs) were utilized to gather pipeline times between critical nodes during the repair process. Empirical data was gathered and consolidated from notes based on first-hand experience at Shaw AFB. Table 2 shows a consolidated list of gathered and incorporated data, while Table 3 illustrates the 2018 system parameters that are incorporated into the simulation at time 0. Additionally, Custodian Inventory Reports (R14s) were gathered from each PRG back shop located at Shaw AFB which contains the item description, quantity on-hand, and original acquisition cost of all capital fixtures necessary to perform repairs. The repair cycle time (RCT) was gathered for the incorporated LRUs from SMEs located at the 635th Supply Chain Operations Wing (SCOW).

Table 2: Consolidated Data Sources

Data	Data Source
2018 Sortie Generation Data	LIMS-EV: Weapon System View
2018 PACAF Break Data	LIMS-EV: Weapon System View
PACAF Transportation Data	USTRANSCOM
PRG Categorization	LIMS-EV: Cost of Logistics
NSN Demand Data	LIMS-EV: Supply Chain Management View
NSN Cost Data	D200: Dr. Marvin Arostegui
Repair Cycle Time (RCT)	635th SCOW: MSgt Marr
Custodian Inventory Report (R14)	PACAF SMEs
CAPEX Estimates	Historical Air Force Construction Cost Handbook (2007)

Table 3: 2018 System Parameters

Base	AC*	Sortie Quant*	Total FH*	Break Rate	Sorties/Day*	Hrs/Sort*	DDay Prob
Eielson	25	2000	4000	13.82	7.69	2.00	0.25
Osan	25	3000	5000	13.82	11.54	1.67	0.25
Kunsan	25	5000	8000	13.82	19.23	1.60	0.25
Misawa	25	6000	9000	13.82	23.08	1.50	0.25

***Data changed in accordance to Distribution Statement A**

3.3 Baseline System Description

This research utilizes SIMIO, a discrete-event simulation software well suited for the design and emulation of complex, multi-layered problem sets requiring the use of many experimental designs (Femano et al., 2019). To develop the most accurate representation of the network, conversations with RNI Node Managers located at the SCOW were used to validate repair capability assumptions for each modeled location. The validity of using repair operations from Shaw AFB to model bases in PACAF was validated with SMEs. The back shops in PACAF for the associated PRGs all have I-level capabilities except for the propulsion capability. Operations are modeled by accurately duplicating the routing of broken LRUs within each PRG. Each base contains flight line maintenance and the respective back shop for each PRG. As broken LRUs are generated, the PRG that contains the specific LRU is determined and used exclusively to route the part to the appropriate back shop. Depending upon the severity, I-level breaks may be laterally shipped to the base with the current capacity to perform the repair. I-level repairs may be laterally shipped to the base that is most in need. Therefore, the network contains organizational (O-level) and intermediate (I-level) capabilities. The only centralized repair facility (CRF) is the propulsion back shop located at Misawa AFB. As breaks are identified, and it is determined to be an engine, Eielson, Kunsan, and Osan all pack, wrap, and ship whole engines to the Misawa propulsion CRF for repair. Therefore, excluding propulsion, all local back shops possess I-level capabilities. Depot level maintenance is not within the scope of this research.

Table 3 shows the quantity of assigned aircraft to each operating location in USAF's PACAF theater. Flying operations are conducted using 2018 flying schedule data. The data is used to create an interarrival time of breaks as an exponentially distributed function of the number of aircraft allocated to each base, the sortie quantity, flying hours, and cumulative PACAF break rate. The interarrival time is given by:

$$Interarrival\ Time = \left(\frac{F_i}{BreakRate}\right)/(A_i * S_i * H_i) \quad (1)$$

where,

$\boldsymbol{F_i}$ *represents the total flying hours for base* i*,*

$\boldsymbol{A_i}$ *is the total number of mission capable aircraft at any given time for base i,*

$\boldsymbol{S_i}$ *is the average number of sorties using a 260-day flying schedule for base i,*

$\boldsymbol{H_i}$ *is the average duration in hours of each sortie for base i.*

As an entity is generated (break occurs), an LRU is assigned, which corresponds to a PRG, thereby determining the routing of the part in the repair process. LRU assignment is based upon the 2018 annual demand for each LRU determined in LIMS-EV.

As the discrepancy is identified by flight line maintenance, crews will determine the PRG and ultimately the LRU that has failed. As Table 4 and Table 5 illustrate, a severity of 1 to 4 is assigned to all breaks for propulsion, avionics, E/E, and hydraulics. The propulsion severity mix is drawn from a separate table to enable this research to more accurately reflect the number of propulsion I-level discrepancies. As the LRU arrives at the appropriate back shop, the associated repair cycle time is determined and assigned as a random exponential distribution. The repair cycle time was assigned to each LRU by using a weighted average based off the corresponding annual demand for each LRU. However, if an engine was routed to the propulsion CRF, a processing time of 30-days is used to represent an accurate depiction of the amount of time to turn the engine serviceable. The weighted average was necessary to realize the benefits from incremental investment in production capacity. The weighted average raised the repair time for higher demanded items, thus allowing a queue to build at the associated back shops. The baseline structure features one propulsion CRF. If a propulsion LRU is generated, and severity 4 is assigned, the entire engine is dropped and routed to the CRF located at Misawa. For propulsion, avionics, E/E, and hydraulics, severities 1 to 3 are routed directly to the local back shop. Excluding propulsion, lateral shipments of severity 4 breaks are permitted which provides the flexibility to ship the part to the base which currently has the available capacity to perform the repair. As the part is repaired at the back shop, the repaired part will be shipped to the base that is currently most in need, where the part will be placed on an awaiting aircraft or increase local on-hand spare inventory as depicted in Figure 5.

Table 4: Avionics, Hydraulics, & E/E Severity Mix

Eng Sev	Sev Mix	Rpr Lvl	BSProcessingTime (Hrs)	Prop CRF (Days)
1	0.45	O-Level	LRU RCT	-
2	0.13	O-Level	LRU RCT	-
3	0.17	O-Level	LRU RCT	-
4	0.25	I-Level	LRU RCT	-

Table 5: Propulsion Severity Mix

Eng Sev	Sev Mix	Rpr Lvl	BSProcessingTime (Hrs)	Prop CRF (Days)
1	0.35	O-Level	LRU RCT	-
2	0.25	O-Level	LRU RCT	-
3	0.2	O-Level	LRU RCT	-
4	0.2	I-Level	-	Random.Exponential (30)

3.4 Model Verification & Validation

Extensive model verification occurred using the model trace function in SIMIO. Tracing allows the step-by-step tracking of individual entities flowing from node to node throughout the duration of the repair process. A method was followed that verified the precise location of each entity within the simulation. This verification ensured the proper assignment of specific PRGs and subsequently, LRUs, which led to the verification of routing to the appropriate back shop and/or CRF. Model assumption validation was achieved based on continuous feedback from conversations with SMEs located at Shaw AFB, the 635th SCOW, and PACAF. Time series outputs of total throughput, processing times, and queues were generated to validate system performance over time.

Each iteration completion generated system statistics that provided metrics such as the number of breaks specific to each location, number of repairs specific to each location, and system utilization metrics such as throughput and time in system. Utilization metrics were validated with phone calls to SMEs located at the specific back shops in PACAF.

3.5 Scenario Development

Baseline scenarios were first developed to aid in the verification and validation process and to gain a fundamental understanding of the system's performance levels. Baseline scenarios were generated with current PACAF repair capabilities to provide an accurate representation of system behavior over time. All scenarios were run over a 2,000-day time period with an incorporated warm-up period of 1200-days. Due to the size and inherent complexities of the model, a 1200-day warm-up period was necessary. Although system statistics are generated for an 800-day time period, this research primarily focuses on the transient states of performance. For instance, a randomized disruption occurs at day 1400. Regardless of the response time frame, all scenarios have recovered by day 1600. Therefore, from day 1400 to 1600, the AUC is utilized to evaluate system performance. The baseline structure represents the PACAF F-16 repair network as it is currently structured. Therefore, all other resilience scenarios and network designs will be compared to the baseline structure in both performance and cost over the specified time period.

This research uses the following classifiers to identify the time periods of interest during a disruption:

Pre-Disruption: *Day 1200 to day 1400*
Post Disruption – Decline: *The time at which the disruption occurs until a specified response has been enacted.*
Post Disruption – Recovery: *Time at which the response occurs until the system performance has recovered (Day 1600).*

Existing within the post disruption time period is the AUC metric used to quantify the level of demand the network can meet during the Post Disruption - Decline and Recovery periods. The AUC for each period is described as follows (Femano et al., 2019):

Area under the Curve – Decline (AUC-Decline): *The total network performance under the Post Disruption – Decline curve.*
Area under the Curve – Recovery (AUC – Recovery): *The total network performance under the Post Disruption – Recovery curve.*
Area under the Curve – Total (AUC – Total): *Cumulative network performance during all stages of the disruption.*

The primary resilience levers are production capacity and response time. However, the simultaneous investment in spare inventory is essential to realize the greatest benefit from increased capacity (Femano et al., 2019). All expanding scenarios include some allocation of inventory, production capacity, and a varying response time. Table 6 illustrates the developed scenarios used for the baseline structure. A cost and performance threshold of 80% MC Rate was used to scope the number of needed scenarios. Baseline structure capacity is varied up to a 30% increase of the originally assigned allocations, while the capacity used to recover from the disruption is increased up to 50% of the initial capacity allocation. Additionally, the scenarios in Table 6 were used in conjunction with a 10, 20, 30, and 40-day response time to emphasize the importance of an expedited response. All designed scenarios were evaluated using the developed AUC metric, in addition to the network's cumulative mission capable (MC) rate. Moreover, 100 replications were performed on each scenario. The AUC is used as the primary metric of resilience because it provides a more accurate representation of system behavior and the ability to meet demand over the disrupted time period.

Table 6: Developed Baseline Scenarios

Initial System					
Scenario	**System Initial Capacity**	**Recovery Capacity**	**Scenario**	**System Initial Capacity**	**Recovery Capacity**
1	1.00	1.00	13	1.20	1.00
2		1.10	14		1.10
3		1.20	15		1.20
4		1.30	16		1.30
5		1.40	17		1.40
6		1.50	18		1.50
7	1.10	1.00	19	1.30	1.00
8		1.10	20		1.10
9		1.20	21		1.20
10		1.30	22		1.30
11		1.40	23		1.40
12		1.50	24		1.50

As replications are completed, SIMIO produces and exports a comma separated value (CSV) file for each replication. The baseline scenarios outlined by Table 6 produced 2,400 CSVs for one response time (100 files for each scenario). After all developed scenarios have been completed, the CSVs are imported into MATLAB, which consolidates, batches, and integrates the area under the curve for each scenario. MATLAB then produces a consolidated table containing the time period metrics associated with each scenario that are used for investment and design comparison. All consolidation, batching, and integration code can be seen in detail in appendix B, C, and D.

