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Simulation Modeling and Analysis of Air Force Depot Engine Repair During Normal and Increased Operational Tempos

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THESIS

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Abstract

Maintaining an adequate level of aircraft availability through Agile Combat Support (ACS) is crucial for the Air Force to perform its mission. During normal day to day operations, demands for depot repair including spare parts and maintenance man-hours typically fall within a range supportable with current assets and capabilities. However, with increased flying operations during a conflict, demand at the depot level may likely exceed current capacity for timely support, resulting in backorders for spares and increased turnaround times. This thesis develops a discrete event simulation of the F-16 engine repair network to investigate the impact on engine availability (a major driver of aircraft availability) from three key factors: the spare engine modules inventory levels, the induction rate of failed modules, and the repair turnaround time for the engine modules. Our baseline simulation captures the F-16 engine repair network at a top level for normal day to day operations. We then insert a range of increases in operational tempo in our simulation and analyze the effects on the engine repair network. Incorporating different policies for replenishing depleted spares levels from increased demands allows us to explore the responsiveness of industrial base output in maintaining aircraft engine availability.

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I would like to express deep gratitude to my thesis advisor, Dr. J.O. Miller, for his patient guidance and gracious support throughout the course of this work. Without your encouragement, expertise, and insight this would not been possible. I also would like to thank Mr. Roger Moulder and Mr. Tom Stafford from AFMC/A9A, for providing data to conduct this study and sharing their expertise on this topic.

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SIMULATION MODELING AND ANALYSIS OF AIR FORCE DEPOT ENGINE REPAIR DURING NORMAL AND INCREASED OPERATIONAL TEMPOS

I. Introduction

Background

The Air Force's capability to fly, fight and win depends on the ability to carry out required missions effectively and timely. In order to support missions over a long duration in such a manner, aircraft must be available over the period of operations. The availability of mission capable aircraft can be modeled based on the rate of repair, induction rate of failed parts, and availability of spares in maintenance inventory. The availability of mission capable aircraft increases when maintenance inventory level and rate of repair are high, but the availability decreases if the induction rate of failed parts increases. However, maintaining a high level of spares and reducing the rate of repair turnaround time is expensive. In today's austere budgetary environment, the Air Force cannot allocate large resources to maintain high level of on-demand inventory and repair turnaround time indefinitely. If the induction rate is consistent, the inventory level and rate of repair can be maintained at a level selected to efficiently support normal operations and desired availability. But the uncertain nature of military demand from a crisis, causing a transition from peacetime to war time operations, would increase induction rate. Additionally, the acquisition lead time for critical aircraft spares is long and the spares production capability is limited by the industrial base output capacity, so the spares cannot be supplied just in time from industry. When sharp increase in spares demand occurs during war time, the decrease in availability of mission capable aircraft is inevitable. Therefore decision makers need to prioritize resource investment to best meet aircraft availability requirements. Our research focuses on three different factors where additional resources could be applied to improve aircraft availability during increased operational tempo. We examine the impact of these factors for the F-16 engine repair network.

Scope and Objective

The aircraft repair network is a complex system involving hundreds of parts. This thesis develops a discrete event simulation to investigate the repair network for the F100-229 engine. Our baseline simulation models this engine repair network using five major engine repair modules for normal day to day operations, with the ability to easily increase the operational tempo and to modify levels of three factors that drive engine availability. According to Hill and others (2015), the five major replaceable modules used in our research are reasonable component units to represent performance of the network. The objective of this research is to explore the impact of three factors: the engine module induction rate, the engine module depot turnaround time, and the engine module spares inventory level to the availability of mission capable aircraft during normal and increased operational tempos. In addition, we also consider the impact of industrial base output when spares levels drop during increasing operations requiring additional spares to be ordered.

Approach

The current repair network is modeled as a discrete event simulation using existing maintenance data provided by AFMC/A9A. The input parameters are modified to represent changes in demand or spares availability to determine how different factors affect engine repair network performance. The performance of the network is measured in terms of spare inventory and back order status. The spares inventory status shows the average number of spares used, and the back order status shows the number of parts awaiting spares at the depot.

Thesis Overview

Chapter 2 reviews the previous literature on aircraft repair network modeling and simulation, and logistics simulation. Chapter 3 discusses formulation of our model with the SIMIO simulation platform, input modifications, and assumptions made in the model. Chapter 4 presents statistical analysis of our simulation results. Chapter 5 provides conclusions and suggestions for future research.

II. Literature Review

In today's environment, logistics is not just a management of transportation network flow. It involves a complex decision making process in a dynamic environment to acquire and allocate resources efficiently to cut overall costs and meet the demand. Such a task requires the ability to explore multiple "what if" scenarios with existing data and predict outcomes for agile implementation for the Air Force. This chapter reviews the literature on logistics support systems to examine some of the assumptions and limitations pointed out by previous works, and discuss approaches appropriate to manage spare parts management at depot level during normal and increased operational tempo.

Overview

According to Shepherd and Lapide (2000), various trends such as customer demand for short cycle times, globalization of operations, and greater outsourcing of manufacturing operations place high importance on optimization of network flow. Such trends can be also found in Air Force Doctrine Document 4-0, Combat Support, where the Air Force is trying to create a combat support system to optimize both peacetime and war time operations while minimizing the forward footprint and maximizing the ability to transition swiftly from home station to a deployed environment (Department, 2013). All of these trends emphasize the ability to make tailored decisions for different situations fast and efficiently. One approach to support this ability is by developing a logistics support system model to better manage the number of spare parts in depots to support repair processes during normal and increased operational tempos. The model should enable users to forecast spare parts demand at different operational tempos, identify potential bottlenecks in the logistics system, and recommend a course of action to mitigate the potential issues. Any recommendation should include identification and projected capabilities of commercial suppliers, commonly referred to as industrial base output in support of Air Force logistics.

Simulation Based Decision Support System

Narayanan and others (2003) examined an automated decision support system (DSS) for logistics planning. Supply chain planning can be very complex in a dynamic environment. In an effort to reduce some of the complexities in the planning, the authors created a simulation model with conditional logic and cognitive decision making processes to perform tasks such as problem identification, evaluation of alternatives, selection of the best alternative, and implementation of the selected alternative. The model uses multi-attribute utility theory to weigh the alternatives, and choose the best one. The simulation model supports real time human interaction to correct for unaccounted dynamics and errors. Its interface module allows the user to control parameters of other modules such as parts inventory level, repair resources number, and supplier information. The performance of the DSS is measured based on its supplier and part identification accuracy. Results from their analysis indicated statistically significant improvement when compared with a model without the decision support module. The classification work indicated that the results were fairly accurate with 0.05 level of significance for Type 1 error. However, the study was conducted with theoretical data, and the model was not validated. As for future work and application of the model, the authors suggested a web-based or wireless real world data feed into the system to validate the system under a real world environment. Although human supervision is still required, this work demonstrated that a model equipped with a decision support module can certainly narrow down some options in demand assessment, supply allocation, and logistics routing.

Forecasting Combat Support Requirements

Pyles and Tripp (1982) studied forecasting logistics support demand during war time. The authors pointed out that logistics resource demands change drastically from peace time to war time, so one cannot use peace time statistics and experiences to project the war time demands. In order to simulate the war time demands, Pyles and Tripp (1982) created two models, one as a Planning Subsystem and one as an Operational Tracking and Control Subsystem. The Planning Subsystem incrementally increases the sortie numbers to see what level of logistics resources are required to sustain the increased flight operations. If meeting the desired operational tempo is not possible, the model evaluates various alternative logistics scenarios and provides predicted effects of higher-than-planned sortie rates. Once the simulation produces the forecasted resource demand, the Operational Tracking and Control Subsystem compares the simulated results with actual logistics performance to identify differences and correct them. Such an approach focuses on forecasting the logistics support demands at desired war time requirements and meeting the demand through analysis of alternatives. However, the model also can be modified to show the maximum mission capabilities that can be maintained with a limited amount of logistics resources. Our previous experience in the Gulf war shows that the level of logistics support did constrain some of our operations, especially at forward operating bases. From this experience, one cannot ignore the combat support side of simulations and assume that logistics resources during combat operations are unlimited. This model can help us assess not only the logistics resource requirements but the mission capabilities impacted by a logistics constraint as well.

