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RESILIENT MAINTENANCE INFRASTRUCTURE: DYNAMIC REPAIR NETWORK DESIGNS TO EFFECTIVELY MANAGE SUPPLY CHAIN DISRUPTIONS

THESIS

David W. Wallace III, Captain, USAF

AFIT-ENS-MS-21-M-193

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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THESIS

Presented to the Faculty

Department of Operational Sciences

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Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Logistics and Supply Chain Management

David W. Wallace III, MBA

Captain, USAF

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Abstract

Supply chains are facing numerous changes contributing to their increase in complexity and vulnerability to disruptions. Subsequently, decision-makers lack a transparent, generalizable tool to quantify supply chain resilience and assess additional resilience investments. This research facilitates a more profound understanding of the intricacies and interrelation of supply chain nodes and constructs. It integrates the Area under the Curve (AUC) metric to quantify performance or any organizational measure of competitive advantage amid a disruption. Due to its structural resemblance to various organizational platforms, the subset United States Air Force (USAF) F-16 engine repair and supply network is modeled employing discrete-event simulation. The purpose of this study is to evaluate investments in inventory and capacity resilience levers to understand how mitigation strategies affect supply chain entity performance. Results indicate that simultaneous investments in these levers yield the most significant effects on resilience. The presented analysis asserts recovery capacity and response time as the most significant recovery influencers following a disruption. Additionally, two design scenarios are further examined to understand how flexibility influences resilience.

Acknowledgments

First, much thanks to my wife, for her steadfast encouragement during times when I faltered, for understanding the extended days and hours, and pushing me when required. I extend my appreciation to Lt Col Aaron Glassburner for his support, flexibility, and diligence throughout this process. Thank you to Zachary Shannon for coaching me to push my boundaries, insight, and persistence to assuring the necessary academic rigor within this research. This journey was one of enlightenment and growth intellectually and mentally.

David W. Wallace III

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RESILIENT MAINTENANCE INFRASTRUCTURE: DYNAMIC REPAIR NETWORK DESIGNS TO EFFECTIVELY MANAGE SUPPLY CHAIN DISRUPTIONS

I. Introduction

Background

A key dynamic within present-day businesses and corporations is that supply chains compete, not the companies themselves. Getting the right product, at the right place, at the right time to the consumer is pivotal to competitive success and survival (Christopher & Towill, 2001). Global-spanning operations, coupled with complexity, have driven organizational supply chains to grow and expand (Christopher & Peck, 2004). Subsequently, as supply chains have lengthened, reliance on strategic partners has risen, creating increased vulnerability to failure through and between critical nodes (Amin, 2002). The business environment is becoming more turbulent as the globalization of procurement and distribution yields more complex supply chains. Increased emphasis on outsourcing and a greater focus on supplier nodes deteriorate flexibility within supply bases (Pettit, Croxton, & Fiksel, 2019). Moreover, as companies employ lean or efficiency-driven concepts, they also introduce limitations that subject their respective supply chains to heightened, volatile conditions (Pettit et al., 2019).

Concurrently, crises of various magnitudes and proportions affect an organization's supply chain. Crises, interchangeable with 'environmental jolts,' are defined as "transient perturbations whose occurrences are difficult to foresee and whose impacts on organizations are disruptive and potentially inimical" (Meyer, 1982). Thus, jolts can be delineated into external events affecting an organization, such as opportunities, threats, crises, or catastrophes (Billings, Milburn, & Schaalman, 1980). Moreover, amid various unknown environmental jolts, organizations recognize the need to shift to a robust posture but fail to understand the mechanics to do so as robustness is inadequately defined (Pettit, Fiksel, & Croxton, 2010).

As a result, during a crisis, the rapid and unexpected organizational change that must occur often renders existing strategies obsolete (Wan & Yiu, 2009). In 2008, a global financial crisis triggered a global market cap loss of 19.4 trillion dollars, a 46 percent decline compared to 2007. The lingering effects surged 208 thousand businesses filing bankruptcy between 2008 to 2010 (Garelli, 2009). In 2020, the coronavirus (COVID-19), originating in Wuhan, China, burdened the world economy. Global outputs dropped by 1%, translating to a per month loss of approximately 40 billion dollars in China and 65 billion dollars globally, indicating the decline of the hub of supply chains inside and outside of China by 40% (Luo, Kwok, & Tsang, 2020). Inherently, several manufacturers such as Fiat Chrysler Automobiles, Hyundai, and Apple decided to adjust or halt production due to the inability to facilitate parts' supply for sustained performance (Haren, P. & Simchi-Levi, D. 2020).

Inherently, there is an evidentiary tradeoff between vulnerabilities and capabilities in pursuit of supply chain efficiency and organizational success. Such resolve and desire for competitive advantage demand a fully integrated and efficient supply chain, usually compromising risk mitigation capabilities elsewhere (Christopher & Peck, 2004; Ponomarov, 2012).

Motivation

Supply chain uncertainty and risks have dramatically increased based on several interrelated growing trends in consumer expectation, global competition, and more complex and longer supply chains. Additionally, decision-makers must manage supply variability and capacity constraints within an environment susceptible to environmental jolts (Masteika & Čepinskis, 2015; Sheffi & Rice, 2005). Supply chains must not only be capable of withstanding the stressors of this tumultuous environment but within acceptable degradation parameters and to recover within an acceptable timeframe and reasonable costs (Zobel & Khansa, 2012).

The ability for an organization to withstand the impact of disruption has been traversed comprehensively in the literature. Approaches to conceptualize an organization's disruption resilience and resistance have been predominately qualitative. Furthermore, the proper organizational actions warranted to facilitate resilience remains unclear throughout the research (Falasca, Zobel, & Cook, 2008). The remaining limited quantitative research generally leverages survey-based strategies rather than encompassing rigorous mathematical analysis of resilience. Finally, research tends to focus on disruption mitigation or response measures without assessing a conjoined phase perspective (Falasca et al., 2008; Munoz & Dunbar, 2015).

This study progresses resilience-based research through a militaristic lens, particularly the USAF's F-16 engine repair network. Holistically, the organizational supply construct and design are with little variation to those found with public and private sectors. It serves as a viable comparison, imposed with various environmental vulnerabilities and peer-nation capabilities, driven by the aspiration of competitive advantage and organizational success. Like many infrastructures, the USAF F-16 engine repair network features integration between supply and repair capabilities, mainly referred to as Repair Network Integration (RNI). This construct leverages supply and repair networks throughout various supply nodes to maximize overall Aircraft Availability (AA), a comparative metric to public and private sector competitive advantage-based metric (Bihansky, 2018; deSouza & Haddud, 2017). The RNI philosophy establishes three tiers of aviation maintenance, repair, and overhaul (MRO), entailing Organizational-Level (O-level), Intermediate-Level (I-level), and Depot-Level (D-Level) repair capabilities. This construct is equivalent to the airline industry's maintenance echelons, wherein airports and fixed-base operators offer maintenance shops. These certified entities perform rudimentary and routine maintenance functions, similarly to I-Level and O-Level repair. Within the airline industry, overhaul or D-Level repair is conducted by a manufacturer such as Boeing or Lockheed Martin.

By design, the majority of repair within the chain occurs at O-level. This high concentration of capability reflects many public and private sector supply chains, wherein centralization sparks fragility to failure, perturbation, and disruption. When affected by such, the jolt rapidly propagates through the network, heavily compromising the system's function (Piccardi & Tajoli, 2018). Hence, if a centralized node experiences a disruption, the capability to sustain competitive advantage is significantly decremented.

Problem Statement

Organizational decision-makers and leaders alike must strike a balance between supply chain vulnerabilities and capabilities (Pettit et al., 2010). The inherent complexity of supply chain networks and associated effects of risks make environmental jolts or disruptions challenging to forecast and manage; therefore, organizations must adequately assure a supply chain capable of resisting unanticipated disruptions and quickly recovering from them (Li & Zobel, 2020). Hence, decision-makers must be afforded a malleable tool and metric to quantify, assess, and anticipate the influence of inventory capacity and production on disruption susceptibility and recovery performance (Femano et al., 2019; Shannon, 2020).

Purpose Statement

The purpose of this research is to stimulate further clarity of the interrelatedness of organizational supply chains utilizing the USAF's F-16 engine repair network. This research further empowers a generalizable tool and methodology to measure network resilience quantifiably. Subsequently, it assesses the incremental and cumulative changes in resilience based on the range of investment in specified resilience capability factors. Moreover, this research postulates the use of the Area Under the Curve (AUC) metric as a suitable measure of AA rate by which the network can support over time (Femano et al., 2019).

Research Questions

This research further explores the following question to more adequately gauge how investments in resilience affect organizational ability to perform before and following a disruption. Notably, this research assesses:

How do the investments in inventory and production capacity influence the USAF's F-16 aircraft engine repair network (Operational, Intermediate, and Depot-level repair) level of resilience when affected by an unexpected disruption?

Investigative Questions

Subsequently, there are several investigative questions necessary to answer the posed research question further.

1. *What is the current layout of the F16 aircraft engine repair network in the USAF?*
2. *In its current state, how resistant is the repair network to a disruption?*
3. *What design or investments permit the greatest range of resilience within the repair infrastructure?*

Research Focus

The research question and investigative questions are answered through discrete-event simulation (DES) modeling and subsequent mathematical analysis, quantifying resilience levels based on varying investment levels. A thorough, exhaustive literature review recognizes the following literature streams: (1) General Resilience Strategies, (2) Investment in Resilience, (3) Production, Capacity, and Inventory, (4) Long-chain Flexibility, and (5) Dynamic Capabilities and Agility. Subsequently, the engine network is modeled to reflect the real system dynamics, yielding an accurate depiction of the supply and repair network. Sequentially, various investment scenarios are applied to the model to quantify resilience and identify means of maximizing overall supply chain resilience.

II. Literature Review

Chapter Overview

Through the further review of existing literature, an evident gap emerges as there is no specific, generalizable tool and methodology for decision-makers to gauge resilience and its response to incremental changes in investments. Generally, relevant research qualitatively addresses supply chain resilience with little support of quantitative measures. This research closes the gap between qualitative and quantitative research by developing a DES framework for assessing resilience from a quantifiable perspective. Further emphasis on the gap is visible as literature streams encircle (1) General Resilience Strategies, (2) Investment in Resilience, (3) Production, Capacity, and Inventory, (4) Long-chain Flexibility, and (5) Dynamic Capabilities and Agility.

General Resilience Strategies

Definitions of resilience are seen within an array of segments to include physical, ecological, economy, disaster management, engineering, and organizational research (Kochan & Nowicki, 2018). Christopher and Peck (2004) were the first to apply the ecosystem definition of resilience to the realm of supply chain management and devise the notion of supply chain resilience (SCR). Subsequently, SCR is defined as "*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). SCR has increasingly gained attention and popularity within the last fifteen years, spanning various researchers and experts who attempt to conceptualize the definition further and develop a mechanism to comprehend, measure, and bolster resilience within an organization's supply infrastructure (Macdonald, Zobel, Melnyk, & Griffis, 2018a; Min, Zacharia, & Smith, 2019; Portillo Bollat, 2009). The concept has also been redefined in several instances. Sheffi and Rice (2005) define SCR as "*An organization's ability to recover from a disruption quickly can be improved by building redundancy and flexibility into its supply chain*." Based on the varying definitions throughout the literature and lack of clarity in relationships between supply chain resilience and its constraints, there are divergent concepts in theory building (Kochan & Nowicki, 2018). Following a thorough meta-analysis of the literature, Ponomarov (2012) consolidated and derived resilience as "*The adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function.*" Thus, this research recognizes Ponomarov (2012) as the foundational and prevailing designation of supply chain resilience.

Initial measures towards decreasing vulnerability within a supply infrastructure can be dated to the late 1990s, when market power shifted from manufacturers to retailers. Customers required significant degrees of customization to fit desired needs. Moreover, competitive globalization increased as the distances between product source and market consumption expanded geographically, seeking higher quality or lower costs (Min et al., 2019; Zubair, Khan, Farooq, & Rasheed, 2019).

As organizations lengthen their supply chains by outsourcing their functions, resources, and information, they inherently become larger and more complex. Consequently, they face increased vulnerability and potential inability to effectively recover from an environmental jolt or disruption (Christopher & Peck, 2004). The heightened vulnerability can further proliferate to other firms or nodes within the chain based on supply chains' complexity and various nodes' interconnectedness. Many organizations are unaware of their susceptibility to a disruption or what it entails.

Disruptions, categorized as natural or human-made, combined with supply chain complexity and global competition have further exacerbated networks to becoming more vulnerable (Kochan & Nowicki, 2018). Innately, a supply chain does have general fluctuations. Steady-state system performance is expected to change gradually, where normal fluctuations generate minor performance fluctuations. Disruptions maintain a distinct effect on overall performance, abruptly altering performance metrics. Such metrics (profits, customer service, sales, production levels, etcetera) are organization-specific but commonly support an organization's desire for competitive advantage. The dynamic integration of logistical capabilities enables SCR, resulting in a sustainable competitive advantage as depicted in Figure 1.