3.6 Flexibility Design

In addition to varying amounts of predetermined resilience levers, network design performance is evaluated using the process flexibility approach introduced by Jordan and Graves (1995) and Simchi-Levi and Wei (2012) in the literature. The process flexibility approach assumes a finite amount of network production capacity and varying amounts of connectedness among repair nodes. For instance, the baseline structure is rather robust, and all locations have avionics, hydraulics, and E/E capabilities. For propulsion, however, centralization exists for I-level capabilities. Hence, the baseline system provides adequate resistance to disruptions that are enacted upon it. However, if the CRF at Misawa for propulsion is affected, the subsequent events that follow and the impact on the network’s ability to perform engine overhauls would be disastrous. Therefore, various levels of flexibility were implemented and tested using allocations of network resources to do so.

This research employs two additional designs selected for their stark cost/resilience difference when facing uncertain futures. Each location is assigned the initial amount of production capacity in proportion to the amount of allocated aircraft as presented in Table 1. The employed network designs strategically increment capacity at various locations to illustrate the impact on the network's ability to maintain system throughput at the back shops in the event of lost capacity at a location. Figure 4 illustrates the differences between the various network designs.

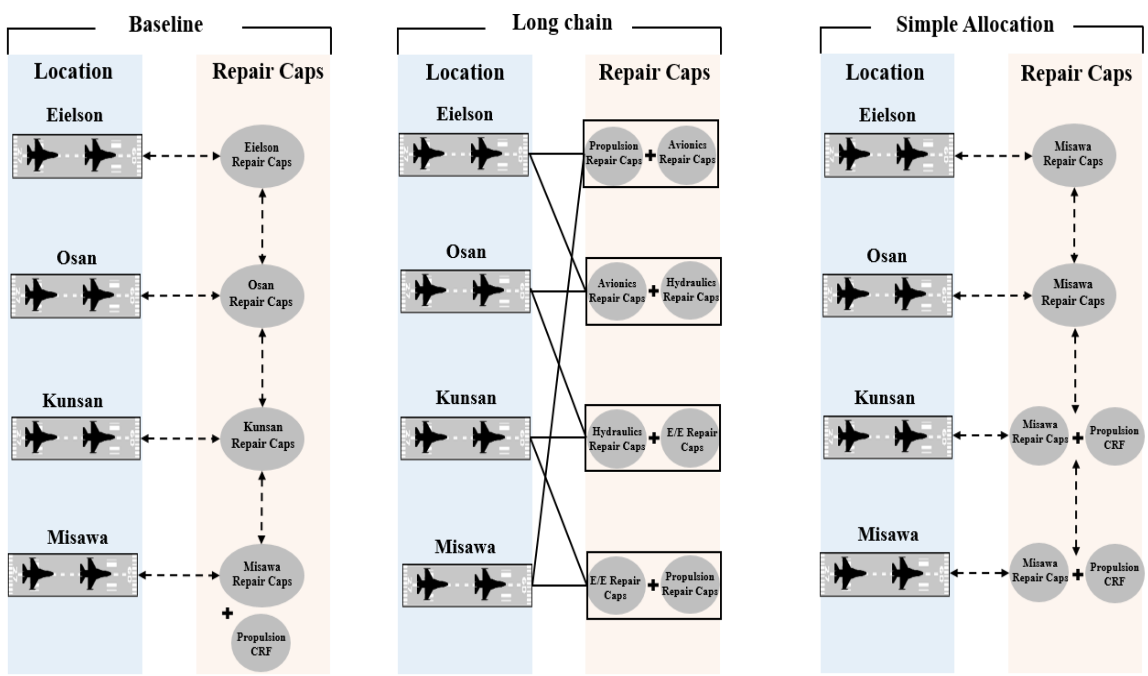


Figure 4: Developed Network Designs

The second design uses the long chain flexibility approach developed by Jordan and Graves (1995). This approach is extremely beneficial for system designs that feature limited flexibility incorporation. However, as the baseline structure is rather flexible regarding the allocation of repair capabilities, it is not flexible when capacity is considered. This research employs the long chain approach to illustrate an alternative design to achieve desired levels of flexibility at tremendous cost savings. The inability to alter PACAF as it is currently structured is recognized. Therefore, we posit the use of the long chain strategy to recommend methods of future capacity expansion. As Jordan and Graves (1995) describe, the capacity for each PRG is allocated to exactly two locations. Every location possesses the ability to perform repairs for exactly two PRGs, which forms "one chain" flexibility as illustrated in Figure 2 and disperses cumulative risk (Jordan & Graves, 1995). The third design, or simple allocation structure, supplements all existing recovery capacity at non-impacted locations with Misawa's production capacity (greatest quantity). Chosen to illustrate the impacts of significantly increasing recovery capacity on the AUC, this design illustrates the cost associated with a higher level of resilience. Additionally, the simple allocation structure realizes a large increase in spare inventory across all locations to illustrate the need for simultaneous investment to support the increase in production capacity. Furthermore, multiple propulsion CRFs are utilized to show the benefits of centralization dispersion. All developed designs are evaluated using the experimentation function in SIMIO to allow the simultaneous manipulation of the identified resilience levers. Additionally, all established designs possess the ability to laterally ship I-level discrepancies.

The long chain structure increases levels of recovery capacity only. The simple allocation structure does not realize an additional investment in initial or recovery capacity due to the extremely large initial resilience investment. Furthermore, the long chain structure increases up to 210% of the original long chain initial capacity allocation. The large investment increase in the long chain scenarios was cost feasible and necessary to reach Pre-Disruption MC Rates. Similar to the simple allocation structure, the long chain structure’s large increase in recovery capacity warranted an increase in spare inventory for the design.

3.7 Disruption Incorporation

All developed scenarios were run using predetermined resilience levers over 2,000-days to gain a fundamental understanding of the impacts of simultaneously manipulating resilience levers on cumulative system performance. To gauge system performance and to determine the level of system resilience, all developed scenarios were run with the incorporation of a randomized disruption (DDay) at day 1400, where, as Table 3 illustrates, a disruption eliminates all the repair capabilities specific to one location via an equal probability. After a specified delay, it is assumed all aircraft that were located at the impacted location are equally distributed to the three remaining bases. Moreover, this research assumes that operations at the impacted location are unrecoverable and therefore, lost for the remaining duration of the simulation. Furthermore, process logic prevents all subsequent I-level breaks from being routed to the impacted location. Figure 5 illustrates the general pre- and post-disruption behavior.

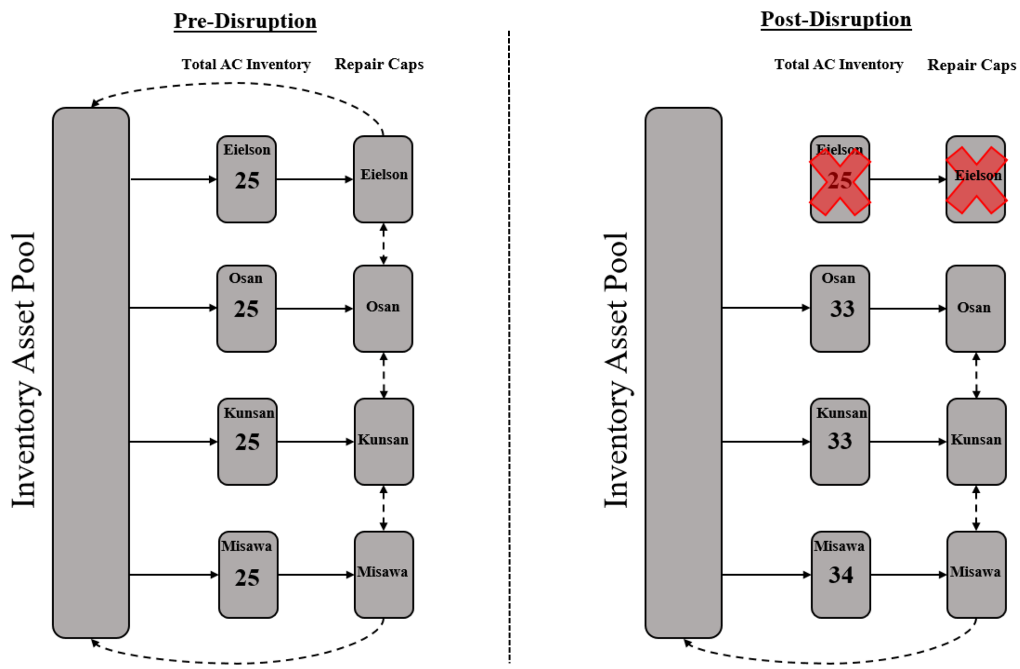


Figure 5: Post-Disruption Behavior

3.8 Resilience Measurement

Consistent with Melnyk et al. (2013), this research argues that system resilience is most accurately assessed during the system's transient states. Shown in Figure 6, each simulation iteration was broken into three distinct time periods as described in section 3.5 (Femano et al., 2019). This research builds upon the foundation set forth in the literature by using the identified concepts to illustrate and quantify the effects of simultaneous manipulation of resilience levers on each of the three time periods. As Figure 6 illustrates, the system's resistance to the disruptive event occurs in the Pre-Disruption time period of the simulation. The recovery of the system begins at the Minimum Performance Level (MPL) of the system during the disruptive event and ends in the Post Disruption – Recovery time period.