Cook and others (2005) viewed peacetime and war time requirements as core capabilities and surge. They pointed out that the Air Force logistics system underutilizes contractors as a source of industrial capabilities, and claimed that the Air Force should incorporate contractors as a surge asset. Furthermore, the authors said unlike the purchasing and supply chain approach of Depot Maintenance Reengineering and Transformation, the Air Force does not have a process to readily acquire contractor services for a surge period. Cook and others (2005) recommended benchmarking commercial practices with depot practices as a method to bring contractors in as a source. People frequently use third party service providers to acquire parts and services because maintaining those production and servicing capabilities is expensive. The outsourcing maintenance service may be able to save a lot of already limited Air Force budget, but one must be cautious not to overuse contractors as a permanent means of providing the services during a sustainment surge period. Overuse of contractor services can reduce the internal expertise on the service and make us more dependent on outside expertise. Even if the use of contractors is limited to short-term surge operations, sometimes it may be hard to determine the duration of a surge.

Regattieri and others (2005) suggested that depending on the demand level of spare parts, certain forecasting techniques can be used to maintain the inventory level of spare parts. The forecasting techniques compared in their article are additive/ multiplicative winter, seasonal regression model, single exponential smoothing, double exponential smoothing, adaptive response rate single exponential smoothing, moving averages, and weighted moving averages. The article used the following four levels of demand: slow moving demand, strictly intermittent demand, erratic demand, and lumpy demand. Although spare part level is strongly related to flying hours, increased flying hours do not necessarily increase the demand of all spare parts, such as landing gears or certain radar parts that are only used when an aircraft is on the ground. Instead of using flying hours to determine the demand level, Regattieri and others (2005) used monthly inter-demand interval (ADI) and its coefficient of variation (CV) to determine the 'lumpiness' of spare parts demand . Figure 1 below shows the area of lumpiness and relative positions of five spare parts points. The lumpy demand area is determined by condition tests of "CV > 0.49", and "ADI > 1.32". Any points with CV higher than 0.49 and ADI higher than 1.32 are considered to have lumpy demand. Within the area of lumpy demand, point *w* has relatively high ADI and CV, so it is lumpier than other points within the area. The point *z* has relatively low ADI and low CV, so it is less lumpy than other points.

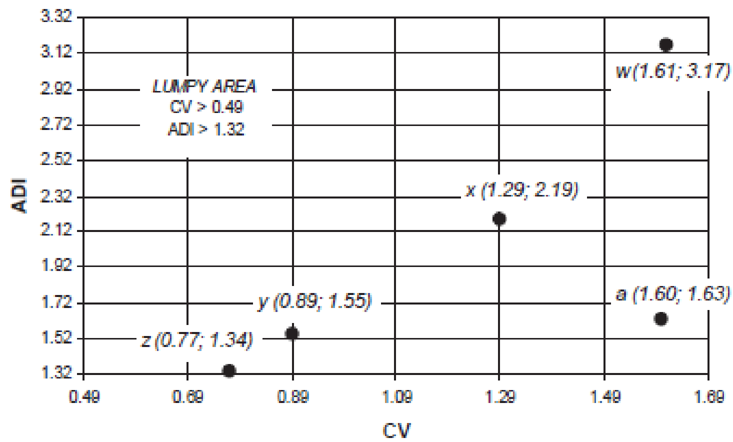

Figure 1: Area of Item Lumpiness (Regattieri and others, 2005)

Performance of the forecasting techniques were compared with historic data, and evaluated in terms of mean absolute deviation (Regattieri and others, 2005). The results indicated that all tested forecasting techniques performed well with small values of CV and ADI (less lumpy demand), especially the single regression model. However, only a few techniques performed well with lumpy demand such as Winter's method. In engine spare part simulation, it may be reasonable to assume that demand is related to flying hours, which can be estimated based on the historic data, and to classify it as having lumpy demand. Alternatively, the demand at war time can be assumed fixed for the duration of the war time at a certain level. Based on the classification of demand level, different forecasting techniques can be implemented to optimize the inventory level of engine spare parts.

Rosienkiewicz (2013) stated that many traditional forecasting techniques based on time series may perform poorly when demand level is lumpy. Instead Rosienkiewicz (2013) suggested use of artificial intelligence (AI) methods, such as artificial neural networks (ANN), for forecasting. The author collected data of three spare parts (labeled SP1, SP2 and SP3) with the highest failure rate. Eight different forecasting methods were selected, which included five traditional forecasting methods such as moving average, simple exponential smoothing, Syntetos-Boylan method, etc. The remaining three methods were based on AI such as ANN, ANN hybrid with econometrical prediction (BIC), and ANN hybrid dedicated to classification tasks. The prediction performance was measured based on the Root Mean Square Error (RMSE), which is a measure of the differences between values predicted by a model and the values actually observed.

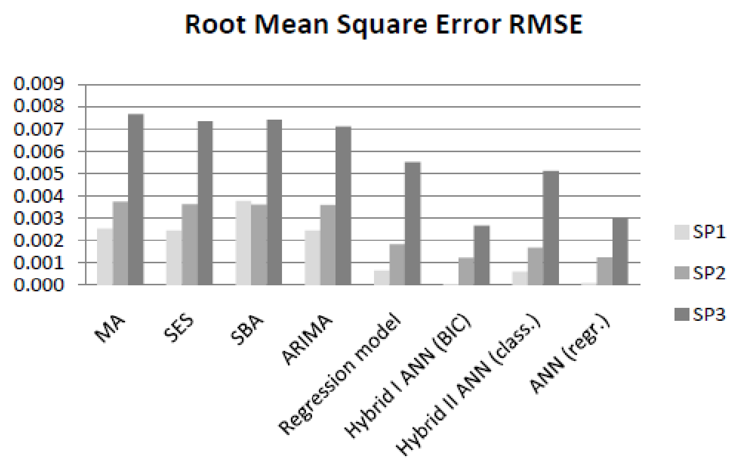

Figure 2: Root Mean Square Error (Rosienkiewicz, 2013)

Figure 2 above shows that all ANN methods performed better than traditional methods, especially Hybrid ANN (BIC) method. The article presents an alternative forecasting method for the spare parts with lumpy demand level, and this can be used to forecast spare parts demand changes from peace time to war time. Our discussion now moves from forecasting logistics requirements to modeling and analyzing Air Force logistics processes.

Air Force Logistics Modeling and Simulation

Isaacson and others (1988) presented an implementation of the Dyna-METRIC version 4 model to assess the effect of war time dynamics and repair constraints on the worldwide operational performance of Air Force Logistics. This model studies the interaction of logistics functions between different echelon systems to enhance overall war time capabilities. Previous studies with the Dyna-METRIC model to assess the logistics support of aircraft components on single aircraft or within a theater do exist, however, no previous work involved worldwide assessment such as this work. The model assumes that the aircraft availability is directly proportional to the aircraft's component availability. The aircraft components are categorized as Line Replaceable Units (LRUs), major components from an aircraft; and Shop Replaceable Units (SRUs), subcomponents of a LRU. The support structures are categorized as Base, Centralized Intermediate Repair Facility (CIRF), and Depot. The component flow process can be seen in the Figure 3.

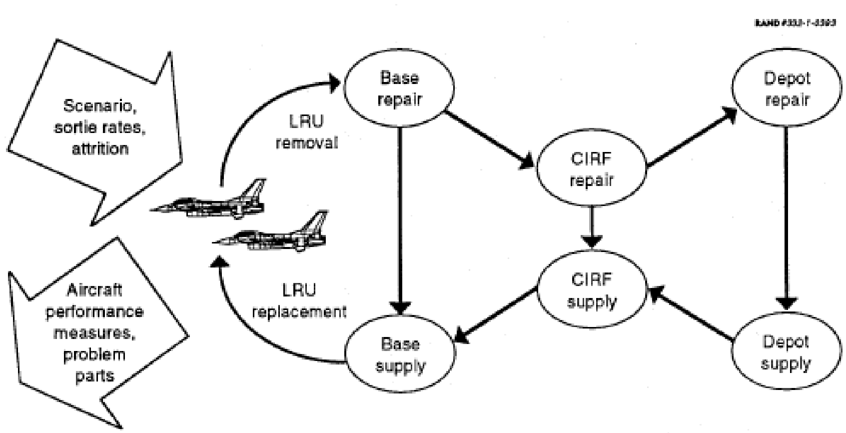

Figure 3: Aircraft Logistics Support Network (Isaacson and Boren, 1993)

