3-21-2019

Examining the EXPRESS Supportability Module: Implementing an Autoregressive Distributed Lag Approach with Air Force Maintenance Data

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AFIT-ENS-MS-19-M-151

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Wright-Patterson Air Force Base, Ohio

AFIT-ENS-MS-19-M-151

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THESIS

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

in Partial Fulfillment of the Requirements for the

Degree of Master of Science in Operations Research

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21 March 2019

AFIT-ENS-MS-19-M-151

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Abstract

Launched in 1996, EXPRESS (Execution and Prioritization of Repairs Support System) is a program integral to the Air Force reparable supply chain. Daily, EXPRESS relies on a number of data sources and individual modules like the Supportability Module to determine which necessary repairs can and should be made. The Supportability Module examines the prioritized list of repairs and checks four constraints in order to decide whether each repair can be made given current resources. According to the logic of the module, a single constraint failure means that subsequent resource checks are not made before evaluating the next repair. Unfortunately, this leads to missing observations in the EXPRESS data table, ultimately masking potential resource issues and possibly contributing to extended mission capability issues. In this study, a time series analysis via explanatory autoregressive distributed lag (ARDL) models was conducted using EXPRESS and MICAP (mission capability) data to examine possible connections between missing constraint values in the EXPRESS table and future MICAPs. These models suggested that up to 0.793 MICAP days are added for each additional parts failure missing in the EXPRESS table. Additionally, the presence of significant relationships between the EXPRESS and MICAP data over time suggest that maintainers examining trends in the EXPRESS data could feasibly reduce future MICAPs. As a byproduct of this study, the potential for the use of time series models with maintenance data was explored. Model diagnostics suggest that maintenance data is too volatile and noisy for regression-based methods and that stochastic methods or simulation may prove more useful.

Acknowledgements

I would like to thank my wife for her unwavering support over the course of my studies in addition to my parents for helping me get to this point. I would also like to thank my advisor, Dr. Hill, and committee member, Dr. Champagne, for their patience and guidance in support of this research. In addition, I would like to thank Marvin Arostegui, Chad Wynkoop and Chad Kimmel of AFSC for helping me understand the Air Force maintenance process.

Troy J. St. Peter

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EXAMINING THE EXPRESS SUPPORTABILITY MODULE: IMPLEMENTING AN AUTOREGRESSIVE DISTRIBUTED LAG APPROACH WITH AIR FORCE MAINTENANCE DATA

I. Introduction

1.1 Background

Sustaining optimal supply chain management processes is of the utmost importance to the daily operations of the Air Force. Maximizing mission capability is a function of moving reparable aircraft parts through the process as quickly and affordably as possible. To this end, the Air Force takes advantage of a variety of programs at each step of the extensive supply chain process to best make decisions about where items should be repaired (local versus depot), what item to repair next and where that item should be assigned upon completion of the repair. Rather than relying on industry supply chain practices for inspiration, the unique nature of the military, which offers extreme variability in daily levels of demand, necessitated the development of programs specific to the Air Force mission. Each of these programs are used in accordance with official Air Force policy.

As instructed by Department of Defense Directive (DoDD) 4140.1-R, the Air Force previously used the Uniform Materiel Movement and Issue Priority System (UMMIPS) "for allocating materiel and other logistics resources among competing demands" [1]. Based on the necessity of a part and the urgency of the maintenance issue, UMMIPS determined how depot repairs should be prioritized. The system was in place from its inception in 1962 until opportunities for improvement became evident [2]. A 1995 report poked holes in the logic of UMMIPS that left the Air Force lacking in both readiness and sustainability [3]. Knowing it was time for change, the Air Force sponsored a project with RAND Corporation to search for a new system.

In developing the comprehensive Distribution and Repair in Variable Environments (DRIVE) prioritization approach, RAND aimed to address some of the shortcomings of the current supply chain process. There was simply too much uncertainty in forecasting future part failures which hurt the prospect of sustaining affordable maintenance scheduling [2]. Many sources of information were combined with DRIVE. Current asset positions, aircraft availability goals and user-specified data such as flying hours were combined to create a bigger picture with two resulting outputs, a sequenced repair list and an asset allocation list [4]. The main objective was aircraft availability as opposed to measures like MICAP (mission capability) and AWP (parts awaiting components for repair), a change which was a "cultural shock to the Air Force logistics system" [4]. Initial results were promising; DRIVE offered increased readiness and sustainability without increased costs [4]. Many organizations including AFIT supported its implementation into official Air Force policy. One thesis in 1996 argued that DRIVE offered many improvements to current processes, a conclusion shared by other researchers [5].

Ultimately, EXPRESS was launched in 1996 as a combination of three programs: the prioritization capabilities and distribution module from DRIVE, the Automated Induction System (AIS) used by the Oklahoma City Air Logistics Complex (ALC), and the Supportability Module used by the Ogden ALC [6]. The AFMC Annual Report detailing their 1996 projects declared that the overall goal of EXPRESS was "to closely link recoverable item depot repair and distribution actions to operational customers' needs" [6]. The EXPRESS program was officially integrated into policy in 1996. Air Force Materiel Command Instruction 23-120 is the foremost document containing the policies and procedures for the execution of EXPRESS [7]. Although the Air Force Sustainment Center (AFSC) runs EXPRESS on a global scale, it relies on the three Air Logistics Complexes to input local constraints [8]. In EXPRESS, there are a variety of functions: data services, prioritization, repair and distribution [7]. This process is shown in Figure 1.

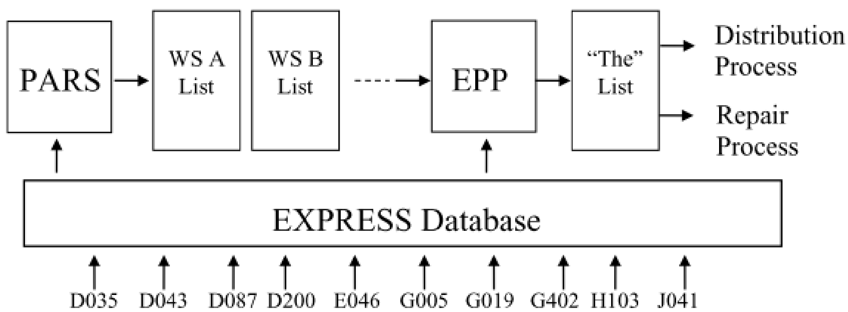

Figure 1. *EXPRESS System Flow [9]*

The most important step is taken before the actual execution of EXPRESS when data is fed into the system from a variety of sources. Then, the Prioritization of All Reparable Spares (PARS) Model and the EXPRESS Prioritization Processor (EPP) together handle the prioritization and determination of requirements [7]. The Supportability Module, which is explained in greater detail in the following paragraph, checks how many repairs can reasonably be made with current resources. The distribution process determines where fixed items should be sent [7]. Overall, four questions are answered with EXPRESS [10]:

1. What should we fix?
2. Which item should we fix first?
3. What can be repaired?
4. Who will receive it when it gets fixed?

The focus of this research is the Supportability Module, a part of the repair process of EXPRESS, which considers the prioritized list and checks four resource constraints. These constraints are described according to 2006 Air Force regulations.

Upon taking in the prioritized list, resources are checked in the following order: carcasses, capacity, funds and parts [7]. The logic for the module is presented in Figure 2. The Supportability Module begins by considering the first requirement. The first check is for carcasses, or reparable assets [7]. The second check, which ensures there are enough personnel and equipment to complete the repair, requires user input for man-hours available [7]. The system then checks that the required funds are available. The final check for parts is the most complex. EXPRESS determines how many parts are required to complete the repair and computes the probability that the parts are available [7]. This probability is compared to the Predetermined Acceptance Probability (PAP), another user input. The PAP "governs the amount of certainty desired that the available level of component parts will support the repair of an end item" [9]. In other words, PAP is a measure of the risk a shop is willing to take. Next, EXPRESS decides whether any items not on hand should be added to the Shopping List for Item Managers (SLIM) Report before adding the action to the final list [9].

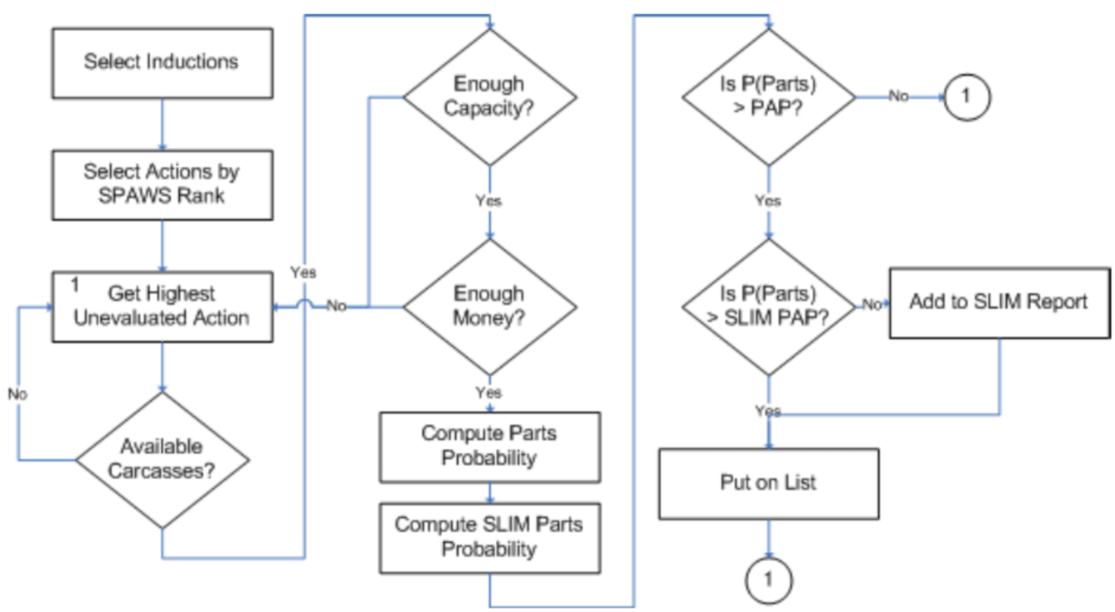

Figure 2. *EXPRESS Supportability Logic [10]*

Issues can arise because each of the constraints are evaluated sequentially rather than simultaneously. Consider the example presented in Table 1 where there are ten items being checked for each constraint. For simplicity, results are listed as pass, P, or fail, F. In reality, there are a multitude of different codes for each check which will be explained later. According to the logic in Figure 2, when requirement six fails for capacity, funds and parts are not checked and the program moves on to the next requirement. The issue compiles when the next requirement also fails for capacity. Table 1 shows an example of the final list that is sent to the depot. It is known that there are enough funds and parts for the first five requirements, but what about the last five? Additionally, the carcasses for the final five requirements are not being officially obligated to those items, so there might not actually be enough carcasses for all the requirements. Being blind to issues involving some of the constraints is dangerous in that the issues can compile over time and become costly.

Table 1. *Scenario Using Current Supportability Module Logic*

Req ID	**Carcass**	**Capacity**	**Funds**	**Parts**
1	P	P	P	P
2	P	P	P	P
3	P	P	P	P
4	P	P	P	P
5	P	P	P	P
6	P	F		
7	P	F		
8	P	F		
9	P	F		
10	P	F		

1.2 Problem Statement

This research addresses a lapse of logic in the ALC Supportability Module of EXPRESS. Since the inception of EXPRESS, the Air Force has sponsored multiple RAND studies looking into possible improvements for the system. A 2014 study on depot-level maintenance in the Department of Defense (DoD) highlighted some of the current issues affecting mission capability. Maintenance depots across all the services had one main issue in common: parts supportability [11]. When the researchers visited each ALC, this was the first issue discussed by the interviewees [11]. Refining the Supportability Module logic in EXPRESS so that each of the four constraints are considered individually could offer improvements in production agility. This would not be a radical change because the supportability process at the HQ level already uses this logic [12]. As opposed to the list generated in Table 1, Table 2 shows a bigger picture view of the resources available for each requirement. This type of list would ensure the depot knows they have no shortage of funds and their main issues involve capacity and parts. While it may be difficult to address capacity, which could theoretically involve adding new employees or expanding shop space, the parts issue can be addressed and mitigated sooner. This research considers the consequences of the existing Supportability Module logic. The main objectives are to analyze the repercussions of checking the four resources sequentially and examine the improvements offered when the resources are evaluated individually such that no values are missing in the table. Do missing values in the supportability data mask issues that will affect mission capability in the future? What improvements are offered by considering the resource constraints individually within the Supportability Module?

Table 2. *Scenario Using HQ Supportability Module Logic*

Req ID	Carcass	Capacity	Funds	Parts
1	P	P	P	P
2	P	P	P	P
3	P	P	P	P
4	P	P	P	P
5	P	P	P	P
6	P	F	P	P
7	P	F	P	F
8	P	F	P	F
9	F	F	P	F
10	F	F	P	F

II. Literature Review

2.1 Introduction

In this section, DoD instructions and memorandums in addition to EXPRESS manuals are used to provide an overview of the entire Air Force reparable supply chain process and EXPRESS, which is only a small part of the reparable supply chain. Additionally, past research involving EXPRESS is reviewed. While there are little to no academic journals referencing EXPRESS and its use in the Air Force supply chain process, there are a number of DoD studies detailed in RAND reports, *Air Force Journal of Logistics* articles, and AFIT theses. Many of these studies are discussed in this section.

2.2 Air Force Supply Chain

After years of debate on how to align the management of the maintenance supply chain, the Air Force has settled with a near complete pull system with an emphasis on demand, priorities and inventory levels [11]. Planning occurs daily which introduces issues due to the uncertainties involved in executing the mission. Two recent emphasis items for the Air Force have been increasing the use of demand history adjustments (DHAs) and demand data exchange (DDE) [11]. A significant issue arises when maintenance crews find a workaround instead of ordering a part - no demand record is created [11]. However, demand records are essential when planning for future demand. The use of DHAs by the depot ensures a complete demand history for an item [11]. Additionally, whenever plans are likely to cause demand to divert from past trends, DDEs are submitted, promoting collaboration and proactiveness [11].

Air Force Materiel Command (AFMC), located at Wright-Patterson Air Force Base, oversees the sustainment and acquisition of weapon systems to meet the needs of the Air Force [11]. The command is organized into five centers, as shown in Figure 1. Most important to the supply chain process is the Air Force Sustainment Center (AFSC), which "provides depot-level weapon system maintenance and Air Force supply chain management functions" [11].

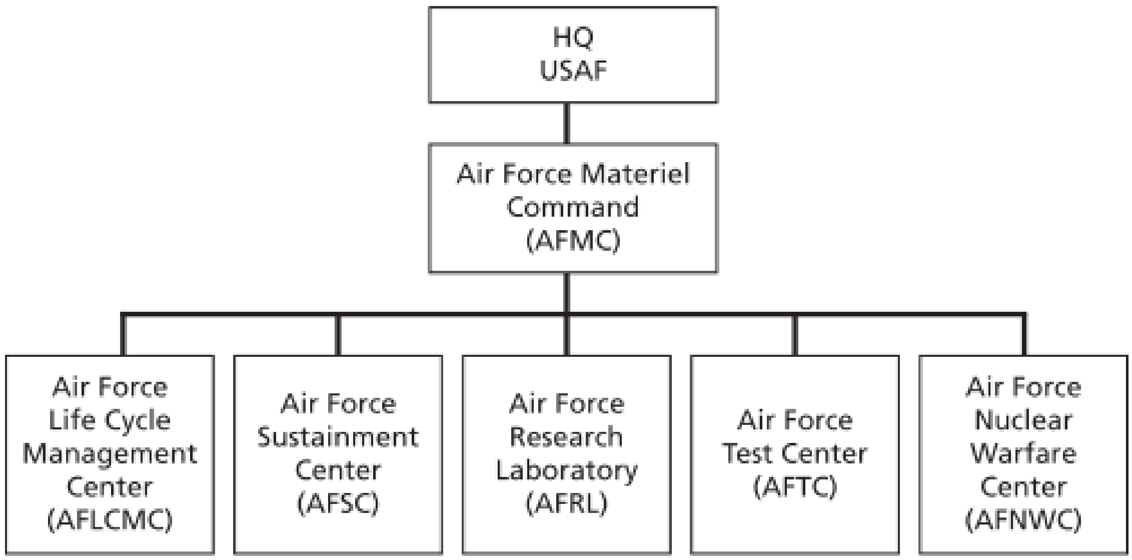

Figure 3. *Air Force Materiel Command Organizational Chart [11]*

The AFSC manages three ALCs at Tinker, Hill and Warner Robins Air Force Bases in addition to two supply chain wings [11]. Each ALC performs a similar mission of depot-level maintenance on differing weapons systems [11]. These organizations perform both scheduled and unscheduled maintenance daily on a variety of aircraft. The daily execution of EXPRESS is a responsibility of the AFSC and each individual ALC. The AFSC executes EXPRESS on a larger scale, creating a global priority list that is sent to each ALC who can apply local constraints [8].

