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THESIS

MV-22 SUPPLY CHAIN AGILITY: A STATIC SUPPLY CHAIN SUPPORTING A DYNAMIC DEPLOYMENT

by

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The U.S. Marine Corps prides itself on the ability to successfully operate within a dynamic environment in an expedient and expeditious manner. No small accomplishment, this burden lies heavily on supply professionals and the agility of the supply network in support of operating forces. Supply chain management (SCM) must cultivate dynamic supply chains to be as fluid as the maneuver units it supports. Though military action is reactive at times, proactive preparations foster an ability to increase momentum and gain the initiative.

This quantitative research assesses the supply chain of a deployed MV-22 Osprey squadron to discover inefficiencies, and makes recommendations to increase supply chain productivity. Specifically, this study takes advantage of Microsoft Excel and big data techniques to sort through structured and unstructured data. By collaborating with the Department of the Navy (DoN) and obtaining data sets, we are able to apply Excel and Lexical Link Analysis (LLA), a text-mining software, to derive relationships between given data sets. Interpreting these relationships helps determine opportunities, shortfalls, and favorable and unfavorable conditions within the MV-22 Osprey supply chain. The results observed can form the basis for supply chain improvement recommendations and can help enhance DoN SCM productivity.

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LIST OF ACRONYMS AND ABBREVIATIONS

A2AD	anti-access area denial
ACE	air combat element
AD	aerial delivery
AMSRR	aircraft maintenance/supply readiness report
AO	area of operation
ARG	Amphibious Ready Group
ASD	Aviation Supply Department
AWP	awaiting parts
BD	big data
BDBA	big data and business analytics
BT	between
CE	command element
CLA	collaborative learning agents
CMD	Consumables Management Division
DIKW	data, information, knowledge, and wisdom
DLA	Defense Logistics Agency
DPB	data science, predictive analytics, and big data
DoD	Department of Defense
DoN	Department of the Navy
EDD	estimated delivery date
EOC	equipment operational capabilities
F/AD	Force/Activity Designator
GCE	ground combat element
IMA	intermediate maintenance activity
IPG	issue priority group
IT	information technology
I-Level	intermediate level
JCS	Joint Chiefs of Staff
JMPAB	Joint Materiel Priorities and Allocation Board
LCE	logistics combat element

LDA	Latent Dirichlet Allocation
LHA	landing helicopter assault
LHD	landing helicopter dock
LLA	Lexical Link Analysis
LPD	amphibious transport dock
LSA	Latent Semantic Analysis
LSD	dock landing ship
LT	less than
MAGTF	Marine Air Ground Task Force
MALS	Marine Aviation Logistics Squadron
MAW	Marine Aircraft Wing
MCAS	Marine Corps air station
MOC	Marine Corps Operating Concept
MCSCG	Marine Corps Security Cooperation Group
MEB	Marine Expeditionary Brigade
MEF	Marine Expeditionary Force
MESM	mission essential subsystem matrix
MEU	Marine Expeditionary Unit
MOA	massive online analysis
MT	more than
NALCOMIS	naval aviation logistics command management information system
NAMP	naval aviation maintenance program
NAS	naval air station
NAVSUP	Naval Supply Systems Command
NLP	natural language processing
NMC	not mission capable
NMCS	not mission capable supply
NTCSS	naval tactical command support system
OOMA	optimized organizational level maintenance activity
O-Level	organizational level
PLSA	Probabilistic Latent Semantic Analysis
PMC	partial mission capable

PMCS	partial mission capable supply
RIC	routing identification code
RMD	Repairables Management Division
ROMO	range of military operations
SAD	Supply Accounting Division
SCA	supply chain analytics
SCM	supply chain management
SCR	supply chain risk
SMD	Supply Management Division
SPAD	Supply Personnel and Administrative Division
SPMAGTF	special purpose Marine Air Ground Task Force
SRD	Supply Response Division
SSD	Squadron Support Division
TAT	turnaround time
TRAP	tactical recovery of aircraft and personnel
T&R	training and readiness
UND	urgent need designators
VMM	Marine medium tilt-rotor
VMMT	Marine medium tilt-rotor training
WSS	weapons system support

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I. INTRODUCTION

The U. S. Marine Corps prides itself on the ability to successfully operate within a dynamic environment in an expedient and expeditious manner. Specifically, the Commandant of the Marine Corps, General Neller, stated in the Marine Corps Operating Concept (MOC) that the U.S. Marine Corps' operational foundation embraces expeditionary operations and maneuver warfare (Department of the Navy [DoN], 2016). One of the key elements within the MOC was the notion that the U.S. Marine Corps must be ready to conduct maneuver warfare and combined arms in every environment and domain (DoN, 2016).