Failed LRUs are removed from aircraft and sent to a base repair. Replacement LRUs arrive from a base supply and get installed to the aircraft. The base repair sends the repaired LRUs to the base supply and sends irreparable LRUs at the base to a CIRF or a depot. When LRUs are not repairable at the depot, the items get condemned, and new replacements are ordered from outside suppliers. The model assumes that resource demands are proportional to either number of sorties or flying hours with such demands known (Isaacson and Boren, 1993). The authors caution the reader that previous studies by Crawford (1988), Stevens and Hill (1973) pointed out that these assumptions may not hold as demand level can differ between organizations and change over time. Issacson and Boren (1993) later addressed these issues in the Dyna-METRIC version 6 by incorporating uncertainties such as component demand variation, repair capacity constraint, information lag, aircraft attrition, battle damage to stock, repair resources, and repair queue in the model. The Dyna-METRIC version 6 model also added management adaptation features such as lateral supply, lateral repair, and priority repair policies. Dyna-METRIC version 6 is a simulation using Monte Carlo sampling techniques to avoid assumptions such as ample repair capacity, and independent content of the components' pipelines. The simulation results provide measures of performance such as daily aircraft availability, sortie generation capability, and status of components in different pipeline segments. Each simulation run provides a single result while in version 4 the analytical model provided expected values and probability distributions. Also, unlike version 4, Dyna-METRIC version 6 does not provide spares requirements. These models are no longer in use, however, in terms of a historic perspective, this effort is one of the first attempts to simulate a large scale logistics system. In order to simulate such a large model with relatively limited computational power, both models have several mathematical assumptions. Later work shows how researchers approached large scale models by dividing the entire model into smaller submodels to avoid such assumptions and limitations.

Frontier Inc. (2013) combined the Logistics Composite Model Analysis Toolkit's (LCOM ATK) performance assessment capability, and data analysis technique of Metrics Progress Analysis Engine (MPAE) to create a tool to perform analysis of operational fleet performance during transition from war time to peacetime to war time. The LCOM ATK is used to model the repair process of aircraft, and the MPAE was used to analyze the LCOM ATK output. The study demonstrates the negative impact a reduction in spares during war time to peacetime transition can have on subsequent war time deployment. Results of their study quantified the impact of peacetime spares levels on readiness in war time deployment, the lead time to restore spares inventory levels, and the necessary spares inventory levels for war time deployment. The model created arbitrary war time and peacetime mission requirements derived from flying hours data in selected reporting periods to test the baseline scenario. Based on the war time and peacetime requirements, the model was first run with enough spares for war time requirement during peacetime to war time transition, and second with just enough spares for peacetime requirement during the peacetime to war time transition. The differences in two runs indicated the negative impact of reduced spares during the transition (Frontier, 2013).

Shyong (2002) simulated the depot level F101 Low Pressure Turbine (LPT) rotor repair process with varying spare parts level and different queuing policies to reduce the repair cycle time and cost. Three queuing policies: first in first out, shortest processing time first, and lowest arrival index value first, were evaluated along with varying levels of spares for a selected set of parts. The baseline assessment of the current repair process and processing time were based on interviews and data provided by subject matter experts. The repair process is broken down as front shop processes and back shop processes. The front shop assembles and replaces parts, while the back shop repairs bad parts. If spare parts are available at the front shop, there is no delay in the replacement of parts at the front shop. If no spare parts are available at the front shop, the replacement process is delayed until the back shop repairs the bad part. When the back shop repairs a bad part, the repair part is delivered to the front shop to be replaced or stocked as a spare part. Increasing the spare parts level can reduce the repair cycle time, but increased spare parts level can be expensive. Also, different parts have different repair flow times, so arbitrarily increasing the spare parts levels is not the most efficient method to reduce the repair cycle time. Increasing the spare parts level for the parts with the longest flow time is the most effective. In order to optimize the tradeoff between the repair cycle time and the cost of spares, multiple objective linear programming was applied. The simulation study indicated that the different policies did not significantly impact the repair cycle, but having a selected level of spare parts reduces the repair cycle time for the rotor engine. This research (Shyong, 2002) assumes that the arrival rate of parts is consistent throughout the simulation, which means the operational tempo does not vary. In addition he does not explicitly model industrial base output in maintaining spare inventory levels. Our research focuses on removing these limitations with our simulation of Air Force depot engine repair

Summary

The aforementioned works all emphasize the importance of making informed decisions regarding the supply chain and other processes for large logistics systems such as Air Force Agile Combat Support managed by Air Force Material Command (AFMC). Effective and efficient logistics planning requires accurate assessment of spare part levels. However, in this dynamic environment, especially during a transition from peacetime to war time, predicting the demand for spares can be challenging. Pyles and Tripp (1982) and FTI (2013) used previous data to derive these demands; while Regattieri and others (2005) and Rosienkiewicz (2013) suggested use of forecasting techniques to project the demand level. A variety of logistics models were used in the studies reviewed, but the common objective was to find the level of spare parts and other support to meet a mission requirement. Our research investigates the impact of industrial base output in maintaining the level of spares and overall depot engine support for the F-16 during a transition from peacetime to war time using a simulation developed with SIMIO. We discuss the design of this model in the next chapter.

III. Methodology

Overview

This study uses real world data to create a top level model of the F100-229 engine repair network, and analyzes the impact and interaction between different factors of the network. Various levels of factors were used to measure significance of the factors. The simulation model is constructed in SIMIO to explore differences between scenarios to assess the sensitivities of network factors in day to day and war time environments. This chapter discusses the development of the top level simulation and the selection of factors and levels used in the study.

Model Development

The baseline model is built using a conceptual model of the Air Force F100-229 engine repair network. The conceptual model captures an aggregated view of the actual repair network process flow as shown in Figure 4. The repair network process starts when an engine arrives at a base maintenance shop. The base shop disassembles the engine into several modules, and checks for failed modules. Failed modules are replaced with spare modules, and the engine gets reassembled. The failed modules are sent to the depot for repair. If the base does not have spare modules at hand, then the base has to wait for good modules to arrive from the depot. The depot sends available spares from the depot inventory to the base if the base does not have enough spares for reassembly. If the base requires spares for reassembly and the depot does not have any spares to send, then the base has to wait for the failed modules to be repaired at the depot. This wait time for the failed modules to be repaired for the base is the backorder queue and it represents the number of non-mission capable modules. After the failed modules are repaired, it first serves the backorder queue, and then restocks the base and depot spares inventory with priority on the base spares inventory. The repairs are conducted at the depot for all five modules with all spares returned to base or depot inventory.

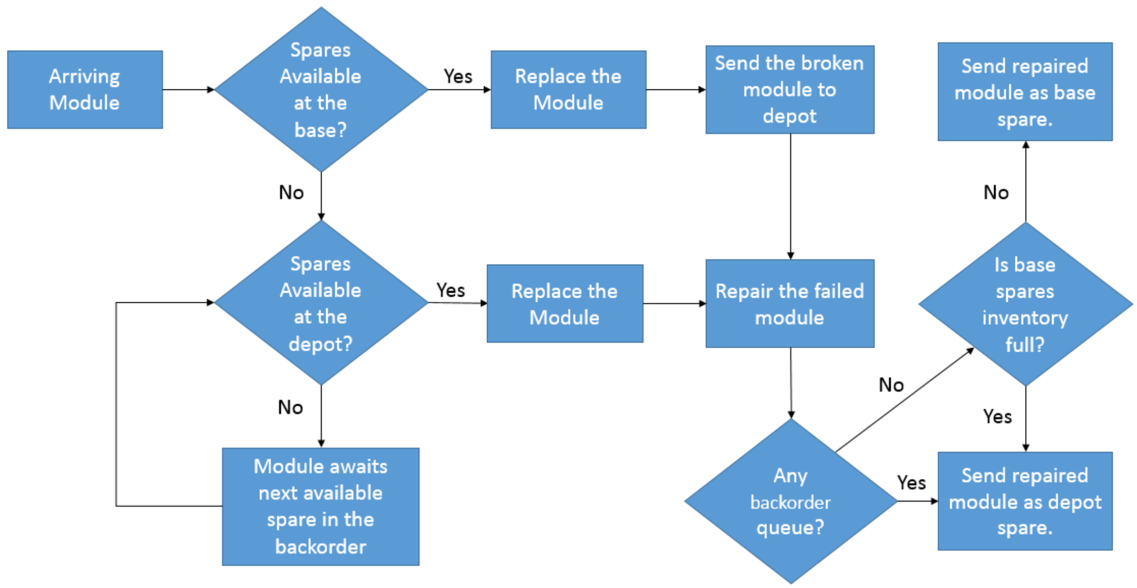

Figure 4: Conceptual Model

The real world system is comprised of multiple bases and depots with lateral supply inventory management policies. The lateral supply policy requires transportation of spares from one base or depot to another to satisfy repair demand for the spares, and it creates transportation delays between the bases and the depots. However, transportation delays are not important in our assessment, are assumed to be generally constant, and are not explicitly modeled in our simulation. Another important assumption made involves the depot process to repair broken models. We do not explicitly model any depot resources such as manpower or equipment along with the waiting times, but roll up the entire repair time (plus the transportation delays just described) into our turnaround times. Based on these assumptions, the conceptual model was modified to develop the following baseline model shown in Figure 5. Note we also consolidated base and depot spares as one.