Kimmel, assigned to AFSC, provides a breakdown of the Air Force repairable supply chain. Aircraft are inspected by maintenance crews daily. Items are classified as consumable, repairable or depot recoverable [13]. Consumable items are low cost items that are never repaired, while depot recoverable items are expensive items repaired at a base or depot [13]. The rest of the items are repairable and are classified as "Not Repair This Station" (NRTS), which are sent to the depot, or "Repair This Station", which are sent to the base repair shop [13]. The NRTS items are routed through depot supply before being repaired as part of the Management of Items Subject To Repair (MISTR) process. Depot-level maintenance of recoverable and replacement items follows the MISTR process in accordance with Air Force Materiel Command Instruction 23-112 [14]. It is in this part of the supply chain that the daily execution of EXPRESS determines which repairs should be inducted.

2.3 EXPRESS

The Air Force launched EXPRESS in 1996 as an implementation of the RAND-developed DRIVE model and other previously developed systems [8]. The program is embedded inside the Weapon System Management Information System (WSMIS) [9]. The purpose of EXPRESS is to use standard data systems to support the prioritization, execution, and distribution of repairs [9]. It is executed daily to promote the "repair-on-demand philosophy" emphasized by the Depot Repair Enhancement Program (DREP) [9]. One important feature is that there are centralized and decentralized processes within EXPRESS. The centralized processes are executed at HQ AFMC while the decentralized processes are performed at the three ALCs [9]. While the primary use of EXPRESS is at the ALCs, a vast number of organizations have influence in the ongoing maintenance and use of EXPRESS. Official policy from HQ USAF dictates the use of EXPRESS while the major commands (MAJCOMs) provide tempo data that influences depot-level maintenance [9]. Other organizations provide pivotal studies into possible improvements for the system.

The logic within EXPRESS emphasizes the supportability of weapon systems [9]. A total of four main modules, identified in Figure 4, make up EXPRESS. The cyclical process includes Data Services, Prioritization, Supportability and Distribution Modules.

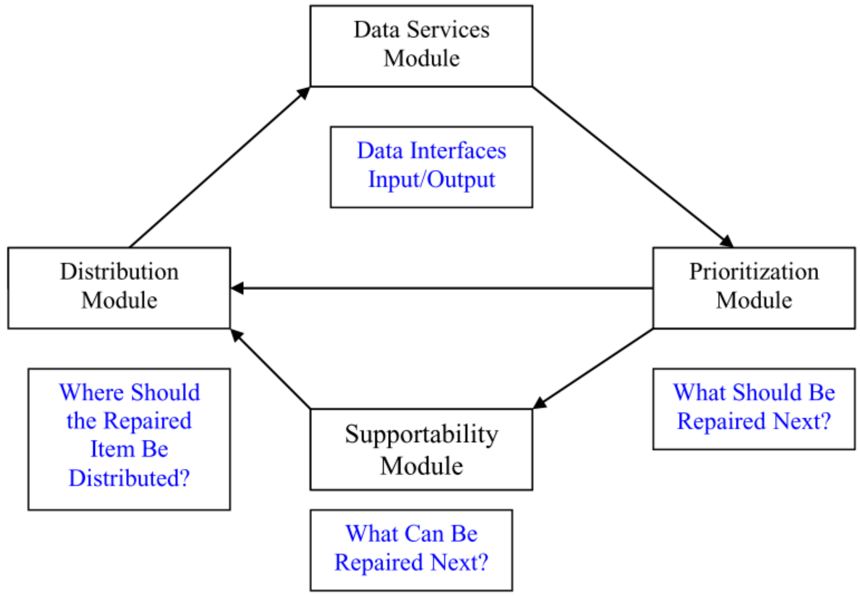

Figure 4. *EXPRESS Module Flow [9]*

The Data Services Module is concerned with providing the data necessary for the execution of the remaining three modules. The Prioritization Module decides what should be repaired next based on current requirements. The Supportability Module determines what can feasibly be repaired with current resources. The Distribution Module decides where to send completed repairs [9]. These modules are described in great detail in a series of EXPRESS guides prepared by the Computer Sciences Corporation for various units within AFMC [12, 15, 16].

The data that flows both in and out of EXPRESS daily impacts the remaining modules. Multiple organizations are responsible for providing data input on an established timeline. The data network operates on both the classified and unclassified levels. On a classified server, EXPRESS receives operational tempo data from the MAJCOMs [16]. Some other examples for the data input in EXPRESS are files reporting worldwide asset status, back order and depot resource information, all of which are updated daily [16]. Every day, EXPRESS loads data onto an unclassified server where it is transferred to the three ALCs for use in the Supportability and Distribution Modules [16]. The thoroughly designed database structure of EXPRESS "facilitates timely data processing and access, including the means for input, storage, extraction, access, and processing of item characteristic, linking, and scenario data" [16]. This level of timeliness in data exchange is necessary to achieve the production agility and operational tempo desired by military leadership. When all the necessary data is in place, EXPRESS begins the prioritization process.

For prioritization, the first executable is the Prioritization of Aircraft Reparables (PARS), which was adapted from the DRIVE model [12]. There are three modules within PARS: Allocation (ALLO), Preparation (PREP) and Computation (COMP) [12]. Prioritization methods and procedures differ based on values set by administrators. The ALLO module computes allocation weights for items based on expected demands and the PREP module calculates expected demands by base; both are executed in the classified environment at AFMC [12]. The COMP module calculates the probability that bases can sustain their aircraft availability goals based on expected demands and available assets [12]. Once all of this information is calculated, PARS determines how to best address current needs. First, if the depot has serviceable assets, the model decides which base should receive them based on the expected increase to their probability of meeting their aircraft availability goals [12]. Next, PARS considers that same probability increase in addition to the cost of each repair until either there are no depot carcasses left, each base has the maximum probability of meeting goals or the impact of further repairs are minimal [12]. Along the way, PARS considers Spares Priority Release Sequence (SPRS) rules which are assigned based on mission priority and need [12]. The highest SPRS number is 84, representing the highest need. Lower SPRS numbers indicate a lower need. The lists output by PARS represent different weapon systems and are sent to the EXPRESS Prioritization Processor (EPP) for further analysis.

The goal of EPP is to refine the priority sequence generated by PARS to find a balance for support across weapon systems [10]. First, Single Prioritization Across Weapon Systems (SPAWS) creates a unified, prioritized list to try to attain some target percentage for each weapon system. Moore [17], one of the key POCs for EXPRESS assigned to AFMC, provides great insight into the logic of SPAWS. The prioritized lists in PARS for each weapon system are based on sort values which are the amount of increase in likelihood of meeting aircraft availability goals per repair hour [17]. Consider the example in Figure 5 with three weapon systems A, B and C. If the final, prioritized list were simply each item sorted by descending sort value, EXPRESS might choose to make the wrong weapon system healthier than others [17]. Instead, SPAWS finds optimal trade-offs between all weapon systems by using percentages for each weapon system. The weapon system percents are the ratio of the catch-up costs for a single weapon system versus the catch-up costs for all weapon systems [17]. The EPP also incorporates Foreign Military Sales (FMS) and other service requirements into the list [17]. The final output from the joint prioritization effort of PARS and EPP is a single, prioritized list for use by the Supportability Module.

The essential functions of EXPRESS lie in the repair and distribution processes. The Supportability Module, part of the repair process, is executed at the ALC level [9]. This module checks what can reasonably be repaired given current resource constraints. It determines how much of the prioritized Net Repair Objective (NRO) list output from the prioritization process can be supported with four available resources: carcasses, capacity, funds and parts [9]. The module takes the highest prioritized action and checks these constraints (success vs fail) sequentially until either the repair

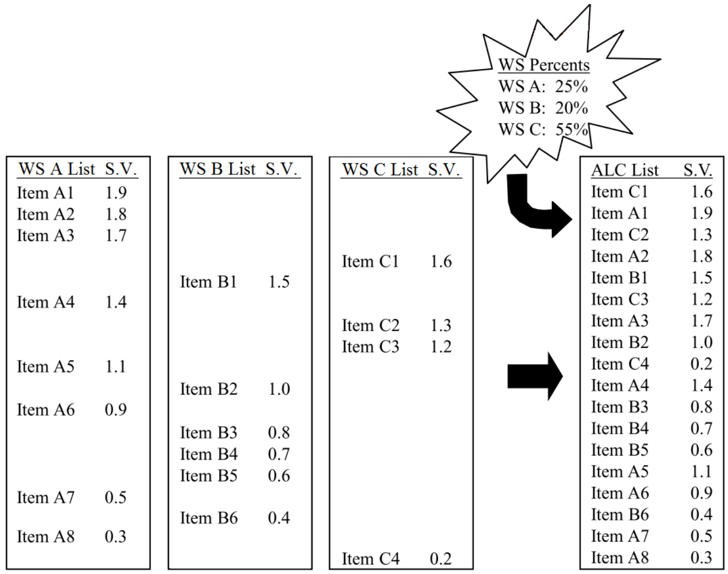

Figure 5. *Illustration of SPAWS [17]*

passes each or fails one of the constraints. The first three constraints are straightforward.

First, the Supportability Module checks for carcass availability in warehouses of the current or other ALCs, contractor locations and off-base storage [7]. The next check is for capacity. Capacity refers to man-hours available and relies on inputs from representatives at each ALC [7]. After that, EXPRESS decides whether or not the repair can be supported with available funds. Depending on settings, the module will apply two types of logic: "Over Funds Available" or "Meet Funds Available" [12]. In the former setting, items will pass funding until the next item would break the budget [12]. In the latter setting, if there are lower prioritized items left that could meet budget goals, they will pass for funding [12].

After checking carcasses, capacity, and funds, the next check is for parts. This constraint check requires a number of background probability calculations. The module considers parts located at the individual ALC [12]. For each subcomponent, the quantity required, replacement percentages and assets on hand are all considered

[10]. These are all inputs into Equation 1 rooted in binomial theory, which outputs a "'goodness' probability for that particular subcomponent" [10].

$$p(y) = \frac{n!}{y!(n-y)!} * p^y * q^{n-y} \tag{1}$$

where n = quantity required, q = replacement percentage and y = available assets

The parts check is highly reliant on ALC input because each of these calculated probabilities are then compared against the Predetermined Acceptance Probability (PAP), a user-defined value between 0 and 1. The PAP is a measure of the risk a shop is willing to take that the necessary parts will be available for the repair. When PAP is set to 0, all repairs will pass for parts. When PAP is set to 1, only items whose necessary parts are all on hand will pass [9].

EXPRESS also affords the opportunity to execute a supportability check at the HQ level [12]. As part of the EXPRESS Constraints Analysis Tool, users can perform a supportability check across all the ALCs [12]. The HQ Supportability Module considers all constraints individually such that an item can fail for multiple resource shortages [12]. Additionally, one important deviation from the ALC Supportability Module is that the required resources are obligated and decremented when each constraint is passed instead of when all four constraints are passed [12]. This research is concerned with implementing this methodology at the ALC level.

The final module executed by EXPRESS is the Distribution Module, part of the distribution process, which also uses the prioritized list generated in earlier processes. The primary function of this module is to preemptively assign repaired items to their destinations by matching backorder requisition numbers to repair actions [12]. This concludes the lengthy EXPRESS process described in the preceding paragraphs and shown visually through both the HQ and ALC levels in Figure 6.

The processes within the Supportability Module of EXPRESS have changed over the years. As of 16 Sept 2016, the current process is described as follows. For the carcass check, which remains first, resources are only obligated if all of the other resource checks are passed. There has been a change in order of operations from this point. The parts check now follows the carcass check. The third and fourth checks are capacity and funds, respectively. There are no issues regarding the discrepancies in Supportability Module logic between different years as only EXPRESS data after this change are considered in this analysis.

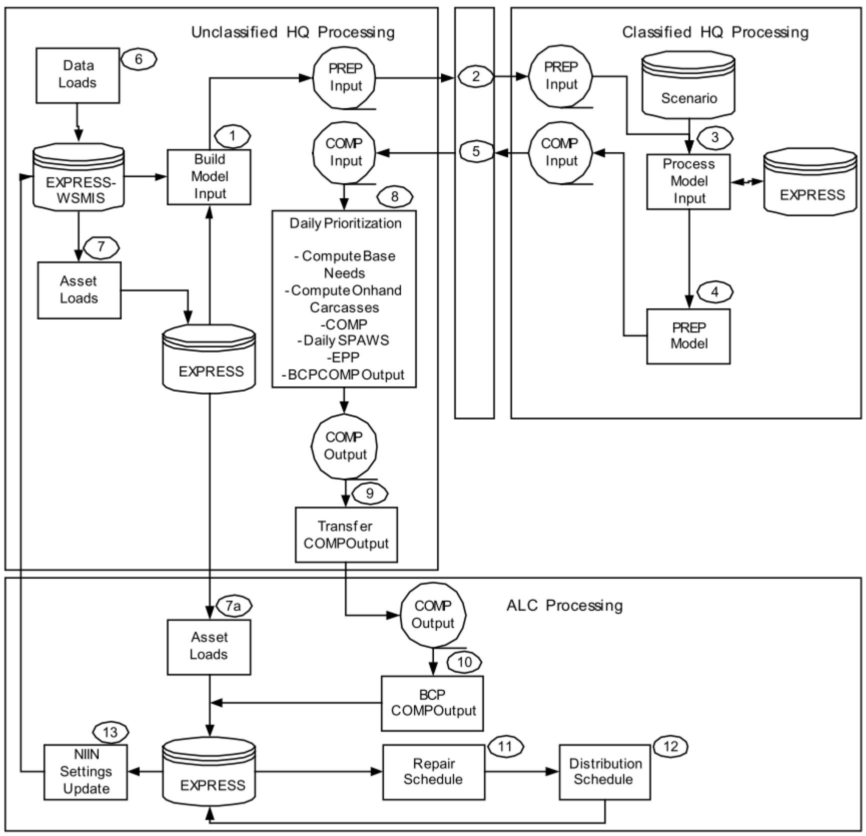

Figure 6. *EXPRESS Daily Process [12]*

2.4 Past Work

In 1996, Anderson [5] provided research supporting the implementation of the DRIVE model into official policy. Anderson provided a direct comparison between the results of the previously used Uniform Material Movement and Issue Priority System (UMMIPS) and the results of DRIVE. He used a limited scenario involving C-130 parts and found that DRIVE utilization increased aircraft availability across all bases with a slight decrease for high priority locations [5]. This was because the goal of DRIVE was to maximize aircraft availability as a whole, which, depending on settings, caused the program to ignore Force Activity Designator (FAD) codes, which indicate higher priority locations [5]. This research not only helped military members better understand the DRIVE process, but also addressed the effect of the new model on mission capability. As previously mentioned, the DRIVE model was later implemented into EXPRESS for use in the reparable supply chain process.

Early on, following the launch of EXPRESS, members of the logistics community were essential in refining and perfecting the process. Analysts provided close scrutiny of EXPRESS and many documented ideas for improvement in *Air Force Journal of Logistics* articles. One such example was Carter and Clarke [18] who identified a need for an additional module in EXPRESS. The authors noted that EXPRESS was severely hampered by resource constraints and hypothesized integrating Depot Repair Enhancement Program (DREP) philosophy into the system [18]. The resulting EXPRESS Planning Module (EPM), a tool which is still operational today, uses forecasting to provide users with financial and repair plans in addition to insights on constraints [18]. This was not the last time Carter offered criticism of EXPRESS.

Carter and London [19] addressed Air Force struggles with repairing and distributing line-replaceable units (LRU). When parts are not available for a repair, a LRU must either be waitlisted for induction or inducted and put into awaiting parts (AWP) status which results in the back ordering of parts [19]. One of the biggest problems causing an excessive number of LRUs in AWP status was not having the right mix of depot resources on the day of EXPRESS execution [19]. This caused

EXPRESS to skip over higher priority repairs in favor of those with lower priority levels, a result of the Supportability Module [19]. Carter and London criticized the use of historical data in forecasting for multiple reasons. First, the military operates in a high tempo environment with fast-changing requirements. Second, when high priority repairs were skipped because parts were unavailable, no demand data for that part were generated. Carter poked holes in the logic for parts supportability and advocated for the use of the EPM in the process [19]. Unfortunately, AWP issues are still prevalent in the Air Force.