As an amphibious force, the U. S. Marine Corps maintains an intimate relationship with its sister service, the U.S. Navy. To deliver power projection from the sea, the Navy/Marine Corps team must perform as a cohesive organization, maneuvering as necessary, and posturing to employ capabilities across the entire spectrum of military operations (DoN, 2016).

To achieve power projection requirements, high states of aircraft, vessel, equipment, and personnel readiness are to be preserved. No small accomplishment, this burden lies heavily on supply professionals and the agility of the supply network in support of operating forces. Supply chain management (SCM) must cultivate dynamic supply chains, to be as fluid as the maneuver units they support. Though military action is reactive at times, proactive preparations foster an ability to increase momentum and gain the initiative. SCM should also adopt a proactive mindset and forecast readiness requirements through critical and balanced consideration.

A. PROBLEM STATEMENT

Inefficiencies within the MV-22 Osprey supply chain must be identified and assessed to maintain high readiness rates with no degradation to current and future operations. Waste within the supply chain can have negative impacts to readiness and employment capabilities. Valuable information flows upstream and downstream, supporting supply operations at every level. Each level is vulnerable to internal and external phenomena such as communication disruptions, financial complications, inventory demands, transportation challenges, and rapid changes in operational tempo. If waste is not identified, such factors will potentially diminish aircraft and weapon system capacity. This research will use Microsoft Excel and big data (BD) analysis toward organizational and intermediate level maintenance supply documentation of the MV-22 supply chain. By applying Microsoft Excel and BD analysis algorithms to structured and unstructured data, this project aims to make inferences concerning downstream management of the supply chain. Outcomes of this research can provide insight to supply chain managers and make recommendations to increase supply chain efficiencies.

B. PURPOSE STATEMENT

The purpose of this quantitative research is to assess the supply chain network of a deployed MV-22 Osprey squadron, discover inefficiencies that may exist, and make recommendations to increase supply chain productivity. Specifically, this study takes advantage of Microsoft Excel and BD techniques to sort through structured and unstructured data. Collaboration with the DoN for requirements and attaining data sets permits the application of Excel and Lexical Link Analysis (LLA), a text-mining software, to derive relationships between given data sets. Extraction of variables such as response times and aircraft part availability, will measure SCM strengths and draw attention to deficiencies. Interpreted relationships can help determine opportunities, shortfalls, and favorable and unfavorable conditions within the organizational and intermediate maintenance levels of the Osprey supply chain. The results observed can also form the basis for supply chain improvement recommendations and assist with enhancing DoN SCM productivity.

C. RESEARCH QUESTIONS

The following questions are the focus of this research:

1. How can MV-22 Osprey aircraft supply documentation determine supply chain agility for deployed units?

2. How can aircraft components be identified for preposition opportunities to improve the combat readiness of deployed MV-22 squadrons?

D. RESEARCH BENEFITS AND LIMITATIONS

Analyzing supply documentation produced from organizational and intermediate level maintenance organizations will potentially highlight shortfalls within the management of supply chains for forward deployed aviation units. Discovering weaknesses will give supply professionals the ability to assess current supply chain states and develop methods to mitigate gaps and improve supply chain efficiencies. Because of the dynamic nature of Marine Expeditionary Units (MEU) and the environment in which they operate, SCM personnel will also be able to apply this research across a wide variety of platforms and organizations.