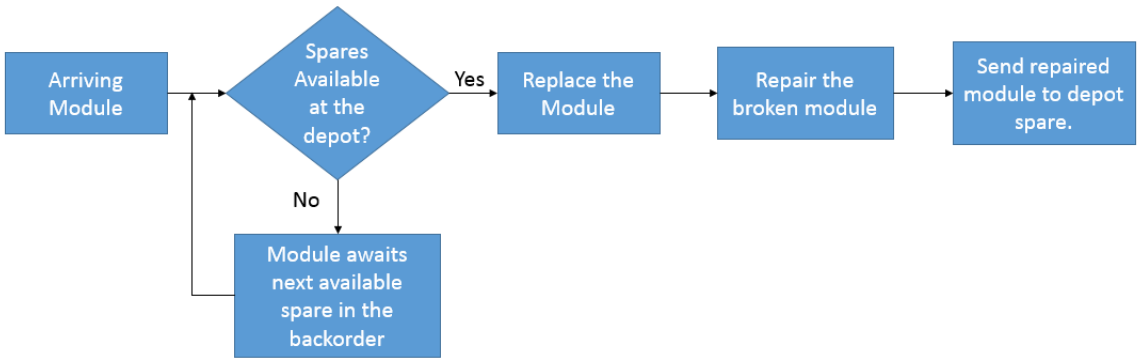

Figure 5: Baseline Model

Data Requirement and Data Processing

The baseline model requires three sources of input data: the induction rate of failed modules, the repair turnaround time (TAT) at the depot, and the initial spares inventory level. The modules selected for this study are Core, Gearbox, Inlet fan, Low-pressure turbine (LPT), and High-pressure turbine (HPT). The core supplies approximately 20 percent of the total engine thrust and torque for operation of all accessories. The gearbox holds accessory engine components. The inlet fan sends air to the forward end of the compressor. The LPT removes energy from the combustion gases to drive the low-pressure compressor (N1) rotor assembly. The HPT removes energy from the combustion gases to turn the high-pressure compressor and accessory gearbox (Hill and others, 2015:426).

Induction Rate of Failed Modules

The data provided by AFMC/A9A contains total number of modules received by depot for repair per year from 2007 to 2011. Based on the data, the average total inductions per year for each module were calculated, and the following formula was used to obtain the individual daily induction rates:

$$\textit{Induction Rate} = 260 \div \textit{Average Total Inductions per Year} \qquad (1)$$

The 260 represents the total working days in a year (using 5 days per week for 52 weeks) and induction rate represents the interarrival time for the baseline model. The induction rate is input as an exponential mean for time between arrivals in the simulation. Table 1 shows the average number inducted and the calculated induction rates for the modules.

Table 1: Module Induction Rate

Module Name	Average Total Induction Number Per year	Induction Rate (Days)
Core	58	4.48
Gearbox	32.2	8.07
Inlet Fan	48.4	5.37
LPT	49.2	5.28
HPT	8.2	31.71

Repair Turnaround Time

Table 2 shows the repair TAT for the five modules at the depot. The original mean and standard deviation provided by AFMC/A9A was fitted into a lognormal distribution, because the repair TAT is better represented by a lognormal distribution than other theoretical distributions (Kline, 1983).

Table 2: Module Repair Turnaround Time (Units in Days)

Module Names	Mean	Std	Lognormal Mean	Lognormal Std
Core	62.5	58.4	3.8222	0.7918
Gearbox	88.3	33.4	4.4137	0.3656
Inlet Fan	80.4	31.9	4.3144	0.3824
LPT	77.6	35.7	4.2555	0.4380
HPT	121.0	39.2	4.7462	0.3162

Spares Inventory Level

The depot carries two types of spares in its inventory, serviceable and unserviceable. The unserviceable spares require additional repairs, so it is not ready for immediate use. The spares inventory data provided by AFMC/A9A was a snap shot of depot spares inventory on a given day, but it did not show the average serviceable spares inventory per year. The mix of serviceable and unserviceable spares varied over time, and the repair time for unserviceable spares was unavailable. Because of the lack of readily available data regarding the separate types of spares and to significantly simplify our simulation logic, we decided to only model serviceable spares, with the assumption that our initial number of spares and repair logic would reasonably approximate both types of spares. Since the spares data provided was only a snap shot, we decided to calculate a reasonable starting level of spares using the provided inductions and TAT as shown in Equation 2 as the serviceable spares.

$$\textit{Spares Inventory} = (\textit{Mean TAT} + \textit{SD TAT} \div 2) \div \textit{Induction Rate} \qquad (2)$$

The calculated spares inventory level using Equation 2 is shown in Table 3. As intended, these values generate enough backorders to assess the impact of factors explored in our analysis. The standard deviation of TAT was divided in half in order to account for the large standard deviation for the Core module. This calculation was not intended to optimize the availability of any particular module, but rather to provide reasonable and interesting starting levels for spares. The main focus of this research is to provide a flexible top level simulation, with the ability to analyze differences in system performance due to changes in selected factors. This simulation can also be easily modified, with the appropriate data, to examine other engine repair networks, such as the JSF F-35 engine.

Table 3: Spares Inventory Level

Module Name	Spares Inventory
Core	20
Gearbox	13
Inlet Fan	18
LPT	18
HPT	4

Selection of Factors and Appropriate Levels

As discussed in Chapter 1, availability of mission capable aircraft is proportional to the availability of the five major engine modules. A measure for availability of the engine modules can be captured in our simulation from metrics obtained from the backorder process in our engine repair network. The two major factors under consideration for analysis are operational tempo and spares inventory level. The factors are assessed based on their impact to our backorder metrics.

Operational Tempo

The transition from a peacetime to war time environment can be represented by changes in the operational tempo. The repair demand of the engine increases with additional sorties and flying hours during war time. We model this increase in operational tempo by increasing the induction rate of the modules. More specifically, with our simulation we multiply each random number draw for the time between arrivals for each module by an *Operational Tempo Multiplier*. The *Operational Tempo Multiplier* is a percentage increase in the induction rate, which decreases the time between arrivals (TBA) of the modules. We selected values of 0.2, 0.4, 0.6 and 0.8 for the *Operational Tempo Multiplier* to represent 20%, 40%, 60%, and 80% decrease in the TBA for each module. In the real world there is likely a different increase in induction rate for each module, which could be implemented within our simulation. For ease of analysis, we used the same value for all modules. Testing the different levels of operational tempo can show how much the transition from peace time to war time affects normal repair network operations and the resiliency level of the baseline model to recover from a sudden increase in repair demand.

Spares Inventory Level

Intuitively, setting higher initial spares inventory level should always decrease the backorder queue and increase the availability of the modules, but maintaining high spares inventory is costly. Instead of modifying the initial inventory levels, different reorder policies were developed for evaluation. Our first reorder policy triggers the reorder process right after the war (which we modeled at 30 days). The second reorder policy we explore triggers the reorder process 30 days after the war. We originally considered exceeding a maximum number of backorders to trigger a reorder, however, the maximum number of backorders always occurred during last days of the war or shortly after. So the results were nearly identical to ordering at the end of the war. This acquisition process (simply a delay in our model for lead time) represents our top level approach to include industrial base output in our simulation. We use this lead time as another factor for our analysis using levels of 130, 150, and 170 days. The first reorder policy is proactive since it expects additional spares requirement after the war is over. The second reorder policy is reactive in a sense that it is not triggered until 30 days after the war. The number of spares ordered with each policy is the difference in spares on hand when the reorder is triggered from the spares on hand when the war started. Other options for calculating reorder sizes are available and could be implemented in our simulation, however, this approach was easy to implement and reasonable.