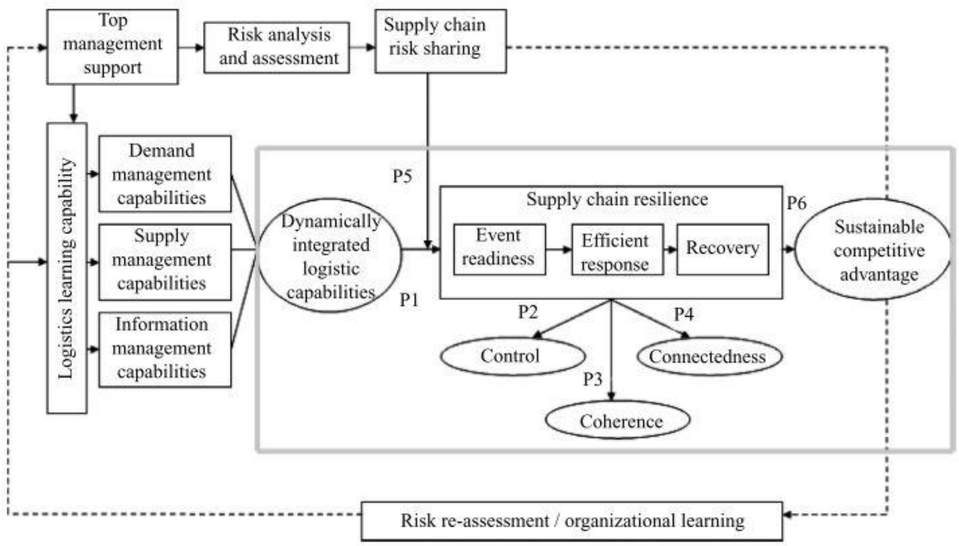

Figure 1. Relationship between Logistical Capabilities, SCR, and Competitive Advantage (S. Ponomarov & Holcomb, 2009)

Subsequently, the greater the SCR, the greater the competitive advantage (S. Ponomarov & Holcomb, 2009; S. Y. Ponomarov, 2012)

There are several organizational stages in conjunction with a disruption (Falasca et al., 2008). Sheffi & Rice (2005) outlined the impact a disruption can have on an entity or supply chain can be assessed within the following series of numbered stages: (1) Preparation, (2) Disruptive Event, (3) First Response, (4) Initial Impact, (5) Full Impact, (6) Preparation for Recovery, (7) Recovery, and (8) Recovery. As illustrated in Figure 2, the most critical stage is the preparation stage, when the network is at a steady state of operations. The starting preparation performance value influences the level at which performance drops and remains when entering stage six (Shannon, 2020). Upon realization of the disruption, decision nodes are levied to determine how recovery will be achieved. Moreover, the recovery stage is essential as it garners organizational investments to reach a new steady state.

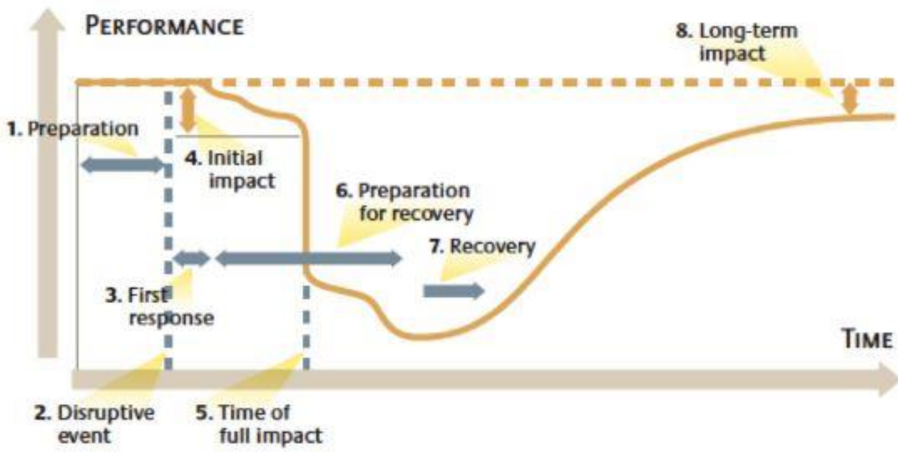

Figure 2. Stages of Disruption (Sheffi & Rice, 2005)

Craighead, Blackhurst, Rungtusanatham, and Handfield (2007) assert disruptions are unavoidable, yet organizations tend to be reactive rather than proactive. Additionally, organizations' unawareness of how to implement and quantify resilience has further perpetuated organizational vulnerabilities and susceptibility. Furthermore, although disaster recovery planning and crisis management do occur, it is often accomplished in isolation rather than a cohesive nature or industry-wide approach required to reduce vulnerability (Christopher & Peck, 2004).

Resilience is pivotal to withstanding such disruptions, yet the actions needed to facilitate resilience to the crisis remain unclear throughout the literature (Kunc & Bandahari, 2011). Research suggests that supply chain resilience is a concept that is not fully comprehended, whereby many organizations lack the awareness or necessity to consider resilience within their supply chains as an approach to risk management (Christopher & Peck, 2004). Sheffi and Rice (2005) assert resilience as achievable when assessed as a function of an organization's competitive position and responsiveness to its supply chain. Companies that incorporate flexibility and redundancy within their supply chain essentially bolster their resilience. When disruptions occur, the system experiences a triangular response, declining system performance, and gradually recovers to a new steady state. Zobel and Khansa (2012) then provided an extension to Sheffi and Rice's (2005) work utilizing a triangular model to quantify resilience, as demonstrated in Figure 3.

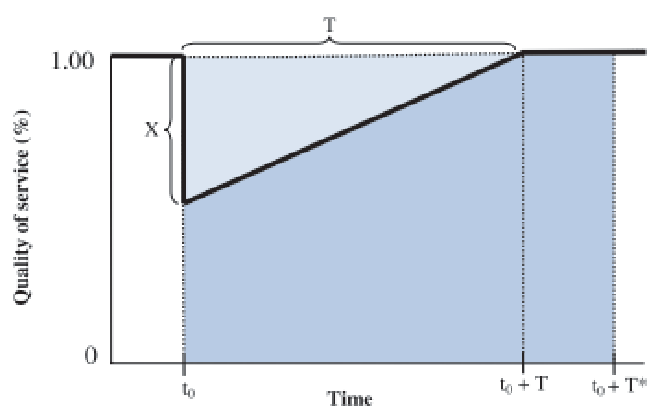

Figure 3. Predicted Resilience (Zobel & Khansa, 2012)

This design permitted the measurement of the Area Above the Curve. Melnyk, Zobel, MacDonald, and Griffis (2014) expound on this design by modifying Sheffi and Rice's disaster stages and incorporating Zobel and Khansa's (2012) resilience triangle as illustrated in Figure 4. This model assesses the transient states of the system response when affected by a disruption to serve as a measurement of the network's collective resilience. Within the figure, transient states serve as stages or critical periods upon the onset of a disruption. Notably, the organization remains within a steady-state until the period at which the triggering event is enacted (TD). Next, the system is studied based on its decline (TO), marking the visible onset of the disruptions affects until the point at which the disruption reaches its climax (TC) and time to system recovery (TP).

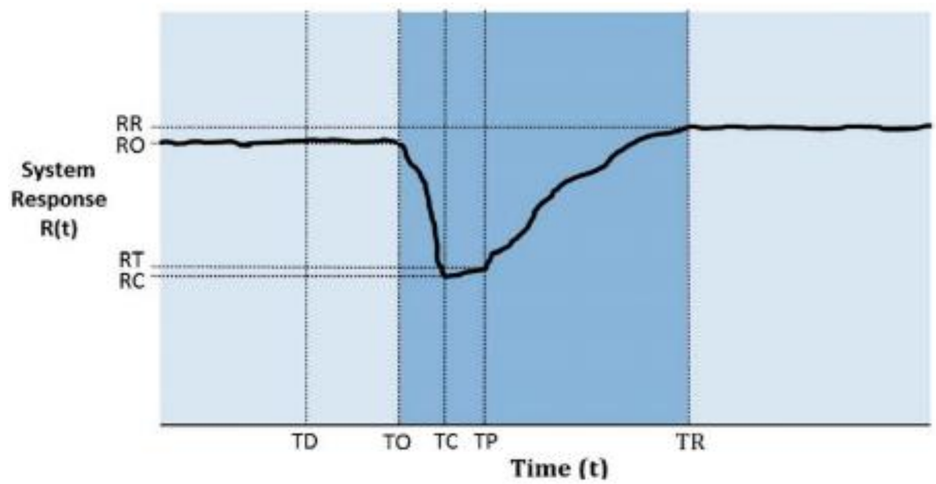

Figure 4. Time Series Critical Points (Melnyk et al., 2014)

The larger the integral, the less resistant the system is against a disruption (Melnyk et al., 2014).

This research assesses resilience via the employment of AUC, a more accurate measurement of network performance over the disruption timeframe and parallel parameter as researchers Zobel and Khansa (2012) and Macdonald, Zobel, Melnyk, and Griffis (2018b). The utilization of AUC to assess resilience is continuously growing. Macdonald et al. (2018) and those within various academic disciplines, including inventory control, psychology, physiology, and information security, validate this form measurement as the relative decline sustained from the disruption. Melnyk et al. (2014) validate this approach, claiming AUC successfully considers and characterizes the tradeoffs between the total amount of system-loss and the total recovery curve. Furthermore, it enables demand forecasting capability utilizing predetermined assets within the midst of the disruption (Shannon, 2020).

Investments in Resilience

Christopher & Peck (2004) identified four fundamental principles to bolster resilience in the event of a disruption: “(1) resilience can be built into a system in advance of a disruption, (2) a high level of collaboration is required to identify and manage risks, (3) agility is essential to react quickly to unforeseen events, and (4) the culture of risk management is a necessity.” Based on these aspects, fourteen capability factors were devised as depicted in Table 1. These capability factors serve as a framework for measuring resilience and determining a resilience score (Chowdhury & Quaddus, 2017). Kochan and Nowicki (2018) suggest investments in these capability factors promote flexibility and redundancy. Flexibility relates to infrastructure and resources before they are needed and restructuring previously existing capacity, whereas redundancy pertains to maintaining the capacity to respond to disruptions and adequately sustain operations (Kochan & Nowicki, 2018). Inclusion and application of flexibility and redundancy serve to improve organizational capabilities and reduce vulnerabilities.

Pettit et al. (2010) introduced the concept of ‘Zone of Resilience,’ advancing three propositions to achieve balance. (1) Excessive vulnerabilities relative to capabilities will cause excessive risk, (2) Excess capabilities relative to vulnerabilities will degrade organizational profitability, and (3) a balanced approach improves supply chain performance and resilience. Moreover, agencies abiding by the first two unbalanced propositions are unsustainable for long-term operations and naturally will become uncompetitive (Pettit et al., 2010).

SCR was adopted to bolster supply chain infrastructures in order to sustain competitive capability. However, it is imperative for corporations, businesses, publicly and privately owned, to strike a balance between supply chain capabilities and vulnerabilities (Pettit et al., 2010).

Primarily, two categories of mitigation capabilities moderate the severity of a disruption to the supply chain: recovery and warning. Mitigation capabilities are defined as agency-based routines, patterns, and actions that, when bundled with resources, enhance the supply chain's abilities to recover expeditiously from disruption or create awareness of a pending or realized disruption (Craighead et al., 2007). Recovery capabilities foster coordination of resources to return the network to its pre-disruption steady state, whereas warning capabilities disseminate information about an impeding disruption through nodes within the network (Craighead et al., 2007). Collectively, mitigation techniques contribute to reducing loss, speed of recovery response, and exposure to disruption.