Huber [20] performed a gap analysis to identify which parts were most influential in causing AWP delays. The AWP problem, a consequence of the trade-off between the cost of inventory and responsiveness to the customer, is a longstanding issue with recent Air Force initiatives focused on minimizing it [20]. While depots can easily see which end items are put into the AWP process, information regarding which parts regularly put them in this process was not available [20]. In addition to running into time constraints, this research experienced informational constraints upon realizing that AWP delay information was not readily available. However, Huber showed that the Air Force may be addressing the issue wrong by taking the end item perspective instead of examining the impact of individual parts. The implementation of an aggregate measure of AWP impact might assist in the prioritization procedure and help depot personnel balance trade-offs between addressing the shortages of different parts [20].

Lee [21] analyzed the potential for the Collaborative Planning, Forecasting and Replenishment (CPFR) business approach to be implemented into the Air Force reparable supply chain. The CPFR process was developed to reduce production costs and inventory levels while also providing increased scheduling flexibility, ultimately resulting in greater profits [21]. This research was essentially an extensive literature review followed by a case study analysis tracking the life of National Stock Number (NSN) 1270-01-384-1108, the F-15E Eagle Multipurpose Display Processor, through the supply chain [21]. Ultimately, Lee showed the potential for using CPFR in the Air Force supply chain, which paved the way for future research. Other authors have advocated for the implementation of different trains of thought into depot-level maintenance.

Branson [22] argued for the use of high-velocity maintenance (HVM) to combat the aircraft availability issues that were especially prevalent in high-demand and low-density weapon systems. The HVM concept was hypothesized to move aircraft through the depot process more quickly than the current process. With the current system, aircraft were waiting long periods of time between programmed depot maintenance (PDM), causing issues with unanticipated maintenance requirements and unneeded repairs [22]. In one of a few criticisms of EXPRESS, Branson noted that the Supportability Module had potential to declare items supportable when resources were not available due to inaccuracies in stock inventories [22]. He argued that the benefits of forecasted requirements and increased efficiency would outweigh the costs and challenges of initial HVM implementation [22].

Other recent efforts used simulation for analyzing changes to the reparable supply chain. Mayhall [23] incorporated the CPFR approach into the Air Force supply chain using simulation. The discrete-event stochastic simulation model exhibited the flow of demand information and parts between the two echelons of the supply chain: base and depot [23]. There were some differences between the CPFR approach and the methods used in the military supply chain. In particular, while CPFR had historically not been used for reparable parts, the Air Force was very interested in repairing and returning many high-cost parts that were important in aircraft operations. Mayhall looked at two main performance metrics, back orders and fill rate, which are both concerned with how well demand is met [23]. The research showed that effective communication between the base and depot and accurate forecasting were of the utmost importance in limiting back orders and maximizing fill rate [23]. This was not the last time the simulation approach was used in EXPRESS research.

In 2012, Williams [2] used simulation to examine a case study of three reparable parts managed by EXPRESS. Williams viewed the EXPRESS process as a whole instead of concentrating on a single part of the program and focused on the mission capability ramifications of running EXPRESS with variable frequencies. The two specific performance metrics of interest were Customer Wait Time (CWT) and Mission Capable (MICAP) hours, which both measure the responsiveness of the repair process [2]. While CWT is simply the amount of time a customer spends waiting for a part from the depot, MICAP status is an indication that stock has been depleted and a weapon system cannot operate until a part arrives [2]. As expected, Williams found that running EXPRESS less frequently resulted in statistically higher MICAP days as this would intuitively cause less responsiveness to customer needs. While a number of simplifying assumptions were made in the analysis, Williams' resulting simulation model was useful for analyzing overarching system performance and was open-ended enough to promote future research.

III. Data Description and Methodology

3.1 Introduction

This chapter details the processes by which EXPRESS and MICAP (mission capable) data sets were prepared for analysis and also highlights limitations. The preparation of the data includes manipulation of the data into variables of interest and merging information contained in multiple data sources. The ALC and HQ supportability data in addition to the MICAP data are described in detail. Finally, the modeling processes used in this study, including the autoregressive distributed lag (ARDL) bounds testing procedure, are outlined.

3.2 Data Description

As previously discussed, the management of accurate data is extremely important in the supply chain process. For this thesis, three major data sources were of interest: ALC EXPRESS tables from 2011 to 2018, the 2018 HQ EXPRESS table, and a table of 2018 MICAP information. Each year of the ALC EXPRESS tables contains millions of records of a number of variables previously discussed, including PAP, sort value and SPAWS ranking. Most importantly, these tables contain values for carcass, parts, capacity and funds availability for each repair. There are a variety of codes for each constraint (see Table 3). Rather than a simple pass versus fail, each of these variables can take on a number of different designators depending on each unique situation. For the purposes of this analysis, the intricacies between designators, such as P versus U for carcass availability, are not significant. While F and S are straightforward and represent either fail or supportable for each resource check, all other designators are treated as a failure except B for parts. In this case, the Bill of Materiel (BOM) is not available, but the repair still passes. Each code is presented in Table 3 along with its explicit meaning and the result for the repair. A pass means that the repair moves onto the next constraint, while a fail means that the repair is not supportable and the Supportability Module moves onto the next one.

Table 3. *Supportability Code Descriptions*

Check	Designator	Description	Status
Carcass	S	Supportable	Pass
	F	Failure	Fail
	P	Awaiting Parts	Fail
	B	Bypass	Fail
	U	Upper Control Limit	Fail
Parts	S	Supportable	Pass
	B	BOM Unavailable	Pass
	F	Failure	Fail
Capacity	S	Supportable	Pass
	F	Failure	Fail
	M	Max Item/Shop Hours Buffer	Fail
Funds	S	Supportable	Pass
	F	Failure	Fail

While there are never missing values for carcass, many of the parts, capacity and funds availabilities are left blank as a consequence of the logic of the Supportability Module. This is the main concern for this research. The extent of this issue is shown in Figure 7, which depicts the percentage observed of each code for the carcass and parts constraints for each year. Summary graphs of the capacity and funds constraints are available in Appendix A. The primary concern are the missing values for parts which might be causing extended MICAP lengths. While the number of missing values for parts have trended downward due to changes in the logic of the Supportability Module in 2016, the issue is still prevalent.

As compared to the ALC data, the HQ EXPRESS data is complete such that there are no empty values for parts, capacity or fund availabilities because all constraints are checked individually instead of sequentially. Unfortunately, the HQ data were available only for 2018. However, this data provides an idea of the usual truth

Figure 7. *Summary of Carcass and Parts ALC Data*

concerning the constraint codes that are sometimes missing in the ALC data.

Although the HQ table does not have the missing data issue that plagues the ALC data, it is not without problems. The primary stock number used to identify parts in the Air Force is the National Item Identification Number (NIIN). The repairs listed in the EXPRESS tables each concern unique NIINs. A NIIN is only included in the table on a certain day if a repair is needed on that day. This leaves massive holes in the data for the majority of NIINs. Even when a NIIN is included in the table on a certain day, there are often no resource constraint failures which means the repair can be completed right away. While it is good that the majority of NIINs have minimal carcass and parts failures, the sparsity of the data can cause issues with modeling approaches when attempting to relate the HQ data to MICAPs. Of all the NIINs in the 2018 HQ table, 58.6% had no carcass failures, 50.8% had no parts failures and 79.5% had no missing parts failures. A NIIN has missing parts failures if there were both carcass and parts failures for an observation meaning that the parts failure would have been masked in the ALC data.

In 2018, some repairs involving certain NIINs struggled with the carcass constraint more than with the parts constraint, while many struggled with both. From left to right, the three tables within Table 4 show the NIINs with the highest occurrence of carcass failures, parts failures and missing parts failures. The top offending NIIN for carcass failures was 12368313, which is a component of a C-135 variant. The top offending NIIN for parts failures was 15614960, which is a component of a C-130 variant. The NIIN involved in repairs that most often had parts failure issues missing in the ALC data was 5675873, which is a component of a C-135 variant.

Table 4. *Top NIINs for Carcass Failures, Parts Failures and Missing Parts Failures*

Rank	NIIN	Carcass Failures	NIIN	Parts Failures	NIIN	Parts Missing
1	12368313	31919	15614960	82337	5675873	21758
2	5675873	22142	15614963	33501	13035871	16312
3	12308578	21642	11479116	30774	13134227	13869
4	15229461	19609	11402105	24532	14679426	13168
5	13297411	17393	145395245	22745	145395245	12276
6	12043672	16606	5675873	22058	13508048	12110
7	13035871	16502	145393070	19579	13297411	11480
8	2499370	16244	10862249	19517	11428094	11325
9	15954096	15371	10833837	19213	12267238	11280
10	13134227	14410	12267238	18663	8188189	11248
11	8188189	13910	14478547	18628	13035872	10609
12	14111338	13517	7961672	17957	12043672	10369
13	14679426	13303	13035871	17656	15994049	10327
14	12828769	13190	13508048	16686	9831597	10261
15	14696512	12922	11106043	16346	14223330	9501
16	145395245	12867	11460722	15431	13586178	9396
17	15867702	12838	10696588	15236	16265537	8756
18	14429628	12665	13134227	14307	12572789	8277
19	9141329	12646	16265537	14224	14429628	8193
20	12773879	12269	11428094	13779	12562481	8091
21	13508048	12250	2671046	13714	11479116	7802
22	13247734	11737	14679426	13343	14696512	7788
23	11428094	11486	11438543	12086	11892936	7503
24	12267238	11481	13381380	12042	2671046	7483
25	13035872	10995	7849693	11926	14444195	7162

The final data set contains MICAP days, which is one of the foremost issues plaguing the Air Force. The MICAPs represent a potential consequence of the logic of Supportability Module that leaves massive holes the data. Some individual parts of an aircraft are considered necessary for mission completion. When these parts break, the aircraft is put into MICAP status. The MICAP data includes the beginning and ending dates of each MICAP record spanning a wide number of years. Data exists for years 1951 to 2018. Every MICAP day is another day when the Air Force has limited mission capability. As such, MICAP days are an effective performance metric for maintenance data to analyze the potential impacts of the current Supportability Module logic as compared to the HQ Supportability Module logic. Minimizing MICAP days saves time and money and enhances mission readiness.

This analysis was concerned with MICAPs that either started in years prior and were still active as of this writing or those that started in 2018. There were 465,473 observations meeting this criteria. While the MICAP data is more complete than the ALC data, there are additional complications. Each MICAP is assigned a unique document number, but most documents contain a number of observations spanning different dates. This can cause some confusion when trying to extract the beginning and ending dates of each MICAP. The example data in Table 5 shows one MICAP involving an F-15 part at Kadena Air Base that started on 2/21/2018 and ended in 3/16/2018, but this information is contained in multiple rows that track various status changes.

Additionally, some of the records do not include an ending date. Some include only a starting date presumably because the MICAP had not ended as of the date the data was pulled. However, there are clearly some data mismanagement issues since there are ongoing MICAPs from the 1960s and earlier. Obviously, these MICAPs are not ongoing, but were never officially closed. For this analysis, it is assumed that each MICAP document number represents one continuous MICAP and the earliest MICAP start date and latest MICAP stop date are used to form the duration. The majority of MICAPs have a length of a few days or less. In many cases, MICAPs last only hours because components are cannibalized from other aircraft at the source of repair. For this analysis, information up to 31 October 2018 was available.

Table 5. *MICAP Document Number FB52708052800*

MICAP Document Number	MICAP Sequence	Start Date	Stop Date	NIIN
FB52708052800	1	2/21/2018	2/25/2018	16136577
FB52708052800	2	2/25/2018	NULL	16136577
FB52708052800	3	2/25/2018	3/16/2018	16136577

3.3 Limitations

This analysis intended to show that problems with the ALC Supportability Module logic were contributing to issues with mission capability and resource (time and money) waste. Making a connection between the ALC and MICAP data by requirement was necessary so that models like multiple linear regression and decision trees could show if missing fields in the ALC data were conducive to increasing MICAP lengths and whether providing a more complete picture of the constraints tended to decrease the length of MICAPs. However, there were a number of issues that prohibited the use of this methodology.

Clearly, there are many moving parts in the supply chain process. Since these data sets encapsulate the entire Air Force, there are many complications. Repair shops and maintainers worldwide are constantly fighting for resources. Since EXPRESS is run every day, the daily changes in priorities makes the four resource constraints convoluted. For example, an aircraft at Luke AFB might be waiting a week for a specific part. On day 8, the part is finally available, but a higher priority repair at Langley AFB that was added the day prior consumes the part. Some actions, or requirements, from the NRO can simply be canceled if the Air Force no longer needs the repair. Additionally, some repairs may be supported laterally, which means parts were swapped between planes. While this solves the issue with one plane, the other plane now has the exact same issue. These issues contribute to the fact that it is not possible to follow a single maintenance requirement through the entire process to see how missing data could have contributed to a MICAP. These limitations diverted the direction of this analysis to manipulating the data via aggregation at the NIIN level to provide an upper bound on the possible benefits of eliminating the missing data issue at the ALC level.

3.4 Data Manipulation

A significant portion of this study was devoted to data manipulation. As stated previously, it was not possible to follow specific repair requirements through the entire process. However, the data could still be aggregated by NIIN and values could be matched between the HQ and MICAP tables.

Initially, the data was aggregated at the annual level. Each repair requirement in the HQ table is complete in relation to carcass, parts, capacity and funds values, making it is easy to infer which fields would have been missing in the ALC tables. For example, if there was a failure for carcass, then the parts, capacity and funds fields would be missing. For all of 2018, the number of failures per NIIN for carcass, parts, capacity and funds were collected. In addition, the number of failures for parts, capacity and funds that would have been missing in the ALC table were counted. From these values, the percent of time that parts, capacity and funds failures were visible for each NIIN were computed. In addition, after extracting the minimum and maximum MICAP dates for each unique MICAP document, the number of MICAPs and the average and maximum length of MICAP in hours was found for each NIIN. Data from each source was then merged by NIIN.

When the first iteration of analysis yielded minimal results, another approach was considered. Aggregating the data at the annual level seemed to smooth out any possible relationship in the data. Obviously, there are cyclical trends in maintenance data. In the HQ data, one NIIN might trend upward in capacity failures during one week and downward during the next week. There are similar trends in the MICAP data. Accordingly, the data should be aggregated at the daily instead of annual level to capture these kinds of trends. Further, it was noted that AFSC only plays a direct part in the carcass and parts requirements, so capacity and funds were not especially relevant to this analysis. For these reasons, the number of failures per NIIN per day for carcass and parts, in addition to the number of missing parts failures, were collected using the R software. The entirety of the code used for data manipulation and time series analysis is available in Appendix B for reproducibility. Figure 8 shows an example of the resulting data for NIIN 11428094.

niin	date	Carcass_Failures	Parts_Failures	Parts_Missing
11428094	2018-01-03	77	77	77
11428094	2018-01-04	75	78	75
11428094	2018-01-05	76	79	76
11428094	2018-01-10	75	78	75
11428094	2018-01-11	76	79	76
11428094	2018-01-12	75	79	75
11428094	2018-01-16	69	74	69
11428094	2018-01-17	69	74	69
11428094	2018-01-18	72	75	72
11428094	2018-01-19	73	76	73
11428094	2018-01-22	72	75	72
11428094	2018-01-23	71	74	71
11428094	2018-01-24	71	74	71
11428094	2018-01-25	74	77	74
11428094	2018-01-26	74	77	74
11428094	2018-01-29	73	76	73
11428094	2018-01-30	14	21	14
11428094	2018-01-31	72	79	72

Figure 8. *Daily Aggregated HQ Sample Data*

One major issue is apparent in Figure 8. Parts failures are only missing if there were carcass and parts constraint failures for a repair. This means that the missing parts failures for a day often matches the lesser of the daily count of carcass and parts failures, which happens in most cases. If there are major carcass failure issues for a NIIN, then the number of parts failures missing would match the daily count of parts failures since the majority of parts issues would be masked in the ALC table.

Conversely, if there are minimal carcass failure issues for a NIIN, then the number of parts failures missing would match the daily count of carcass failures since the majority of parts issues would be visible in the ALC table. This is a significant multicollinearity problem that must be accommodated. For this reason, any models involving the missing parts failures variable are formed absent of the carcass and parts failures variables for the remainder of this study.