Simulation Setup and Design

The total length of each simulation replication is 1300 days, which represents a 5 year period with 260 working days per year. In order to provide a reasonable initialization of the system before collecting data, we used the first 260 days as a warm up period and collect data over 4 years. Because the model does not have large variability, 20 replications were conducted for the different scenarios and provided approximately normal data with acceptable standard deviations. The transition to war time starts at 260 days (at the beginning of our data collection) and lasts 30 days. The induction rate for the modules and repair TAT are randomly generated using dedicated random number streams (specified as last parameter for distributions in SIMIO) to reduce the random variation between scenarios. Figure 6 shows an example of our induction rate input in SIMIO using stream 1.

Entity Arrival Logic	
Entity Type	**EntPart1**
Arrival Mode	Interarrival Time
⊟ Time Offset	**0**
Units	**Days**
⊟ Interarrival Time	**Random.Exponential(P1_MeanTBA, 1) * IncreasedOps_Multiple**
Units	**Days**
Entities Per Arrival	1

Figure 6 : Induction Rate Using Assigned Random Number Seed

Once the baseline designs are set up, parameters (treated as experiment controls by SIMIO) can be included within the process logic to easily allow simulation of different scenarios. The control panel can be accessed in the Model Facility view in SIMIO. Figure 7 shows how the Input Control Panel can be used to modify the initial spares level, induction rates, repair TATs, Operational Tempo, start of war, war time, and different reorder policies for a single replication. The controls shown here are also available when creating a SIMIO experiment with a model. This is the approach we use for setting up our scenarios used for analysis in the next chapter.

Controls	
⊟ Spares	
P1DSpare	**21**
P2DSpare	**15**
P3DSpare	**20**
P4DSpare	**21**
P5DSpare	**5**
⊟ Parameters-Induction	
⊞ P1_MeanTBA	4.48
⊞ P2_MeanTBA	8.07
⊞ P3_MeanTBA	5.37
⊞ P4_MeanTBA	5.28
⊞ P5_MeanTBA	31.71
⊟ Parameters-Depot_PT	
⊞ P1_TAT	Random.Lognormal(3.8214 , 0.7922,6)
⊞ P2_TAT	Random.Lognormal(4.4139 , 0.3657,7)
⊞ P3_TAT	Random.Lognormal(4.3139, 0.3824,8)
⊞ P4_TAT	Random.Lognormal(4.2556 , 0.4382,9)
⊞ P5_TAT	Random.Lognormal(4.7459 , 0.3159,10)
⊟ Design#1	
OpsFactor	**.2**
⊞ StartWar_Time	**0**
⊞ WarTime	30
⊟ Design#2	
Reorder_Yes	0
⊞ ReorderTime	**130**

Figure 7: Input Control Panel

IV. Analysis and Results

Overview

This chapter presents results of the simulations discussed in Chapter 3, and analysis of the simulation outputs to assess the impact of increased operational tempo and the spares reorder policies on the repair network. The increased operational tempo places additional stress to the network, and the reorder policies, which attempt to capture industrial base output, have different influence on the network performance. The interactions between these factors are analyzed to identify the factor combinations with the most impact on the network. We do not perform a formal design of experiment, but rather provide plots and statistical analysis of differences between our scenarios which we refer to as Design Points (DP).

For all production runs with our simulation we use a 260 day (52 weeks with 5 work days or 1 year in our model) warm up period to provide an intelligent initialization state for our simulation before we begin our data collection over 4 years. SIMIO automatically resets all tally (observational) statistics to zero, however many of our defined state variables had to be adjusted at the end of the warm up period. As discussed in Chapter 3, we run 20 replications for each scenario or DP, which provides us with approximately normal data with reasonable standard deviations.

Operational Tempo

For all scenarios involving an increased Operational Tempo, we model the start of the ‘war’ at the beginning of year one after initialization with a duration of thirty days, after which the Operational Tempo returns to baseline level. In order to compare the impact of different Operational Tempo levels on the network, the baseline model (no increase) was compared with different levels of increased Operational Tempo. The increase in Operational Tempo was simulated with an increase in the module induction rates. This was implemented in our model by reducing the Time Between Arrival (TBA) for induction of each modules by a set percentage. For example, an Operational Tempo factor of 0.8 multiplied by a random draw for each particular TBA, results in a 20% increase in the induction rate for each module. We use the same rate for each module. Figure 8 shows the average total number of backorders for baseline (DP 1), 20% increase (DP 2), 40% increase (DP 3), 60% increase (DP 4) and 80% increase (DP 5). Although all backorder numbers increase when the Operational Tempo level increases as Figure 8 indicates, not all Operational Tempo levels show a statistically significant difference from the previous level. The 95% confidence intervals (brown rectangles in Figure 8) overlap for DP 1, DP 2, and DP 3, which indicates that the differences are not significant. The confidence intervals for DP 4 and DP 5 are both statistically different from DP 1, with DP 5 showing a statistically significant jump over DP 4. This increase in back orders is nonlinear, where it increases gradually before the 40% level, but starts to increase sharply after 60%.

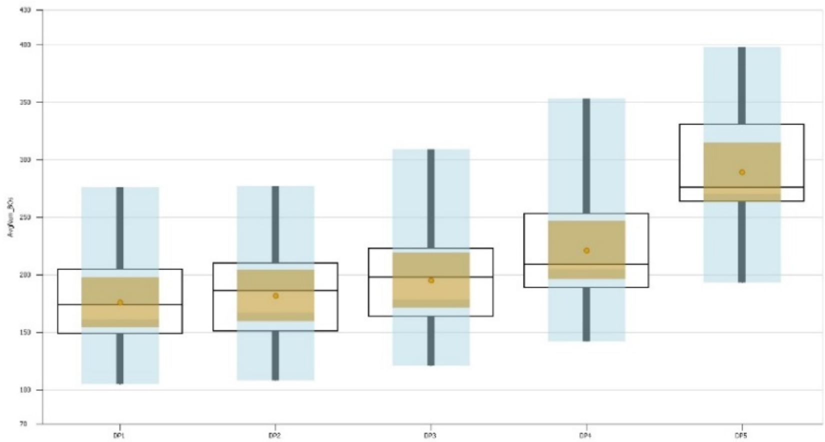

Figure 8. Average Total Number of Backorders

In order to assess how the increased operational tempo affects the backorder number, the total number of backorders over the 4 year period was broken down into individual rows by year as shown in Table 4. The Table 4 results shows that the major increase in the number of backorders occurs in year 1, the period that includes war, but the impact on subsequent years was minimal. For example, DP 5 with an 80% increase in Operational Tempo, has 156.45 backorders in year 1. However, in the following year, the number goes down to 43, which is the same as the backorders in the baseline with no Operational Tempo increase. In fact, the average yearly backorder numbers of different DPs after year 1, all settle down to about 43 to 45, with no statistically significant difference.

Table 4. Average Number of Backorders by Year

Year	DP 1	DP 2	DP 3	DP 4	DP 5
1	41.6 ± 10.8324	47.1 ± 11.6116	60.1 ± 13.6986	86.05 ± 15.9336	156.45 ± 17.4179
2	43 ± 11.0167	43.1 ± 10.9273	42.85 ± 10.5912	43.85 ± 9.8443	43 ± 8.9342
3	44.95 ± 11.9005	45.3 ± 12.1693	46.6 ± 12.2329	46.3 ± 11.9388	45.65 ± 11.5113
4	46.45 ± 6.616	46.5 ± 6.8992	45.55 ± 6.9175	45.25 ± 7.7259	43.75 ± 10.0134

In order to examine whether this apparent leveling off of backorders extended past our study period of 4 years, we collected data over 14 years for DP1, DP2, and DP3. As shown in Figure 9, all DPs reached a steady state mean around 41. This shows that the increase in Operational Tempo has a short term impact on backorder numbers.