Table 1. Capability Factors (Pettit et al., 2010)

Capability Factor	Definition	Sub-Factors
Flexibility in sourcing	Ability to quickly change inputs or the mode of receiving inputs	Part commonality, Modular product design, Multiple uses, Supplier contract flexibility, Multiple sources
Flexibility in order fulfillment	Ability to quickly change outputs or the mode of delivering outputs	Alternate distribution channels, Risk pooling/sharing, Multi-sourcing, Delayed commitment, Production postponement, Inventory management, Re-routing of requirements
Capacity	Availability of assets to enable sustained production levels	Reserve capacity, Redundancy, Backup energy sources and communications
Efficiency	Capability to produce outputs with minimum resource requirements	Waste elimination, Labor productivity, Asset utilization, Product variability reduction, Failure prevention
Visibility	Knowledge of the status of operating assets and the environment	Business intelligence gathering, Information technology, Products, Assets and People visibility, Information exchange
Adaptability	Ability to modify operations in response to challenges or opportunities	Fast re-routing of requirements, Lead time reduction, Strategic gaming and simulation, Seizing advantage from disruptions, Alternative technology development, Learning from experience
Anticipation	Ability to discern potential future events or situations	Monitoring early warning signals, Forecasting, Deviation and Near-miss analysis, Contingency planning, Preparedness, Risk management, Business continuity planning, Recognition of opportunities
Recovery	Ability to return to normal operational state rapidly	Crisis management, Resource mobilization, Communications strategy, Consequence mitigation
Dispersion	Broad distribution or decentralization of assets	Distributed decision-making, Distributed capacity and assets, Decentralization of key resources, Location-specific empowerment, Dispersion of markets
Collaboration	Ability to work effectively with other entities for mutual benefit	Collaborative forecasting, Customer management, Communications, Postponement of orders, Product life cycle management, Risk sharing with partners
Organization	Human resource structures, policies, skills and culture	Learning, Accountability and Empowerment, Teamwork, Creative problem solving, Cross-training, Substitute leadership, Culture of caring
Market position	Status of a company or its products in specific markets	Product differentiation, Customer loyalty/retention Market share, Brand equity, Customer relationships, Customer communications
Security	Defense against deliberate intrusion or attack	Layered defenses, Access restrictions, Employee involvement, Collaboration with governments, Cyber-security, Personnel security
Financial strength	Capacity to absorb fluctuations in cash flow	Insurance, Portfolio diversification, Financial reserves and liquidity, Price margin

Moreover, simultaneous deployment and investment in mitigation techniques can enhance supply chain performance and competitiveness (Carvalho, Azevedo, & Cruz-Machado, 2012). Investment in isolation leads to inefficiencies in improving resilience within the system (Femano et al., 2019). Subsequently, this research employs this rationale, simultaneously balancing investments in production, capacity, and inventory.

Ivanov (2017) expounded upon the mitigation strategies utilizing discrete-event simulation (DES) to explore the effects of inventory buffer and backup sourcing on supply chain performance. Utilizing a three-stage supply chain comprised of a supplier, distribution centers, and customer, varying capacity levels were modeled to assess the range of mitigation to a disruption. Models with elevated capacity were more sufficiently prepared and equipped to withstand the disruption. Moreover, while capacity affords mitigation capability, responsiveness or speed of response is crucial. The speed by which the system can recover quickly influences resilience with the chain (Gligor, Gligor, Holcomb, & Bozkurt, 2019; Pires Ribeiro & Barbosa-Povoa, 2018). Ultimately, responsiveness or speed can be more influential than capacity (Femano et al., 2019).

Production Capacity versus Inventory

Supply chain resilience is multifaceted, comprising of several internal and external processes and environmental interactions. Intrinsically, tradeoffs plague and prevent organizations from achieving the highest ranges of resilience. Specifically, resilience is closely related to efficiency and redundancy's tradeoff, which is also analogous to the tradeoff of Cost and Service Level (Ivanov & Rozhkov, 2017). Investments in resilience further emphasize the tradeoffs of maximizing system capability. Particularly, decision-makers must choose between enabling faster repairs (referred to as production capacity) and allocating more inventory on a tactical level (Basten & van Houtum, 2014; Rappold & Van Roo, 2009).

Ivanov & Rozhkov (2017) employed simulation to understand how disruption can affect a firm's production capacity. These researchers incorporated real data from a fast-moving consumer goods company to derive practical recommendations on inventory, on-time delivery, and service level control metrics. Modeling a disruption, production capacity immediately experienced a 50% decrease. Investments in capacity buffers and a backup facility as additional capacity reservations partially mitigated the reduction in overall production and capacity and performance level (Ivanov & Rozhkov, 2017). Assessing its effect on inventory, Ivanov & Rozhkov (2017) found increases in inventory tempered the effects of multiple short-term disruptions and singular extended duration disruptions. Thus, if capacity or inventory mitigation techniques are increased without supplementing the other respectively, the full resilience potential will not be realized (Femano et al., 2019).

Long-Chain Flexibility

Literature attests flexibility as a prime determinant of supply chain resilience, indicating an organization's propensity to respond to a disruption adequately. Flexibility is pivotal as it serves as firms' ability and enterprising to adapt themselves to the dynamically changing environment within minimal effort (Hosseini, Ivanov, & Dolgui, 2019). Grigore (2007) defines flexibility as the ability to adapt, remaining operational in changing conditions, and completely different or not from the conditions known in advance. Flexibility may increase organizational service level, cost, and applied practices such as flexible transportation and sourcing can contribute to resiliency within supply chains (Hosseini et al., 2019; Ivanov, Sokolov, & Dolgui, 2014).

Collectively, a flexible supply chain infrastructure is essential to mitigating vulnerabilities. Saghafian & Van Oyen (2016) posit that a critical strategy for achieving robustness is increasing the supply base's flexibility. Firms can institute backup capacity, thus flexibility, by having a dedicated backup supplier for products or extra inventories. More economically friendly, flexibility is achievable by having a single pooled flexible backup supplier capable of assuring supply continuity at a given capacity level (Saghafian & Van Oyen, 2016). Supply chains can also become more flexible by adapting production and delivery quantities to respond in shifts or changes in supply (Shekarian, Reza Nooraie, & Parast, 2020).

Total flexibility can be financially draining for an organization; therefore, limited flexibility remains a viable option and can yield most of the total flexibility benefits. Jordan & Graves (1995) introduced the "long-chain" flexibility concept conjoining production plants and products. Within this construct, two capabilities are afforded: each plant can produce various products, and multiple plants can produce more than one product (Deng & Shen, 2013). Total flexibility, wherein each plant (depicted as a square in Figures 5 and 6) can produce every product (depicted as a circle in Figures 5 and 6), is inadvisable. However, rather limited flexibility is achievable by each plant producing an additional product. The design differences between full and limited flexibility are significant, yet from a capability perspective, the limited flexibility yields results similar to the total flexibility illustrated in Figure 5. Furthermore, Jordan and Graves (1995) employ one and three chain (interchangeable with "long-chain"), limited flexibility approaches with ten links to meet demand.

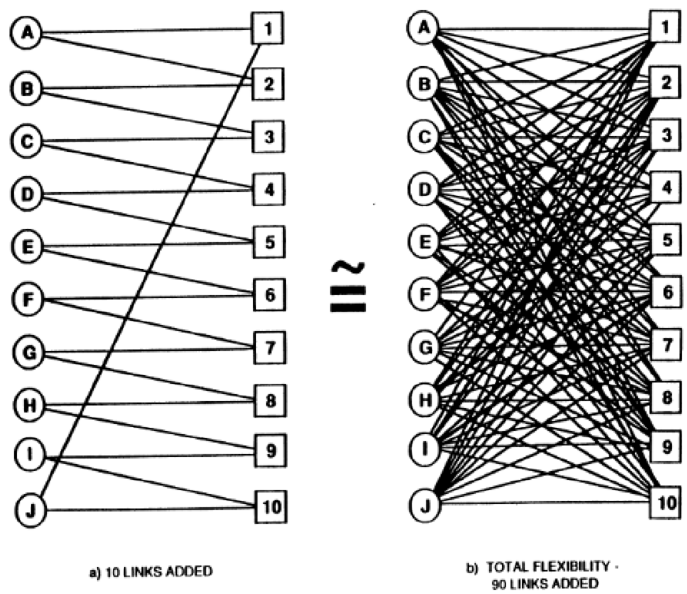

Figure 5. Flexibility Configurations with Equal Flexibility Benefits (Jordan & Graves, 1995)

The limited flexibility approaches yield a capacity utilization of 86.6%, whereas total flexibility increases capacity utilization to 94.7%. The differences between limited and total flexibility are negligible when factoring in the astronomical costs associated with closing the utilization gap between limited and total flexibility (Jordan & Graves, 1995).

Deng & Shen (2013) builds on the essential intuition from limited flexibility research, representing the chain as a circle and further refining the following chaining guidelines:

(a) equalizing the number of plants to which each product is directly connected.

(b) equalizing the number of products to which each plant is directly connected.

(c) creating a circuit that encompasses as many plants as possible (Deng & Shen, 2013).

Chaining guidelines are graphically depicted in Figure 6 as a circular representation of the long-chain.

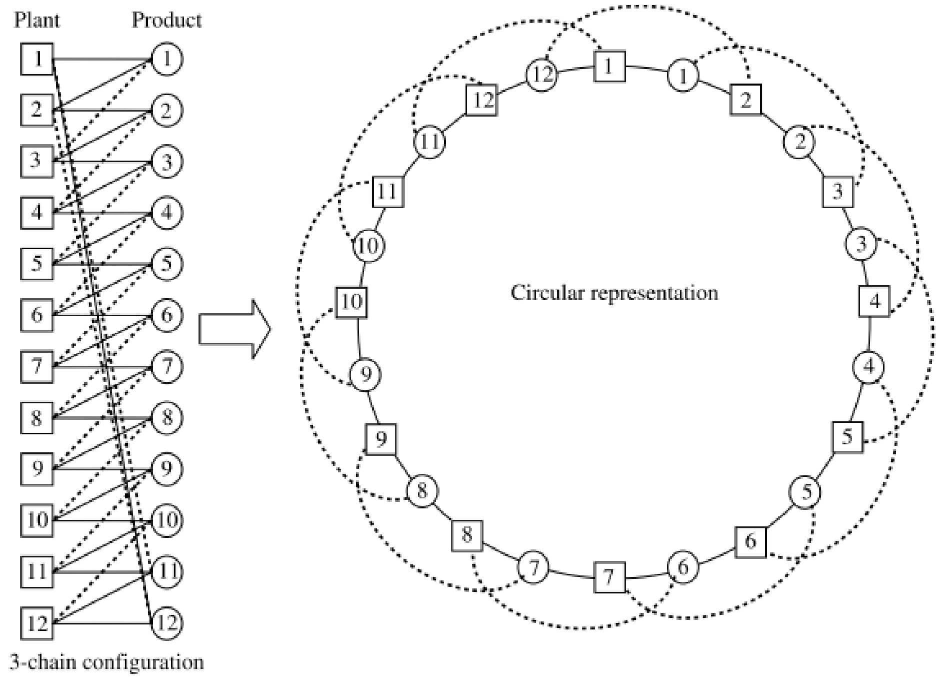

Figure 6. Three Chain Configuration and Its Circular Representation (Deng & Shen, 2013)

The limited flexibility strategy will be employed throughout this research and referred to as a "long-chain" design.

Dynamic Capability

Teece, Pisano, and Shuen (1997) address how firms could develop and sustain a resilient posture introducing the Theory of Dynamic Capabilities (DC), facilitating a competitive advantage guideline. Dynamic capabilities are defined as "the ability of an organization and its management to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Teece et al., 1997). Others have added to the definition to include strategic decision making wherein managers pool various business, functional, and personal expertise to shape the significant strategic moves (Eisenhardt & Martin, 2000). Firms must leverage the levers of sensing, seizing, and transforming or reconfiguring. Sensing is the organization determining or gauging the timing or opportunity to invest and determining how potential competitors may respond. Seizing entails mobilizing resources to address and exploit such opportunities (Teece et al., 1997). Transforming is continued renewal through guiding policy or coherent action.

Multiple firms have adopted this theory within respective supply chains, furthering extending its conceptions throughout numerous facets. SCR and DC are recently interweaving, providing a platform for more resilient, secure supply chain networks (Masteika & Čepinskis, 2015). Supply chain resilience and DC depict similar characteristics to withstand the dynamics of an environment, particularly in the presence of a disruption. Figure 7 depicts relatability amongst the two concepts, under the premise of absorption, or ability to absorb the shock of a disruption, ability to adapt or response capability, and an organization's propensity to capitalize or innovate capacity, offsetting or effectively recovering from turbulence or a disruption (Brusset & Teller, 2017; Yao, Y. & Meurier, 2012).

Where DC and flexibility are simultaneously aligned, they contribute significantly to competitive advantage and overall resilience (Wetering, Mikalef, & Pateli, 2017). Application of DC, interchangeable with flexibility, can be achieved by an array of forms.

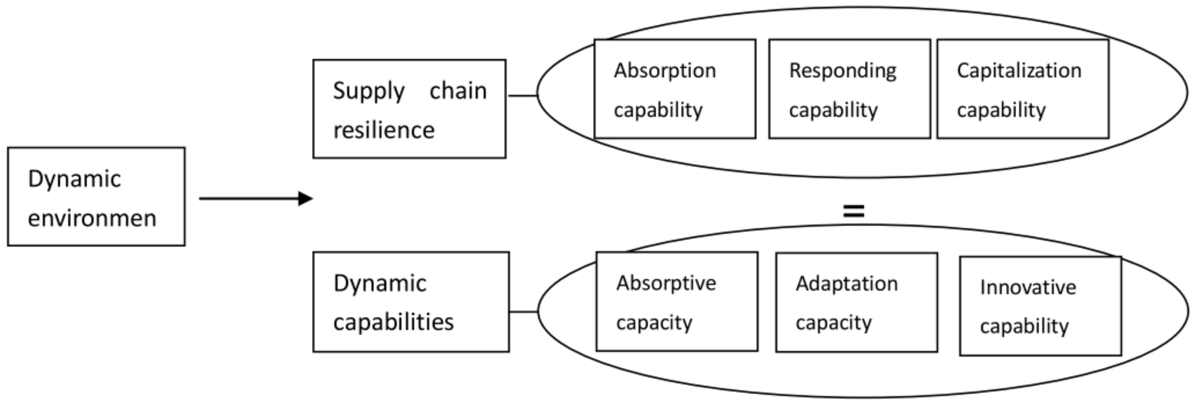

Figure 7. DC & Supply Chain Resilience Traits (Yao, Y. & Meurier, 2012)

Saghafian and Van Oyen (2016) indicate dynamism as incorporating backup suppliers, reinforcing production capacity and inventory before the disruption. However, Djelic and Ainamo (1999) suggest dynamic capability to shift structurally into a flexible embedded network during environmental turbulence. Alternatively, Helfat and Winter (2011) affirm that dynamic capability is a systematic, repeated capacity to extend the firm's assets. This capability is inherently causing changes to the organizational resource-base and how assets are combined and deployed. These adjustments directly represent a dynamic capability and align with previous research, especially as firms must management complex bundles of resources and inventory pools (Helfat & Winter, 2011; Teece et al., 1997).