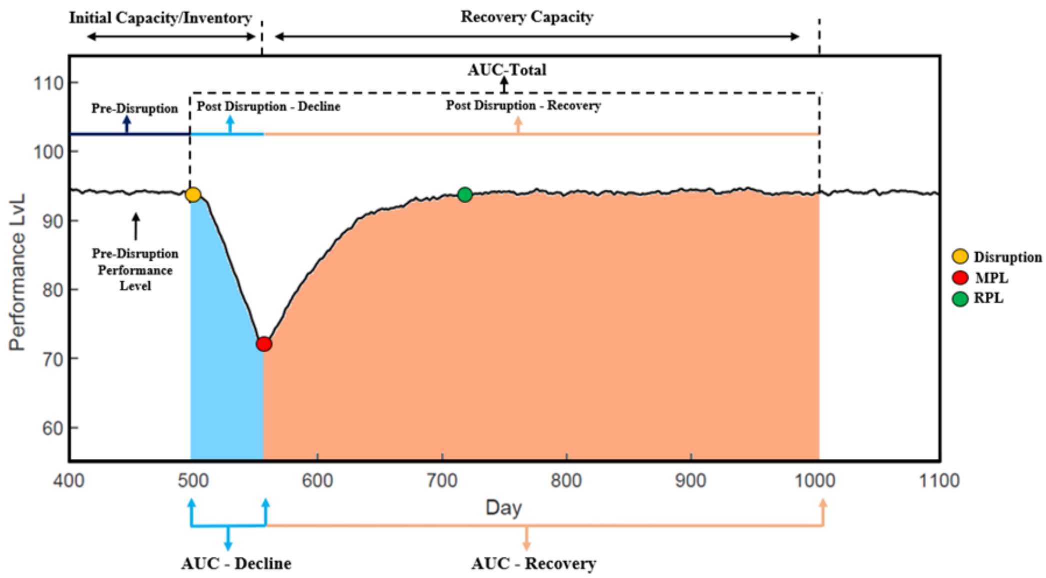


Figure 6: Performance Metrics & Disruption Time Periods (Femano et al., 2019)

This research employs the concept of the AUC to quantify the number of MC days that the system can support resulting from various levels of resilience investment (Femano et al., 2019). Contrary to Melnyk et al. (2013), who employ the use of the area above the disruption curve, this research argues that the AUC provides a more accurate representation of cumulative performance over the disruption time period. The area above the curve measures lost performance in the event of a disruption, which ultimately, deemphasizes network starting performance (Femano et al., 2019). Additionally, this research further develops a generalizable resilience metric, which represents the networks achieved AUC in proportion to the desired AUC, or total realized demand over the disruption time period (Femano et al., 2019).

$$Resilience\ Metric = \frac{AUC_t}{D_t} \tag{2}$$

This metric proves extremely generalizable because regardless of the organization, it will experience some drop in performance resulting from a disruption, and it will experience some level of demand that must be met during the disruption. Hence, this resilience metric provides an indication of the level of demand that can be met due to various levels of resilience investment. The analysis and results section builds upon the associated time periods and AUC by introducing the various time period metrics illustrated in Figure 6.

3.9 Cost Assignment

Essential to the foundation of this research is the ability to monetarily quantify varying levels of investment. Cost estimates of the associated capacity and inventory allocations, as well as the capital expenditures necessary to house them, allows decision makers to associate the required level of investment needed to reach a desired level of resilience. This research employs USAF R14s to assign a cost to the ability to perform a simultaneous repair at each specific back shop. For example, the propulsion R14 for Shaw AFB was used as the basis of cost for one unit of incremental capacity across all propulsion locations in the developed scenarios. Cost was linearly assigned to provide a representation of the necessary investment.

Spare inventory quantities were gathered specific to each location using the D200 database. Furthermore, the cost of each LRU was gathered from D200 and linearly assigned to each incremental unit of spare inventory.

An accurate representation of the necessary capital expenditures is essential for illustrating the benefits of the long chain strategy. Hence, generalizable costs associated with the CAPEX repair facilities were gathered using the *Historical Air Force*

Construction Cost Handbook (2007). Costs were determined using the given size (square feet) and cost per square foot. Additionally, location specific factors, which account for the specific costs of construction associated with each modeled location, were used in generating a final cost estimate.

Lastly, the cost of personnel needed at each location was determined by taking the average annual base pay of personnel with the pay grade of E-1 to E-7 with 2 through 20 years in service to generate an average annual salary. This figure was multiplied by the number of individuals located at each repair back shop across all locations. This research recognizes that as the level of production capacity increases, so too does need for personnel. Hence, the cost of personnel is increased by the cost percentage increase in production capacity as compared to the initial production capacity investment for each design.

An important distinction must be made regarding cost assignment. All incorporated costs represent the fixed costs necessary to perform a repair. Personnel, however, border the line between fixed and operational costs. Personnel costs are included for the purpose of this research because personnel are a fixed requirement for a given repair capability over the time periods for which the model is run.

IV. Analysis and Results

This research tests three network designs: baseline structure, simple allocation structure, and the long chain structure. PACAF was strategically chosen as the test case to apply this simulation because of the rising capabilities of US adversaries and vulnerabilities of the network to natural disaster. The simple allocation and the long chain structure reiterates the need for simultaneous investment in inventory and production capacity, while also illustrating the realized benefits and cost differences in various levels of flexibility incorporation. All scenarios used to test the various network designs are evaluated during their transient states. Numerous disruption response times are implemented that “turn on” predetermined amounts of recovery capacity for the specific scenario. Hence, this research shows the importance of predetermined asset allocations on a location’s ability to respond to a disruption. An important distinction will be made regarding the costs of these production capacity assets in the resilience cost section.

Associated with the established time periods outlined in section 3.5 are three performance metrics: The Pre-Disruption MC Rate, the Minimum Performance Level (MPL), and the Recovery Performance Level (RPL). Fully understanding the performance of a network in the event of a disruption requires a deep understanding of the interconnectedness of the mentioned performance metrics. They are defined as follows:

Pre-Disruption MC Rate: *The average daily MC Rate from day 1200 to day 1400.*
Minimum Performance Level (MPL): *The network’s minimum level of performance resulting from a disruption.*

Recovery Performance Level (RPL): *The average daily performance after network performance has recovered.*

The following sections illustrate the importance of these metrics on network performance. The emphasis is on the ability to maintain performance after the disruption has occurred. In doing so, the ability to meet a specified level of demand during a disruption begins where the Pre-Disruption MC Rate ends. In other words, a network's starting performance is extremely important for cumulative system performance throughout all stages of a disruption.

4.1 Baseline Structure

The baseline structure represents PACAF as it currently operates. It provides valuable insight as to how the network resists and recovers from a disruption due to its inherent flexibility and current capabilities. Table 7 shows the output generated from the developed scenarios outlined in Table 6. Each scenario represents a predetermined level of initial capacity and recovery capacity. The scenario with 1.00 of initial and recovery capacity represents PACAF's performance without any additional investment in resilience. No additional investment in production capacity leads to grave consequences. For instance, all bases have an equal probability of experiencing a disruption. If Misawa experiences the disruption, the CRF and all other repair capabilities are lost, further exacerbating the consequences on PACAF cumulative performance.

4.1.1 Impacts on Transient Performance Metrics

The baseline structure does not simultaneously increase the investment in spare inventory as the amount of capacity increases. However, Table 7 emphasizes the importance in a network's ability to maximize its Pre-Disruption MC Rate in the event of a disruption. The transient performance of the network starts with the Pre-Disruption MC Rate, and the higher the starting point for the decline to occur, the greater the AUC - Decline will be. Shown in Table 7, as the investment in initial capacity increases, so too does the Pre-Disruption MC Rate, yielding a higher AUC – Decline and MPL. Subsequently, a higher MPL leads to the ability to meet a greater level of demand during the Post Disruption – Recovery period as illustrated by the increase in AUC – Recovery and ultimately a higher RPL. Similarly, Figure 7 illustrates the impact of an expedited response time and additional production capacity investment on the network's AUC – Total. However, an important phenomenon is illustrated in the baseline structure. Notice that the RPL realizes marginal gains as the Pre-Disruption MC Rate increases. This further reiterates the necessity of simultaneous investment in inventory and production capacity. Although the network's ability to perform in the face of disruption undoubtedly increases with a greater level of investment, a sub-optimal output is realized when only production capacity is increased. This point is further illustrated using the simple allocation and long chain structure. Alternatively, the investment in recovery capacity has the greatest benefit to RPL in the baseline structure.

Table 7: Baseline 40-Day Response Output

Scenario		Pre Disruption	Post-Disruption - Decline		Post Disruption - Recovery			
Initial Cap	Recovery Cap	Avg MC Rate	MPL	AUC-D	RPL	AUC-R	AUC-Total	Total $$
1.00	1.00	70.74	53.04	11,261	N/A	N/A	11,261	$ 126,246,142
	1.10	70.74	58.06	2,560	58.84	9,481	12,041	$ 127,402,468
	1.20	70.74	58.09	2,560	61.83	9,870	12,430	$ 128,405,856
	1.30	70.74	58.09	2,560	65.85	10,463	13,023	$ 129,233,582
	1.40	70.74	58.09	2,560	71.82	11,355	13,915	$ 130,546,799
	1.50	70.74	58.09	2,560	74.75	11,815	14,374	$ 131,319,197
1.10	1.00	75.08	54.61	2,686	54.51	9,157	11,842	$ 127,402,468
	1.10	75.08	57.10	2,686	55.56	9,437	12,123	$ 128,558,794
	1.20	75.08	59.01	2,686	58.36	9,770	12,456	$ 129,562,182
	1.30	75.08	59.88	2,686	63.34	10,391	13,077	$ 130,389,908
	1.40	75.08	59.95	2,686	71.03	11,261	13,947	$ 131,703,125
	1.50	75.08	59.95	2,686	74.33	11,739	14,425	$ 132,475,523
1.20	1.00	77.71	60.35	2,844	59.13	9,820	12,663	$ 129,992,628
	1.10	77.71	62.54	2,844	60.27	10,099	12,943	$ 131,148,954
	1.20	77.71	64.22	2,844	62.17	10,358	13,202	$ 132,152,342
	1.30	77.71	64.61	2,844	66.90	11,012	13,855	$ 132,980,068
	1.40	77.71	64.66	2,844	73.57	11,697	14,540	$ 134,293,285
	1.50	77.71	64.69	2,844	77.03	12,167	15,011	$ 135,065,683
1.30	1.00	82.86	63.80	3,030	63.20	10,512	13,542	$ 130,820,354
	1.10	82.86	65.90	3,030	64.52	10,973	14,003	$ 131,976,679
	1.20	82.86	67.59	3,030	66.48	11,125	14,155	$ 132,980,068
	1.30	82.86	69.46	3,030	67.84	11,388	14,419	$ 133,807,793
	1.40	82.86	69.46	3,030	72.36	12,239	15,269	$ 135,121,011
	1.50	82.86	69.46	3,030	75.42	12,389	15,419	$ 135,893,408