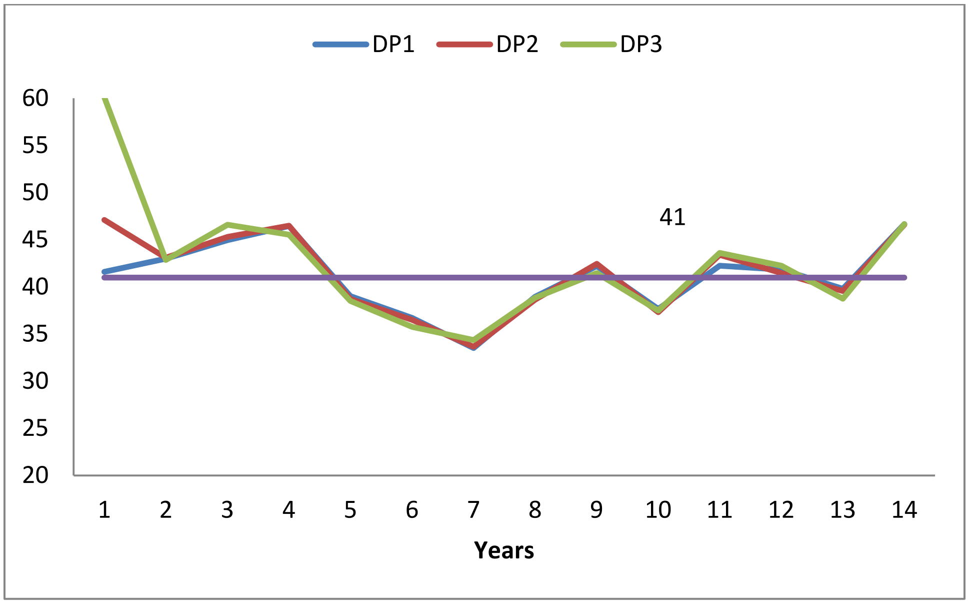

Figure 9. Backorder Numbers Over 14 Years

Because the increase in Operational Tempo only increases the backorders in year 1, the monthly changes in backorder numbers were further investigated as shown in Figure 10. Most of the backorders occur in the beginning of year 1 when the war takes place. More specifically, the results indicate that 61.7% of the backorders occurred in the first 3 months with an 80% increase (DP 5) while only 31.1% occurred during the same months for the baseline.

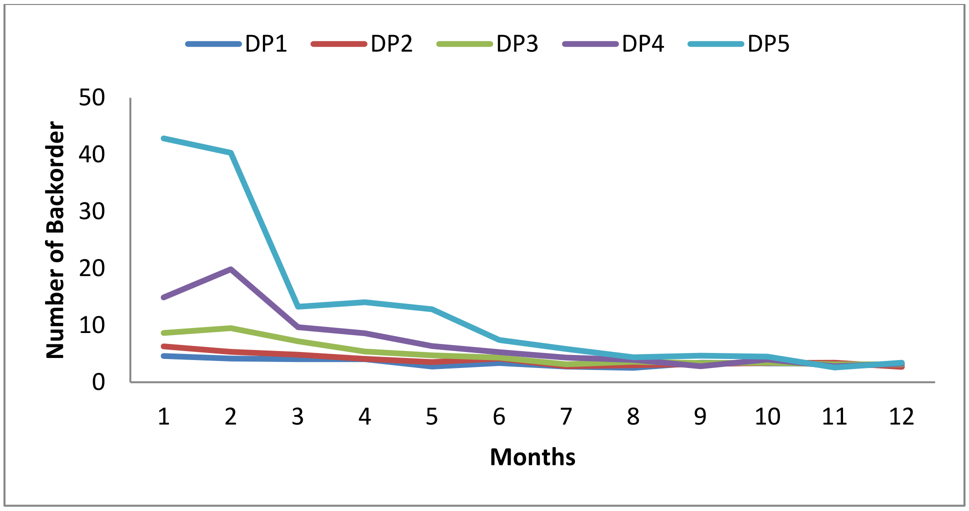

Figure 10. Monthly Backorders in Year 1

The impact of a sudden increase in backorders was assessed by evaluating the changes in number of available spares in inventory, to see how the spares inventory reacts to the surge. Figure 11 indicates that the total number of available spares approaches zero as time reaches year 4. This figure also shows the sharp drop in the spares level between months 1 through 8, caused by the surge in demand from the war, but recovers quickly in month 10. This results indicates that the repair network is resilient to surges in demand, but in the long run, the level of spares approaches zero. This result indicates that with the current induction rates for each module and associated depot TATs, the number of spares available in the repair network are eventually depleted. Our initial spares level took us out to roughly the end of year 4. Increased spare levels would push the depletion point out further. In order to maintain some positive level of spares in the long run, there needs to be a reduction in the induction rate and/or a reduction in the TAT at the depot. More spares **only** provide a short term solution without other improvement.

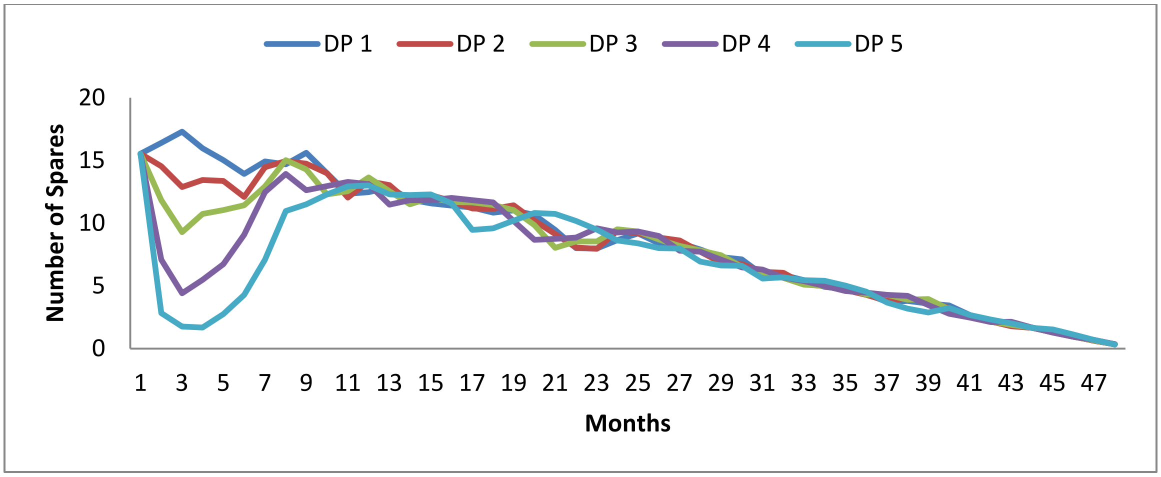

Figure 11. Monthly Changes in the Number of Spares

The number of backorder by modules were examined to see individual module's contribution to the total number of backorders in Figure 12. The results show that most of the backorders are caused by Gearbox, Inlet Fan, and LPT, however Core, Inlet Fan, and LPT are more sensitive to changes in Operational Tempo. This indicates that during day to day operations, Gearbox, Inlet Fan, and LPT may require additional support to reduce the overall backorder numbers, but when there is a surge in demand, Core may also require additional support.

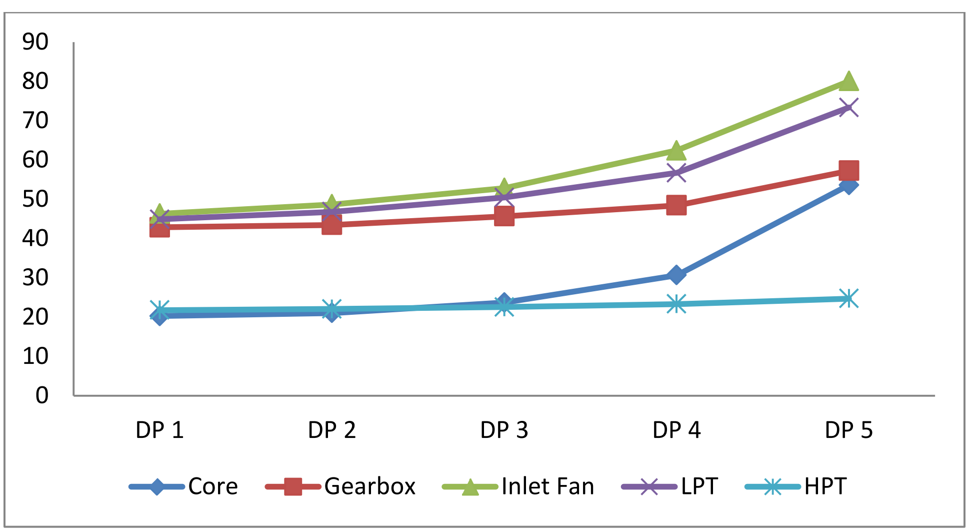

Figure 12. Number of Backorders by Modules

Figure 13 shows that the number of individual modules processed follows the same increasing trend as the average total number of backorders in Figure 8, but at lesser rate. Core, Inlet Fan, and LPT follow a similar nonlinear trend, but Gearbox and HPT show a smaller increase in number. Note that the vertical scale is not the same for all modules. However, when the result was compared to the number of backorders by modules, both trends are similar to each other.