Subsequently, this research distinguishes long-chain flexibility and dynamic capabilities as adjoined concepts to enhancing supply chain resilience.

Conclusion

This research extends supply chain resilience literature, assessing the various impact of resilience strategies. Explicitly, this research narrows identified gaps in the literature. Leveraging general resilience strategies, this research provides a distinct, generalizable tool and methodology for decision-makers to quantifiably gauge resilience and response to incremental investment changes in production capacity and inventory. Moreover, it explores the infrastructure's dynamic flexibility and long-chain potential. Lastly, it advances supply chain resilience literature and hones a foundation for a more profound understanding of network performance to a disruption.

III. Methodology

Chapter Overview

Simulation modeling was chosen as the methodology for assessing the system under study. In recent years, supply chain resilience has been extensively studied via the modeling approach. It provides the most flexibility and fluidity in understanding a realistic environment of achieving system performance in the presence of disruptions (Carvalho, Barroso, MacHado, Azevedo, & Cruz-Machado, 2012; Ivanov & Rozhkov, 2017; Melnyk et al., 2014). Simulation permits supply chain behavior to be observable under various conditions and design strategies to assess and improve resilience (Carvalho, Barroso, et al., 2012). This research considers production capacity (repair capability and test cells), spare inventory, and disruption responsiveness as key resilience investment levers. Subsequent manipulation of these levers will yield the maximum pre-disruption and post-disruption performance levels and overall resilience metric. Moreover, this research expounds on previous research, particularly conducted by Femano et al. (2019) and Shannon (2020), encompassing a more holistic F-16 engine repair network, 13 various nodes within the network, and three tiers of repair.

The methodology is approached in the following manner:

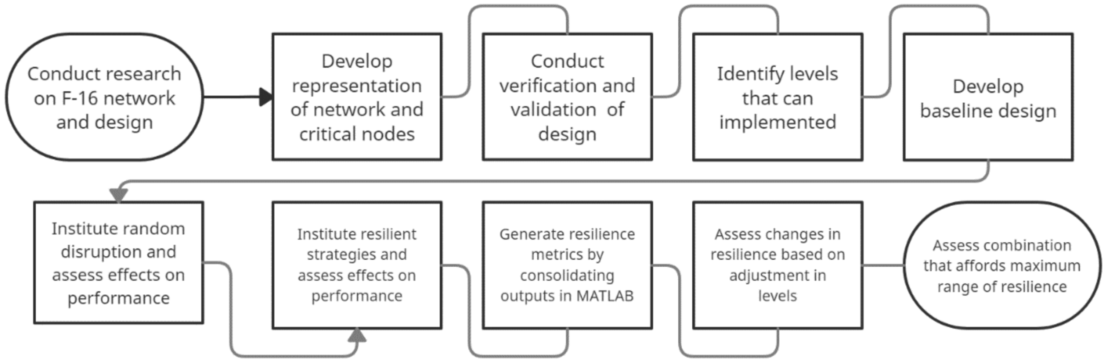

Figure 8. Methodology Flowchart

Conceptual Design

A simulation model was developed to replicate the holistic behavior of the F-16 engine repair supply chain. It features 13 predominant repair network nodes (hereafter referred to as bases), wherein each base maintains a respective individual production capacity, inventory, repair capability, and test bench functionality. The distribution of resources (spares) necessary for each location is equalized for each repair node. Table 2 illustrates production capacity and resource allocation for the baseline network.

Simulation Model Development

The simulation was developed using SIMIO 11.0 simulation software and MATLAB. SIMIO interacts with a myriad of secondary applications, affording access to a vast array of methods and routines. Each simulation cycle generates an Excel workbook output for analysis within MATLAB, as illustrated in Figure 9. This approach was applied by several researchers, particularly Abar, Theodoropoulos, Lemarinier, & O’Hare (2017) and Dehghanimohammadabadi & Keyser (2017).

Table 2. Baseline System Allocation

	Production Capacity	Inventory/Capacity
Base	**Test Benches**	**Spares**
1	2	1
2	2	1
3	2	1
4	2	1
5	2	1
6	2	1
7	2	1
8	2	1
9	2	1
10	2	1
11	2	1
12	2	1
13	2	1
Total	**26**	**13**

Within the realm of resilience, authors Iriondo, Estévez, Orive, & Marcos (2014) and Vijayan, Harikrishnakumar, Krishnan, Cheraghi, & Motavalli (2020) implemented a combined simulation and MATLAB approach.

Data Collection

The Air Force's maintenance data repository Logistics, Installation, and Mission Support-Enterprise View (LIMS-EV) was the model's predominant data source. LIMS-EV served as the prime mechanism for obtaining information about the USAF supply chain's F-16 engine posture. Specifically, subsystems within LIMS-EV such as Weapon Systems, Supply Chain Management, and Engines Views were used to obtain the necessary data for the model and data analysis. Like previous authors, namely Kontokosta and Malik (2018) and Sarker, Yang, Lv, Huq, and Kamruzzaman (2020), this research scopes the LIMS-EV data to model the Air Force F-16 engine network appropriately.

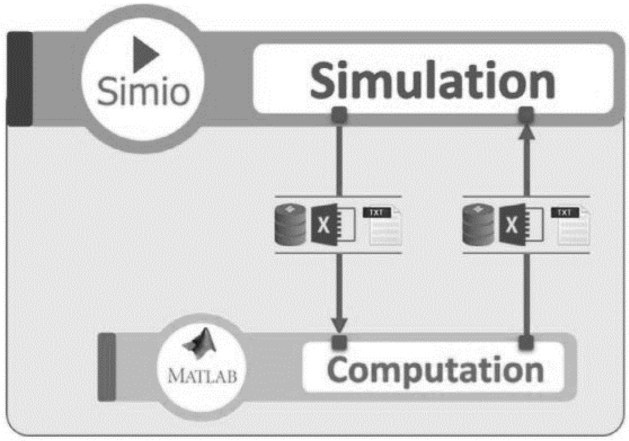

Figure 9. SIMIO and MATLAB: Generalized Framework (Dehghanimohammadabadi & Keyser, 2017)

Additional data were obtained from the USAF: Life Cycle Management Center and 635th Supply Chain Operations Wing to ensure realistic data assessment and modeling.

Table 3 illustrates the composite 2019 system parameters gathered and instituted in the Baseline System model.

Table 3. 2019 System Parameters

Base	Available N	Depot N	Depot_Pert	TAI N	Breaks N	Breaks_Pert	Breaks_Rate	Hours Flown H	Sorties Flown N	Hours_Sorties	Sorties_260
1	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
2	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
3	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
4	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
5	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
6	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
7	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
8	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
9	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
10	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
11	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
12	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38
13	9.00	2.20	9.43%	19.00	191.00	12.00%	14.00	2,779.00	1,659.00	1.68	6.38

Data masked for confidentiality

Baseline System Description

The baseline model incorporates 13 base nodes of the overall system and three echelons of the repair network: Organizational (O-level), Intermediate (I-level), and Depot (D-level). The model served as a fully integrated network in which system operations are codified, replicating holistic broken engines. O-level repair is accomplished locally by back-shop maintenance personnel. I-level repair requires outsourcing entity repair to a centralized repair facility (CRF) for repair. CRF's generally possesses additional repair capability not present at the local level. In certain instances, the base may have both I-level and O-level repair capability if the node also functions as a CRF. This model features two distinct CRF's, one for supporting CONUS nodes and another for OCONUS node support. D-level requires overhaul repair of the engine, wherein bases will pack, wrap, and ship it to a singular, centralized repair node.

Each engine (also referred to as 'entity') is assigned to an aircraft facilitating flying operations based on 2019 flying data illustrated in Table 3. As engine breaks occur, the entity is routed through the respective base repair chain, dependent on severity. Breaks serve as the system interarrival entity, distributed about the number of aircraft allocated to each base, the sortie quantity, flying hours, and respective break rate. Interarrival time of entities is given by:

$$Interarival\,Time = \left(\frac{F_i}{Breakrate}\right)/(A_i * S_i * H_i) \tag{1}$$

(Femano et al., 2019; Shannon, 2020)

where,

$F_i = \ total\ flying\ hours\ for\ base\ i$

$A_i = \ total\ available\ aircraft\ at\ any\ given\ time\ for\ base\ i$

$S_i = average\ daily\ number\ of\ sorties, using\ a\ 260 - day\ flying\ schedule\ for\ base\ i$

$H_i = \ average\ sortie\ during\ for\ base\ i$

Interarrival time also inherently considers the human element of sortie generation. As A_i decreases, the model will fly fewer sorties. This acts as a natural balancer for system performance and allows the model to reach steady-state flying operations.

At entity generation (break occurrence) following flying operations, the entity is sent to flight-line maintenance to determine the break's severity. The model designates four types of severities, sequenced from one to four, stochastic in nature. Type one breaks are considered repairable at the O-level whereas, type two and three breaks are deemed I-level repair, and type four breaks are reserved for D-level overhaul. Table 4 visualizes the types of severities, probability of severity, and respective repair echelon. Of note, each node maintains a separate value for type three and four breaks, providing a more accurate representation of probabilistic system engine severity. Following O-level engine repairs, the simulation models the time for maintenance personnel to conduct a function test utilizing a test bench, then reattach the engine into an available aircraft. Subsequent O-level and D-level repairs will not transport the engine back to the originating node but transport the entity to the base with the lowest relative percentage of available aircraft.

Table 4. Severity and Repair Level

Severity	Severity Mix	Repair Level
1	0.85	O-Level
2	0.03	I-Level
3	*	I-Level
4	**	D-Level

***Derived by (1 – all other severities)**
**** Specific to base i Depot Percent (See Table 3)***

This model approaches Aircraft Availability (AA) as a variable or metric comparable to a commercial company's competitive metric. This metric is calculated as:

$$AA = \left(\frac{Operational\ Requirement\ (OR)}{Total\ Active\ Inventory}\right) * 100 \qquad (2)$$

(Ingram, 2020)

Concerning the Air Force, AA provides the most noteworthy system-level measurement, assessing the impact of aligning inventory in a service parts environment (Boone, Craighead, Hanna, & Nair, 2013).

During an entity's generation (i.e., engine break), one unit of OR is decremented from the originating base, affecting AA as an aircraft is no longer capable of conducting a mission. Following the engine break's repair, one unit of OR is incremented at the base receiving the repaired engine. For example, if a Type 2 severity occurs at node four, it is transported to a CRF for repair, and node four OR is decremented by one. After repair, the CRF scans the system for the lowest relative node AA and determines node seven as requiring the repaired engine. Subsequently, node seven is incremented by one OR. Finally, each base is initially allocated one spare engine. Therefore, when an engine failure occurs, maintenance immediately replaces the entity with a spare, if available, without any

OR loss. When routing repaired entities, if a node chain receives an engine increasing OR greater than the respective Total Active Inventory, the local spare inventory is increased, and OR remains unchanged.

Model Verification and Validation

Simulation models are heavily reliant on their validity; therefore, objective methods are essential to verify and validate simulation models. For verification, we are confronted with a critical question: *Does the system behave the way it is intended?* Verification is achieved by exhaustive execution of SIMO model trace functionality. Tracing allows for the critical analysis of process logic, ensuring entities flow from node to node as intended. Validation evaluates the relationship between the model and the real system. It questions: *Does the simulation produce performance measures or metrics comparable to the real system?* Validation of model frameworks was achieved by coordination with the primary experts and conduits of F-16 engine repairs, Air Force Life Cycle Management Center. Furthermore, output metrics such as AA and the number of breaks produced by the system were compared with historical LIMS-EV data.