Shortfalls within this project lie with the accuracy of the data received. Results that will be uncovered and potential recommendations to enhance SCM will stem from the data provided. Errors in the Aircraft Maintenance/Supply Readiness Report (AMSRR) documentation, such as erroneous estimated delivery dates and not updating routing identification codes (RIC), should be evaluated prior to making SCM recommendations and conclusions.

E. METHODOLOGY

The intent of this study is to unearth relevant and recent information concerning the dynamic management of the supply chain for a deployed MV-22 Osprey squadron attached to a MEU. This project will be completed in three phases, beginning with DoN coordination and finishing with recommendations derived from analysis. Initial collaboration with the Office of the Chief of Naval Operations Fleet Supply Directorate (OPNAV N41) will begin phase one. The focus of this phase will be to scope the research and ensure the desired end-state is achieved. Once the requirements are identified, coordination with the U.S. Marine Corps division of Installations and Logistics, Marine Aircraft Logistics Squadron 26, the V-22 program office (PMA) 275, and PMA - 261 will occur to consolidate and obtain the data required.

The second phase will commence once the data is obtained. Initial analysis of the data seeks to identify items of interest for further examination. Preprocessing data will modify supply documents for ease of information extraction and compatibility with LLA. Post preprocessing, data analysis will occur by applying Microsoft Excel and LLA to structured and unstructured data components.

Phase three, the last phase of research, will begin at the completion of data analysis. From statistical relationships derived from Excel and LLA, the research questions concerning supply chain agility and part prepositioning, will be considered. To complete phase three, proposed recommendations, future research, and conclusions will be suggested.

F. THESIS ORGANIZATION

Following the introduction chapter, this thesis will include four additional chapters and one appendix. Chapter II is broken down into three distinct sections; SCM, BD, and the MV-22 Osprey. Outlined and explained are a brief history and description of the development and growth of SCM fundamentals. A discussion of Department of Defense (DoD) SCM application concludes this segment. The second section of this chapter discusses BD and BD analytics concerning supply chains. It defines BD and reviews various implementation methods of BD techniques, such as predictive and descriptive analysis tools when evaluating supply networks and effectiveness. The final portion of Chapter II describes the MV-22 Osprey tilt-rotor aircraft and employment by the U. S. Marine Corps. Emphasis is placed on maintenance structure and Marine Air Ground Task Force operations.

Chapter III, the methodology behind this study, is also divided into three segments. Beginning with dialogue concerning data mining, this paper explains numerous data mining techniques with a focus centered on text mining. The second portion filters down to the text mining tool that this research will employ, LLA. Once data is preprocessed, LLA will be applied to both structured and unstructured elements. Lastly, measurements of success are defined to furnish the specified criteria that will be investigated.

The fourth chapter outlines and highlights all of the analysis performed on the data, using both Microsoft Excel and LLA.

The last chapter, Chapter V, draws out conclusions concerning the analysis and makes recommendations related to the research questions. This chapter also includes future research, suggesting further exploration of MV-22 SCM.

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II. LITERATURE REVIEW

A. SUPPLY CHAIN MANAGEMENT

As the "Internet of Things" impacts individuals and organizations on a global scale, private sector businesses are forced to continuously find innovative methods to streamline business practices. Reducing waste and boosting efficiency is a focal aspect of organizations to maintain a competitive edge. The philosophy of supply chain management (SCM) is one approach many organizations embrace as a force multiplier. When suppliers, manufacturers, distributors, and vendors form a cohesive partnership, benefits throughout the supply chain can be recognized while minimizing unwanted consequences. Just as SCM provides positive outcomes for the private sector, so too can the government and Department of Defense (DoD) realize many of the same advantages.

The concept of SCM has grown over the past few decades, with organizations developing supply chain systems to increase their competitive advantage. Ellram and Cooper (2014) stated that the definition of SCM is "a supply chain is defined as a set of three or more entities (organizations or individuals) directly involved with the upstream and downstream flows of products, services, finances, and/or information from a source to a customer, (and return)" (p. 9). Previous work 13 years earlier by Mentzer et al. (2001) demonstrates the consistency that SCM has remained. Essentially, organizations must collaborate with their supply chain partners and develop an aligned strategic policy to recognize the benefits of SCM. As Mentzer et al. (2001) stated, the same holds true today: managers must visualize the supply chain not as independent organizations but as a network of nodes facilitating a system of interaction, each impacting the function of the whole. With this perception, the integration of each supply chain member is vital to the success of the supply chain.