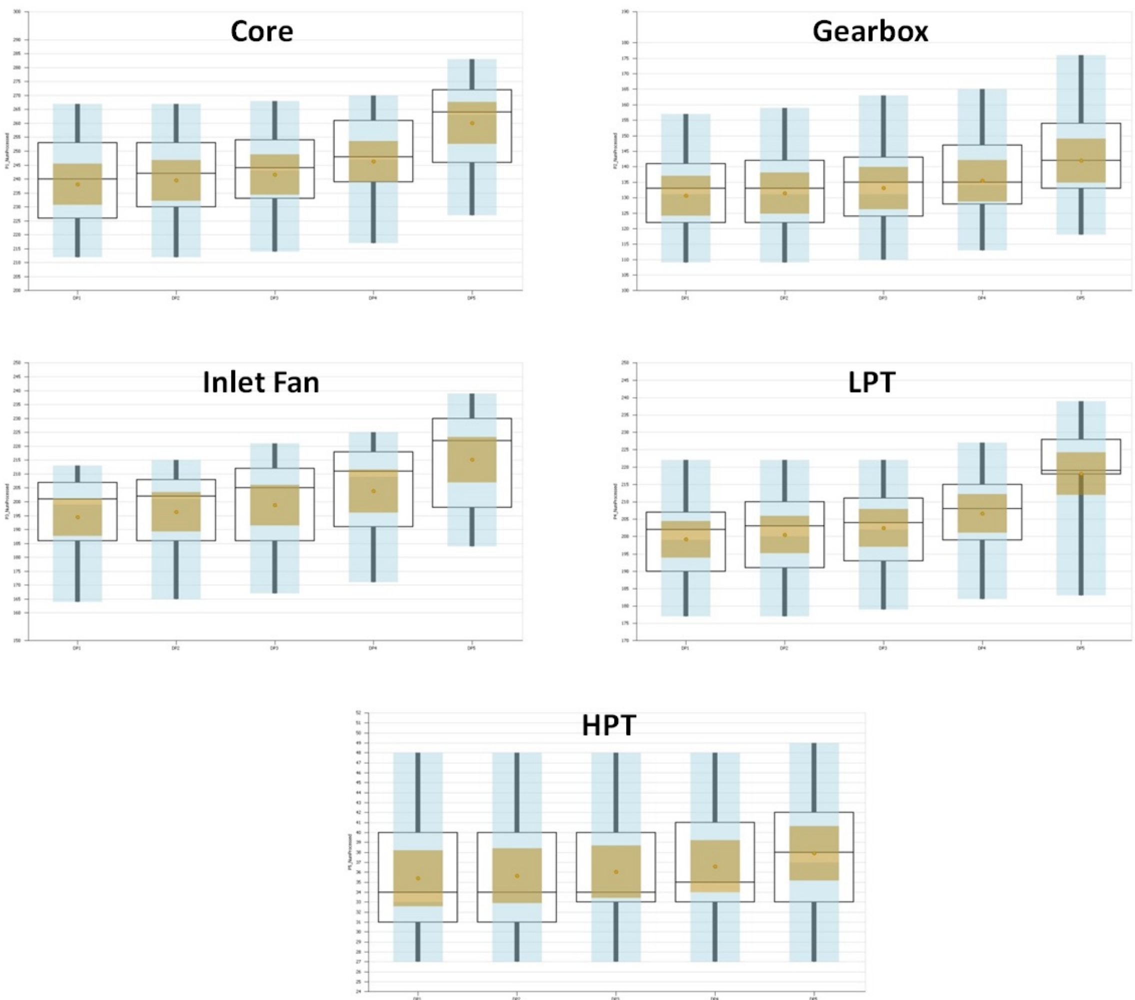

Figure 13. Number of Modules Processed

The average time in backorders by modules in Figure 14 follows a similar pattern as the number of backorders by modules, and the number of modules processed. All these results indicate that Core, Inlet Fan, and LPT are more vulnerable to the changes in Operational Tempo, while Gearbox and HPT are more resistant.

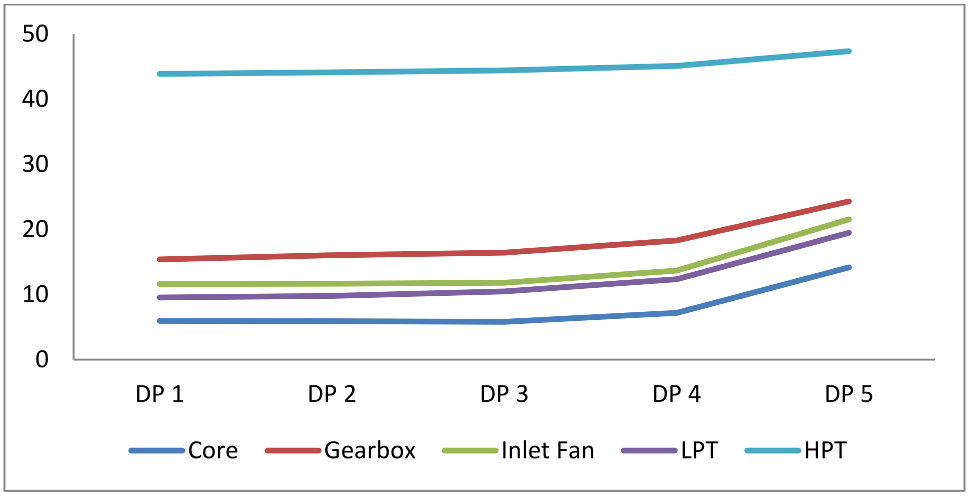

Figure 14. Average Time in Backorder (Days) by Modules

Reorder Policy Comparison

For this part of our analysis our baseline model now uses the 0.6 Operational Tempo factor (40%) increase in induction rate with no additional spares ordered. This baseline model is then compared with two different order polices to take an initial look at levels of industrial base output in producing additional spares to reduce the number of backorders. The first policy initiates the acquisition process immediately after the war, and the second policy initiates the acquisition process 30 days after the war. The 30 days delay for the second policy was a simple attempt to implement a less proactive policy, demonstrating the impact of a delay in requesting spares. For both policies, the number of spares ordered is the difference in the inventory level of each module at the start of the war and the inventory level when the order is placed. In Figure 15, policy 1 refers to ordering immediately after the war, while policy 2 refers to the 30 day delay. We also explore the different levels of lead time: 130 days, 150 days, and 170 days. As shown in Figure 15, the reduction in backorders becomes larger as the acquisition lead time becomes shorter. When the acquisition delay approaches the end of year 1, the benefit of acquiring additional spares diminishes as shown in Reorder Policy 2 with 170 day acquisition delay. The previous analysis on Operational Tempo revealed that the most of backorders in year 1 occur in the first 3 months of the year, and this trend intensified as the Operational Tempo increases. After the first six months, the number of backorders recovers back to the normal Operational Tempo level, regardless of the level of increase in the Operational Tempo. This indicates that the additional spares at the latter half of the year are less effective, but the acquisition delays under consideration are generally longer than six months. The percent reduction in backorders from Policy 1 with 130 days acquisition delay, the fastest policy, only reduced total backorders by 8.9% in year 1.