Scenario Design

The baseline model corresponds to the representation of the existing network system. Other scenarios and designs were compared to the baseline in performance over a predetermined timeframe to analyze the supply chain's performance behavior. Collectively, all scenarios were simulated through a 5,000-day time frame, encompassing an initial 3,500-day warm-up period. Due to the model's complexity, a substantial warm-up period was necessary to eliminate significant performance fluctuations and assure steady-state operations within the model. Following the warm-up, day 3500 serves as "new day 0" of steady-state network performance and disruption analysis, permitting a concentration on transient states amid a disruption. Therefore, from day 0 to day 1100, steady-state is assessed, followed by a randomized disruption occurring at day 1100. By day 1500, each scenario has fully recovered, facilitating transient state progression and AUC's utilization from day 1100 to 1500. Based on this approach, three transient periods are identified: (1) Pre-Disruption, (2) Post-Disruption – Decline, and (3) Post Disruption – Recovery. The Pre-Disruption stage is assessed from day 1000 to day 1100. Post-Disruption – Decline is categorized as the time at which the disruption occurs until a specified response has been enacted. Finally, Post Disruption – Recovery is when the response occurs until the system performance has recovered (Femano et al., 2019; Shannon, 2020). Existing within the post-disruption period, the AUC metric quantifies the level of demand the network can meet during the Post Disruption - Decline and Recovery periods. The AUC isolates three segments to formulate resilience: (1) ***AUC – Decline***, (2) ***AUC – Recovery***, and (3) ***AUC – Total***. AUC – Decline is the total network performance under the Post Disruption – Decline curve, AUC- Recovery is the total network performance under the Post Disruption – Recovery curve, and AUC – Total is the cumulative network performance during all disruption stages (Femano et al., 2019; Shannon, 2020). Figure 12 further illustrates the transient states and applicable AUC periods.

The primary resilience levers within this research are production capacity, inventory, and response time. As previously described in the literature review, these levers will be utilized in unison to achieve the most significant resilience potential. Thus, scenarios will vary in allocations of production capacity, inventory, and response time. Baseline structure capacity is assessed up to a 30% increase, whereas production capacity is varied up to 50%

of initial allocations. Such variations in resilience levers are organizational-specific and require variations inherent to the network being assessed. These variations are most appropriately aligned to analyzing investments with AA impact within the engine repair and supply network. Finally, responsiveness to the disruption is analyzed at 10- and 60-day values. Responsiveness values were selected based on Macdonald and Corsi (2013), who outlined average expected discovery and recovery time, their responsiveness, and disruption. Based on the substantial warm-up period, scenarios underwent 20 replications to secure consistent overall data and ensure data outputs are centered within a 95% confidence interval. Likewise, scenarios are measured based on the AUC metric and respective AA. The AUC is utilized as the primary metric of resilience and representation of system behavior over time, while AA provides how investments affect overall competitive advantage. Table 5 outlines the developed scenarios.

Following each replication, SIMIO generates a comma-separated value (CSV) file, wherein 500 CSVs are produced for one response, translating to 25 files for each design. CSVs are then imported into MATLAB, which batches, fits, and executes the area under the respective scenario curve. Following, MATLAB generates a table featuring pertinent timeframe metrics associated with each scenario. Complete MATLAB coding is detailed in Appendices B, C, and D.

Table 5. Scenario Framework

<table>
<tr><th>Scenario</th><th>System Initial Capacity</th><th>Recovery Production Capacity</th><th>Scenario</th><th>System Initial Capacity</th><th>Recovery Production Capacity</th></tr>
<tr><td>1</td><td rowspan="6">1.00</td><td>1.1</td><td>13</td><td rowspan="6">1.20</td><td>1.1</td></tr>
<tr><td>2</td><td>1.1</td><td>14</td><td>1.1</td></tr>
<tr><td>3</td><td>1.2</td><td>15</td><td>1.2</td></tr>
<tr><td>4</td><td>1.3</td><td>16</td><td>1.3</td></tr>
<tr><td>5</td><td>1.4</td><td>17</td><td>1.4</td></tr>
<tr><td>6</td><td>1.5</td><td>18</td><td>1.5</td></tr>
<tr><td>7</td><td rowspan="6">1.10</td><td>1.1</td><td>19</td><td rowspan="6">1.30</td><td>1.1</td></tr>
<tr><td>8</td><td>1.1</td><td>20</td><td>1.1</td></tr>
<tr><td>9</td><td>1.2</td><td>21</td><td>1.2</td></tr>
<tr><td>10</td><td>1.3</td><td>22</td><td>1.3</td></tr>
<tr><td>11</td><td>1.4</td><td>23</td><td>1.4</td></tr>
<tr><td>12</td><td>1.5</td><td>24</td><td>1.5</td></tr>
</table>

Scenario 0 - System Initial Capacity and Recovery Production Capacity = 1.00

(Femano et al., 2019; Shannon, 2020)

Dynamic Long-Chain Flexibility Design

The design of the system is also pivotal to assessing resilience within the system. In conjunction with adjustments to investments, this research considers a dynamic long-chain flexibility design. This construct emulates the same design and process logic built of baseline model with a singular exception in the repair routing of severity 2, 3, and 4 engines. Inherently, I-level and D-level nodes create a centralization or bottleneck of repair capability.

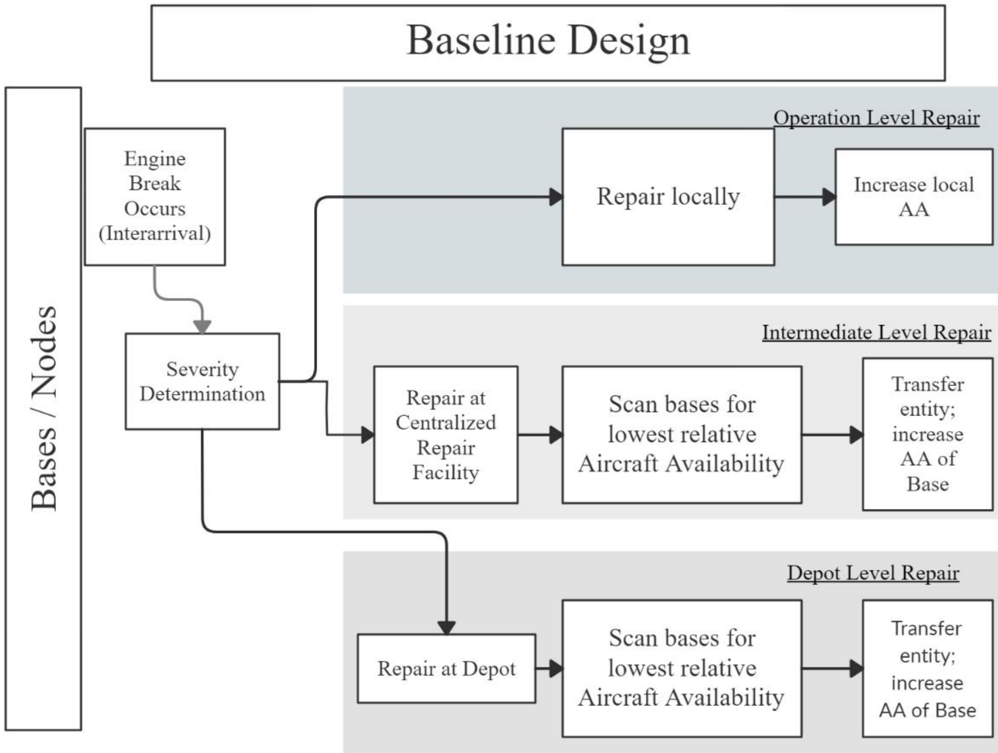

Figure 10. Baseline Network Design

Therefore, the long-chain model is dynamic as it will assess whether a CRF or D-level repair queue is significantly backlogged. If so, it will redirect the entity to another CRF if a repair can be achieved quicker. A D-Level perspective will scan the network of CRFs and determine whether a repair can be accomplished quicker and route accordingly. The long-chain flexibility design is recognized as a dynamic capability, capable of absorption system functions and adapting appropriately. Figures 10 and 11 exemplify the structural difference between the two system designs. Within each scenario, the disruption occurs at day 1100, where repair capabilities at a specific base (node) are eliminated.

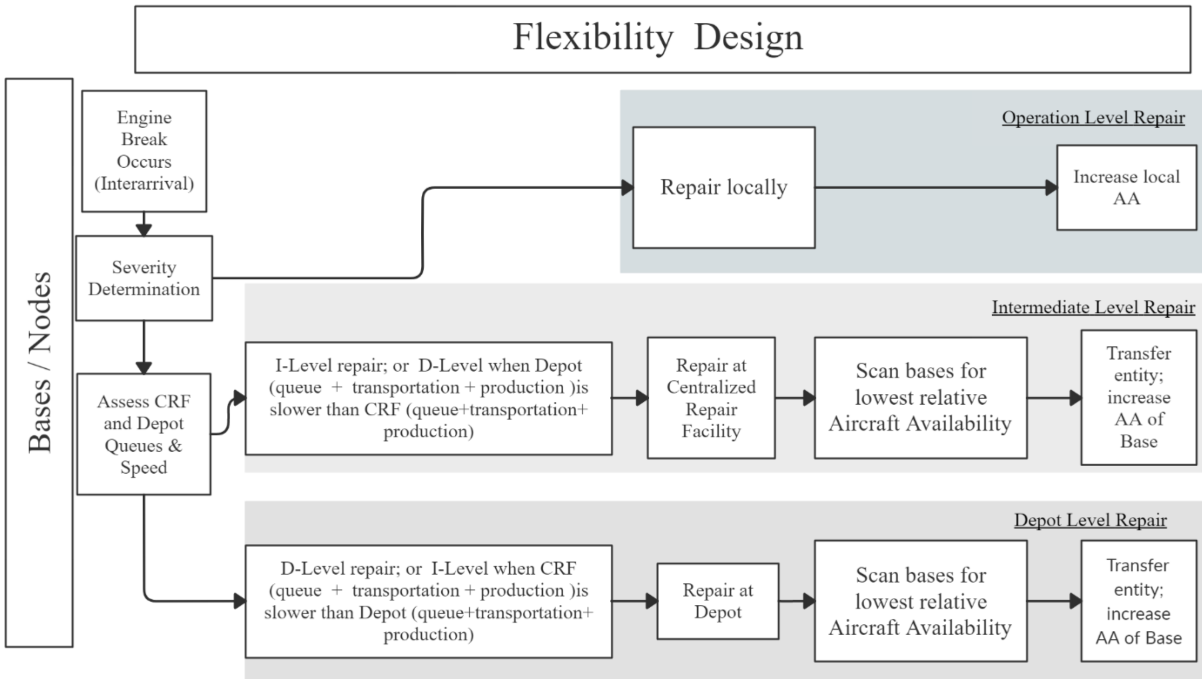

Figure 11. Dynamic Long-chain (Flexibility) Network Design

After a predetermined delay, it is assumed all available aircraft at the location impacted are equally dispersed to three separate bases within the nearest geographic proximity. The model also assumes production capacity and inventory are irrecoverable and spent for the simulation's remaining duration. Moreover, process logic impedes I-level and D-Level repaired engines from routing back to the impaired location as it is no longer operational due to the disruption. Finally, supporting bases receive OR and Total Active Inventory increases relative to the number of dispersed aircraft received.

Disruption Implementation

Assessing system performance, level of resilience, and transient states, each scenario incorporates a disruption. This research applies the framework from previous literature to quantify the effects of resilience levels or investments through three distinct timeframes.

Figure 12 depicts the system's resistance amid a disruption, decline of performance, recovery measures, and new steady-state realization.

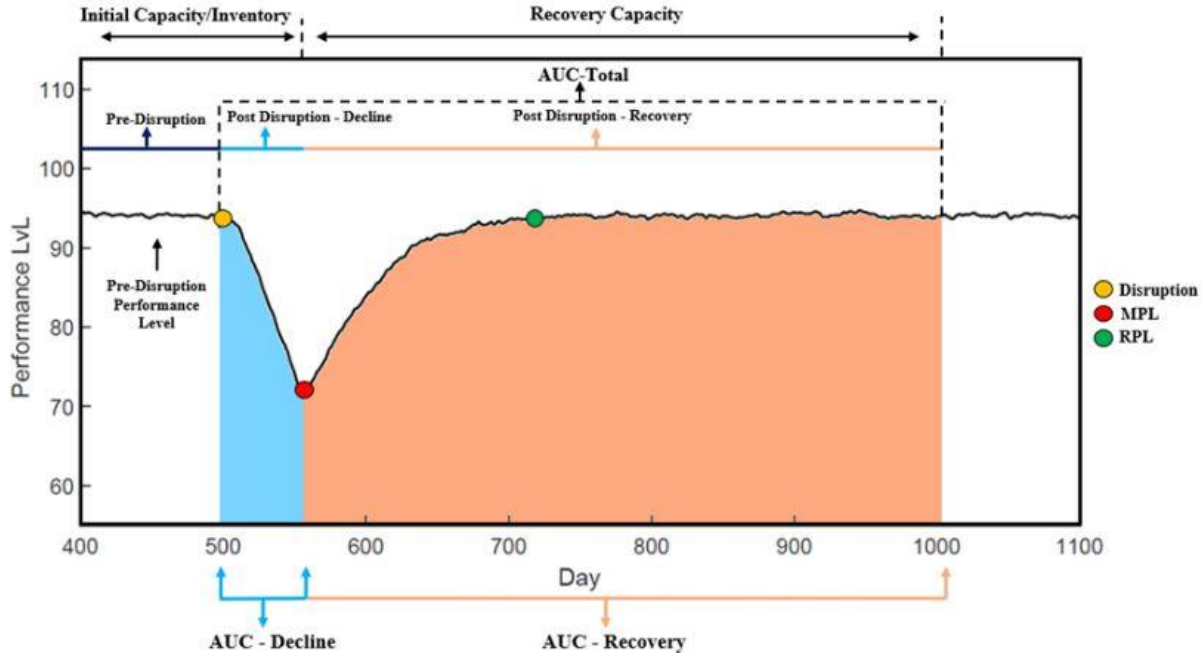

Figure 12. Performance Metrics & Disruption Time Periods (Femano et al., 2019; Shannon, 2020)

The system's resilience to disruption is translatable to the Pre-Disruption state. Upon initiating a disruption, the system performance level begins to decline, entering the Post-Disruption Decline state. A Minimum Performance Level (MPL) is reached when investments or allocations are inserted into the system, launching the Post-Disruption Recovery state until a new Recovery Performance Level (RPL) is reached.