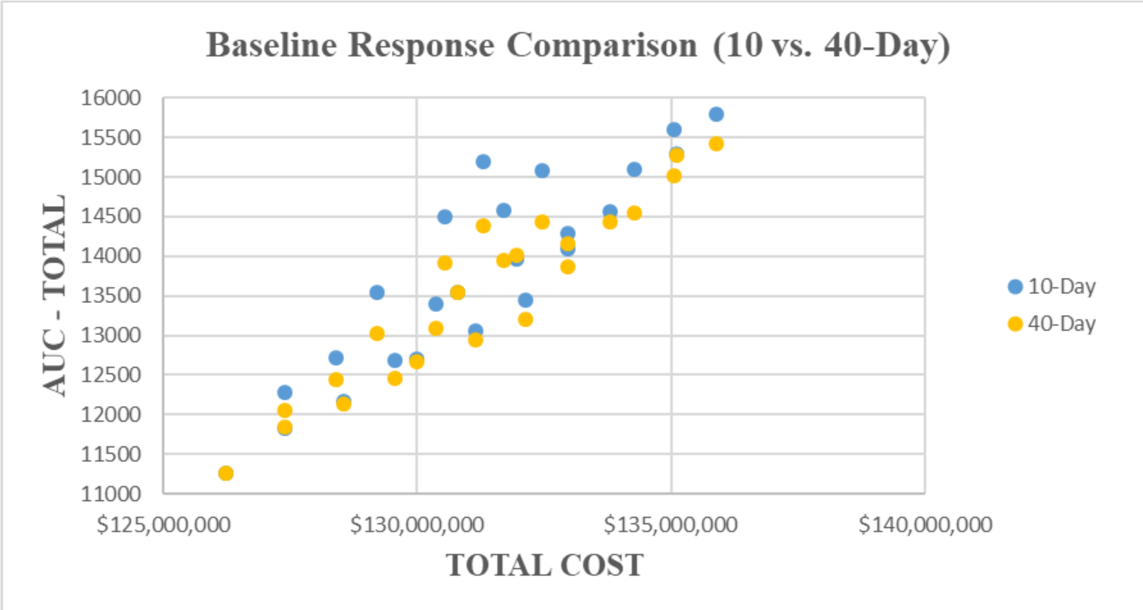


Figure 7: Baseline Response Comparison (10 vs. 40-Day)

4.1.2 Criticality of Response Time

An organization's ability to quickly identify and respond to a disruption is essential to its performance during and after a disruption. The disruption response time is varied after a disruption occurs and assumes that the response time is tied directly to the ability to "turn on" the predetermined asset allocations of recovery capacity at the remaining locations. The response time is a function of an organization's ability and willingness to invest in predetermined asset allocations. Figure 8, Figure 9, and Table 8 illustrate the consequences of a prolonged response time on cumulative network performance.

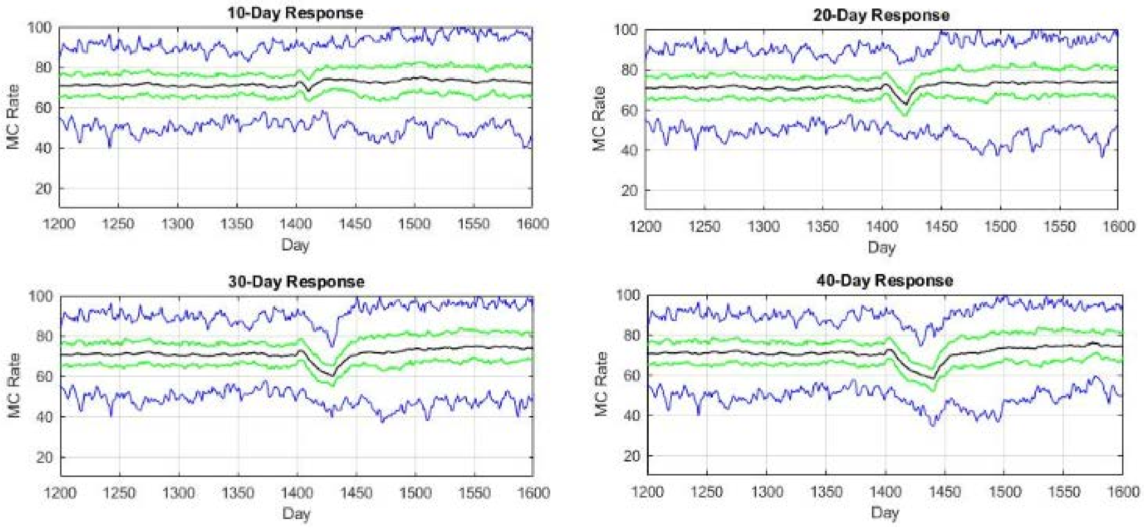


Figure 8: Varying Response Time - Baseline Structure (1.00 Initial Cap, 1.40 Recovery Cap)

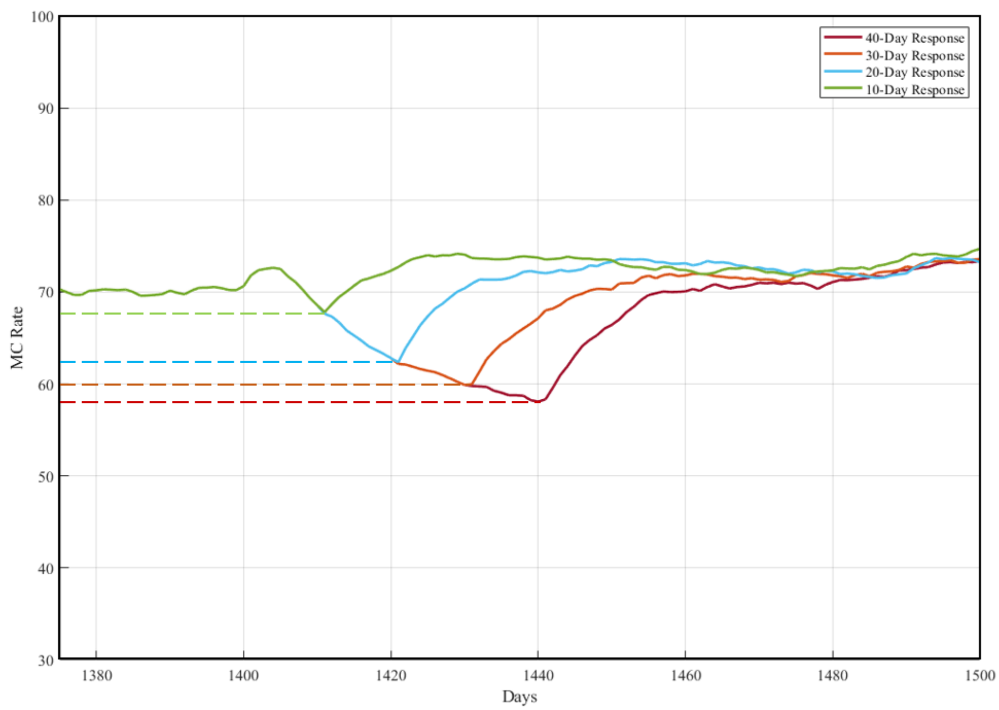


Figure 9: All Responses – Baseline Structure (1.00 Initial Cap, 1.40 Recovery Cap)

Table 8: Baseline Performance with Prolonged Response Times

	Scenario		Pre Disruption	Post-Disruption - Decline		Post Disruption - Recovery			
Response Time	Initial Cap	Recovery Cap	Avg MC Rate	MPL	AUC-D	RPL	AUC-R	AUC-Total	Total $$
10-Day	1.00	1.40	70.74	67.82	705	71.45	13,779	14,484	$130,546,799
20-Day		1.40	70.74	62.36	1,359	71.32	12,793	14,152	$130,546,799
30-Day		1.40	70.74	59.91	1,971	71.23	12,015	13,986	$130,546,799
40-Day		1.40	70.74	58.09	2,560	71.82	11,355	13,915	$130,546,799

Illustrated by the decline in Figure 8 and Figure 9, an expedited response time is greatly beneficial to the network's ability to meet demand during the disruption by yielding a higher MPL and AUC - Total across all associated time periods. This research assumes that regardless of the response time, the investment level across all response times is the same. It is important to note that, realistically, this may not be the case. A higher cost may be associated with an expedited response time. Additionally, the ability to expedite a disruption response significantly limits the network's downside risk. For instance, Figure 8 shows the average MC Rate (Black line), the 50th percentile (Green lines), and the minimum and maximum MC Rates (Blue lines) across all replications. Moreover, Figure 9 shows the impact of a prolonged response time on MPL of the network. The dashed lines point to the exact minimum reached on the y-axis resulting from the associated response time. The minimum MC Rate is significantly higher with a 10-day response as compared to a prolonged response time.

Response time is a critical driver to an organization's ability to facilitate a recovery to pre-disruption performance levels. If, for instance, decision makers lack the ability to increase investment in inventory and production capacity, an expedited response time provides the ability to mitigate downside risk and maintain performance in the event of a disruption. Therefore, an expedited response time is a viable alternative to hedge against the inability to use resources that have been lost in the event of a disruption.

4.2 Simple Allocation Structure

The simple allocation structure realizes a significant increase in resilience investment across all locations. The simple allocation structure allocates the network's greatest capacity quantity (Misawa) and assigns it as recovery capacity at all other locations. Furthermore, the simple allocation structure incorporated an additional propulsion CRF at Kunsan to illustrate the beneficial impacts of decentralization on network performance while facing disruptions. Additionally, and in a similar manner to production capacity, the simple allocation structure allocated Misawa's spare inventory quantity across all locations to illustrate the need for simultaneous inventory investment to realize the greatest benefit from the increase in recovery capacity. Therefore, the simple allocation structure demonstrated the highest level of resilience resulting from the large increase in resilience investment. Table 9 highlights the performance and costs of the simple allocation structure. Due to the large increase in resilience and subsequent performance, an increased investment in initial and recovery capacity was not utilized. Hence, the number of needed scenarios was drastically reduced.

Table 9: Simple Allocation Structure Output

	Scenario		Pre Disruption	Post-Disruption - Decline		Post Disruption - Recovery			
Response Time	Initial Cap	Recovery Cap	Avg MC Rate	MPL	AUC-D	RPL	AUC-R	AUC-Total	Total $$
10-Day	1.00	1.00	72.66	68.82	727	84.84	16,783	17,510	$177,264,060
20-Day		1.00	72.66	61.00	1,453	85.42	15,263	16,716	$177,264,060
30-Day		1.00	72.66	55.39	2,180	85.57	14,418	16,598	$177,264,060
40-Day		1.00	72.66	53.91	2,858	86.17	13,632	16,490	$177,264,060

4.2.1 Impacts on Transient Performance Metrics

Table 9 illustrates the impact of higher initial inventory quantities on the network's Pre-Disruption MC Rate. Spare inventory has a greater impact on the ability of the system to resist the occurrence of a disruption (Melnyk et al., 2013). As shown, the Pre-Disruption MC Rate is greater in the simple allocation structure than in the baseline structure at the same level of initial capacity investment. Thus, the simple allocation structure leads to a higher MPL across all scenarios and response times at the same level of initial capacity as compared to the baseline structure. Furthermore, due to the high level of investment in recovery capacity, the corresponding RPL and AUC – Recovery all meet significantly higher demand. Thus, recovery capacity has the greatest impact on a network's ability to recover from a disruption.