The number of ongoing MICAPs per day were also calculated using a multistage process. As discussed previously, the duration of each unique MICAP document was found by extracting the minimum and maximum MICAP date as a first step. This resulted in a table of MICAPs with a sample provided in Figure 9. Next, for each pair of NIIN and date, the number of ongoing MICAPs was found using the MICAP duration table. This step simply counted the number of active MICAP documents involving each NIIN on each day. This value could be more than one if a NIIN was involved in multiple MICAPs during a given day.

niin	MICAP.Document.Number	Start	End
11428094	FB203980090559	2018-01-19	2018-02-13
11428094	FB203980121245	2018-01-24	2018-03-05
11428094	FB203980130530	2018-01-26	2018-03-22
11428094	FB203980171961	2018-01-26	2018-04-03
11428094	FB203980270331	2018-02-15	2018-04-03
11428094	FB203980321793	2018-02-15	2018-04-05
11428094	FB203980450288	2018-02-15	2018-04-03
11428094	FB203980730936	2018-03-19	2018-04-03
11428094	FB203980730946	2018-03-19	2018-04-03
11428094	FB203980730953	2018-03-19	2018-04-17

Figure 9. *MICAP Document Durations Sample Data*

The two resulting HQ and MICAP data sets were merged by both NIIN and date. The final data set presented a number of issues that would have to be addressed. First, the HQ data suffers from missing data differently than the ALC data. There are missing dates in the HQ EXPRESS table which happens in two situations. When there are no repairs necessary for a NIIN on a certain day, there are no inclusions of that NIIN in the table on that date. Also, EXPRESS data is unavailable on the weekends. These issues are addressed using data imputation techniques before running time series models.

Further, time series models rely on sufficient amounts of training data. For many NIINs, there were little to no occurrences in the HQ table simply because they needed few repairs in 2018. Even when observations were not missing, the majority of NIIN and date pairs contained zeros for constraint failures because EXPRESS deemed that the repair could be made right away. Likewise, many NIINs were involved in few MICAPs in 2018. Additionally, there were NIINs involved in MICAPs that would never appear in the HQ table because those repairs are outside of Air Force control. No meaningful connection can be made between constraint failures in the EXPRESS table and MICAPs without adequate amounts of training data. For these reasons, a subset of ten NIINs that had sufficient data available were chosen for analysis. The main connection of interest to be made was between missing parts failures and MICAPs. Accordingly, the ten NIINs that had the most missing parts failures and at least 100 ongoing MICAPs in 2018 were chosen. For these ten NIINs, the number of carcass failures, parts failures, missing parts failures and MICAP documents in 2018 are shown in Figure 10. They were involved in 2,017 ongoing MICAPs in 2018.

niin	Carc_Failures	Parts_Failures	Parts_Missing	NumberOfDocuments
792295	5762	6376	5703	120
11402105	6938	24532	6863	143
11428094	11486	13779	11325	234
12043672	16606	10369	10369	225
12511153	5909	6769	5590	435
12902065	7469	8630	7007	105
13134227	14410	14307	13869	322
14429628	12665	8218	8193	132
14696512	12922	7788	7788	107
145395245	12867	22745	12276	194

Figure 10. *Annual Counts for Subset of NIINs*

3.5 Methodology

As previously discussed, two views of the data were taken, at the annual and daily level. First, a top-level approach using summarized supportability and MICAP data over an entire year attempted to connect missing supportability data to MICAPs. The variables of interest for each NIIN were the percent of time maintainers were blind to constraint issues and the number of MICAPs, maximum length of MICAP and average length of MICAP in 2018. Simple correlation analysis and graphical procedures were used on the annual data which both showed that a connection between missing parts supportability data and MICAP days could not be meaningfully established at the annual level.

In the second method, rather than aggregating data over the entire year, a time-series analysis approach was used with the data aggregated at the daily level. For each day and each NIIN in the HQ data, the number of carcass failures, parts failures, missing parts failures and the number of ongoing MICAPs were counted. While this approach still does not allow for the tracking of a particular repair requirement over time to see potential opportunities for a reduction in MICAP days, these savings can still be estimated.

Time Series Analysis Approach

An unknown is the connection between the EXPRESS data and MICAPs. According to representatives from AFSC, there are certain trends in the EXPRESS data. Carcass problems usually arise first. When these issues are resolved or reserve carcasses are expended, parts problems come next. It is hypothesized that MICAPs follow some time after carcass and parts problems. Knowing that there are cyclical trends in maintenance data, running time series models may be the best approach to establishing a relationship between these variables.

For this study, a dynamic model is used because multiple explanatory variables are available to predict a dependent variable. The dependent variable of interest is the daily count of active MICAPs. In dynamic models, lags of the predictor variables are used. Lags are past observations of each variable. There are multiple types of dynamic models depending on whether the dependent or independent variables or a combination of both should be used to predict future values of the dependent variable.

Time series model selection requires careful consideration. It is hypothesized that carcass and parts failures in addition to previous MICAPs are contributing to future MICAPs. It would be tempting to use a simple distributed lag model where future MICAPs are predicted using many lags of the carcass and parts failure time series. However, the first step to time series analysis is to establish the order of integration of each variable. This refers to the stationarity of the time series. Establishing the stationarity of the time series is analogous to performing hypothesis tests to find a unit root. It is customary to perform more than one test to check for stationarity. In this study, two common methods to test for a unit root, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test, are used. The ADF test uses the model in Equation 2 and involves a hypothesis test where the null is that δ equals zero [24]. In the equation, the user supplies k, the number of lags to include in the model. Clearly, this is an autoregressive process as the variable is regressed on its past values.

$$\triangle y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{k} \beta_i \triangle y_{t-1} + e_t \tag{2}$$

Conversely, the PP method is a non-parametric test that uses the model in Equation 3. One difference between the methods is the inclusion of a deterministic trend component, D [24]. Similarly to ADF, the hypothesis test checks whether the coefficient on the first lag of y (π) equals zero.

$$\triangle y_t = \pi y_{t-1} + \beta_i D_{t-i} + e_t \tag{3}$$

Analysis in the subsequent chapter shows that the EXPRESS and MICAP time series are primarily non-stationary, meaning they exhibit a trend and have a nonconstant mean over time. A distributed lag model requires that both the dependent and independent variables are stationary. If that model were used with this data, a high R-squared value would suggest a great model fit simply because of spurious regression. Due to the non-stationarity of both the dependent and independent variables, model output might show significant relationships that do not represent the truth. One solution may be to take the first difference of each variable and fit the model, but this eliminates any long-term relationships that can be gleaned from the output [24]. Additionally, it is intuitive to expect that past MICAPs, in addition to carcass and parts failures, are contributing to future MICAPs.

For these reasons, the ARDL model was chosen as the primary model for this analysis. This model was originally conceived by Pesaran and Shin [25]. In the ARDL model, both the dependent and independent variables are used to predict future values of the dependent variable. The benefit of the ARDL model is that the independent variables can be either I(0) or I(1). However, the dependent variable must be I(1) since meaningful results cannot be attained with a stationary dependent variable that has repeated, cyclical patterns. Specifically, the dynamic error correction variant of the ARDL is used. This model utilizes both lagged values and lagged differences to predict a future change in the dependent variable and allows extraction of both short and long-term relationships. There are numerous methods for selecting the number of lags in the ARDL model. However, according to AFSC, it is reasonable to expect that EXPRESS failures have a weekly impact on future MICAPs as far as one month out. For this reason, four iterations of error-corrected ARDL models are fit with lags of seven, fourteen, twenty-one and twenty-eight days. As mentioned previously, there are collinearity issues between the carcass and parts failure time series and the missing parts failures. For this reason, two separate models are fit. Equation 4 is the seven day lagged ARDL model using carcass and parts failures. Since lags are cut off at seven days, this is a finite model [24].

$$\begin{aligned}\triangle MICAPs_t = \alpha_0 + \sum_{i=1}^{7} \beta_i \triangle MICAPs_{t-i} + \sum_{i=1}^{7} \gamma_i \triangle CarcassFailures_{t-i} + \\ \sum_{i=1}^{7} \delta_i \triangle PartsFailures_{t-i} + \lambda_1 MICAPs_{t-1} + \lambda_2 CarcassFailures_{t-1} + \\ \lambda_3 PartsFailures_{t-1} + u_t\end{aligned} \tag{4}$$

where:

$MICAPs$ = Number of Active MICAPs

$CarcassFailures$ = Number of Carcass Failures

$PartsFailures$ = Number of Parts Failures

u = Error Term

Obviously, the remaining iterations of the model simply include more lagged differences of the variables. Equation 5 shows the second model of interest involving the missing parts failures.

$$\triangle MICAPs_t = \alpha_0 + \sum_{i=1}^{7} \beta_i \triangle MICAPs_{t-i} + \sum_{i=1}^{7} \delta_i \triangle PartsMissing_{t-i} + \lambda_1 MICAPs_{t-1} + \lambda_2 PartsMissing_{t-1} + u_t \quad (5)$$

where:

$PartsMissing$ = Number of Parts Failures Missing in EXPRESS table

The coefficients in these models are interpreted in the usual way as with all regression models. The long-run coefficients describing the impact of constraint failures on the number of MICAPs can be calculated from these coefficients in a process described in the subsequent chapter.

As with all regression methods, there are a number of model assumptions that should hold in order to trust the results. Residual diagnostic tests are most important for ARDL models. It is crucial that the residuals are not autocorrelated. In this analysis, the Breusch-Godfrey test is employed to check for autocorrelation in the residuals. Also important is that the residuals are independently and identically distributed and can be considered white noise [24].

The benefit of using the error correction ARDL model is that Pesaran, Shin and Smith have developed a bounds test to see whether the variables in the model are cointegrated [26]. Variables that share a cointegrated relationship with each other have similar movement over time [24]. Referring to the coefficients from Equation 4, the ARDL bounds F-test process is the hypothesis test shown as Equation 6 [27].

$$\begin{aligned} H_0 &: \lambda_1 = \lambda_2 = \lambda_3 = 0 \\ H_A &: \text{At least one } \lambda \neq 0 \end{aligned} \tag{6}$$

As a secondary check, Pesaran et al. also include a t-test that uses the following hypotheses [27].

$$\begin{aligned} H_0 &: \lambda_1 = 0 \\ H_A &: \lambda_1 < 0 \end{aligned} \tag{7}$$

Equation 6 is a hypothesis test that the first-lagged variables are all equal to zero while Equation 7 tests whether the coefficient on the first-lagged dependent variable is equal to zero. Rejecting the null hypothesis indicates that there is a long-run relationship in the data [27]. This is useful information for trying to establish a relationship between the EXPRESS and MICAP data. Pesaran et al. [26] established critical values for performing both a t-test and an F-test. The relevant tables for this analysis are provided in Figure 11. In these tables, k refers to how many first-lagged variables there are in the model in excess of the lagged dependent variable. Use of these tables is demonstrated in the next chapter.

	0.100		0.050		0.025		0.010	
k	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
0	6.58	6.58	8.21	8.21	9.80	9.80	11.79	11.79
1	4.04	4.78	4.94	5.73	5.77	6.68	6.84	7.84
2	3.17	4.14	3.79	4.85	4.41	5.52	5.15	6.36
3	2.72	3.77	3.23	4.35	3.69	4.89	4.29	5.61
4	2.45	3.52	2.86	4.01	3.25	4.49	3.74	5.06
5	2.26	3.35	2.62	3.79	2.96	4.18	3.41	4.68
6	2.12	3.23	2.45	3.61	2.75	3.99	3.15	4.43
7	2.03	3.13	2.32	3.50	2.60	3.84	2.96	4.26
8	1.95	3.06	2.22	3.39	2.48	3.70	2.79	4.10
9	1.88	2.99	2.14	3.30	2.37	3.60	2.65	3.97
10	1.83	2.94	2.06	3.24	2.28	3.50	2.54	3.86

	0.100		0.050		0.025		0.010	
k	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$	$I(0)$	$I(1)$
0	−2.57	−2.57	−2.86	−2.86	−3.13	−3.13	−3.43	−3.43
1	−2.57	−2.91	−2.86	−3.22	−3.13	−3.50	−3.43	−3.82
2	−2.57	−3.21	−2.86	−3.53	−3.13	−3.80	−3.43	−4.10
3	−2.57	−3.46	−2.86	−3.78	−3.13	−4.05	−3.43	−4.37
4	−2.57	−3.66	−2.86	−3.99	−3.13	−4.26	−3.43	−4.60
5	−2.57	−3.86	−2.86	−4.19	−3.13	−4.46	−3.43	−4.79
6	−2.57	−4.04	−2.86	−4.38	−3.13	−4.66	−3.43	−4.99
7	−2.57	−4.23	−2.86	−4.57	−3.13	−4.85	−3.43	−5.19
8	−2.57	−4.40	−2.86	−4.72	−3.13	−5.02	−3.43	−5.37
9	−2.57	−4.56	−2.86	−4.88	−3.13	−5.18	−3.42	−5.54
10	−2.57	−4.69	−2.86	−5.03	−3.13	−5.34	−3.43	−5.68

Figure 11. *F-critical (top) and t-critical (bottom) values for ARDL bounds testing [26]*

IV. Analysis

4.1 Introduction

This chapter details the results of both modeling approaches using the annually and daily aggregated HQ supportability and MICAP data. Annual analysis related aggregated EXPRESS and MICAP data for all of 2018. When the annual analysis yielded minimal results, a time series regression approach using past daily data to predict future MICAPs was used. Specific steps included imputing missing EXPRESS data, establishing time series stationarity, fitting four ARDL models of differing lag lengths with carcass and parts failures as predictors, fitting an ARDL model with only missing parts failures as a predictor, testing model validity and testing for cointegration of the time series. Two modeling processes are shown in full involving NIIN 14429628, an F-15 part, and NIIN 14696512, an F-16 part. Summary output is provided for the remaining eight NIINs identified in Chapter 3.

4.2 Annual Analysis

Correlation Analysis

Before fitting any models with the annual data, graphs relating the variables of interest were formed before computing the Pearson correlation coefficient between each pair of variables. The variables of interest for each NIIN were the percent of time parts, capacity and funds failures were missing in the ALC supportability table, the number of MICAPs and the average and maximum length of MICAP in hours. All of these variables were collected using 2018 data. Three plots relating the parts, capacity and funds variables to the mean length of MICAP are shown in Figure 12. It is evident that there are minimal relationships between the variables. Plots relating the parts, capacity and funds variables to the number of MICAPs and maximum length of MICAP for each NIIN showed similar results. There are clearly NIINs that had minimal missing variable issues, but still had frequent and long MICAPs in 2018. Also, there are NIINs that had many missing variable issues, but did not suffer from many MICAP issues.

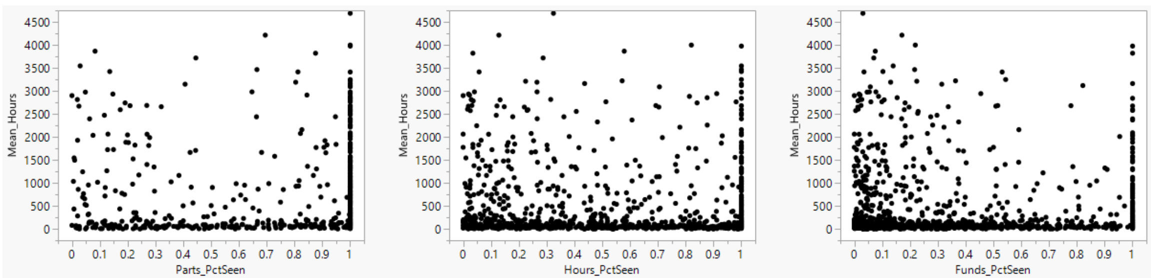

Figure 12. *Plots Relating Three Supportability Variables to Mean MICAP Length in Hours*

The Pearson correlation coefficients for each pair of variables were also calculated. These correlations are shown in Figure 13. The correlation between the percent of time parts, capacity and funds failures were missing in the ALC supportability table and the MICAP variables was minimal. These results indicated that any type of modeling approach, such as multiple linear regression, would fail to show any meaningful relationship between missing variable issues in the ALC table and MICAP lengths aggregated at the annual level. Using this information, a second approach using data aggregated at the daily level was implemented.