To assess the transient state and quantifiably analyze the drop and recovery in performance, thus resilience, the AUC metric is utilized. The area above the curve indicates lost performance in the event of a disruption, whereas AUC emphasizes collective performance throughout the transient states (Femano et al., 2019). Therefore, to quantify system resilience, the achieved AUC is considered in proportion to the realized demand over the disruption timeframe.

$$Resilience = \frac{AUC_t}{D_t} \tag{3}$$

(Femano et al., 2019; Shannon, 2020)

AUC is implemented within the provided designs through further analysis and results, and the validity of transient system states is achieved.

IV. Analysis and Results

Chapter Overview

This research analyzes two network designs: baseline structure and dynamic long-chain flexibility structure, wherein each initialized design tests transient states, disruption response, recovery, and investments. Each design validates the requirement of simultaneous investments in inventory and production capacity and subsequent effects on AA, this research's measure of competitive advantage. Designated disruption responses (10- and 60 days) for each design activate predetermined recovery capacity allocations. Thus, this research confirms the significance of predetermined asset allocation, reactiveness, and recovery allocations as pivotal to post-disruption performance.

In conjunction with previous research, Figure 12, and "Scenario Design" section, three distinct performance metrics are analyzed: (1)Pre-Disruption AA, (2) Minimum Performance Level (MPL), and (3) Recovery Performance Level (RPL).   Pre-Disruption AA is assessed as the average daily AA rate from 1000 to day 1100. MPL is the network's minimum level of performance as a result of the disruption. RPL is the average daily performance after the network has recovered. The interaction of these three metrics provides a more profound understanding of overall system resilience. Emphasis is placed upon maintaining performance following a disruption and meeting required demand or maintaining competitiveness. Specifically, this emphasis is directed where Pre-Disruption AA ends, when disruption impact is realized. Moreover, starting performance is pivotal in overall performance throughout the transient states.

Baseline Design

Generally, a baseline model captures the current operational environment of its real-world structure. This model depicts the USAF F-16 engine repair network and limited supply chain, affording awareness of the system's current environment and how it resists and recovers from a disruption.

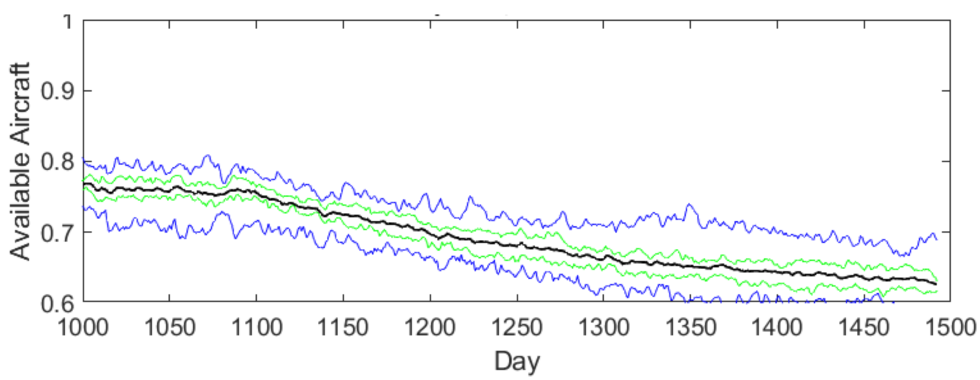

Figure 13. Baseline Design with Disruption

Figure 13 illustrates the system's steady-state and disruption at day 1100 before investments in resilience levers. The figure shows the average AA Rate (Black line), the 50th percentile (Green lines), and the minimum and maximum AA Rates (Blue lines) across all replications. Table 6 depicts the 10-day response output derived from the scenarios established in Table 5. Each scenario symbolizes established investment levers of initial inventory capacity and recovery (production) capacity. Moreover, scenarios assigned a value of 1.00 in either investment lever indicate respective current capability without additional resilience investment.

Table 6 reinforces the importance of the network's ability to maximize its Pre-Disruption AA rate in the event of a disruption. The transient states of the scenario are quickly visible as the larger the starting AA, the more significant the AUC Decline. Thus, as initial capacity investments occur, Pre-Disruption AA, AUC – Decline, and MPL also increase. Naturally, a higher MPL indicates a more remarkable ability for the system to support demand or maintain a competitive advantage within the Post-Disruption – Recovery period following a disruption. Furthermore, RPL improves respective to the Pre-Disruption AA and directly reflects the simultaneous inventory and production capacity investments. Thus, the network's ability to withstand and recover from disruption is sub-optimal when no investments or investments in singular resilience levers are made and when a singular lever is manipulated (Femano et al., 2019; Shannon, 2020). Investments in inventory initially realize a lesser impact than leveraging production capacity following a disruption. Collectively, investments in recovery capacity realize the most significant benefit to RPL within the baseline structure.

Table 6. Baseline 10-Day Output

	Investments		PreDisruption	Post Disrup. - Decline		Post Disrup. - Recovery		
Scenario	Initial Cap	Recovery Cap	Average AA	MPL	AUC-D	RPL	AUC-R	Total AUC
0	1.00	1.00	79.21%	67.47%	86.62	N/A	N/A	86.620
1		1.05	79.21%	67.47%	7.49	73.83%	80.23	87.72
2		1.10	79.21%	67.47%	7.51	73.95%	80.68	88.20
3		1.20	79.21%	67.47%	7.51	74.69%	81.61	89.12
4		1.30	79.21%	67.47%	7.51	74.63%	81.54	89.06
5		1.40	79.21%	67.47%	7.63	76.94%	93.12	100.74
6		1.50	79.21%	67.47%	7.68	79.16%	93.39	101.07
7	1.10	1.00	80.22%	68.48%	7.56	74.46%	81.33	88.89
8		1.10	80.22%	68.48%	7.58	74.71%	81.32	88.90
9		1.20	80.22%	68.48%	7.58	75.16%	82.44	90.02
10		1.30	80.22%	68.48%	7.58	75.65%	82.55	90.13
11		1.40	80.22%	68.48%	7.70	77.63%	93.46	101.16
12		1.50	80.22%	68.48%	7.75	79.54%	93.92	101.67
13	1.20	1.00	80.95%	69.49%	7.67	75.16%	81.88	89.55
14		1.10	80.95%	69.49%	7.69	75.91%	82.48	90.16
15		1.20	80.95%	69.49%	7.68	76.34%	83.90	91.58
16		1.30	80.95%	69.49%	7.69	76.53%	83.87	91.56
17		1.40	80.95%	69.49%	7.84	79.45%	94.60	102.43
18		1.50	80.95%	69.49%	7.87	82.23%	94.88	102.75
19	1.30	1.00	82.16%	70.50%	7.75	76.74%	82.75	90.49
20		1.10	82.16%	70.50%	7.75	76.48%	82.27	90.02
21		1.20	82.16%	70.50%	7.75	77.14%	84.21	91.96
22		1.30	82.16%	70.50%	7.75	76.92%	83.85	91.61
23		1.40	82.16%	70.50%	7.88	79.58%	94.16	102.04
24		1.50	82.16%	70.50%	7.95	81.85%	94.40	102.35

An organization's ability to rapidly identify, adapt, and respond is crucial to the system's performance before and following a disruption. From a competitive-advantage perspective, responsiveness is a predominant factor in assuring an organization maintains capability and competitiveness. Responsiveness is directly associated with the ability to activate specifically designated asset allocations of recovery capacity. Table 7. Baseline Response

(10 v 60-Days)and Figure 14 depict the consequences of prolonged disruption response on overall system performance.

Table 7. Baseline Response (10 v 60-Days)

	Investments		PreDisruption	Post Disrup. - Decline		Post Disrup. - Recovery		
Response Time	**Initial Cap**	**Recovery Cap**	**Average AA**	**MPL**	**AUC-D**	**RPL**	**AUC-R**	**Total AUC**
10-Day	1.00	1.10	79.21%	67.47%	7.51	73.95%	80.68	88.20
		1.20	79.21%	67.47%	7.51	74.69%	81.61	89.12
		1.30	79.21%	67.47%	7.51	74.63%	81.54	89.06
60-Day		1.10	79.21%	66.46%	11.24	70.13%	76.65	87.89
		1.20	79.21%	66.46%	11.25	72.68%	77.26	88.51
		1.30	79.21%	66.46%	11.24	72.79%	77.30	88.54

Accelerated responsiveness is beneficial to the network resulting in a higher MPL and RPL. Moreover, Total AUC or cumulative network performance during all disruption stages is higher between the 10- and 60-day response times. It is assumed that the same recovery allocations are provided at the response, but realistically, a lengthy response can be substantially more costly and detrimental to competitiveness.

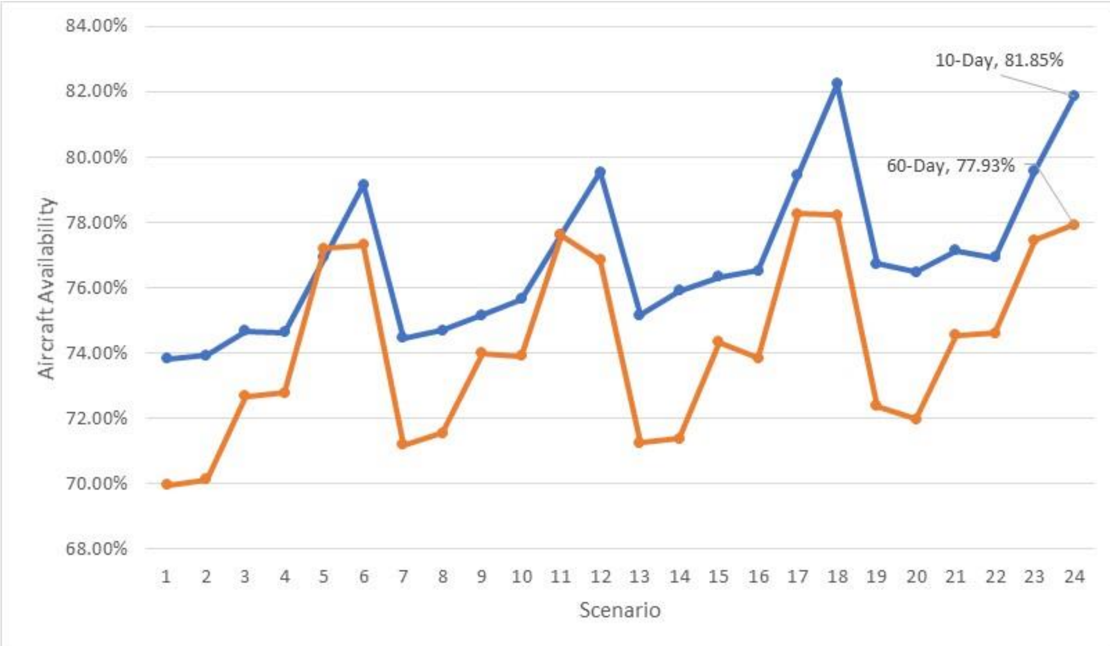

Figure 14. AA: 10 v. 60-Day Response

Dynamic Long-Chain Flexibility Design

The second design capitalizes upon the concept of dynamic long-chain flexibility as identified within the literature, allocating inventory and production capacity while subsequently dispersing capability amid a disruption. Understandably, the baseline construct is fundamentally dynamic and flexible, wherein specific nodes can perform O-Level and I-Level repair capabilities. Within this research, flexibility and dynamism are further heightened, permitting certain CRFs to perform limited D-level repair during periods of heightened demand. Conjoining the works of Jordan and Graves (1995) and Saghafian and Van Oyen (2016), this research fuses dynamic capability and long-chain flexibility to bolster resilience.