4.2.2 Criticality of Response Time

The ability of an organization to expedite its disruption response is further emphasized using the simple allocation structure design. Regardless of the investment in recovery capacity, decision makers must emphasize the need of a rapid response to realize the full potential of the recovery capacity.

4.3 Long Chain Structure

The third design uses the long chain flexibility approach identified in the literature to allocate production capacity across PACAF (Jordan & Graves, 1995). Note that the baseline structure is inherently flexible. For instance, each location possesses I-level repair capabilities for at least three PRGs. The exception is Misawa due to its ability to perform the repair of propulsion I-level discrepancies. Therefore, the long chain approach eliminates a portion of the inherent flexibility of the network by allocating the ability to perform the repair of only two PRGs at each location. In doing so, the original production capacity allocation for each PRG is split and assigned to the two locations that possess capabilities for that specific PRG in equal sums. The initial capacity quantity for the network is equal to that of the baseline structure. Furthermore, only recovery capacity is increased in the developed scenarios. Due to the large investment necessary in recovery capacity to recover to pre-disruption performance levels, the developed long chain scenarios were duplicated, once with no added spare inventory, and once with an additional investment in spare inventory. The results are compared in Table 10 and Table 11, which also show the developed scenarios and response output for the 10-day response time. Figure 10 shows the impact of additional resilience investment and an expedited response time on the network's AUC – Total.

Table 10: Long Chain 10-Day Response Output Original Inventory Levels

	Scenario		Pre-Disruption	Post Disruption - Decline		Post Disruption - Recovery			
Response Time	Initial Cap	Recovery Cap	Avg MC Rate	MPL	AUC-D	RPL	AUC-R	AUC-Total	Total $$
10-Day	1.00	1.00	68.19	46.92	10,412	N/A	N/A	10,412	$ 93,286,471
		1.10	68.19	44.34	680	44.34	9,954	10,634	$ 94,465,440
		1.20	68.19	48.58	680	48.58	10,354	11,034	$ 95,775,334
		1.30	68.19	51.14	680	51.14	10,562	11,243	$ 97,337,275
		1.40	68.19	53.71	680	53.71	10,921	11,602	$ 98,559,419
		1.50	68.19	57.21	680	57.21	11,427	12,107	$ 99,938,087
		1.60	68.19	58.44	680	58.44	11,588	12,269	$ 101,005,107
		1.70	68.19	60.22	680	60.22	11,864	12,544	$ 102,227,250
		1.80	68.19	63.04	680	63.04	12,174	12,854	$ 103,789,191
		1.90	68.19	64.75	680	64.75	12,500	13,180	$ 105,099,086
		2.00	68.19	65.19	680	65.19	12,667	13,347	$ 106,278,054
		2.10	68.19	66.03	680	66.03	12,973	13,653	$ 107,457,023

Table 11: Long Chain 10-Day Response Output Increased Inventory Levels

	Scenario		Pre-Disruption	Post Disruption - Decline		Post Disruption - Recovery			
Response Time	Initial Cap	Recovery Cap	Avg MC Rate	MPL	AUC-D	RPL	AUC-R	AUC-Total	Total $$
10-Day	1.00	1.00	71.14	51.37	11,121	N/A	N/A	11,121	$ 96,038,078
		1.10	71.14	52.51	711	52.68	10,602	11,313	$ 97,217,046
		1.20	71.14	55.69	711	55.33	11,151	11,863	$ 98,526,941
		1.30	71.14	57.04	711	57.07	11,465	12,176	$ 100,088,882
		1.40	71.14	58.10	711	58.90	11,640	12,351	$ 101,311,025
		1.50	71.14	60.11	711	60.99	11,996	12,707	$ 102,689,694
		1.60	71.14	61.61	711	62.52	12,199	12,910	$ 103,756,713
		1.70	71.14	62.73	711	63.85	12,410	13,121	$ 104,978,857
		1.80	71.14	64.68	711	65.36	12,684	13,396	$ 106,540,798
		1.90	71.14	66.88	711	67.67	13,069	13,780	$ 107,850,692
		2.00	71.14	68.48	711	68.81	13,327	14,039	$ 109,029,661
		2.10	71.14	68.61	711	69.90	13,476	14,188	$ 110,208,629

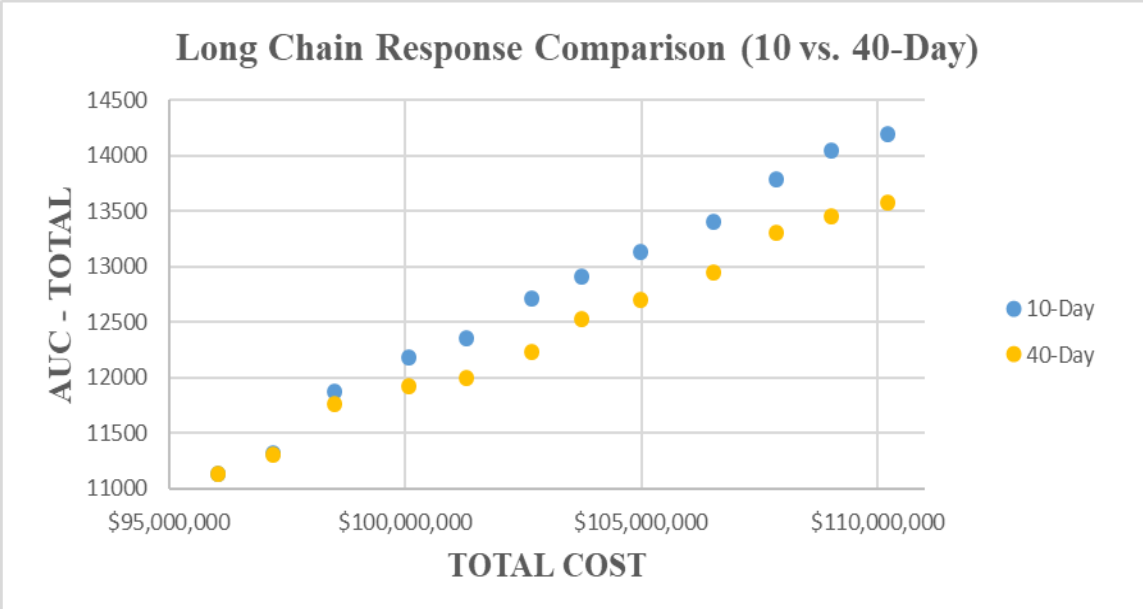


Figure 10: Long Chain Response Comparison (10 vs. 40-Day)

4.3.1 Impacts on Transient Performance Metrics

Perhaps there is no better example of the need for simultaneous investment than the developed long chain scenarios. Although the realized benefits of increased investment on disruption performance is consistent with the previous designs, the impacts of increased inventory on the network's ability to maintain a higher level of demand are undeniable. Mentioned throughout this research is the need to invest in inventory and production capacity in unison. To invest in one without the other will lead to a sub-optimal output (Femano et al., 2019). Table 11 greatly reiterates this point. Within all stages of the disruption, the scenarios with an increased investment in inventory outperformed the scenarios that did not simultaneously increase the investment. For instance, higher quantities of inventory facilitated a higher Pre-Disruption MC Rate, which led to a higher MPL across all scenarios. Furthermore, and contrary to the baseline scenarios which experienced a higher starting point due to the increased investment in initial capacity, the greater starting point facilitated a greater RPL for the scenarios with increased inventory. Once again, this is due to the need for an increase in inventory to realize the greatest potential from the increase in production capacity.

4.3.2 Criticality of Response Time

Due to the inherent structure of the long chain design, the total production capacity for one PRG is halved and allocated to each assigned location. When a disruption occurs, the network loses a greater portion of the allocated production capacity as compared to the baseline or simple structure. Hence, the impact of a disruption without an appropriate predetermined asset allocation is further exacerbated. As shown in the following section, the benefits from employing the long chain approach comes from the ability to invest in a greater amount of capacity to respond to a disruption at a much lesser cost. This production capacity allocation inherently places a greater need to respond after a disruption has occurred. Figure 11 and Figure 12 show the beneficial impacts of an expedited recovery using the long chain approach. Similar to Figure 8, Figure 11 provides the average MC Rate (Black line), the 50th percentile (Green lines), and the minimum and maximum MC Rates (Blue lines) across all replications.

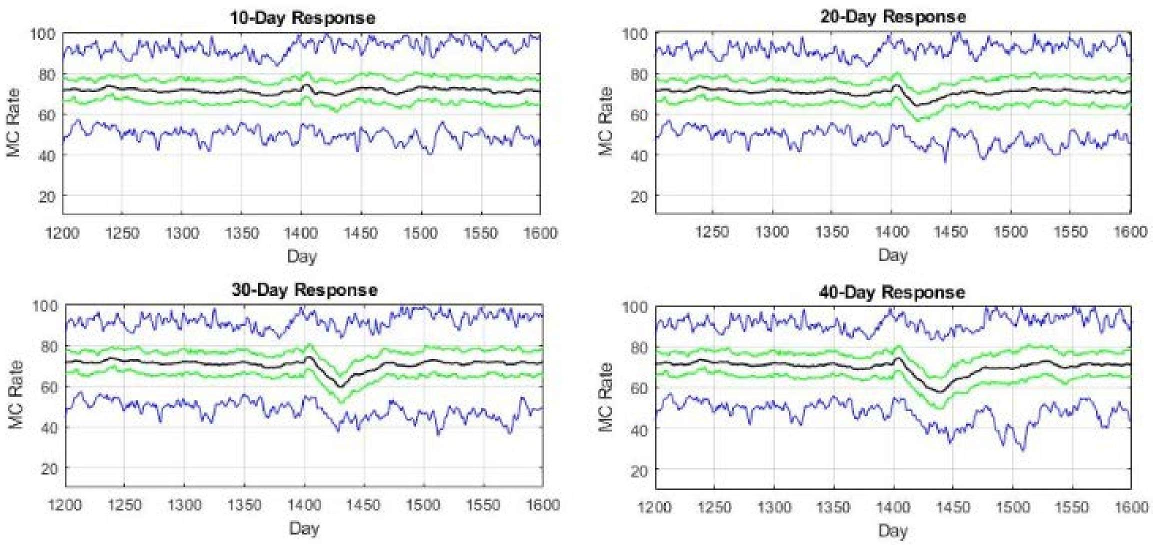


Figure 11: Varying Response Time – Long Chain Structure (1.00 Initial Cap, 2.10 Recovery Cap)