4.3 Daily Analysis

NIIN 14429628

Data Imputation

As discussed previously, the HQ EXPRESS data is not without missing data issues primarily due to weekends. If ARDL models were formed using the raw HQ data, many observations would be dropped due to missing data. The regions of missing data

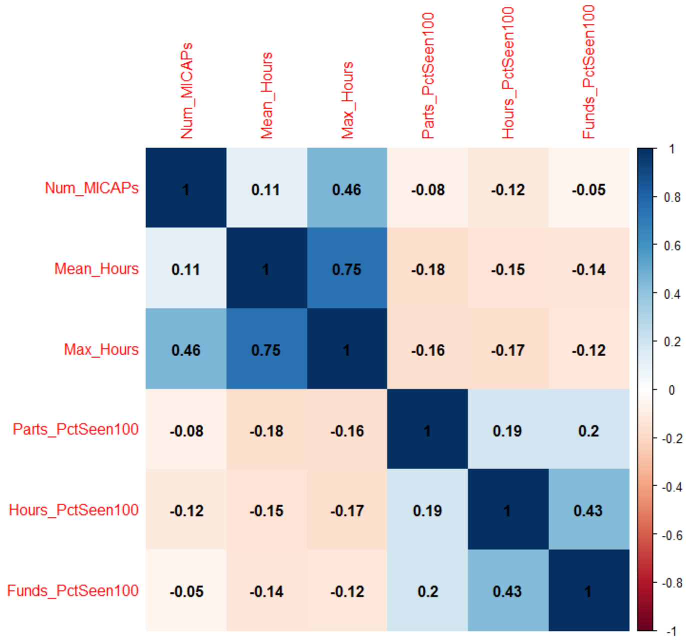

Figure 13. *Pearson Correlation Coefficient Values*

were filled using an imputation method within the R package imputeTS, which was developed specifically for imputation of missing data in time series variables [28]. The "last observed carried forward" technique was used for data imputation. Using the known data, this method fills gaps with values that were last observed. As opposed to more advanced methods, this method was chosen to preserve integer values and avoid artificially improving model performance by smoothing the independent variables. For NIIN 14429628, the imputation resulted in the full carcass failure data in Figure 14, in which the imputed data is highlighted in red. The same imputation method was used for parts failures and missing parts failures to prepare the data for modeling.

Unit Root Testing

The first step in any time series analysis is determining whether or not the time series are stationary or non-stationary. Time series with a constant, common mean over time are stationary. Looking at plots of the time series can give some idea of

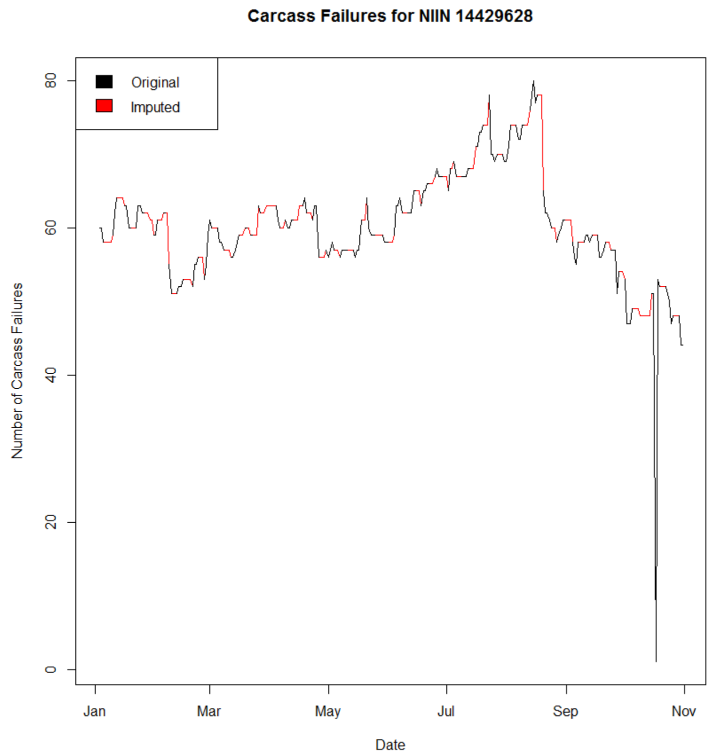

Figure 14. *Imputation Results*

the stationarity of a time series. Plots that resemble a sine wave would be considered stationary, while plots that show trends over time are non-stationary. There are multiple formal tests for a unit root, which time series have if they are non-stationary.

This analysis uses the Augmented Dickey-Fuller Test and the Phillips-Perron Unit Root Test. These tests are both easily performed using functions within the tseries package [29]. Time series that are deemed stationary are declared I(0), while those that become stationary after differencing once are considered I(1). Results are presented in Table 6.

A p-value exceeding 0.05 indicates a non-stationary time series. Both tests indicate that parts failures, missing parts failures and number of MICAPs are non-stationary. Since taking the first difference of these variables makes a stationary time series, they are I(1). However, there is a discrepancy between the two tests for carcass failures,

Table 6. *Unit Root Test Results*

	Variable	Level		First Difference	
Test		Statistic	p-value	Statistic	p-value
ADF	Carcass Failures	-1.4779	0.7964	-8.7191	<0.01
	Parts Failures	-1.321	0.8625	-6.451	<0.01
	Parts Missing	-1.2814	0.8792	-6.3972	<0.01
	MICAPs	-2.3554	0.4265	-6.7723	<0.01
PP	Carcass Failures	-37.568	<0.01	-368.58	<0.01
	Parts Failures	-5.5371	0.7999	-367.55	<0.01
	Parts Missing	-5.2293	0.8172	-365.2	<0.01
	MICAPs	-17.083	0.1525	-343.87	<0.01

which might be I(0) or I(1). As previously mentioned, the independent variables may be either I(0) or I(1) in the ARDL model, so this has minimal impact.

ARDL Models

The carcass failures, parts failures and number of MICAPs are shown visually in Figure 15. The number of MICAPs have a separate axis due to differing scales. From this plot, some idea of the relationship between the variables can be hypothesized.

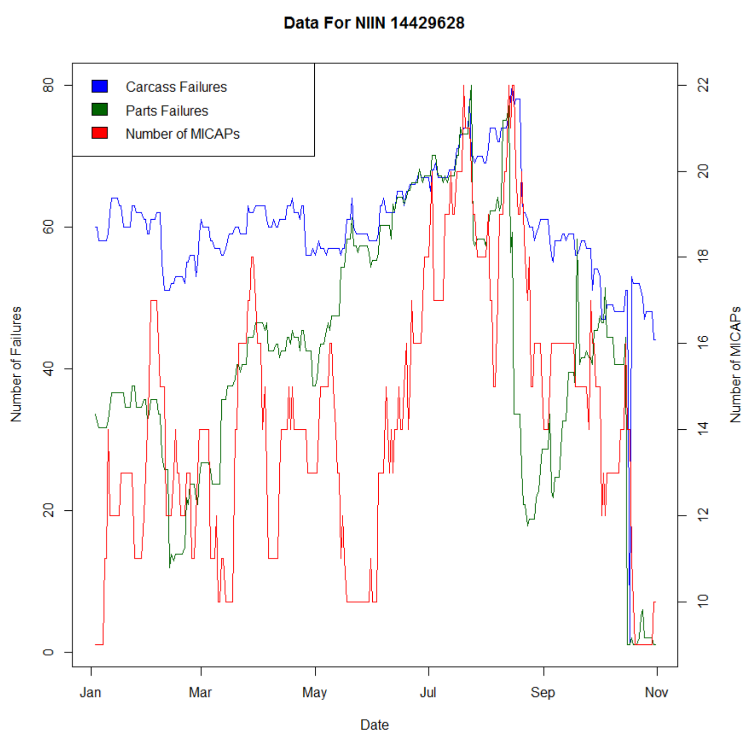

Figure 15. *MICAPs, Carcass Failures and Parts Failures for NIIN 14429628*

The error-corrected variant of the ARDL model was fit for lags of seven, fourteen, twenty-one and twenty-eight days using the dynamac package in R [30]. The independent variables were carcass and parts failures. The first model output is shown in Table 7. Lagged difference coefficients past seven days are omitted for brevity.

Table 7. *First ARDL Model Results*

	(7)	(14)	(21)	(28)
Constant	-0.435(0.573)	-0.897(0.622)	-1.802(0.824)**	-1.492(1.253)
l.1.NumMICAPs	-0.104(0.029)***	-0.118(0.035)***	-0.154(0.042)***	-0.122(0.055)**
l.1.Carcass_Failures	0.029(0.014)**	0.039(0.016)**	0.063(0.021)**	0.052(0.032)
l.1.Parts_Failures	0.004(0.005)	0.005(0.005)	0.005(0.005)	0.002(0.007)
ld.1.NumMICAPs	-0.026(0.06)	0.014(0.067)	0.061(0.07)	0.048(0.083)
ld.2.NumMICAPs	0.087(0.06)	0.089(0.066)	0.087(0.071)	0.073(0.083)
ld.3.NumMICAPs	0.051(0.059)	0.062(0.065)	0.111(0.07)	0.048(0.081)
ld.4.NumMICAPs	0.084(0.059)	0.115(0.065)*	0.163(0.07)**	0.145(0.08)*
ld.5.NumMICAPs	-0.064(0.059)	-0.057(0.065)	-0.067(0.07)	-0.05(0.08)
ld.6.NumMICAPs	-0.105(0.058)*	-0.054(0.064)	-0.051(0.069)	-0.053(0.079)
ld.7.NumMICAPs	0.104(0.058)*	0.077(0.064)	0.047(0.069)	0.024(0.077)
ld.1.Carcass_Failures	-0.013(0.02)	-0.021(0.023)	-0.041(0.025)	-0.031(0.036)
ld.2.Carcass_Failures	-0.004(0.022)	-0.012(0.024)	-0.031(0.027)	-0.028(0.036)
ld.3.Carcass_Failures	0(0.022)	-0.013(0.024)	-0.032(0.026)	-0.024(0.035)
ld.4.Carcass_Failures	-0.009(0.021)	-0.03(0.024)	-0.051(0.026)*	-0.041(0.034)
ld.5.Carcass_Failures	0.013(0.021)	-0.01(0.024)	-0.022(0.026)	-0.005(0.032)
ld.6.Carcass_Failures	-0.015(0.019)	-0.026(0.024)	-0.05(0.025)*	-0.044(0.032)
ld.7.Carcass_Failures	-0.009(0.015)	-0.011(0.024)	-0.026(0.026)	-0.017(0.031)
ld.1.Parts_Failures	0.002(0.013)	-0.001(0.014)	0.009(0.014)	0.012(0.016)
ld.2.Parts_Failures	0.021(0.015)	0.015(0.015)	0.012(0.016)	0.02(0.017)
ld.3.Parts_Failures	0.009(0.015)	0.003(0.016)	-0.001(0.016)	0.005(0.017)
ld.4.Parts_Failures	-0.006(0.015)	-0.007(0.016)	0.002(0.017)	0.003(0.018)
ld.5.Parts_Failures	-0.001(0.015)	0.004(0.016)	-0.003(0.017)	-0.004(0.018)
ld.6.Parts_Failures	-0.014(0.015)	-0.018(0.016)	-0.02(0.016)	-0.024(0.018)
ld.7.Parts_Failures	0.029(0.015)*	0.015(0.016)	0.015(0.017)	0.021(0.018)
R^2	0.1526	0.2406	0.3517	0.4229
Adjusted R^2	0.07702	0.09886	0.1508	0.1515
Residual Std. Error	0.9256(df = 269)	0.9172(df = 241)	0.8947(df = 213)	0.9005(df = 185)
F statistic	2.019***(df = 24;269)	1.697***(df = 45;241)	1.715***(df = 66;213)	1.558***(df = 87;185)

***p<0.01; **p<0.05; *p<0.1

Model selection was performed based on both R^2 values and model diagnostics performed in the next section. The final model chosen was the twenty-one day lag model. With an R^2 of 0.3517 and an adjusted R^2 of 0.1508, this is not a very strong model by most standards. However, there are still significant variables which can be interpreted in the usual way. As expected, the lagged value of MICAPs are significant in predicting changes in the number of MICAPs the following day. However, the lagged value of carcass failures is also significant in the model. This indicates that carcass failures are influential on future changes in the number of MICAPs in the long run. The actual long-run multiplier between carcass failures and the number of

MICAPs is calculated in Equation 8 [27]. The relevant values from Table 7 are the coefficients on the number of MICAPs and carcass failures, which were identified as λ_1 and λ_2 in Equation 4. One additional carcass failure leads to an increase of 0.409 MICAPs in the long run.

$$-\frac{\lambda_2}{\lambda_1} = -\frac{0.063}{-0.154} = 0.409 \tag{8}$$

Due to multicollinearity issues, a second model using only missing parts failures as a predictor was formed. Missing parts failures and the number of MICAPs are shown visually in Figure 16.

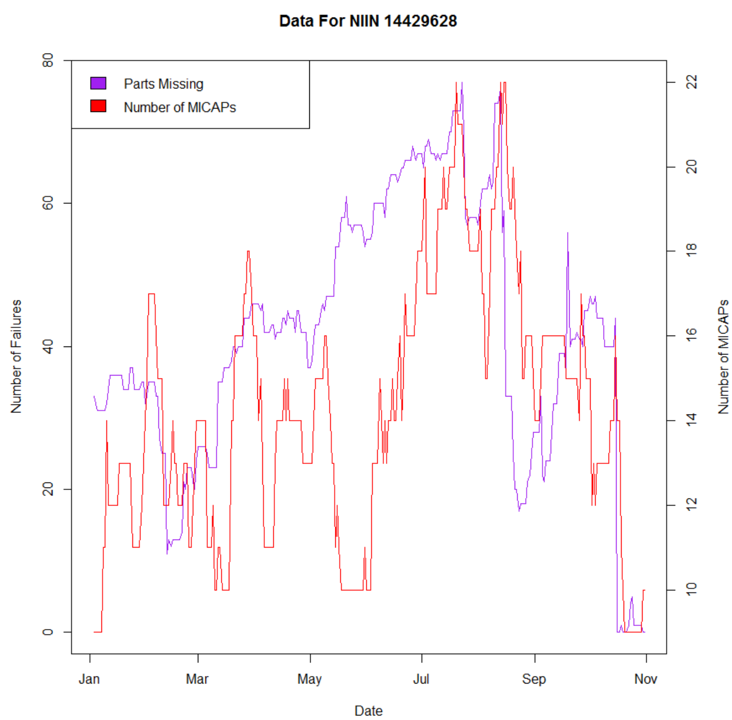

Figure 16. *MICAPs and Parts Failures Missing for NIIN 14429628*

Model results are shown in Table 8. With low R^2 values, this model also suffers from poor fit, but an interesting long run relationship was uncovered. Missing parts failures are significant predictors of MICAPs in the long run. The long-run multiplier between missing parts failures and the number of MICAPs is 0.197, indicating that one additional part failure that is missing in the EXPRESS table leads to an increase of 0.197 MICAPs in the long run.

Table 8. *Second ARDL Model Results*

	(21)
Constant	0.404(0.358)
l.1.NumMICAPs	-0.066(0.029)**
l.1.Parts_Missing	0.013(0.005)***
ld.1.NumMICAPs	-0.067(0.067)
ld.2.NumMICAPs	0.088(0.067)
ld.3.NumMICAPs	0.055(0.068)
ld.4.NumMICAPs	0.099(0.068)
ld.5.NumMICAPs	-0.101(0.068)
ld.6.NumMICAPs	-0.115(0.067)*
ld.7.NumMICAPs	0.046(0.068)
ld.1.Parts_Missing	0.004(0.014)
ld.2.Parts_Missing	0.02(0.014)
ld.3.Parts_Missing	0.007(0.014)
ld.4.Parts_Missing	-0.015(0.014)
ld.5.Parts_Missing	-0.013(0.014)
ld.6.Parts_Missing	-0.016(0.014)
ld.7.Parts_Missing	0.011(0.014)
R^2	0.2365
Adjusted R^2	0.0935
Residual Std. Error	0.9244(df = 235)
F-statistic	1.654***(df = 44;235)
	***p<0.01;**p<0.05;*p<0.1

Model Diagnostics

An important assumption for ARDL models is that the residuals are i.i.d. (independently and identically distributed). This implies that the residuals not autocorrelated and do not suffer from heteroskedasticity issues. Most important for ARDL models is that the residuals are not autocorrelated. Typical diagnostics involve performing autocorrelation and normality tests and viewing residual plots.