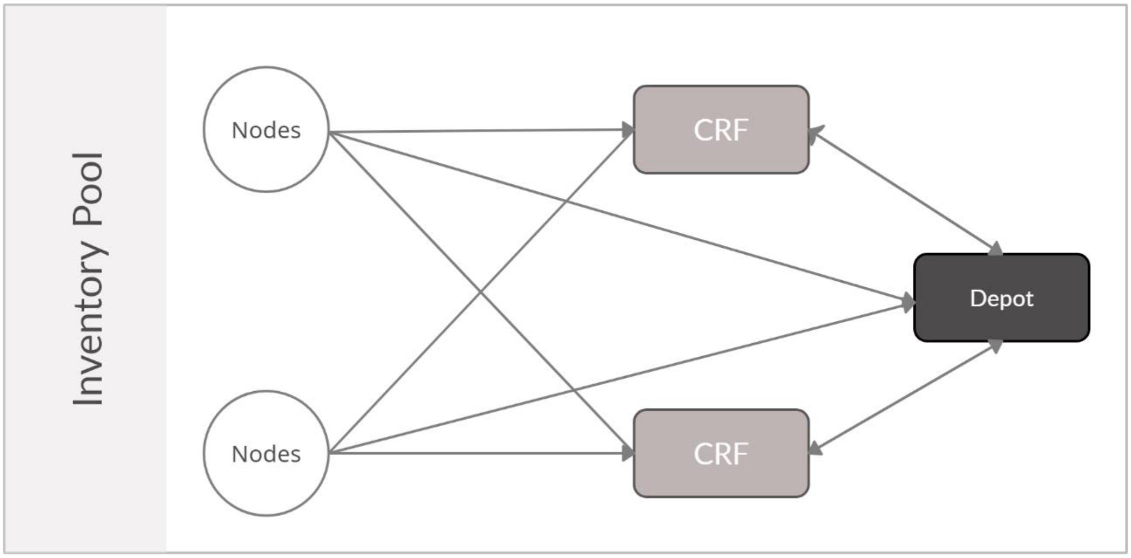

Figure 15. Dynamic Long-Chain Construct

Within this construct, the CRF and respective Depot system can dynamically absorb the shock of a disruption. As with the baseline design, the system will still assess the severity of the break and route accordingly but will first analyze the network's state. The system will assess which has the greatest queue of repairs with travel time and route to the quickest CRF server for repair. Moreover, severity four breaks are still routed to the depot for repair wherein the system will probabilistically assess whether the CRF can support the D-Level repair. If the respective CRF queue, repair time, and transportation time are greater than that of the depot, the entity is allocated to the CRF. Otherwise, the depot will assign the entity to its queue for repair. Furthermore, this design is present before the disruption and assessed throughout the transient states. Figure 15 visualizes this construct utilized within this research and simulation.

Table 8. Dynamic Long-chain 10-Day Output

	Investments		PreDisruption AA	Post Disrup - Decline		Post Disrup - Recovery		
Scenario	Initial Cap	Recovery Cap	Average AA	MPL	AUC-D	RPL	AUC-R	AUC - Total
0	1.00	1.00	79.21%	68.48%	154.08	N/A	N/A	154.077
1		1.05	79.21%	68.48%	47.99	74.30%	111.58	159.58
2		1.10	79.21%	68.48%	48.14	75.17%	112.52	160.66
3		1.20	79.21%	68.48%	48.53	76.21%	114.42	162.95
4		1.30	79.21%	68.48%	48.49	76.07%	114.46	162.94
5		1.40	79.21%	68.48%	51.49	81.88%	125.39	176.88
6		1.50	79.21%	68.48%	51.49	81.45%	125.61	177.10
7	1.10	1.00	80.39%	69.48%	48.68	75.95%	113.58	162.26
8		1.10	80.39%	69.48%	48.73	75.91%	113.75	162.48
9		1.20	80.39%	69.48%	49.11	76.87%	116.14	165.25
10		1.30	80.39%	69.48%	49.23	77.20%	115.73	164.96
11		1.40	80.39%	69.48%	52.25	82.36%	125.50	177.76
12		1.50	80.39%	69.48%	52.25	82.65%	125.54	177.79
13	1.20	1.00	80.94%	69.30%	48.99	76.03%	114.30	163.29
14		1.10	80.94%	69.30%	49.31	76.68%	114.13	163.44
15		1.20	80.94%	69.50%	49.77	78.12%	118.02	167.79
16		1.30	80.94%	69.50%	49.79	77.92%	117.86	167.65
17		1.40	80.94%	69.50%	52.61	83.63%	127.11	179.72
18		1.50	80.94%	69.50%	52.61	83.32%	127.19	179.80
19	1.30	1.00	82.20%	71.30%	49.73	77.09%	114.70	164.43
20		1.10	82.20%	71.30%	49.42	76.26%	113.79	163.20
21		1.20	82.20%	71.30%	49.97	78.15%	118.16	168.13
22		1.30	82.20%	71.30%	49.88	78.14%	117.21	167.09
23		1.40	82.20%	71.30%	53.43	83.23%	126.30	179.72
24		1.50	82.20%	71.30%	53.43	82.73%	126.12	179.55

Similar to the baseline model, the dynamic long-chain flexibility design is analyzed based on inventory and production capacity. Additionally, recovery responsiveness is assessed and gauged based on overall network AA and AUC – Total. Table 8 further outlines the output generated based on resilience lever allocations and 10-day recovery response. Based on the output, simultaneous investments in inventory and recovery capacity are also pivotal in achieving optimal resilience within the dynamic long-chain design. Investments in these resilience levers in union not only maximizes the cumulative AA but increases Total AUC. Thus, throughout all stages, scenarios which increase inventory and recovery capacity holistically outperformed scenarios activating a singular lever. Moreover, higher investments in inventory generated higher Pre-Disruption AA and MPL, leading to higher RPL values.

Responsiveness within the dynamic long-chain design also proved vital to influencing cumulative AA. In every scenario, collectively responding within 10-days versus 60-days yields higher MPL, RPL, and Total AUC.

Table 9. Dynamic Long-chain Response (10- v 60-Days)

	Investments		PreDisruption	Post Disrup. - Decline		Post Disrup. - Recovery		
Response Time	Initial Cap	Recovery Cap	Average AA	MPL	AUC-D	RPL	AUC-R	Total AUC
10-Day	1.00	1.10	79.21%	68.48%	48.14	75.17%	112.52	160.66
		1.20	79.21%	68.48%	48.53	76.21%	114.42	162.95
		1.30	79.21%	68.48%	48.49	76.07%	114.46	162.94
60-Day		1.10	79.21%	67.47%	48.08	72.32%	110.68	158.76
		1.20	79.21%	67.47%	48.18	74.68%	113.22	161.41
		1.30	79.21%	67.47%	48.24	74.79%	113.31	161.55

Table 9 and Figure 16 further validates responsiveness literature as an organization's ability to respond to a disruption affects its recovery trajectory and overall performance.

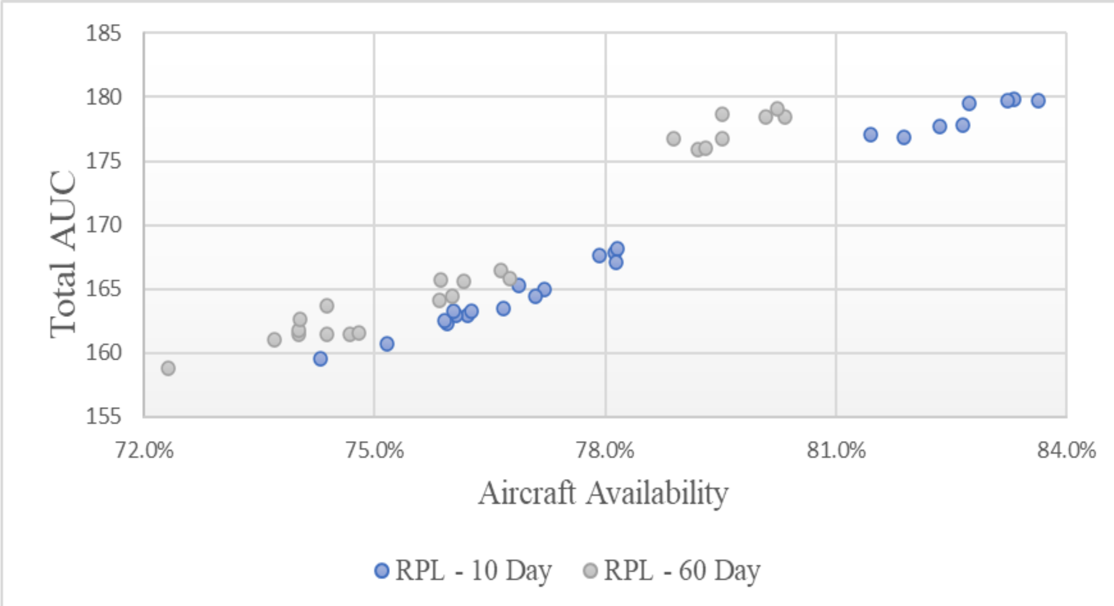

Figure 16. Long-Chain 10- v. 60-day RPL (Total AUC and AA)

Baseline vs. Long-chain / 10- vs. 60-Day Response

Figure 17 outlines the baseline and long-chain structures for AA. As investments in resilience increase, overall AA increases linearly. Furthermore, there are distinct differences between: (1) 10- and 60-day recovery responses and (2) baseline and long-chain structures. This research further employed the Paired T-Test to statistically test for the difference to assess and validate differences within these two categories. A Paired T-Test was selected to test for the difference between two dependent samples. Collectively, four relationships were individually assessed at a 99.9% confidence level or alpha of 0.001. Table 10 outlines these four tests, indicating significance throughout all scenarios and designs as every derived T-statistic exceeds the critical two-tailed T-value.

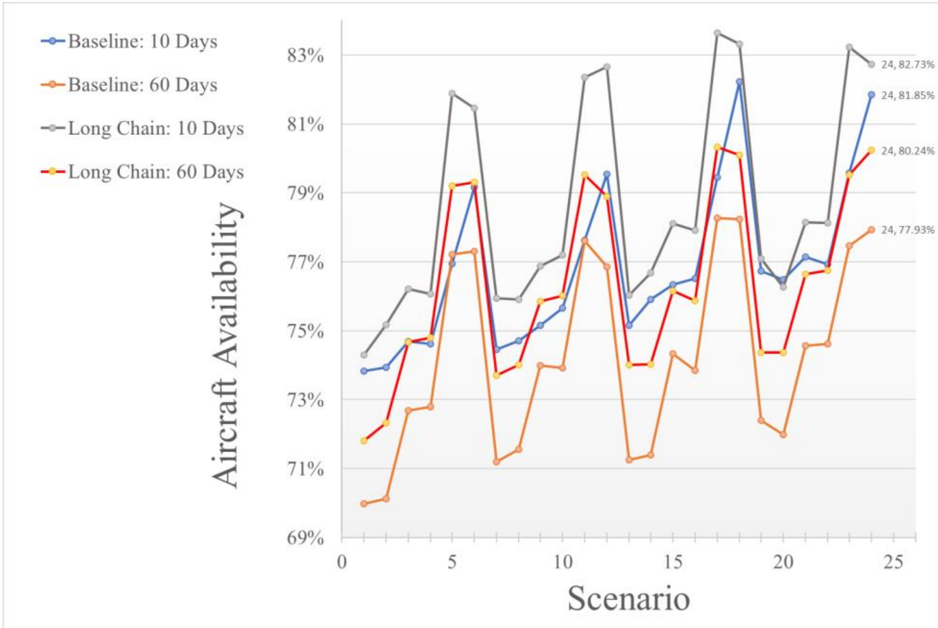

Figure 17. Baseline/Long-chain AA Comparison

Herein there are significant differences between the 10- and 60-day responses respective to each design. As anticipated, this validates the differences in an organization's responsiveness to a disruption. The difference between designs is most notably astounding, particularly between Baseline 60- and Long-chain 60-days.

Table 10. Baseline and Long-chain Paired T-Test

	Baseline 10 -and Baseline 60-days	Baseline 10- and Long Chain 10-days
T-Stat	9.621	-6.375
P(T<=t) two-tail	<.001	<.001
t Critical two-tail	3.768	3.768
	Long Chain 10- and Long Chain 60-days	Baseline 60- and Long Chain 60-days
T-Stat	14.535	-41.016
P(T<=t) two-tail	<.001	<.001
t Critical two-tail	3.768	3.768

These outputs further emphasize the importance of expedited response to disruption and the impact the dynamic long-chain design has on network performance. Further validating the data, this research then considers each design and varying response as independent groups, facilitating a test to determine statistical significance between means, also referred to as analysis of variance (ANOVA). A one-way ANOVA performed and illustrated in Table 11 reveals a p-value of 4.349E-06, substantially more significant than the null hypothesis rejection value of 0.001. Thus, we can reject the null hypothesis that the means are similar. Moreover, with great probability, the ANOVA indicates a significant difference between the various designs and response scenarios.