To take advantage of the benefits SCM can produce, members must align processes and policies to foster a collaborative environment throughout the supply chain. Ellram and Cooper (2014) identified five categories SCM embodies; processes, discipline, philosophy, governance structure, and function. Every member must integrate processes, aligning strategic activities to gain a competitive advantage. Each must believe in a philosophy where unity of effort is more productive than the efforts of individual members. The network of organizations must be structured in ways which relationships are understood and supervisory organizations can manage supply chain expectations. Finally, functionality focuses on internal and external coordination among various functional areas such as operations, logistics, and financial (Ellram & Cooper, 2014). Applying these five categorizations will enhance a broad range of outputs, including inventory management, order fulfillment, response time, the bullwhip effect and bottlenecks, long term relationships, and customer satisfaction (Giannakis & Papadopoulos, 2016; Mentzer et al., 2001). The challenges organizations experience when developing a SCM model are those where collaboration is critical to the success of the supply chain and the enhancement of all participants within the supply system.

1. Integration of Supply Chain Participants

a. Collaboration

Ellram, and Cooper (2014) stated that the implementation of SCM is a more advantageous way of managing resources and assets. Furthermore, Ellram and Cooper (2014) specified that for SCM to be successful, it must be managed as a single entity rather than a group of organizations with individual goals and strategies. Because of how vital integration is, organizations need to collaborate at a level where a competitive advantage can be gained. Some, however, measure competition not between individual companies, but on the strength of the established supply chains (Wu, Chuang, & Hsu, 2014). From this perspective, Wu et al. (2014) believed that collaborative behaviors are instrumental when developing a common strategy. Focusing all supply chain participants toward a common goal can be arduous. Though Ramanathan and Gunasekaran (2014) mentioned that collaboration between businesses has become the norm, Kumar, Banerjee, Meena, and Ganguly (2017) stressed that real collaboration is hard to achieve. For true collaboration to exist, trust and commitment must be maintained for stability within the system (Wu et al., 2014). Additionally, cooperation is not only an external activity, integration must occur between logistics and other business functions internal to a company or corporation (Ellram & Cooper, 2014). This was further expressed by Ellram and Cooper (2014) by describing how companies need to "emphasize inter-organizational and intra-organizational coordination, avoiding functional silo mentality" (p. 14). This refers to operations, logistics, financial, and other business activities internal to a supply chain participant (Ellram & Cooper, 2014).

Integration also synchronizes processes within the supply chain, and each participant must develop relationships which foster a collaborative approach (Mentzer et al., 2001). As shown in Figure 1, Mentzer et al. (2001) depicted three example supply chains and the complexity of the relationships. Each chain, whether simplistic as the Direct Supply Chain or complex as the Ultimate Supply Chain, collaboration must occur to synchronize processes and strategies. Although displayed as linear entities, these chains operate as networks with each network sharing upstream and downstream processes (Ellram & Cooper, 2014; Mentzer et al., 2001).