Two prominent tests are available within the dynamac package [30]. The Breusch-Godfrey test checks for autocorrelation and the Shapiro-Wilk test checks for normality. The output of these tests for the first twenty-one day lag model is shown in Figure 17. These tests indicate that there are no autocorrelation or normality issues since the null hypotheses cannot be rejected at the 95% confidence level. The normality of the residuals is confirmed by the quantile-quantile plot available in Appendix A which showed that no residuals caused the distribution to stray from normality. In addition, there were no heteroskedasticity issues evident when viewing a standard residual plot shown in Appendix A. The variance of the residuals does not change with time. Diagnostic tests for the second ARDL model with only missing parts failures as a predictor showed similar results, confirming a valid model. The twenty-one day lag model follows the necessary assumptions. With a well-behaved model, another logical step in time series analysis is testing for cointegration.

```
-----------------------------------------------------
Breusch-Godfrey LM Test
Test statistic: 1.802
p-value: 0.179
H_0: no autocorrelation up to AR 1

-----------------------------------------------------
Shapiro-Wilk Test for Normality
Test statistic: 0.993
p-value: 0.172
H_0: residuals are distributed normal

-----------------------------------------------------
```

Figure 17. *Diagnostic Test Results for First ARDL Model*

Cointegration Testing

Cointegration testing is a way to formally determine whether time series variables are in a long-term relationship. The ARDL bounds test proposed by Pesaran, Shin and Smith [26] can be used to see whether the time series in the model are cointegrated. The F and t statistics for the hypothesis tests are computed in R and compared to the critical values in Figure 11. When the F-statistic exceeds the upper critical value, there is significant evidence of cointegration. When the absolute value of the t-statistic exceeds the absolute value of the upper critical value, there is significant evidence of cointegration. Statistics that are within the bounds are inconclusive at that confidence level. Figure 18 shows the bounds test results for both ARDL models.

```
PESARAN, SHIN AND SMITH (2001) COINTEGRATION TEST

Observations: 280
Number of Regressors (k): 2
Case: 3

------------------------------------------------------
-                        F-test                      -
------------------------------------------------------
                   <------- I(0) ------------ I(1) ----->
10% critical value       3.17             4.14
5% critical value        3.79             4.85
1% critical value        5.15             6.36

F-statistic = 7.153
------------------------------------------------------
-                        t-test                      -
------------------------------------------------------
                   <------- I(0) ------------ I(1) ----->
10% critical value       -2.57            -3.21
5% critical value        -2.86            -3.53
1% critical value        -3.43            -4.1

t statistic = -3.652
------------------------------------------------------
```

```
Observations: 280
Number of Regressors (k): 1
Case: 3

------------------------------------------------------
-                        F-test                      -
------------------------------------------------------
                   <------- I(0) ------------ I(1) ----->
10% critical value       4.04             4.78
5% critical value        4.94             5.73
1% critical value        6.84             7.84

F-statistic = 7.318
------------------------------------------------------
-                        t-test                      -
------------------------------------------------------
                   <------- I(0) ------------ I(1) ----->
10% critical value       -2.57            -2.91
5% critical value        -2.86            -3.22
1% critical value        -3.43            -3.82

t statistic = -2.308
------------------------------------------------------
```

Figure 18. *Cointegration Tests for First (left) and Second (right) Model*

For the first ARDL model, the output indicates cointegration among the variables. The F-test indicates that cointegration is evident with 99% confidence since the F-statistic exceeds the upper 1% critical value. The t-test indicates that cointegration is present with 95% confidence. Since carcass failures were most significant in the model, it is likely that carcass failures and number of MICAPs have a cointegrating relationship. For the second ARDL model, the F-test suggests cointegration with 95% confidence and the t-test rejects that there is cointegration between the variables. Missing parts failures and the number of MICAPs may or may not be in a cointegrating relationship.

NIIN 14696512

Data Imputation

The same data imputation process was used for NIIN 14696512. The regions of missing data for carcass failures, parts failures and missing parts failures were filled using the "last observed carried forward" technique to prepare the data for further analysis.

Unit Root Testing

The Augmented Dickey-Fuller Test and the Phillips-Perron Unit Root Test were again performed on each time series of interest. Results are presented in Table 9. Both tests indicate that all four time series are I(1).

Table 9. *Unit Root Test Results*

	Variable	Level		First Difference	
Test		Statistic	p-value	Statistic	p-value
ADF	Carcass Failures	-1.7262	0.6917	-5.9844	<0.01
	Parts Failures	-1.8096	0.6566	-8.7385	<0.01
	Parts Missing	-1.8096	0.6566	-8.7385	<0.01
	MICAPs	-1.8388	0.6443	-5.6061	<0.01
PP	Carcass Failures	-6.1646	0.7647	-368.58	<0.01
	Parts Failures	-16.078	0.2089	-253.03	<0.01
	Parts Missing	-16.078	0.2089	-253.03	<0.01
	MICAPs	-7.3235	0.6998	-299.65	<0.01

ARDL Models

The time series variables for the data used to fit the first ARDL model are shown in Figure 19. The different time series seem to move together in some fashion. Model results are shown in Table 10.

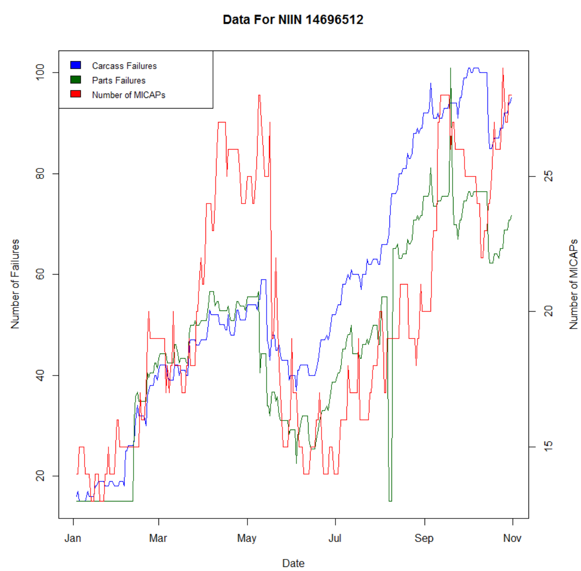

Figure 19. *MICAPS, Carcass Failures and Parts Failures for NIIN 14696512*

Based on both R^2 values and the model diagnostics performed in the next section, the seven day lag model was superior. The chosen model had a small R^2 of 0.153 and an adjusted R^2 of 0.07745. However, information can be gleaned from the significance of variables. Again, the lagged value of MICAPs were significant in predicting changes in the number of MICAPs the following day. In this model, both the lagged values of carcass and parts failures were also significant. This indicates that both carcass and parts failures influence daily changes in the number of MICAPs in the long run. The long-run multiplier between carcass failures and the number of MICAPs is -0.15, meaning an additional carcass failure leads to a decrease of 0.15 MICAPs in the long run. Parts failures, the more significant predictor, has a long-run multiplier of 0.38, meaning an additional parts failure leads to an increase of 0.38 MICAPs.

Table 10. *First ARDL Model Results*

	(7)	(14)	(21)	(28)
Constant	1.58(0.4)***	1.735(0.544)***	1.847(0.7)***	2.496(0.854)***
l.1.NumMICAPs	-0.097(0.023)***	-0.105(0.031)***	-0.11(0.04)***	-0.15(0.049)***
l.1.Carcass_Failures	-0.015(0.007)**	-0.019(0.008)**	-0.017(0.01)*	-0.002(0.079)
l.1.Parts_Failures	0.037(0.011)***	0.044(0.014)***	0.043(0.018)**	0.005(0.077)
ld.1.NumMICAPs	-0.014(0.06)	-0.01(0.065)	-0.016(0.073)	-0.037(0.078)
ld.2.NumMICAPs	-0.027(0.059)	-0.004(0.065)	-0.022(0.073)	0.114(0.077)
ld.3.NumMICAPs	-0.084(0.06)	-0.076(0.065)	-0.08(0.072)	0.122(0.079)
ld.4.NumMICAPs	0.063(0.06)	0.079(0.065)	0.08(0.071)	0.18(0.079)**
ld.5.NumMICAPs	0.049(0.06)	0.065(0.066)	0.057(0.071)	0.23(0.081)***
ld.6.NumMICAPs	0.075(0.06)	0.102(0.066)	0.116(0.072)	-0.027(0.012)**
ld.7.NumMICAPs	0.14(0.06)**	0.156(0.065)**	0.188(0.073)**	0.064(0.022)***
ld.1.Carcass_Failures	0.009(0.034)	0.014(0.036)	0.007(0.04)	0.017(0.043)
ld.2.Carcass_Failures	-0.064(0.034)*	-0.053(0.036)	-0.057(0.04)	-0.052(0.043)
ld.3.Carcass_Failures	0.074(0.034)**	0.079(0.036)**	0.066(0.04)	0.071(0.043)
ld.4.Carcass_Failures	-0.051(0.034)	-0.038(0.037)	-0.048(0.041)	-0.036(0.044)
ld.5.Carcass_Failures	0.001(0.034)	0.003(0.037)	-0.019(0.041)	-0.016(0.044)
ld.6.Carcass_Failures	0.003(0.034)	0.013(0.037)	0.016(0.041)	0.02(0.044)
ld.7.Carcass_Failures	0.034(0.034)	0.056(0.037)	0.044(0.042)	0.061(0.045)
ld.1.Parts_Failures	-0.027(0.016)*	-0.035(0.019)*	-0.03(0.022)	-0.052(0.026)
ld.2.Parts_Failures	-0.023(0.015)	-0.03(0.019)	-0.028(0.022)	-0.055(0.025)
ld.3.Parts_Failures	-0.029(0.015)**	-0.036(0.018)**	-0.033(0.022)	-0.055(0.026)
ld.4.Parts_Failures	-0.016(0.015)	-0.024(0.019)	-0.02(0.023)	-0.039(0.026)
ld.5.Parts_Failures	0.002(0.013)	0(0.019)	0.006(0.023)	-0.011(0.026)
ld.6.Parts_Failures	-0.012(0.013)	-0.022(0.019)	-0.013(0.023)	-0.03(0.026)
ld.7.Parts_Failures	-0.013(0.013)	-0.021(0.019)	-0.013(0.023)	-0.029(0.026)
R^2	0.153	0.2009	0.2473	0.3263
Adjusted R^2	0.07745	0.05169	0.0141	0.009429
Residual Std. Error	0.9412(df = 269)	0.9624(df = 241)	0.9899(df = 213)	0.998(df = 185)
F-statistic	2.025***(df = 24;269)	1.346*(df = 45;241)	1.06(df = 66; 213)	1.03(df = 87; 185)

***p<0.01; **p<0.05; *p<0.1

A second iteration of the chosen model was fit with only missing parts failures as a predictor. This model uses the data shown in Figure 20.

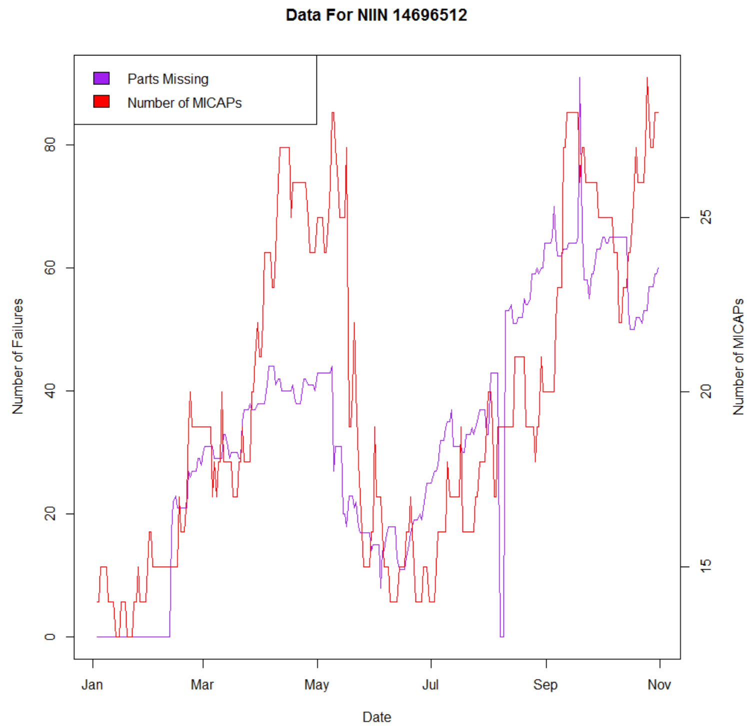

Figure 20. *MICAPS and Parts Failures Missing for NIIN 14696512*

The results of the second ARDL model are given in Table 11. Again, this model suffers from poor fit, but includes several significant predictors of interest. As expected, past values of MICAPs are significant predictors of future MICAPs. Additionally, missing parts failures are significant predictors of MICAPs in the long run. The long-run coefficient between missing parts failures and the number of MICAPs is 0.20, indicating that one additional part failure that is missing in the EXPRESS table leads to an increase of 0.20 MICAPs in the long run. The short-run coefficients offer no information of interest.

Table 11. *Second ARDL Model Results*

	(7)
Constant	1.058(0.323)***
l.1.NumMICAPs	-0.079(0.022)***
l.1.Parts_Missing	0.016(0.005)***
ld.1.NumMICAPs	-0.039(0.059)
ld.2.NumMICAPs	-0.006(0.059)
ld.3.NumMICAPs	-0.102(0.059)*
ld.4.NumMICAPs	0.069(0.059)
ld.5.NumMICAPs	0.061(0.059)
ld.6.NumMICAPs	0.074(0.06)
ld.7.NumMICAPs	0.129(0.06)**
ld.1.Parts_Missing	-0.011(0.013)
ld.2.Parts_Missing	-0.016(0.013)
ld.3.Parts_Missing	-0.009(0.013)
ld.4.Parts_Missing	-0.01(0.013)
ld.5.Parts_Missing	0.01(0.012)
ld.6.Parts_Missing	-0.003(0.012)
ld.7.Parts_Missing	-0.006(0.012)
R-Squared	0.09817
Adjusted R-Squared	0.04608
Residual Std. Error	0.957(df = 277)
F-statistic	1.885**(df = 16; 277)
	***p<0.01;**p<0.05;*p<0.1

Model Diagnostics

Before making any conclusions with confidence, model assumptions must be verified. The Breusch-Godfrey and Shapiro-Wilk tests were performed to rule out autocorrelation of the residuals and to check for normality of the residuals. The output of these tests for the first seven day lag model is shown in Figure 21.

```
-----------------------------------------------------
Breusch-Godfrey LM Test
Test statistic: 0.015
p-value: 0.902
H_0: no autocorrelation up to AR 1

-----------------------------------------------------
Shapiro-Wilk Test for Normality
Test statistic: 0.911
p-value: 0
H_0: residuals are distributed normal

-----------------------------------------------------
```

Figure 21. *Diagnostic Test Results for First ARDL Model*

There appears to be an issue with the distribution of the residuals that requires further investigation. The quantile-quantile plot for the residuals is shown in Figure 22. The residuals do not seem to follow the normal distribution and seemingly cannot be called white noise. While there are many problem residuals, the 136th and 251st are the most problematic. Upon further inspection, the number of ongoing MICAPs for the 135th observation, which was 19 May 2018, was 27. The number of MICAPs on the following day was only 19. This is an unusual drop and is easily visible in Figures 19 and 20. Observations such as this one are problematic for any type of predictive model. The non-normality of the residuals speaks to the noise and volatility of maintenance data. However, the most important assumption that there is not autocorrelation in the residuals is verified for this model. Additionally, there were little to no issues with heteroskedasticity evident when viewing a standard residual plot, which is available in Appendix A. Diagnostics for the second ARDL model produced similar results. Using the ARDL bounds test, the models were next checked for the presence of cointegration.