Table 11. One-Way ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.024	3	0.008	10.676	4.349E-06	5.897
Within Groups	0.068	92	0.001			
Total	0.092	95				

V. Conclusion and Future Research

This research facilitates a generalizable tool to quantify network resilience from defined inventory and production capacity allocations and various structural designs amid a disruption. Simultaneous investments within both resilience levers yield the most optimal range of resilience wherein the inability to enact such levers within a timely manner appropriately can be substantially detrimental to recovery.

This research has public, private, militaristic applicability as all environments experience susceptibility to supply chain disturbances. This research employs discrete-event simulation to assess the USAF engine repair network's various structures. Moreover, it assesses how investments in the resilience levers of inventory and production capacity affect resilience based on AA's predefined metric. Simultaneous investment in these levers provides increased resilience and improving recovery, achieving the same performance before disruption and, in certain instances, improving performance following a disruption.

The develops a model reflective of the current F-16 aircraft engine repair network. This design is reflective of similar designs across various airframes, platforms, and networks. A baseline model is established with 1.00 inventory and recovery capacity, outlining the network's current state with no investments. Resilience levers must be tailored to the organization's needs but should be gauged based on which factors directly affect organizational competitive advantage. Thus, appropriately selecting impactful resilience levers is pivotal in understanding firms' resilience to disruption. Two independent designs were established: Baseline and Dynamic Long-Chain Flexibility, leveraging various investments in resilience.

Moreover, the designs were assessed based on organizational responsiveness to a disruption. Organizations that employ similar methodology should vary investments based upon the structure of the respective system. Maintaining a baseline approach with simultaneous investment remains acceptable as a disruption mitigation strategy, yet optimal resilience is reached when employing a dynamic long-chain approach.

This research adequately facilitates a means of metrically measuring system performance and analyzing investments. Therefore, organizations across various domains, environments, and industries are afforded a benchmark to understand and assess variables that enhance competitive advantage, particularly concerning the supply chain. By establishing a predetermined inventory range and simultaneously allocating resources, firms can achieve the desired performance range. The AUC metric serves as a generalizable tool or metric to appropriately evaluate network resilience through various transient states of disruption. Additionally, firms are provided a more profound understanding of how to employ necessary resilience levers to achieve the desired performance.

As supply chain disturbances increase in number and frequency, affecting normal operations, resilience is critical. Optimal resilience is achieved via simultaneous investment in inventory and production capacity. Increasing inventory alone fails to promote recovery. Allocating production capacity upon recovery is essential to achieve pre-disruption steady-state performance or a higher range of performance. However, suppose a firm lacks the resources for recovery. In that case, inventory affords a suitable means of gradually declining performance, permitting the firm to maintain the highest possible performance level for a prolonged period of time (Shannon, 2020). Furthermore, shifting to a dynamic long-chain flexibility design is optimal for overall resilience. Permeating this flexibility construct decentralizes operations and further bolsters resilience throughout the system. Finally, organizational responsiveness cannot be overemphasized. While specific resources may not become available until well into the recovery phases, immediate action with available resources significantly impacts recovery.

Managerial Implications

As stated by Pettit et al. (2010) and various researchers aforementioned with the literature, organizational decision-makers and leaders alike must strike a balance between supply chain vulnerabilities and capabilities. This study extends the existing literature by addressing how managers can systematically invest in resilience levers to bolster resilience. More so, based on resource availability, managers can strategically adjust investments and production capacity to achieve the desired performance range. For example, if there are limited test benches that influence production capacity, managers can circumvent this by increasing the spares' inventory to achieve approximately the same performance range. Additionally, managers must consider the overall effects of investments on AA. A 10% increase in either inventory or production capacity, specific to this network, generally equates to a 1% increase in AA. Thus, managers must appropriately weigh the monetary implications for subsequent AA improvements.

Assumptions / Limitations

A central assumption and limitation of this study is that all engine discrepancies feature a singular break wherein it is feasible for an engine to experience multiple breaks. Therein, all breaks, regardless of severity, result in a decrease in overall AA. From a realistic approach, specific severity breaks, particularly those within severity one tiers, may not necessarily prevent an aircraft from being available, thus not affecting AA.

Opportunities for Future Research

This study's results permit a comparison of supply chain behavior before and following a disruption under two resilience constructs. Both strategies effectively assess resilience and determine the necessary course of action to withstand and recover from disruption, yet there is an additional opportunity for further research. When a particular node is affected by a disruption, it loses all repair capability, which may not fully be possible. Therefore, future research can implement similar based analysis to assess how the system responds to a node becoming reactivated following a disruption. Subsequently, salvageable resources have not been examined to be dispersed to the remaining nodes. Dispersal of these assets could further empower recovery rather than remain idle or nonmeaningful.

Moreover, costs have not been explored within this design. Understanding the costs associated with implemented resilience further affords decision-makers in understanding where to affordably placed their next resource investment. Finally, future research gains to employ AUC within another context to validate its transferability and applicability across multiple realms.

Conclusion

AUC is a powerful metric for decision-makers to suitably balance vulnerabilities and capabilities. It yields a quantifiable resilience measurement when coupled with investments in resilience levers, time, and system performance. Although an understanding of investments is essential, synchronized investments in resilience levers are optimal.

Organizations that align with a baseline construct still achieve performance benefits and adequately resist disturbances, but further optimization is feasible when implementing a decentralized dynamic long-chain flexibility strategy. Finally, speed of response validates existing literature, as agility in intentional investments attains better performance recovery and overall competitive advantage.

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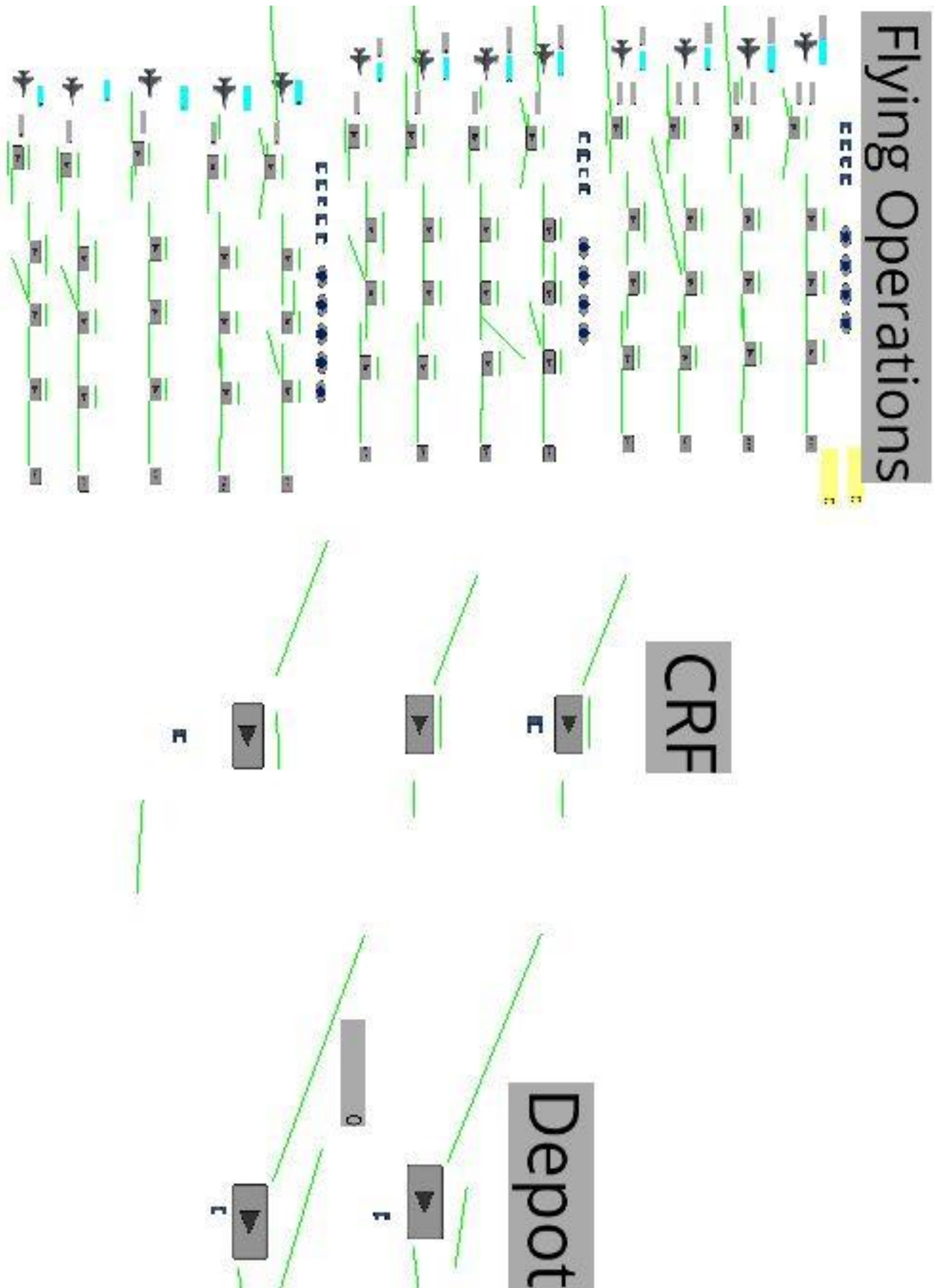
Appendix A: Simulation Baseline Framework



Appendix B: Output Batch Analysis Code (Femano, et al., 2019; Shannon, 2020)

```
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 disruptionKeep
         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
%           TS = agg_TS(agg_TS(:,1)==spares(i) & agg_TS(:,2)==servers(j), :);
%           T = TS(:,4);
%           SL = TS(:,5);
%           T = reshape(T, numel(T)/reps, reps);
%           SL = reshape(SL, numel(SL)/reps, reps);
%           %figure;
%           %plot(T(:,1), max(SL,[], 2));
%           hold on;
%           %plot(T(:,1), min(SL,[], 2));
%           SL_mean = mean(SL,2);
%           plot(T(:,1), movmean(SL_mean,12), 'LineWidth', 4);
%           axis([0 500 100 226]);
         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; Shannon, 2020)

```
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(1)-x(3))*exp(-x(2)*(Tdis - x(4)))+x(3);
    %fun_dis=@(x,Tdis)(x(1)-x(3))*(1-(1./(1+(exp(-x(2)*(Tdis-x(4)))))) )+x(3);
    %fun_dis = @(x,Tdis)(x(1)-x(3))*(1+x(5)*(Tdis - x(4))).^x(6)+x(3);
    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;
    %spares(i),0,T_dis, T_rec, A_pre, k_dis, c_dis, A_max, A_dis, T_dis_begin
```

```
    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];
    %subplot(numel(spares), numel(servers), z);

    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([400 990 .3 1]);

    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]
            %try
            %          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, :);
            %              if(numel(TS) > 0)
            %                  T = TS(:,5);
            %                  SL = TS(:,6);
            %                  km = analyze_ts(T,SL, 500, 564,0);
            %                  key_measures = [key_measures;spares(i),servers(j),k, km];
            %              end
            %          end
            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)];
%                    T = [T,TS(:,5)];
```

```
%                  SL = [SL, TS(:,6)];
            end
           T = T(:,1);
           km = analyze_ts(T,mean(SL,2), T_dis, T_rec, A_dis, 1,1);

%          km = key_measures(key_measures(:,1)== spares(i) &
key_measures(:,2)==servers(j),:);
           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);
           %subplot(numel(spares), 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);
           subplot(6,4, z)
           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([400 990 .3 1]);

           title([s,' Spares',', ',c,' Servers']);
           xlabel('Day');
           ylabel('Available Aircraft');
           %z= z+1;

           %catch
```

```
            %    warning('No such scenario. Going to next scenario');
            % end

        end
         z= z+1;
    end
end
key_measures = real(key_measures);
save(['key_measures_', Exp_name],'key_measures');
```

Appendix D: Time Series Plot Code (Femano et al., 2019; Shannon, 2020)

```
figure;

z =1;

%Get number of days in time series and time unit
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(2,1, z)
              %subplot(numel(spares), numel(servers), z);
               plot(T(:,1), max(SL,[], 2), '-b', 'LineWidth', .5 );
               hold on;
              plot(T(:,1), min(SL,[], 2), '-b', 'LineWidth', .5);
               %            SL_mean = mean(SL,2);
               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', 1.00);
               %            plot(T(:,1), movmean(SL_mean,12), 'LineWidth', 4);
               axis([1000 1500 .6 1.0]);

               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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14. ABSTRACT
Leaders lack a generalizable tool to quantify supply chain resilience and assess additional resilience investments. This research facilitates understanding of the intricacies and interrelation of supply chain nodes and constructs. It integrates the Area under the Curve metric to quantify performance or any organizational measure of competitive advantage amid a disruption. Due to its structural resemblance to various organizational platforms, the subset USAF F-16 engine repair and supply network is modeled employing discrete-event simulation. The purpose of this study is to evaluate investments in inventory and capacity resilience levers to understand how mitigation strategies affect supply chain performance.

15. SUBJECT TERMS
Supply Chain Resilience, Discrete-Event Simulation, Inventory and Capacity, Disruption

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