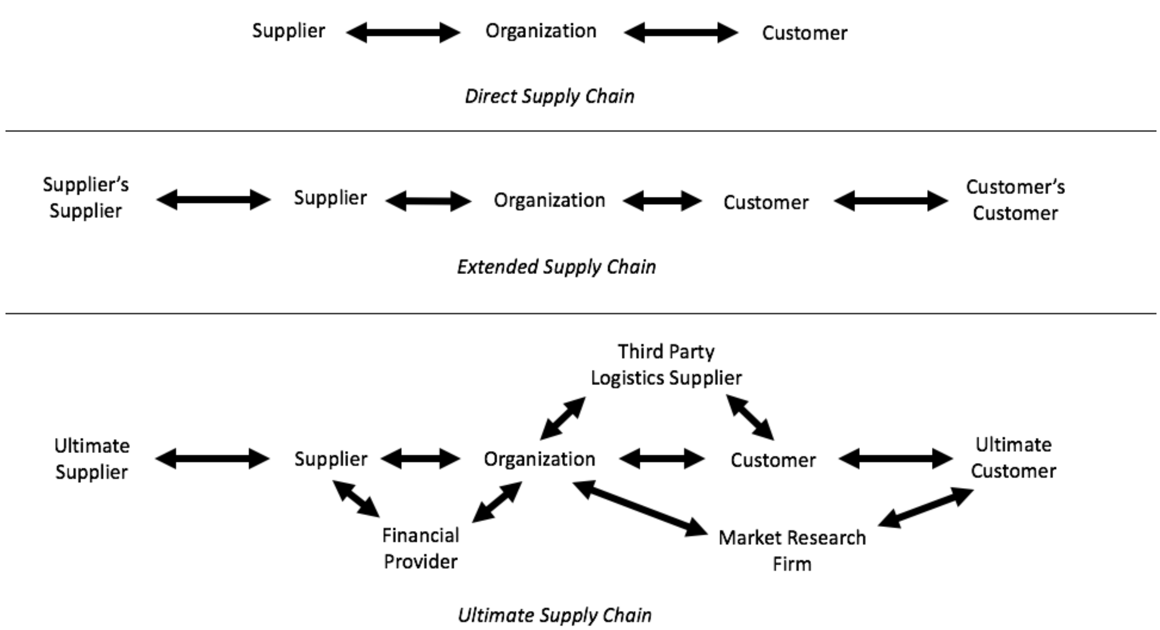

Figure 1. SCM Relationships. Source: Mentzer et al. (2001).

Developing strong alliances, the supply chain begins to act as a unified effort, from supplier to customer (Mentzer et al., 2001). Bhatt, Bector, and Appadoo (2014) added that these relationships must be a long-term endeavor, not something simply contractual but a substantial association. Intimate associations will cultivate an environment where participants will align processes and maximize efficiency through combined efforts of synchronizing strategies, planning, and communication (Bhatt et al., 2014).

b. Information Sharing

Information sharing is a key ingredient to the success of a supply system (Zhou & Benton, 2007). It ensures every participant in a supply chain is making decisions harmoniously, in a manner that benefits all members and reduces risk. Prajogo and Olhager (2011) alluded that supply chain integration is not only a flow of goods, but a flow of information; it is the sharing of information both upstream and downstream of the supply chain with the use of Information Technology (IT). Prajogo and Olhager continued to mention how the sharing of information directly impacts the quality of SCM processes and the performance of the supply chain. Additionally, better information flow through the use of IT and communications leads to more integrated and efficient SCM (Prajogo & Olhager, 2011). Lotfi, Mukhtar, Sahran, and Zadeh (2013) further emphasizes that it is not only about the ability to share information, but the information must be of high quality. Lofti et al., (2013) expressed this as knowledge sharing. The information shared must be of value to the system to have a positive impact on the efficiency of the supply chain and its members.

Understanding who needs what information when is important in reducing redundancy, sharing costs, and minimizing response times for materials and products (Lofti et al., 2013). Knowing the type of information required by the various supply chain participants adds to SCM performance. Lofti et al. (2013) mentioned various categories of information that may be shared to improve production; “inventory information, sales data, sales forecasting, order information, product availability, and exploitation information of new products” (p. 300). As this information is contributed by the numerous participants, benefits such as cost and risk reduction occur with the outcome of improved customer satisfaction (Lofti et al., 2013). Furthermore, participants in a supply chain can use information to alter plans and determine future operations, and manufacturers can benefit by improving inventory management, increasing productivity and profit, and enhancing resource distribution.

2. Inventory Management and Bullwhip

a. Uncertainty and Errors

One aspect of SCM is an organization's ability to manage inventory and efficiently meet demand fluctuations. Gunicheva (2016) stated that inventory management was the ability to reduce time and minimize cost through the implementation of appropriate inventory condition controls which assist decision-making. Organizations should emphasize inventory optimization and management due to the impacts they have on the supply chain and on competitive advantage (Gunicheva, 2016). Because of globalization and the internet, communication and transportation technologies have given customers the ability to leverage their needs from any location at any time (Bayraktar, Koh, Gunasekaran, Sari, & Tatoglu, 2008). This behavior has made it increasingly more challenging for companies to satisfy customer demands and meet their expectations anywhere on the globe.