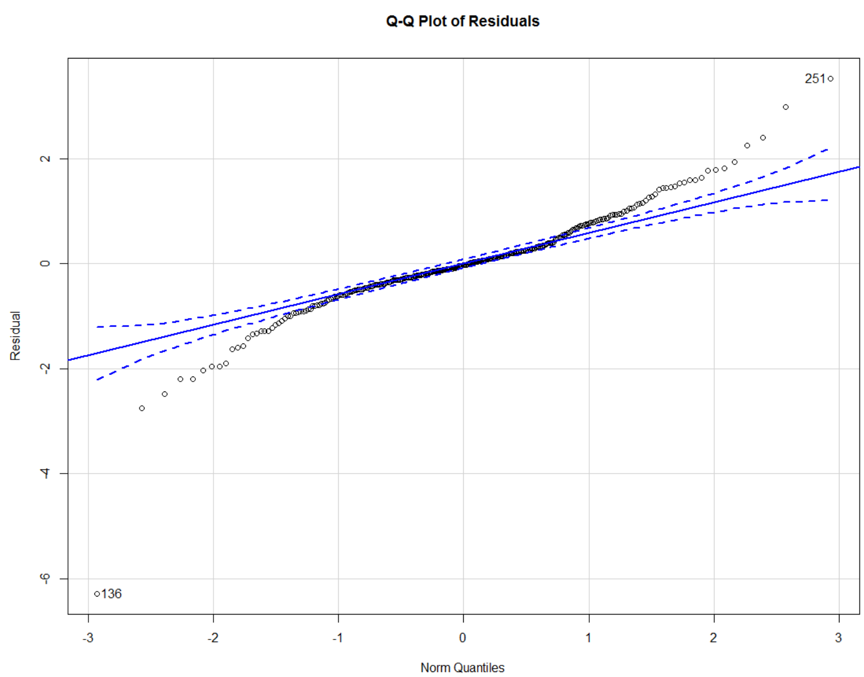

Figure 22. *Q-Q Plot of Residuals for First ARDL Model*

Cointegration Testing

Both models were tested for cointegration to see if the time series variables are in a long-term relationship. The F and t statistics calculated in R were compared to the critical values in Figure 11. Figure 23 shows the bounds test results for both models. The bounds tests overwhelmingly indicates cointegration among the time series in the first ARDL model since both the F and t statistics lie outside the critical value for 99% confidence. There is a cointegrating relationship between the number of MICAPs and carcass and parts failures. For the second ARDL model, the F-test suggests cointegration with 99% confidence and the t-test accepts the hypothesis of cointegration between the variables with 95% confidence. There is evidence of a cointegrating relationship between missing parts failures and the number of MICAPs.

```
PESARAN, SHIN AND SMITH (2001) COINTEGRATION TEST

Observations: 294
Number of Regressors (k): 2
Case: 3

------------------------------------------------------
-                       F-test                       -
------------------------------------------------------
                 <------- I(0) ------------ I(1) ----->
10% critical value       3.17             4.14
5% critical value        3.79             4.85
1% critical value        5.15             6.36


F-statistic = 7.977
------------------------------------------------------
-                       t-test                       -
------------------------------------------------------
                 <------- I(0) ------------ I(1) ----->
10% critical value       -2.57            -3.21
5% critical value        -2.86            -3.53
1% critical value        -3.43            -4.1


t statistic = -4.181
------------------------------------------------------
```

```
Observations: 294
Number of Regressors (k): 1
Case: 3

------------------------------------------------------
-                       F-test                       -
------------------------------------------------------
                 <------- I(0) ------------ I(1) ----->
10% critical value       4.04             4.78
5% critical value        4.94             5.73
1% critical value        6.84             7.84


F-statistic = 11.544
------------------------------------------------------
-                       t-test                       -
------------------------------------------------------
                 <------- I(0) ------------ I(1) ----->
10% critical value       -2.57            -2.91
5% critical value        -2.86            -3.22
1% critical value        -3.43            -3.82


t statistic = -3.646
------------------------------------------------------
```

Figure 23. *Cointegration Tests for First (left) and Second (right) Model*

Additional Models

Data from eight additional NIINs were analyzed using the ARDL approach. The summary results are available in Table 12 and additional statistics are available in Appendix A. For each NIIN, the model using carcass and parts failures is listed first followed by the model using missing parts failures. These models offered mixed results.

In cases such as NIIN 13134227, there was significant evidence of cointegration and evidence that each part failure missing from the EXPRESS table adds 0.424 MICAP days. In other cases, models suffered from poor fit and offered minimal evidence of cointegration. Sometimes, even past values of MICAPs were not great predictors of future MICAPs. Ultimately, these models exemplified the nature of maintenance data. These are parts from a variety of bombers, fighters and cargo aircraft and the EXPRESS data seemingly impacts MICAPs on differing timelines. The volatility of the data was evident again because each model suffered from issues with normality. While using time series models is arguably one of the best approaches to characterize any relationship between the EXPRESS and MICAP data, these issues suggest that there may be a better method than ARDL. Additionally, while it would be great if a "one size fits all" model could be fit and used daily to predict future MICAPs for all NIINs, this is infeasible since data from each NIIN should be treated as its own time series and such a model would produce results that could not be trusted.

Table 12. *Additional ARDL Model Results*

NIIN	Aircraft	Lag	Model	R-Squared	Adj R-Squared	Significant Terms (Long Run Coefficient)	Cointegration
13134227	F-15E	21	1	0.3377	0.1324	Carcass_Failures***(0.285)	13.843***;-5.398***
			2	0.2719	0.1355	Parts_Missing***(0.424)	22.622***;-5.012***
145395245	C-135	7	1	0.2891	0.2257	Carcass_Failures**(0.032)	2.04;-4.148***
			2	0.2809	0.2394	Parts_Missing**(0.031)	4.065ˆ;-4.246***
11428094	C-135	7	1	0.1843	0.1116		5.705**;-3.569**
			2	0.118	0.06702	Parts_Missing***(0.275)	13.853***;-3.714**
12043672	F-16	28	1	0.4075	0.1289	Parts_Failures**(1.714)	3.252ˆ;-0.612
			2	0.2278	0.01848	Parts_Missing**(0.793)	4.443ˆ;-1.012
12902065	C-135	28	1	0.4887	0.2482	Carcass_Failures*(-0.079); Parts_Failures**(0.073)	1.978;-2.556
			2	0.4174	0.2595		0.003;-3.433**
11402105	C-135	7	1	0.1116	0.0323		0.665;-3.374*
			2	0.08949	0.0369		0.199;-3.19*
792295	B-52 C-135	14	1	0.2209	0.07541		0.661;-2.912ˆ
			2	0.196	0.1018		1.704;-3.146*
12511153	F-15E	28	1	0.3949	0.1103	Parts_Failures**(0.477)	4.068ˆ;-2.522
			2	0.2832	0.08889	Parts_Missing*(0.302)	2.952;-1.444

***p<0.01; **p<0.05; *p<0.1; ˆinconclusive

V. Conclusions and Future Research

5.1 Conclusion

This research related EXPRESS data to MICAPs using ARDL models in the explanatory sense to find evidence of long-run relationships between relevant variables and explored the use of time series models for this purpose. As hypothesized, the EXPRESS data seemingly impacted MICAPs over time rather than instantaneously. In some cases, ARDL models showed that constraint failures, and the absence of constraint failures due to Supportability Module logic, in the EXPRESS table were significant predictors of future MICAPs up to 28 days out. In the two models presented in full, the long-run coefficient between missing parts failures and the number of MICAPs indicated that each additional parts failure that was missing in the EXPRESS table led to 0.197 and 0.2 additional MICAP days. Other models suggested that up to 0.793 MICAP days were added as a consequence of each parts failure that was masked in the EXPRESS table. Many models indicated the existence of cointegrating relationships, suggesting that the variables of interest seemed to move together over time. Overall, it seems that missing values in the supportability data impact mission capability in many cases. Carcass failures and parts failures, which are available in the HQ EXPRESS table, were also significant predictors of future MICAPs in most cases. This suggests that it may be helpful for maintainers to be looking at trends in the HQ data to best prevent future MICAPs. The HQ data is available to shops and maintainers, but is not as readily available as the ALC EXPRESS data and is not directly involved in the maintenance process. While many of the models offered interesting results, various model diagnostics suggested that the ARDL approach may not have been the best for maintenance data. Obviously, maintenance data is volatile over time. There are certain times when some parts require more repairs. Time series plots in this analysis showed noise in both the EXPRESS and MICAP data that would impede success of most forecasting methods, including ARDL which is regression-based. The volatility in the data led to non-normality of the residuals in most cases, violating a fundamental assumption and suggesting that any conclusions should be made with caution. There were often starkly atypical observations, such as sudden drops to zero parts failures, but it was assumed that the data used in this analysis was accurate. Precise data management is crucial to the success of any modeling procedure.

As a byproduct of this analysis, the potential for the use of time series models in forecasting maintenance data was explored. Even if these models were perfectly valid, periodically updating and fitting new time series models for the purpose of forecasting MICAPs would not be feasible. While a single "one size fits all" model would be great, data related to each unique NIIN is distinct and should be treated as separate time series. Additionally, while this study used NIINs with a sufficient amount of data available to fit ARDL models, many NIINs were not present in both the EXPRESS and MICAP data. For example, there were NIINs that required a lot of repairs, but had no MICAP documents associated with them. Further, recent changes in the Supportability Module logic reduced the percent of time that parts failures were missing such that only about 20% of NIINs that needed repairs in 2018 dealt with this issue. These observations suggest that the initial issue posed for this study may not be as prevalent as expected.

5.2 Future Research

This analysis used only data from 2018 due to limitations in the availability of the HQ EXPRESS data. Further analysis should be conducted as more data becomes available. Further, while this study looked at a subset of ten stock numbers, a more large-scale modeling procedure would be required to increase confidence in conclusions about any causation between EXPRESS data and MICAPs. This study attempted to relate the EXPRESS data to MICAPs, but many models exhibited poor fit. There may be a different dependent variable of interest that is better impacted by the EXPRESS data. However, there is the possibility that regression-based time series models such as ARDL are simply ill-suited for maintenance data due to noise and volatility. In this case, some of the newer nonlinear time series approaches might be considered. Time series modeling using advanced computing software is a growing field and new models will be developed in the future, some of which may be more appropriate for this data. Additionally, there seems to be randomness involved in this data. Sometimes, even past MICAP values are not an accurate predictor of future MICAPs. With randomness and probabilities involved, stochastic methods or simulation might be more appropriate for future modeling efforts with EXPRESS or MICAP data. Future research might involve examining other assumptions and logic in the Air Force supply chain process instead of the Supportability Module.

Appendix A

Additional ALC Summary Graphs

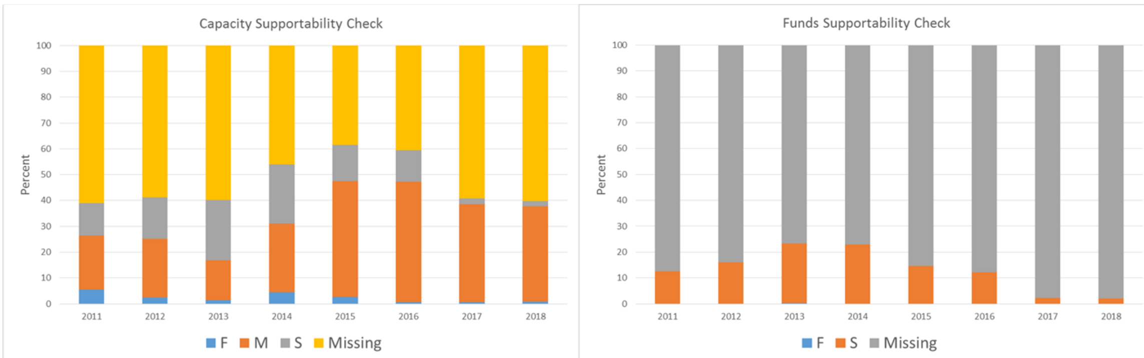

Figure 24. *Summary of Capacity and Funds ALC Data*

NIIN 14429628 21 Day ARDL Model Q-Q Plot

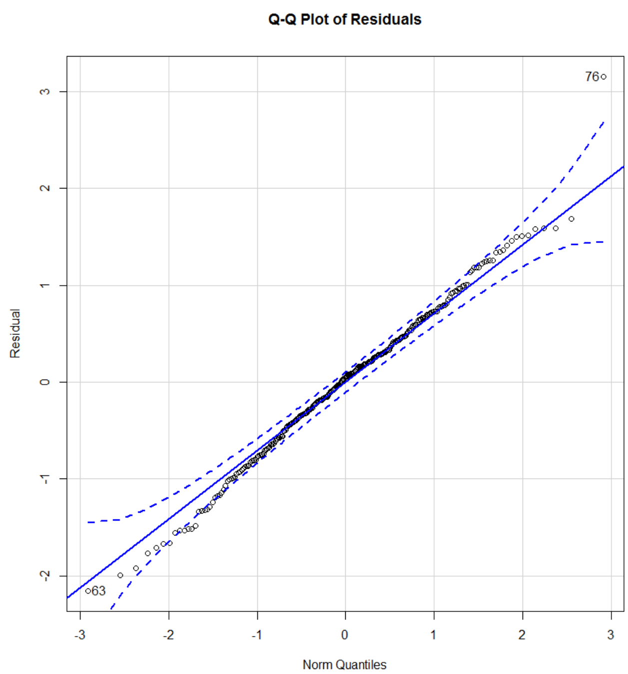

Figure 25. *Q-Q Plot of Residuals for First ARDL Model*

NIIN 14429628 21 Day ARDL Model Residual Plot

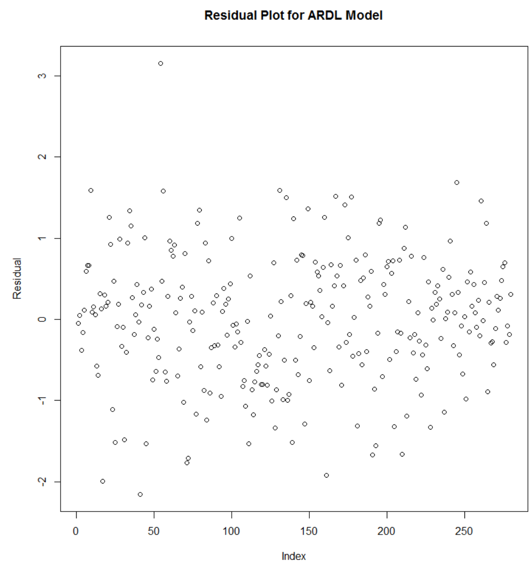

Figure 26. *Residual Plot for First ARDL Model*

NIIN 14696512 7 Day ARDL Model Residual Plot

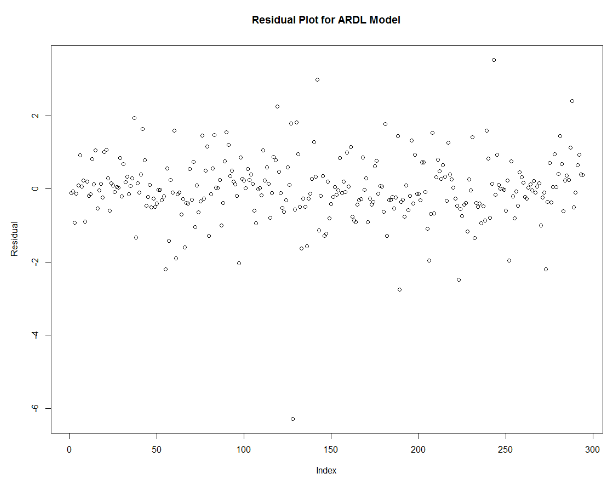

Figure 27. *Residual Plot for First ARDL Model*

Additional Model Statistics

Table 13. *Additional Statistics for Supplemental Models*

NIIN	Aircraft	Lag	Model	Res. Std. Error	F-statistic
13134227	F-15E	21	1	1.798(df = 213)	1.645***(df = 66;213)
			2	1.795(df = 235)	1.994***(df = 44;235)
145395245	C-135	7	1	1.76(df = 269)	4.558***(df = 24;269)
			2	1.744(df = 277)	6.764***(df = 16;277)
11428094	C-135	7	1	1.311(df = 269)	2.533***(df = 24;269)
			2	1.343(df = 277)	2.315***(df = 16; 277)
12043672	F-16	28	1	0.8256(df = 185)	1.463**(df = 87 ;185)
			2	0.8763(df = 214)	1.088(df = 58;214)
12902065	C-135	28	1	1.14(df = 185)	2.032***(df = 87;185)
			2	1.131(df = 214)	2.643***(df = 58;214)
11402105	C-135	7	1	1.323(df = 269)	1.408*(df = 24;269)
			2	1.32(df = 277)	1.702**(df = 16;277)
792295	B-52 C-135	14	1	0.5086(df = 214)	1.518**(df = 45;241)
			2	0.5012(df = 256)	2.08***(df=30;256)
12511153	F-15E	28	1	1.331(df = 185)	1.387**(df = 87;185)
			2	1.347(df = 214)	1.458**(df = 58;214)

***p<0.01; **p<0.05; *p<0.1

Appendix B

Packages Used in Analysis

```
library(data.table)

library(zoo)

library(dplyr)

library(imputeTS)

library(tseries)

library(dynamac)

library(car)

library(lubridate)

library(corrplot)

library(xtable)
```