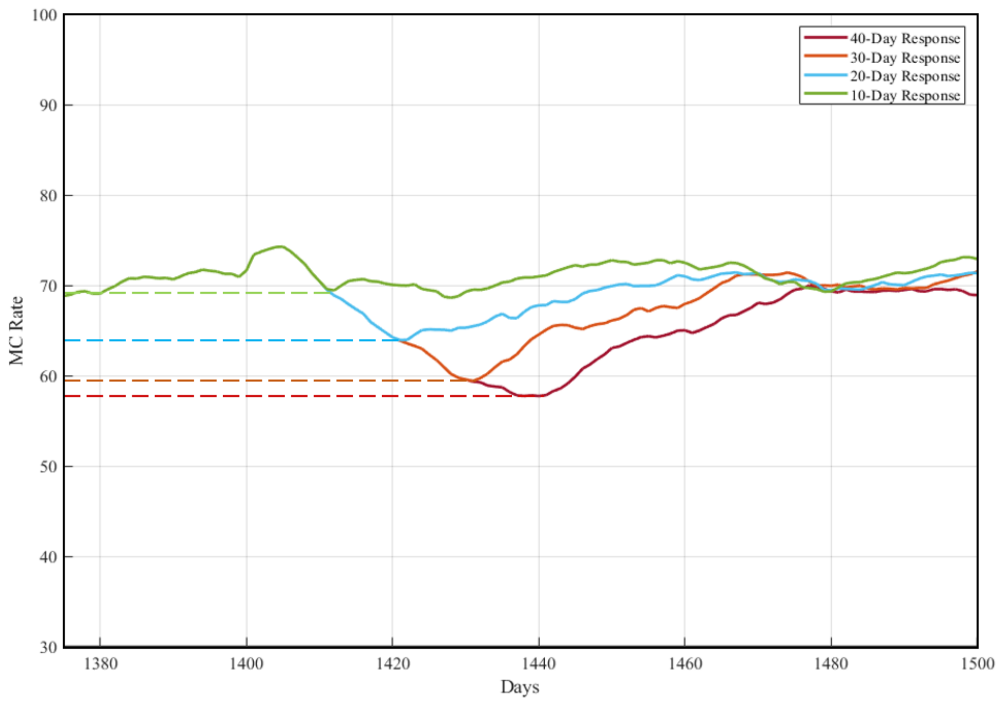


Figure 12: All Responses – Long Chain Structure (1.00 Initial Cap, 2.10 Recovery Cap)

Table 12: Long Chain Performance with Prolonged Response Times

	Scenario		Pre Disruption	Post-Disruption - Decline		Post Disruption - Recovery			
Response Time	Initial Cap	Recovery Cap	Avg MC Rate	MPL	AUC-D	RPL	AUC-R	AUC-Total	Total $$
10-Day	1.00	2.10	71.14	68.61	711	69.90	13,476	14,188	$110,208,629
20-Day		2.10	71.14	63.93	1,385	70.18	12,524	13,909	$110,208,629
30-Day		2.10	71.14	59.40	2,004	69.93	11,730	13,734	$110,208,629
40-Day		2.10	71.14	57.73	2,587	70.06	10,989	13,576	$110,208,629

As outlined in the literature, if an organization's ability to respond to a disruption is obstructed, the use of increased inventory creates a resistance to the disruption by enabling the organization to maintain a higher level of performance after the disruption occurs (Melnyk et al., 2013; Femano et al., 2019). Table 11 shows that the greater quantity of inventory provides a greater AUC – Decline and AUC – Recovery. Therefore, if an expedited response time is not feasible, greater levels of inventory provide the ability to hedge against downside risk by providing resistance to the disruption.

4.4 Resilience Costs

The PACAF theater is used to demonstrate the applicability of the developed tool, but this research provides a generalizable simulation tool that may be applied across multiple domains. The assigned costs are specific to that of PACAF, but the structure of this tool allows ease of translatability across numerous theaters, airframes, and industry related repair networks.

From a cost feasibility standpoint, this research recognizes that the simple allocation structure is not likely to be implemented. It is included to further emphasize the importance of decentralization and simultaneous investment. The long chain structure inherently subtracts from the flexibility of the baseline and simple allocation structure.

However, the cumulative performance of the overall network is extremely comparable to that of the baseline structure at a substantially reduced cost. When implementing the long chain design, the massive cost savings are realized from the decrease in the large capital expenditures necessary to house the repair capabilities of four PRGs at one location.

Figure 13 illustrates the usefulness of the resilience metric when comparing performance across multiple structures and response times. Specifically, Figure 13 provides insight into the level of resilience investment needed to reach Pre-Disruption MC Rates (1.00) after a disruption occurs using the baseline and long chain structures. More importantly, Figure 13 highlights the overlapping performance and stark cost difference between the baseline and long chain structures.

The resilience metric provides a direct indication of how an organization performs in the event of a disruption. When a disruption strikes, demand does not cease to exist. Therefore, regardless of the organization, some level of demand will need to be met when a disruption occurs. The resilience metric allows decision makers and organizations to predict the level of demand that can be met resulting from predetermined investments in resilience.

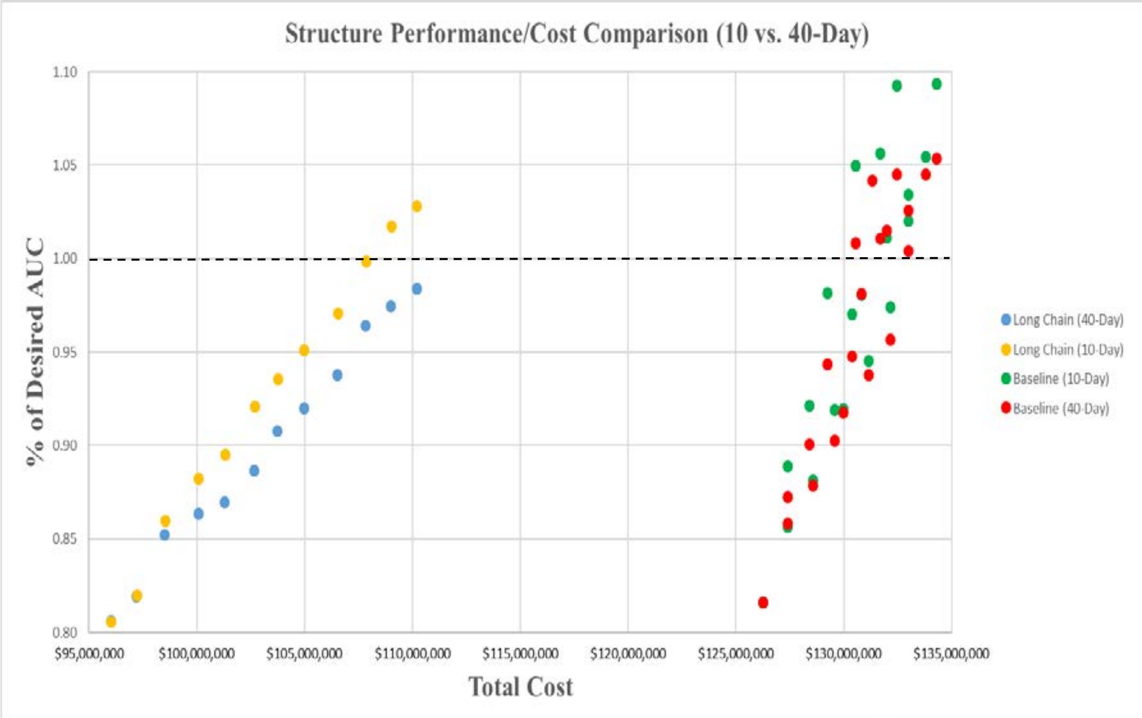


Figure 13: Structure Performance/Cost Comparison

4.5 Validity of an Expedited Response Time

Figure 13 combines the scatter output from the baseline and long chain structures for performance and cost comparison. As the investment in resilience increases using the long chain structure, the resulting AUC – Total increases linearly. Additionally, the difference between the 10- and 40-day response time is clear. However, as the resilience investment is increased using the baseline structure, the results are not as distinct between the 10- and 40-day response. To validate that there is in fact a difference between an expedited and a prolonged response time in AUC - Total, this research employed the Paired T-Test to statistically test the difference between varying responses. A Paired T Test was chosen to test the difference between the two dependent samples (Milton & Arnold, 2003). Specifically, this test allows the researcher to evaluate the following:

$$H_0: u_x = u_y$$
$$H_1: u_x > u_y \tag{3}$$

which determines whether there is a statistical difference between the response time means. To conduct the statistical test, a test statistic was developed from the following equation (Milton & Arnold, 2003):

$$T\ Stat = \frac{u_D - 0}{S_D/\sqrt{n}} \tag{4}$$

where,

$\boldsymbol{u_D}$ *is the mean of the differences between two response times,*

0 *is the hypothesized difference between two response times,*

$\boldsymbol{S_D}$ *is the standard deviation of the difference in means between two response times,*

n *is the sample size.*

Since multiple response times are being analyzed, the chance of rejecting the null hypothesis when it is true (type 1 error), drastically increases (Statistics Solutions, 2019). Hence, the Bonferroni correction was implemented to lower the significance level by dividing 0.05 by 4 (the number of response time comparisons) (Statistics Solutions, 2019). This maintains a cumulative 95% confidence level that regardless of the comparison, an expedited response is more beneficial than a prolonged response. Using *n* and the developed *T Stat*, a p-value is determined and compared to the new alpha of 0.0125. Table 13 and Table 14 illustrate the p-values associated with the developed *T Stat* for each structure and response time. The simple allocation structure was not included because it did not meet the minimum required investment scenarios.

Table 13: Baseline Structure Response P-Values

Baseline Structure				
Response	**10**	**20**	**30**	**40**
10	-	-	-	-
20	0.00056	-	-	-
30	0.00003	0.00346	-	-
40	0.00001	0.000002	0.00075	-

Table 14: Long Chain Structure Response P-Values

Long Chain Structure				
Response	**10**	**20**	**30**	**40**
10	-	-	-	-
20	0.00078	-	-	-
30	0.00009	0.00074	-	-
40	0.00006	0.00018	0.00083	-

As illustrated by Table 13 and Table 14, the p-values for each response time comparison prove extremely significant across all scenarios. As expected, as the time between two comparisons increase, the p-value decreases, which further validates the benefits of an expedited response. Hence, this research can reject the H_0 and conclude that regardless of the structure and response time comparison, an expedited response time yields a higher AUC – Total than that of a prolonged response time.