Uncertainty is a major factor when managing inventories and assessing demand. Future demand is unknown and affected by numerous internal and external influences, such as economic, governmental, social, and environmental. Thus, quantifying future demands is near impossible (Bayraktar et al., 2008). Unpredictability may lead to numerous adverse outcomes, such as unmet demand and an increase in response time, or a surplus of inventory which can escalate costs and overhead (Gunicheva, 2016). To combat uncertainty and demand fluctuations, Gunicheva recommended that organizations should create and implement inventory analysis and forecasting tools, with the expectation of quantifying demand as part of an inventory management system and the determination of optimal inventory values.

Inventory management, is not only influenced by the uncertainty of demand, it also experiences inherent challenges internal to the organization. Various inaccuracies can plague managers and the inventories they maintain. Errors including misplacement of stock in the wrong locations or warehouses, and transactional errors such as counting, receiving, and transferring of items affecting information systems, can impact an organization's awareness of current holdings (Khader, Rekik, Botta-Genoulaz, & Campagne, 2014). In a study completed by Shteren and Avrahami (2017), they found that 65% of inventory entries for a particular retailor were erroneous. Shteren et al. (2017) alluded to inventory shrinkage, misplacement, and wrong scanning as three types of inventory management errors, and each of which impact inventories differently. Shrinkage are those errors attributed to an actual loss of inventory without an impact to the IT inventory, and such errors maybe explained by theft or breakage (Shteren et al., 2017). Misplacement, as stated earlier, is an error where an item is stored in the wrong location, decreasing the available inventory, however, not affecting the actual or IT inventories (Shteren et al., 2017). The third error Shteren et al. studied was wrongful scanning errors. These errors can affect both the IT and physical inventories. If not reported to the IT inventory, actual inventories will increase or decrease or if entered into the IT inventory before the item is physically handled; the IT inventory will change but will not impact the actual inventory (Shteren et al., 2017). A disconnect between an organization's real inventory and those in the IT system will only perpetuate the difficulty an organization experiences when managing inventories.

b. Demand Fluctuations

The study of the bullwhip effect can be traced back to Jay Forrester in the early 1960s (Bayraktar et al., 2008). In 1961, he coined the phrase "demand amplification" and, since then numerous people have researched this phenomenon: John Sterman in 1989 with the creation of the "Beer Distribution Game," and Proctor and Gamble in the mid-1990s naming it the "bullwhip effect" (Bayraktar et al., 2008). Realizing the influence demand has on an organization, many have tried to quantify the bullwhip effect and grasp its significance. Vokhmyanina, Zhuravskaya, and Osmolski (2018) stated that it is the uncertainty of demand forecasts and the high fluctuations of demand throughout the supply chain that cause the bullwhip effect. By quantifying the bullwhip effect, organizations would be able to optimize the supply chain performance (Vokhmyanina et al., 2018).

The need to manage demand is imperative in gaining a competitive advantage; it is essential to reduce fluctuations caused by demand. Typically, organizations use historical data to forecast demand because previous experiences provide insight into future behavior (Bayraktar et al., 2008). However, as inaccurate forecasts are employed, supply chain participants rationalize demand and distort those forecasts further upstream, misleading other supply chain members. The amplification of erroneous demand forecasts is what evolves into the bullwhip effect. As depicted, Figure 2 shows how demand forecasting is amplified within the supply chain. Over time, customers' demand fluctuates and each entity within the supply chain forecasts a demand to maintain customer needs. At each subsequent level upstream, the forecast fluctuates to maintain demand. However, due to inherent order and delivery delays, variation off-balances the supply chain as inventories trail demand.