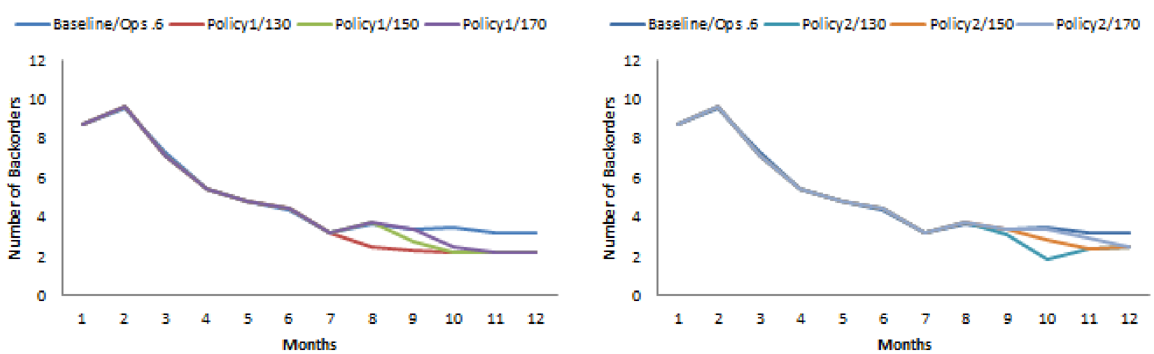

Figure 15. Monthly Backorders in Year 1 at 40% Increase in Operational Tempo

We also repeated our reorder policy analysis at the 60% and 80% increase in the Operational Tempo and the results were comparable to previous results. The reduction in backorders is higher at the 60% and 80% level than the lower Operational Tempo level, because the total number of backorders with at the higher Operational Tempo level is larger. However, the percent reduction in backorders decreased as the Operational Tempo increased. For example, the percent reduction in backorders for Policy 1 with 130 day acquisition delay at 40% was 8.9%, at 60% was 6.9%, and at 80% was 5.1%. This decrease in percent reduction is caused by the resiliency of the repair network. Previous results indicate that all policies only affect the number of backorders in the latter part of year 1, and the backorder numbers at various Operational Tempo level returns to the normal Operational Tempo level at the latter part of year 1. Because of this, the degree of the drop from increased backorder number to the normal backorder number increases as the Operational Tempo increases, and the percent area under the curve served by different policies gets smaller as the Operational Tempo level increases. The decrease in percent reduction in backorder number is observed with shorter acquisition delays such as 90 and 110 days. These results indicated that the additional spares have to arrive within the first 3 months of year 1 to effectively reduce the backorders, and any spares added more than 150 days after the war only reduces total backorders by about 5% in year 1.

Previous results from Figure 11 indicated that the spares level eventually approaches zero at the end of year 4. This result was revisited with additional spares to see how added spares affect the spares inventory level in the long run. Figure 16 shows that the additional spares increase the spares inventory level over a period of a couple of years, but the increased spare level also gradually approaches zero at the end of year 4. This shows that additional spares can help reduce backorders in the short term, but do not provide a permanent solution.

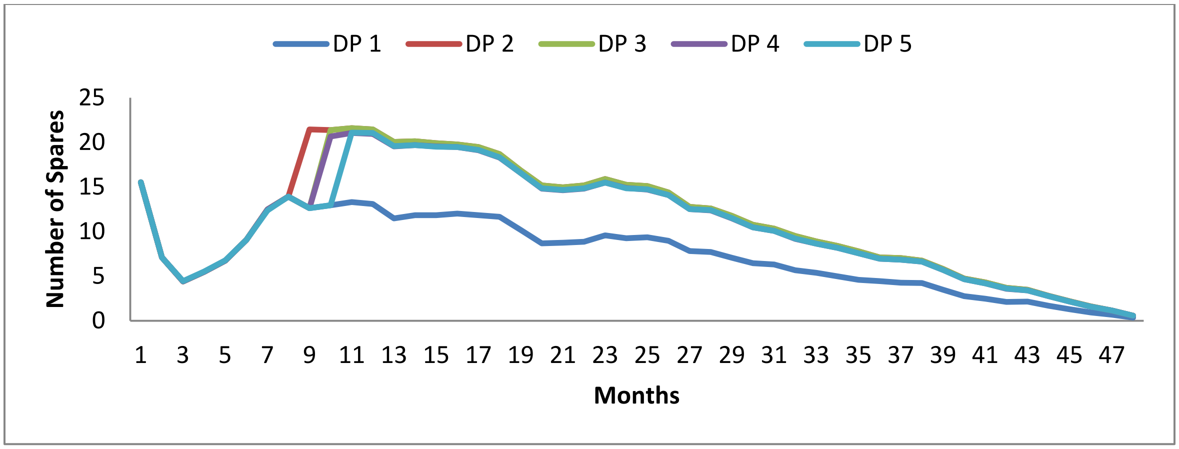

Figure 16. Monthly Changes in the Number of Spares with Additional Spares

Summary

The Operational Tempo analysis revealed that the number of backorders increase proportional to the level of increased Operational Tempo. Most of the increase in backorders occur in the year that contains war, and the backorder numbers return to normal Operational Tempo level in the subsequent years. Most of backorders in year 1 occur in the early part of the year, and the number of backorders and spares inventory levels returns to the normal level after 9 months. During normal operations, backorders are mainly comprised of Gearbox, Inlet Fan, and HPT, but during the increased Operational Tempo, Core also increases to a significant level.

The Reorder Policy analysis identified that additional spares have to arrive within the first 3 months of the year 1 to effectively reduce the backorders. Any spares added 150 days after the war do not significantly reduce backorders. The additional spares can be used as a temporary solution to reduce surges in backorders, but it cannot be a permanent solution as the spares inventory level eventually approaches zero with given induction rates and TATs.

V. Conclusions and Recommendations

Overview

Previous chapters presented literature review, research methods, and analysis of results to investigate the research question of the impact of Operational Tempo on the repair network. In this chapter, the individual results from previous chapters are discussed to show how they answer the research question, which is to find which of the three factors, the induction rate, repair TAT, or spares inventory level is the most significant to the availability of mission capable aircraft. Also, based on findings from previous chapters, future work is recommended.

Conclusions of Research

In Chapter 2, most previous research reviewed in the area of sustainment of repair networks can be classified in three areas. First approach uses various forecasting techniques to predict future demand with historic data. With the forecasting approach, the significance of factors could be determined by their contributions to the future prediction. The second approach uses an interactive model that adapts to the dynamic environment of the repair network to build a decision support system. The third approach uses discrete event simulation to model the flow of major components of the repair network such as the engine to represent the system. This model does not require active collaboration such as the interaction model, but is still able to determine the impact of the factors through simulation. The data presented by AFMC/A9A was adequate to build a top level simulation of the F-16 engine repair network.

In Chapter 3, changes to the induction rate were modeled by different Operational Tempos, changes to the spares inventory level were modeled through two reorder policies, and the repair TATs were not varied. Analysis of our simulation results in Chapter 4 showed that the repair network recovers from the war within six months. Overall our results indicated that during day to day operation that changes to the spare inventory levels are insignificant in long term sustainment. This is due to the fact that with the current induction rates and TATs, any reasonable spare levels eventually go to zero. However, during periods of conflict with sudden surges in demand, additional spares can have an immediate short term impact in reducing backorders, if the acquisition lead time is short enough. In the long term, the induction rates and repair TATs are the most significant factors in sustainment of the repair network.

Recommendations for Future Research

The repair network consists of spares demand, supply chain requirements, and repair manpower requirements. Although this study models varying levels of induction rates through different Operational Tempos, it does not model different levels of repair TATs. As discussed in Chapter 4, the spares levels during day to day operations eventually reaches zero. Varying levels of repair TAT can be tested to find an efficient repair TAT reduction point that minimizes the spares use. Also, different types of repair policy such as cannibalization of same modules in backorder queue to reduce the repair TAT can be implemented to see the significance in backorder reduction. The reorder policies tested in the model are based on an assumption of infinite service life of spares. The revised reorder policy with actual service life of the spares, may change the reorder point and frequency, placing more importance on the acquisition lead time. Cost analysis of the revised reorder policy with varying TATs to maintain an adequate spares inventory level would be interesting. Lastly, as mentioned in Chapter 3, this simulation can be modified with appropriate data to examine other engine repair network such as JSF F-35.

Summary

This thesis presents a top level model of F100-229 engine repair network to find the impact of Operational Tempo on the repair network. Our simulation showed that the current induction rates are higher than the repair TATs, so the spares inventory is eventually depleted. Increasing the number of spares can alleviate surges in demand during increased Operational Tempo if the spares arrive during the period of the surge. Additional spares do not significantly improve the number of backorders in long term. Therefore in order to reduce the number of backorders in the long term, the induction rates and/or the repair TATs have to improve.

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14. ABSTRACT
Maintaining an adequate level of aircraft availability through Agile Combat Support (ACS) is crucial for the Air Force to perform its mission. During normal day to day operations, demands for depot repair including spare parts and maintenance man-hours typically fall within a range supportable with current assets and capabilities. However, with increased flying operations during a conflict, demand at the depot level may likely exceed current capacity for timely support, resulting in backorders for spares and increased turnaround times. This thesis develops a discrete event simulation of the F-16 engine repair network to investigate the impact on engine availability (a major driver of aircraft availability) from three key factors: the spare engine modules inventory levels, the induction rate of failed modules, and the repair turnaround time for the engine modules. Our baseline simulation captures the F-16 engine repair network at a top level for normal day to day operations. We then insert a range of increases in operational tempo in our simulation and analyze the effects on the engine repair network. Incorporating different policies for replenishing depleted spares levels from increased demands allows us to explore the responsiveness of industrial base output in maintaining aircraft engine availability.

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