V. Conclusions and Recommendations

The research provides a generalizable simulation tool to quantify the level of network resilience resulting from predetermined asset allocations and various network designs in the face of disruption. The PACAF theater is used to demonstrate the application of the model. Additionally, the importance of bolstering network resilience by simultaneously investing in multiple resilience levers is demonstrated. The research illustrates the grave consequences of a lack of preparedness on performance following a disruption. Moreover, this research demonstrates how a well-designed network can meet demand at a reasonable cost.

5.1 Problem Statement Resolution

For both military and industry, the need to recognize and accept an inherently uncertain future is essential for the going concern of any organization (de Neufville & Scholtes, 2011). Decision makers must possess the ability to analyze and evaluate how an organization's identified resilience levers may be implemented in building lasting organizational resilience. Specifically, decision makers must be able to forecast future levels of resilience resulting from predetermined asset allocations and their associated cost levels.

To answer Research Question 1, this research developed a discrete-event simulation tool to properly identify and apply organizational resilience levers to build cumulative resilience. The profound impacts on network performance are illustrated when inventory and production capacity are increased in unison. The methodology proposed is translatable across theaters, airframes, and multiple other domains. The three scenarios illustrate the tradeoffs between resilience investment and network performance. However, resilience levers are dependent upon the organization utilizing this tool. The quantity and complexity of the chosen resilience levers must be tailored to fit the needs of the specific organization or industry using this method.

Research Question 2 addresses the allocation of assets while facing disruption. Specifically, in addition to the baseline structure, this research employs two additional network designs to evaluate asset allocations on disruption mitigation. Strategically chosen to illustrate the impacts of simultaneous investment, the simple allocation and long chain structures greatly alter the amount of investment needed to achieve a desired performance level. By varying the amount of capital expenditure necessary to support repair operations and the amount of production capacity at each location, the simple allocation and long chain structures illustrate the impacts of various levels of flexibility on overall performance and cost of network resilience. The simple allocation and long chain structures provide a worst- and best-case scenario in terms of cost feasibility of reaching a desired performance level. More importantly, implementing multiple network designs shows the ease of drastically shifting the structural integrity of the tool, further illustrating its adaptable nature.

5.2 Findings

This research provides an approach to evaluate resilience investment decisions across multiple domains. Metrically and monetarily quantifying specific levels of predetermined asset allocations on cumulative network performance allows an organization to more effectively allocate organizational resources to achieve a desired level of performance.

Additionally, the proposed AUC metric provides a generalizable method to gauge various levels of network resilience during the network's transient states of a disruption.

This research facilitates a deep understanding of the identified resilience levers and their associated impacts on the transient performance of a network. Understanding the key phases following a disruption is essential to optimizing the investment in resilience levers to mitigate the impact on performance.

When faced with an imminent disruption, the greatest mitigating impacts result from the simultaneous investment in spare inventory and production capacity. The combination of initial capacity and inventory is essential to an organization's ability to withstand the impact of a disruption, while the ability to respond with predetermined asset allocations is essential to the ability to recover. The level of network performance recovery is a direct result of the response time and pre-disruption performance. Therefore, the criticality of an organization's pre-disruption performance level must be emphasized. Additionally, the ability to optimize the recovery of a network is a function of the inventory-capacity investment prior to the disruption occurring, as shown using the long chain structure. Hence, this tool provides a means of striking the delicate balance between inventory and capacity by quantifying the impact on performance resulting from a specified investment level.

Additionally, when implementing capacity expansion, the long chain flexibility approach provides the most cost-effective means to do so. The ability to limit the capital expenditure associated with expansion is the greatest realized benefit of implementing the long chain approach. The inherent freeing of capital provides a more cost-effective means of facilitating resilience by allowing an increased investment in resilience levers, specifically in inventory and recovery capacity to hedge against the impacts of a disruption.

5.3 Future Research Opportunities

The study of disruption impacts on network performance is not recommended without a deep knowledge and understanding of an organization's network and capabilities. This tool aids in developing an understanding of the intricacies and interconnectedness of a USAF repair network. An opportunity for future research exists for implementing a more realistic disruption impact. For instance, within the developed scenarios, once a disruption occurs, the impacted location instantly loses all repair capabilities. This may not be the case. A deep-dive analysis into the impacts of a disruption on the applied network would prove beneficial in implementing a more general approach to disruption evaluation and ultimately, the shifting of salvageable resources from the impacted location.

The chosen repair network and airframe represents a small, yet extremely important part of cumulative USAF performance. This model was specifically built with the necessary foundations needed for airframe expansion. Multiple airframes and theaters could be applied within this tool to accurately measure and quantify resilience and associated investment from a wider Air Force perspective.

Furthermore, an extensive review of the many organizational resilience levers is necessary to determine the level of investment needed to maximize their performance. A thorough cost-analysis is necessary for organizations to maximize the impact of investment dollars across all identified resilience levers. Additionally, necessary sociotechnical layers could be implemented that considers the behaviors of decision makers when experiencing a disruptive event (de Neufville & Scholtes, 2011). Ultimately, this would provide a more accurate representation of network performance when faced with budgetary and capacity constraints.

5.4 Limitations

The use of product repair groups and their associated LRUs further facilitated a deep understanding of the many intricacies of PACAF during disruption. Additionally, location specific spare quantities and their associated costs were necessary to generate the most accurate cost representation of PACAF resilience. However, this research assumes every identified discrepancy is a Level-3 break and that only one failure may occur on an aircraft at a time. As breaks are generated and identified by flight line maintenance, regardless of the break severity, the cumulative MC Rate is lowered. Realistically, more failures may occur at once and lower severity breaks may not drop the aircraft out of mission-capable status. For a more accurate performance and cost representation of the applied network, logic could be inserted that allows the failure of multiple parts on one aircraft simultaneously.

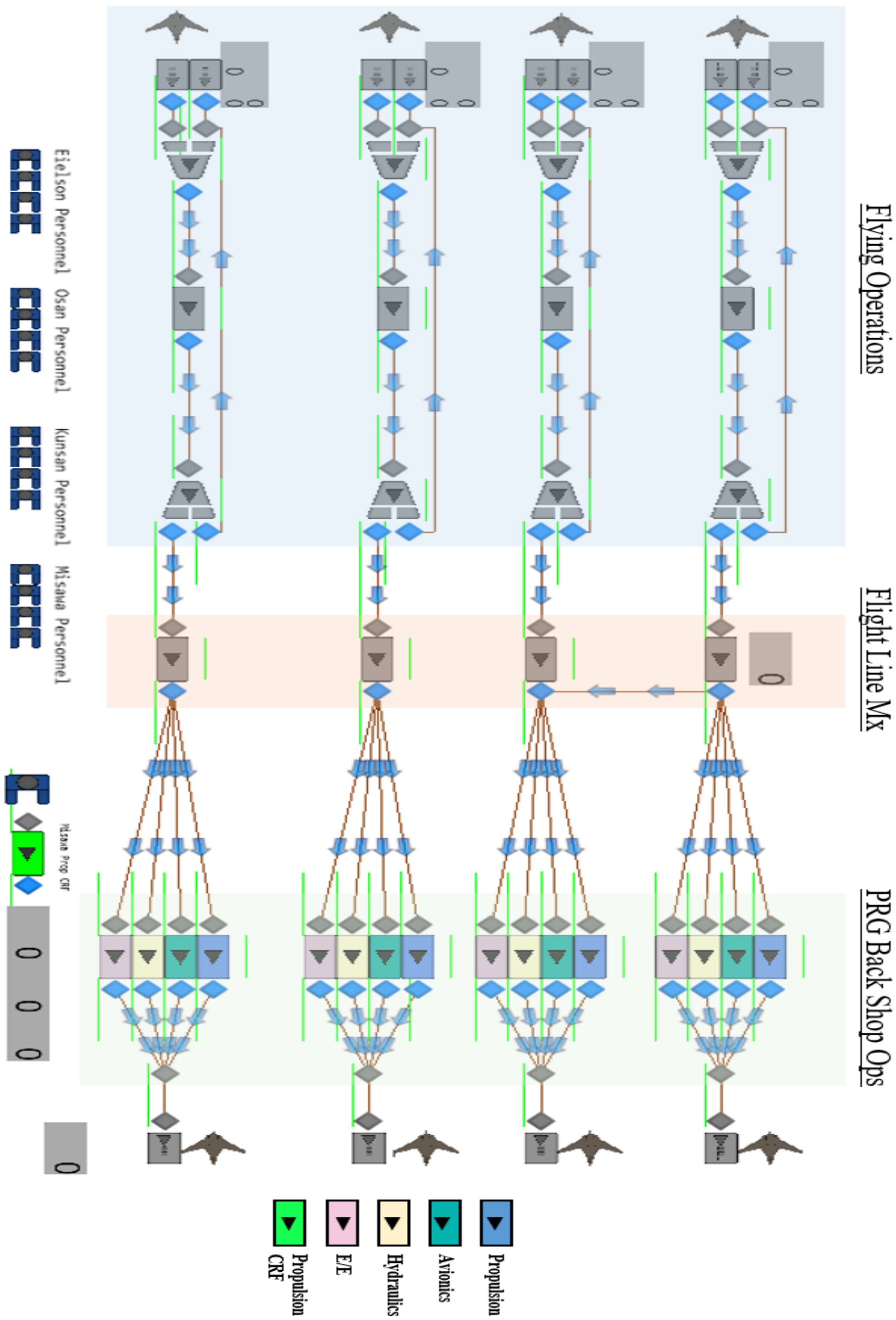
5.5 Conclusion

This research established a generalizable methodology and tool to quantify and assess how incremental investment in resilience levers equates to additional resilience. This research employed the USAF PACAF F-16 repair network as the illustrative example of its usefulness, but this tool is extremely applicable across many platforms. This research posits the use of the AUC metric to better understand an organization’s ability to meet demand during the transient states of a disruption. Additionally, the inherent tradeoff of spare inventory and production capacity is illustrated by comparing the corresponding AUCs and cost of each design scenario.