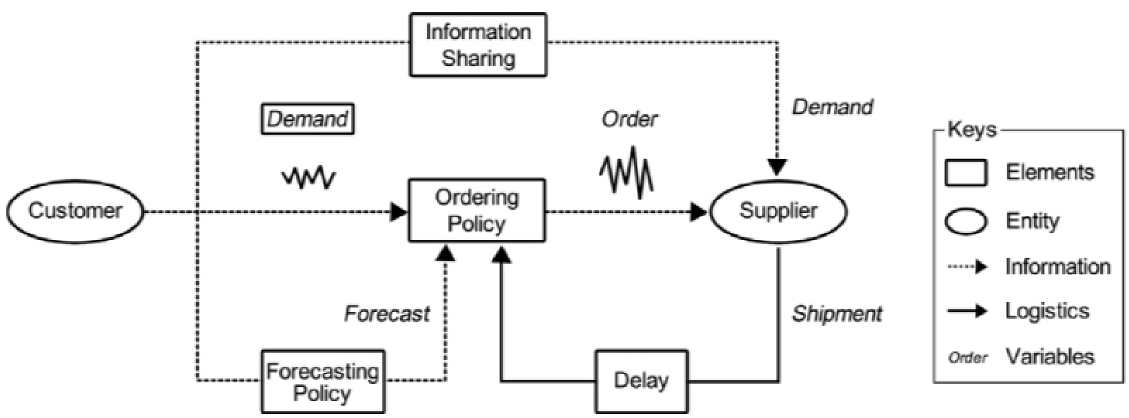

Figure 2. Bullwhip Model. Source: Wang and Disney (2016).

Causes of the bullwhip effect are numerous. Bayraktar et al. (2008) mentioned demand forecasting, order batching, price fluctuations, and shortage gaming. However, others argued control systems, activity times in the supply chain, information transparency, supply chain echelons, and demand forecasting (Bayraktar et al., 2008). The key takeaway is that demand fluctuation is unpredictable and to curtail the bullwhip effect, organizations must recognize the potential factors effecting supply chain and manage those to improve efficiency.

3. Leveraging Information Technology

As stated earlier, to create and maintain a cohesive supply chain, organizations must be willing to collaborate, build lasting partnerships, and share information. They must operate under a common strategy, implementing processes and procedures that benefit every member in the supply chain. Additionally, the decisions made must take into account the welfare of the other organizations in the chain. Miraldes, Garrido Azevedo, Charrua-Santos, Mendes, and Oliveira Matias (2015) implied that IT is one of the most common elements connecting suppliers, manufacturers, distributors, retailers, and customers to a supply chain. Because of IT, supply chains can synchronize activities and integrate processes, allowing organizations to centralize strategic planning while decentralizing daily operations (Miraldes et al., 2015).

An important factor concerning IT systems and SCM is to ensure the IT system is an appropriate system for the supply chain. Qrunfleh and Tarafdar (2014) emphasized that an organization must choose an IT system that aligns with the supply chain, one that provides value and information facilitating the organizational strategy. Additionally, because IT systems are a long-term investment, managers must assess the IT strategy and make certain that it is also aligned with the overall organizational strategy (Qrunfleh & Tarafdar, 2014). Organizations must determine what systems will create value and assist with the business' competitive advantage (Miraldes et al., 2015). For example, Qrunfleh and Tarafdar (2014) referenced two types of information system strategies, one focused on efficiency and one toward flexibility. Each having their own characteristics suited for an organization's particular needs. Additionally, Miraldes et al. listed potential benefits from IT and supply chain infrastructure alignment; global error reduction, increase the quality of processes, innovation of services and products, and strategic growth.

Companies equipped with stronger IT capabilities can gain a competitive advantage over those who are not. IT systems provide better communication and additional sharing of information such as delivery statuses and production planning, however, it is the strategy behind the system which impacts SCM and the collaboration it requires (Prajogo & Olhager, 2011). It is not the investment in IT which provides enhanced supply chain performance, it is the IT strategy which allows for information flow, cooperation, and fostering relationships in an information sharing environment (Prajogo, & Olhager, 2011).