MICAP Data Cleaning and Preparation

```
# Import data from csv file
MICAPs ← read.csv("MICAP Data v2.csv", header=TRUE)


# Remove leading zeroes in NIIN for to match format from
   EXPRESS tables
MICAPs$niin ← gsub("(?<![0-9])0+", "", MICAPs$NIIN, perl =
   TRUE)


# Replace any NULL values with NA for ease of use
MICAPs ← apply(MICAPs,2,function(x) suppressWarnings(levels(
   x)←sub("NULL",NA,x)))
MICAPs ← data.table(MICAPs)
```

```
# Format date columns as dates
MICAPs$StartDate <- as.Date(MICAPs$MICAP.Start.Date)
MICAPs$StopDate <- as.Date(MICAPs$MICAP.Stop.Date)

# Subsetting to the top 10 NIINs with missing values for
   parts that had at least 100 MICAPs in 2018
MICAP_Subset <- subset(MICAPs,niin==13134227|niin==145395245|
   niin==11428094|niin==12043672|niin==14429628|niin
   ==14696512|niin==12902065|niin==11402105|niin==792295|
   niin==12511153)

# Drop any observations that started after 10/31/2018
MICAP_Subset <- MICAP_Subset[MICAP_Subset$StartDate<="
   2018-10-31"]

# Finding the duration of each unique MICAP document
MICAP_Durations <- MICAP_Subset %>%
  group_by(niin,MICAP.Document.Number) %>%
  summarize(Start = min(StartDate), End = max(StopDate, na.
     rm = TRUE))

# If no maximum stop date was found, then there were no end
   dates for that MICAP on record - fill in with 10/31/2018
MICAP_Durations$End <- as.character(MICAP_Durations$End)
MICAP_Durations$End[is.na(MICAP_Durations$End)] <- "
   2018-10-31"
MICAP_Durations$End <- as.Date(MICAP_Durations$End)
```

```
# Creating data table of each NIIN with each date
# First date of data is 1/3/2018 and last date is 10/31/2018
time_series_full ← seq(ymd("2018-01-03"), ymd("2018-10-31"),
    by="day") # vector of relevant dates

# Creating repeated vectors of each NIIN to combine with the
    date vector
NIINs ← c(13134227, 145395245, 11428094, 12043672, 14429628,
    14696512, 12902065, 11402105, 792295, 12511153)
i = 1
for (value in NIINs){
  name ← paste("NIIN_", value, sep = "")
  assign(name,rep(value, length(time_series_full)))
}

# Combining into one data frame
NIIN_Vectors ← c(NIIN_13134227,NIIN_145395245,NIIN_11428094,
   NIIN_12043672,NIIN_14429628,NIIN_14696512,NIIN_12902065,
   NIIN_11402105,NIIN_792295,NIIN_12511153)
Date_Vector ← rep(time_series_full,10)

# Make a blank vector for number of MICAPs
NumMICAPs ← rep(0,length(Date_Vector))

# Check "MICAP_Durations" for each pair of NIIN/date to see
   if that date is between any of the start/end dates in
   that table
for (row in 1:length(Date_Vector)){
```

```
    NIIN ← NIIN_Vectors[row]
    date ← Date_Vector[row]
    datasubset ← subset(MICAP_Durations,niin==NIIN)
    NumMICAPs[row] ← sum(datasubset$Start<=date & datasubset$
       End>=date)
}

# Make final MICAP data table
MICAPsByNIINandDate ← data.table(NIIN_Vectors,Date_Vector,
   NumMICAPs)
colnames(MICAPsByNIINandDate) ← c("niin_id","date","
   NumMICAPs")
```

HQ EXPRESS Data Cleaning and Preparation

```
# Import data from csv file
HQ_Supp ← read.csv("HQ spt results v2.csv", header=TRUE)
HQ_Supp ← as.data.table(HQ_Supp)

# Forming a more understandable date column from "Date of
   Data"
colnames(HQ_Supp)[1] ← "DateOfData"
HQ_Supp$date ← substr(HQ_Supp$DateOfData,0,10)
HQ_Supp$date ← as.Date(HQ_Supp$date)

# Replacing carcass codes - B, F, P are all failures. S is
   success. New column will be 1 if there was a failure.
HQ_Supp$Carcass[!HQ_Supp$carc_avail == "S"] ← 1
HQ_Supp$Carcass[HQ_Supp$carc_avail == "S"] ← 0
```

```
# Replacing parts codes - F is a failure. B and S are
   success. New column will be 1 if there was a failure.
HQ_Supp$Parts[HQ_Supp$parts_avail == "F"] ← 1
HQ_Supp$Parts[!HQ_Supp$parts_avail == "F"] ← 0

# Counting number of failures per NIIN per day for carcass
Carcass_Failures ← HQ_Supp %>%
  group_by(niin_id, date) %>%
  summarize(Number_Failures = sum(Carcass))

# Counting number of failures per NIIN per day for parts
Parts_Failures ← HQ_Supp %>%
  group_by(niin_id, date) %>%
  summarize(Number_Failures = sum(Parts))

# Adding a column to check if a NIIN failed for carcass and
   parts
HQ_Supp$PartsMissing[HQ_Supp$Carcass == 1 & HQ_Supp$Parts ==
    1] ← 1
HQ_Supp$PartsMissing[is.na(HQ_Supp$PartsMissing)] ← 0

# Counting number of times per NIIN per day that there was a
    Carcass and Parts failure
Parts_Missing ← HQ_Supp %>%
  group_by(niin_id, date) %>%
  summarize(Number_Missing = sum(PartsMissing))
```

```
# Change format of data tables so information can be joined
    easily
Carcass_Failures ← as.data.table(Carcass_Failures)
Parts_Failures ← as.data.table(Parts_Failures)
Parts_Missing ← as.data.table(Parts_Missing)

# Join data tables
HQ_Table ← cbind(Carcass_Failures,Parts_Failures[,3],Parts_
    Missing[,3])
colnames(HQ_Table)[3:5] ← c("Carcass_Failures","Parts_
    Failures","Parts_Missing")

# Finding NIINs with the most failures over the year
HQ_Year ← HQ_Supp %>%
  group_by(niin_id) %>%
  summarize(Carc_Failures = sum(Carcass), Part_Failures =
     sum(Parts), Part_Missing = sum(PartsMissing))

# Viewing the correlation of the variables
M ← cor(HQ_Year[,c("Carc_Failures","Part_Failures","Part_
    Missing")])
corrplot(M,method="square")

# Calculating summary percentages
table(HQ_Year$Carc_Failures)[1]/dim(HQ_Year)[1] # percent of
     NIINs with NO carcass failures in year 2018
table(HQ_Year$Part_Failures)[1]/dim(HQ_Year)[1] # percent of
     NIINs with NO parts failures in year 2018
```

```
table(HQ_Year$Part_Missing)[1]/dim(HQ_Year)[1] # percent of
   NIINs with NO parts missing in year 2018

# Forming LaTeX tables of top offending NIINs
xtable(head(HQ_Year[order(HQ_Year$Carc_Failures,decreasing=
   TRUE),],25)[,c(1,2)],caption = "Top NIINs for Carcass
   Failures", digits = 0)
xtable(head(HQ_Year[order(HQ_Year$Part_Failures,decreasing=
   TRUE),],25)[,c(1,3)],caption = "Top NIINs for Parts
   Failures", digits = 0)
xtable(head(HQ_Year[order(HQ_Year$Part_Missing,decreasing=
   TRUE),],25)[,c(1,4)],caption = "Top NIINs for Parts
   Missing", digits = 0)
```

Merging Information from HQ and MICAP Data Tables

```
# Subsetting to the top 10 NIINs for carcass failures that
   had at least 100 MICAPs in 2018 (at least 100 unique
   MICAP document numbers)
HQ_Subset ← subset(HQ_Table,niin_id==13134227|niin_id
   ==145395245|niin_id==11428094|niin_id==12043672|niin_id
   ==14429628|niin_id==14696512|niin_id==12902065|niin_id
   ==11402105|niin_id==792295|niin_id==12511153)
HQ_Subset ← HQ_Subset[HQ_Subset$date <= "2018-10-31"]

# Merge with MICAP daily aggregated data
FullData ← merge(HQ_Subset,MICAPsByNIINandDate,by=c("niin_id
   ","date"), all=TRUE)
```

Preparing Data For Time Series Analysis

```
# Extract data for NIIN of interest from the 10 in the table
NIIN_Subset ← subset(FullData, niin_id == 14429628, select =
    c("niin_id","date","Carcass_Failures","Parts_Failures","
   Parts_Missing","NumMICAPs"))

# Form univariate time series data sets
carcass ← NIIN_Subset[,3]
parts ← NIIN_Subset[,4]
parts_missing ← NIIN_Subset[,5]
num_micaps ← NIIN_Subset[,6]
carcass_failures_zoo ← zoo(carcass, NIIN_Subset$date)
parts_failures_zoo ← zoo(parts, NIIN_Subset$date)
parts_missing_zoo ← zoo(parts_missing, NIIN_Subset$date)
num_micaps_zoo ← zoo(num_micaps, NIIN_Subset$date)

# Perform LOCF missing data imputation
carcass_failures_smooth ← na.locf(carcass_failures_zoo)
parts_failures_smooth ← na.locf(parts_failures_zoo)
parts_missing_smooth ← na.locf(parts_missing_zoo)
ts_df ← cbind(num_micaps_zoo,carcass_failures_smooth,parts_
   failures_smooth,parts_missing_smooth)

# Plots showing the interpolation for carcass failures, can
   be repeated for other variables - imputed values are
   shown in red
par(mar = c(5, 5, 5, 5))
plot(carcass_failures_smooth, type = "l", col = "red", ylab
   = "Number of Carcass Failures", xlab = "Date", main = "
```

```
    Carcass Failures")
par(new = TRUE)
plot(carcass_failures_zoo, type = "l", col = "black", xaxt =
     "n", yaxt = "n", ylab = "", xlab = "") # Parts
legend("topleft",legend = c("Original","Imputed"), col = c("
    black","red"), fill = c("black","red"), cex = 1)

# Plotting carcass failures, parts failures and MICAPs on
    the same plot with two y axes
par(mar = c(5, 5, 5, 5))
plot(ts_df[,2], type = "l", col = "blue", ylab = "Number of
    Failures", xlab = "Date") # Carcass Failures
par(new = TRUE)
plot(ts_df[,3], type = "l", col = "darkgreen", xaxt = "n",
    yaxt = "n", ylab = "", xlab = "") # Parts Failures
par(new = TRUE)
plot(ts_df[,1], type = "l", col = "red", xaxt = "n", yaxt =
    "n", ylab = "", xlab = "") # MICAPs
axis(side = 4)
mtext("Number of MICAPs", side = 4, line = 3)
legend("topleft",legend = c("Carcass Failures","Parts
    Failures","Number of MICAPs"), col = c("blue","darkgreen"
    ,"red"), fill = c("blue","darkgreen","red"), cex = 0.8)

# Plotting parts missing and MICAPs on the same plot with
    two y axes
par(mar = c(5, 5, 5, 5))
plot(ts_df[,4], type = "l", col = "purple", ylab = "Number
```

```
    of Failures", xlab = "Date") # Parts Missing
par(new = TRUE)
plot(ts_df[,1], type = "l", col = "red", xaxt = "n", yaxt =
    "n", ylab = "", xlab = "") # MICAPs
axis(side = 4)
mtext("Number of MICAPs", side = 4, line = 3)
legend("topleft",legend = c("Parts Missing", "Number of
    MICAPs"), col = c("purple","red"), fill = c("purple","red
    "), cex = 1)

# Form data set for dynamac package, which doesn't work with
     time series objects
df ← cbind(num_micaps, as.vector(carcass_failures_smooth),
    as.vector(parts_failures_smooth), as.vector(parts_missing
    _smooth))
colnames(df)[2:4] = c("Carcass_Failures", "Parts_Failures","
    Parts_Missing")
```

Performing Time Series Analysis

```
# Testing for unit root
# Augmented Dickey-Fuller Test
adf.test(carcass_failures_smooth)
adf.test(parts_failures_smooth)
adf.test(parts_missing_smooth)
adf.test(num_micaps_zoo)
adf.test(diff(carcass_failures_smooth))
adf.test(diff(parts_failures_smooth))
adf.test(diff(parts_missing_smooth))
```

```r
adf.test(diff(num_micaps_zoo))

# Phillips-Perron Test
pp.test(carcass_failures_smooth)
pp.test(parts_failures_smooth)
pp.test(parts_missing_smooth)
pp.test(num_micaps_zoo)
pp.test(diff(carcass_failures_smooth))
pp.test(diff(parts_failures_smooth))
pp.test(diff(parts_missing_smooth))
pp.test(diff(num_micaps_zoo))

# Running ARDL models for carcass and parts failures for
   lags of 7, 14, 21 and 28 days
my_model7 <- dynardl(NumMICAPs ~ Carcass_Failures + Parts_
   Failures, data = df, lags = list("NumMICAPs" = 1, "
   Carcass_Failures" = 1, "Parts_Failures" = 1), lagdiffs =
   list("NumMICAPs" = c(1:7), "Carcass_Failures" = c(1:7), "
   Parts_Failures" = c(1:7)), ec = TRUE, simulate = FALSE,
   trend = FALSE)
summary(my_model7)

my_model14 <- dynardl(NumMICAPs ~ Carcass_Failures + Parts_
   Failures, data = df, lags = list("NumMICAPs" = 1, "
   Carcass_Failures" = 1, "Parts_Failures" = 1), lagdiffs =
   list("NumMICAPs" = c(1:14), "Carcass_Failures" = c(1:14),
    "Parts_Failures" = c(1:14)), ec = TRUE, simulate = FALSE
   , trend = FALSE)
```

```
summary(my_model14)

my_model21 <- dynardl(NumMICAPs ~ Carcass_Failures + Parts_
   Failures, data = df, lags = list("NumMICAPs" = 1, "
   Carcass_Failures" = 1, "Parts_Failures" = 1), lagdiffs =
   list("NumMICAPs" = c(1:21), "Carcass_Failures" = c(1:21),
    "Parts_Failures" = c(1:21)), ec = TRUE, simulate = FALSE
   , trend = FALSE)
summary(my_model21)

my_model28 <- dynardl(NumMICAPs ~ Carcass_Failures + Parts_
   Failures, data = df, lags = list("NumMICAPs" = 1, "
   Carcass_Failures" = 1, "Parts_Failures" = 1), lagdiffs =
   list("NumMICAPs" = c(1:28), "Carcass_Failures" = c(1:28),
    "Parts_Failures" = c(1:28)), ec = TRUE, simulate = FALSE
   , trend = FALSE)
summary(my_model28)

# Check model diagnostics for chosen model
dynardl.auto.correlated(my_model21) # Function that checks
   for autocorrelation and normality of residuals
qqPlot(my_model21$model$residuals, ylab = "Residual", xlab =
    "Norm Quantiles", main = "Q-Q Plot of Residuals") # Q-Q
   Plot
plot(my_model21$model$residuals, ylab = "Residual", main = "
   Residual Plot for ARDL Model") # Checking for
   Heteroskedasticity
```

```
# Testing for cointegration of variables
pssbounds(my_model21)

# Running ARDL model for missing parts failures for chosen
    lag
my_model21 <- dynardl(NumMICAPs ~ Parts_Missing, data = df,
    lags = list("NumMICAPs" = 1, "Parts_Missing" = 1),
    lagdiffs = list("NumMICAPs" = c(1:21), "Parts_Missing" =
    c(1:21)), ec = TRUE, simulate = FALSE, trend = FALSE)
summary(my_model21)

# Check model diagnostics of model
dynardl.auto.correlated(my_model21) # Function that checks
    for autocorrelation and normality of residuals
qqPlot(my_model21$model$residuals, ylab = "Residual", xlab =
    "Norm Quantiles", main = "Q-Q Plot of Residuals") # Q-Q
    Plot
plot(my_model21$model$residuals, ylab = "Residual", main = "
    Residual Plot for ARDL Model") # Checking for
    Heteroskedasticity

# Testing for cointegration of variables
pssbounds(my_model21)
```

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REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704–0188

1. REPORT DATE *(DD–MM–YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From — To)*
21–03–2019	Master's Thesis	Sept 2017 — March 2019

4. TITLE AND SUBTITLE

Examining the EXPRESS Supportability Module: Implementing an Autoregressive Distributed Lag Approach with Air Force Maintenance Data

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

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5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

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8. PERFORMING ORGANIZATION REPORT NUMBER

AFIT-ENS-MS-19-M-151

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

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10. SPONSOR/MONITOR'S ACRONYM(S)

AFSC/LGPS

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT

Distribution Statement A:
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT EXPRESS (Execution and Prioritization of Repairs Support System) is a program integral to the Air Force reparable supply chain. Daily, EXPRESS relies on a number of data sources and modules like the Supportability Module to determine which necessary repairs can be made. The Supportability Module examines the prioritized list of repairs and checks four constraints in order to decide whether each repair can be made given current resources. A single constraint failure means that subsequent resource checks are not made before evaluating the next repair, leading to missing data in the EXPRESS table. In this study, a time series analysis via explanatory autoregressive distributed lag models was conducted using EXPRESS and MICAP (mission capability) data to examine possible connections between missing constraint values in the EXPRESS table and future MICAPs. These models suggested that up to 0.793 MICAP days are added for each additional parts failure missing in the EXPRESS table. The potential for the use of time series models with maintenance data was also explored. Model diagnostics suggest that maintenance data is too volatile and noisy for regression-based methods and that stochastic methods or simulation may prove more useful.

15. SUBJECT TERMS

EXPRESS, aircraft maintenance, supply chain, autoregressive distributed lag model

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Dr. Raymond R. Hill (ENS)
					19b. TELEPHONE NUMBER *(include area code)*
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