When evaluating network performance in the event of a disruption, decision makers must possess a deep understanding of the disruption time periods and the inherent interconnectedness of the associated time period metrics. The proactive use of predetermined asset allocations is only as useful as an organization's understanding of their impacts on disruption time period metrics. In other words, the importance of the simultaneous investment in inventory and production capacity is essential to maximizing pre-disruption performance. As illustrated using the baseline structure, sub-optimal performance will be realized with investment in isolation (Femano et al., 2019). Furthermore, an organization's disruption response time drives its ability to recover. Regardless of the resilience investment level, a prolonged response time poses grave consequences on an organization's ability to meet pre- and post-disruption demand.

Although the illustrative example lies military centric, it is strategically chosen for its similarities and applicability across multiple domains. Paired with the use of the developed time period metrics and AUC, this tool provides decision makers a greater ability to predict network performance following a disruption and therefore make more informed resource allocation decisions.

Appendix A: PACAF Baseline Simulation Design



Appendix B: Output Consolidation Code (Femano et al., 2019)

```
agg_TS = [];
is_filename = 1;
for i=1:numel(spares)  %spares
    for j =1:numel(servers) %added servers
        for k = 1:numel(ddays) %date of disruption
            is_filename = 1;
            for r = 1:reps
                s = num2str(spares(i));
                c = num2str(servers(j));
                d = num2str(ddays(k));
                try
filename = [Exp_name, '_',s,'Spares','_',c,'Cap','_','DDay',d,'_Rep',num2str(r),'.csv']
                    [T, SL] = AggregateStateData(filename,time_unit);
                    size(T)
                    agg_TS = [agg_TS;repmat(spares(i), numel(T),1), repmat(servers(j),
numel(T),1),repmat(ddays(k), numel(T),1), repmat(r, numel(T),1), T,SL];
                catch
                    warning('No such scenario. Going to next scenario');
                    is_filename = 0;
                    r = reps;
                end
            end


            end
        end
end
    save(['agg_TS_' Exp_name], 'agg_TS');
    parameters = [spares, servers, ddays reps, time_unit];
    save(['parameters_',Exp_name], 'parameters' );
```

Appendix C: Area Under the Curve Code (Femano et al., 2019)

```
TS = agg_TS(agg_TS(:,1)==spares(1) &
agg_TS(:,2)==servers(1)&agg_TS(:,3)==ddays(1)&agg_TS(:,4)==1, :);
T = TS(:,5);
maxT = T(end);
time_unit = T(2)-T(1);
endT = (maxT-5*time_unit)/time_unit;

figure;
z =1;
key_measures = [];

%Fit Baseline disruption case first
for i=1:numel(spares)  %spares
        s = num2str(spares(i))
        c = num2str(servers(1))
        d = num2str(ddays(1))
        [Exp_name,' ',s,' Spares',' ',c,' Servers',' ','Dday on ',d]
        T=[];
        SL = [];
   for r = 1:reps
        TS = agg_TS(agg_TS(:,1)==spares(i) &
        agg_TS(:,2)==servers(1)&agg_TS(:,3)==ddays(1)&agg_TS(:,4)==r, :);
        T = [T,TS(1:endT,5)];
        SL = [SL, TS(1:endT,6)];
        end
        km = analyze_ts(T(:,1),mean(SL,2), T_dis, T_rec,0,1,0)
        %area under disruption
        fun_pre = @(x,Tpre)x(1)+Tpre*0;
        fun_dis = @(x,Tdis)(x(3)-x(4))*exp(-((Tdis - x(5))./x(1)).^x(2))+x(4);
        A_pre = km(1);
        x_dis = km(2:end-1);
        A_All_Min = km(end);

        au_dis = integral(@(T)fun_dis(x_dis,T), T_dis, T_end);
        au_rec = 0;
        key_measures = [key_measures;spares(i),0,T_dis, T_rec, km(1:end-1), au_dis,
        au_rec, au_dis+au_rec, A_All_Min];


        plot(T, fun_pre(A_pre, T), 'LineWidth', 2)
        hold on
        plot(T, fun_dis(x_dis,T), 'LineWidth', 2)
```

```
            plot (T(:,1),mean(SL,2), 'LineWidth', .5)

            axis([0 2000 0 100]);

            title([s,' Spares',', ',c,' Servers']);
            xlabel('Day');
            ylabel('Available Aircraft');
end
figure;
A_dis = mean(key_measures(:,9));
for i=1:numel(spares)  %spares
    z=1;
    for j =2:numel(servers) %added servers
        for k = 1:numel(ddays) %date of disruption
           s = num2str(spares(i))
           c = num2str(servers(j))
           d = num2str(ddays(k))
           [Exp_name,' ',s,' Spares',' ',c,' Servers',' ','Dday on ',d]
           T=[];
           SL = [];
           for r = 1:reps
            TS = agg_TS(agg_TS(:,1)==spares(i) &
            agg_TS(:,2)==servers(j)&agg_TS(:,3)==ddays(k)&agg_TS(:,4)==r, :);
                        T = [T,TS(1:endT,5)];
                        SL = [SL, TS(1:endT,6)];
            end
            T = T(:,1);
            km = analyze_ts(T,mean(SL,2), T_dis, T_rec, A_dis, 1,1);

            fun_pre = @(x,Tpre)x(1)+Tpre*0;
            fun_dis = @(x,Tdis)(x(3)-x(4))*exp(-((Tdis - x(5))./x(1)).^x(2))+x(4);
            fun_rec = @(x,Trec)(x(3)-x(4))*(1-exp(-((Trec - x(5))./x(1)).^x(2)))+x(4);

            A_pre = km(1);
            x_dis = km(2:6);
            x_rec = km(7:end-1);
            A_All_Min = km(end);

            au_dis = integral(@(T)fun_dis(x_dis,T), T_dis, T_rec);
            au_rec = integral(@(T)fun_rec(x_rec,T), T_rec, T_end);
            key_measures = [key_measures;spares(i),servers(j),T_dis, T_rec, km(1:end-1),
            au_dis, au_rec, au_dis+au_rec, A_All_Min];
                        subplot(1, numel(servers)-1, z);

            Tpre = T(T<=T_dis);
```

```
            SLpre = SL(T<=T_dis);
            Tdis = T(T>=T_dis&T<=T_rec);
            SLdis = SL(T>=T_dis&T<=T_rec);
            Trec = T(T>=T_rec);
            SLrec = SL(T>=T_rec);

            plot(Tpre, fun_pre(A_pre, Tpre), 'LineWidth', 2)
            hold on
            plot(Tdis, fun_dis(x_dis,Tdis), 'LineWidth', 2)
            plot(Trec, fun_rec(x_rec,Trec), 'LineWidth', 2)

            plot (T(:,1),mean(SL,2), 'LineWidth', .5)

            axis([0 2000 30 100]);

            title([s,' Spares',', ',c,' Servers']); xlabel('Day'); ylabel('Available Aircraft');
            %z= z+1
        end
         z= z+1;
    end
end
key_measures = real(key_measures);
save(['key_measures_', Exp_name],'key_measures');
```

Appendix D: Plot Time Series Code (Femano et al., 2019)

```
TS = agg_TS(agg_TS(:,1)==spares(1) &
agg_TS(:,2)==servers(1)&agg_TS(:,3)==ddays(1)&agg_TS(:,4)==1, :);
T = TS(:,5);
maxT = T(end);
time_unit = T(2)-T(1);
endT = (maxT-5*time_unit)/time_unit;


for i=1:numel(spares)  %spares
  for j =1:numel(servers) %added servers
      for k = 1:numel(ddays) %date of disruption
         s = num2str(spares(i))
         c = num2str(servers(j))
         d = num2str(ddays(k))
         [Exp_name,' ',s,' Spares',' ',c,' Servers',' ','Dday on ',d]
         try
         T=[];
         SL = [];
       for r = 1:reps
         TS = agg_TS(agg_TS(:,1)==spares(i) &
         agg_TS(:,2)==servers(j)&agg_TS(:,3)==ddays(k)&agg_TS(:,4)==r, :);
         T = [T,TS(1:endT,5)];
         SL = [SL, TS(1:endT,6)];
         End
         subplot(numel(spares), numel(servers), z);
         hold on;
         plot(T(:,1), prctile(SL,25, 2), '-g', 'LineWidth', .5);
         plot(T(:,1), prctile(SL,75, 2), '-g', 'LineWidth', .5);
         plot(T(:,1), mean(SL,2),'-k', 'LineWidth', 1.25);
         axis([1200 2000 10 100]);


         title([s,' Spares',', ',c,' Servers']);
         xlabel('Day');
         ylabel('Available Aircraft');
         z= z+1;
         catch
         warning('No such scenario. Going to next scenario');
         end
      end
  end
end
```

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REPORT DOCUMENTATION PAGE			Form Approved OMB No. 074-0188

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
26-03-2020	Master's Thesis	January 2019 – March 2020

TITLE AND SUBTITLE	
Resilient Aircraft Sustainment: Quantifying Resilience through Asset and Capacity Allocation	**5a. CONTRACT NUMBER**
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	**5d. PROJECT NUMBER**
Shannon, Zachary, B	**5e. TASK NUMBER**
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)	**8. PERFORMING ORGANIZATION REPORT NUMBER**
Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Way, Building 640 WPAFB OH 45433-7765	AFIT-ENS-MS-20-M-288
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)**
Intentionally left blank	**11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

12. DISTRIBUTION/AVAILABILITY STATEMENT
DISTRUBTION STATEMENT A. APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
Decision makers lack a clear, generalizable method to quantify how additional investment in inventory and capacity equates to additional levels of resilience. This research facilitates a deeper understanding of the intricacies and complex interconnectedness of organizational supply chains by monetarily quantifying changes in network resilience. The developed Area under the Curve metric (AUC) is used to quantify the level of demand that each asset allocation can meet during a disruptive event. Due to its applicability across multiple domains, the USAF F-16 repair network in the Pacific theater (PACAF) is modeled utilizing discrete event simulation and used as the illustrating example. This research uses various levels of production capacity and response time as the primary resilience levers. However, it is essential to simultaneously invest in inventory and capacity to realize the greatest impacts on resilience. Real-world demand and cost data are incorporated to identify the inherent cost-resilience relationships, essential for evaluating the response and recovery capabilities across the developed scenarios. Results indicate that recovery capacity and response time are the greatest drivers of recovery after a disruption. Additionally, numerous network designs employing various levels of design flexibility are evaluated and recommended for future capacity expansion.

15. SUBJECT TERMS
Discrete-Event Simulation, Supply Chain Resilience, Network Disruption, Quantifying Resilience

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			Maj Timothy Breitbach, AFIT/ENS
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