4. Supply Chain Risk Management

Risks associated with SCM and globalization of organizations can encompass a variety of aspects internal and external to the supply chain and individual businesses. "On average the percentage of global companies reporting a loss of income due to a supply chain risk increased from 28% in 2011 to 42% in 2013" (Li, Fan, Lee, & Cheng, 2015, p. 84). Mitigating these risks allows supply chains to increase their competitive advantage and strategically operate in numerous environments that may not be advantageous to competitors. Wiengarten, Humphreys, Gimenez, and Mcivor (2016) began their article by expressing how organizations have established facilities such as production plants, warehouses, and distribution centers in a variety of geographic locations to reduce cost, take advantage of raw materials, and increase efficiencies. However, increased geographic dispersion not only increases the risk, it also increases the complexity of supply chain integration, management and businesses with global facilities may experience "geopolitical risks, sovereign risks, and exchange rate risks" (Wiengarten et al., 2016, p. 362). Depending on geographic location and country an organization chooses to cooperate with, companies may have to further invest in various security measures to protect assets and resources (Wiengarten et al., 2016). Wiengarten et al. further argued that countries with weak rules, deprived economic capacity, and corruption may expose organizations to behaviors such as cheating or theft. Another major supply chain risk (SCR) organizations must be familiar with from a collaborative perspective is information sharing. SCR plans must incorporate all firms within the supply chain and must be willing to share risk information and accept joint risks (Li et al., 2015). Information accuracy, security, and relevancy play an important part in ensuring the supply chain is aligned and decisions are made with the most precise information (Hallikas &Lintukangas, 2016). Li et al. also alluded to the fact that confidentiality and withholding of information can hamper supply chain performance and create negative impacts such as increased inventories and the bullwhip effect. Hallikas and Lintukangas (2016) continued to mention uncertainties as supply, demand, and environment collaboration among supply chain members is vital to the reduction of risk and strong partnerships and relationships will serve to increases supply chain performance.

With growing environmental awareness another SCR that may be a factor is sustainability. Giannakis and Papadopoulos (2016) discussed sustainability as a competitive advantage and strategy that balance natural and social environmental uncertainties. Corporations must assess the ecological effects of their actions and the impact on their individual and supply chain reputations (Giannakis & Papadopoulos, (2016). Giannakis and Papadopoulos further added that companies must embrace a "moral capital" and evaluate risks "greenhouse gas emissions, natural disasters, accidents, energy consumption, packaging waste, environmental damages during logistics and transportation." (pp. 455–456).

As stated above, SCM performance relates to the collaboration and information sharing organizations cultivate. Tethered to performance is the mitigation and reduction in SCR. The complexity of global supply chains and the increased reliance on other firms and uncertainty, supply chain strategies must analyze the SCR and continue to foster integration and information sharing at the appropriate levels to mitigate and reduce identified risks (Hallikas & Lintukangas, (2016).

5. Department of Defense Supply Chains and Challenges

DoD supply chains are large, complex, and deal with unpredictable demand signals from a variety of sources (Tsadikovich, Levner, Tell, & Werner, 2016; Wilhite, Burns, Patnayakuni, & Tseng, 2014). In 2001, the DoD adopted SCM as a process "to increase reliability and reduce its logistical footprint" (Haraburda, 2016, p. 14). DoD supply chains account for over 100,000 suppliers and 2,000 controlling systems, managing an inventory of $92.6 billion in 2015 (Haraburda, 2016). Haraburda continued to mention that "in 2011, the DoD had 19 maintenance depots, 25 distribution depots, and over 30,000 customer sites" (p. 13). Because of the innate complexity of DoD supply systems, coordination shortfalls between participants can lead to inefficiencies and supply responsiveness for users within the operating forces (Tsadikovich et al., 2016). Therefore, the key contributor to ensuring DoD supply chains are efficient is to build quality relationships and continuously improve upon coordination between supply partners, just as in the private sector (Tsadikovich et al., 2016). Tsadikovich et al. described two metrics military supply chains measure themselves to, response time which is how quickly the force is fielded with the required item, and effectiveness, ensuring the right supply asset is given at the right time. To ensure responsiveness, logistic systems historically maintained larger inventories to sustain appropriate readiness rates (Snow, 2011). During Operation DESERT STORM "$2.7 billion worth of spare parts went unused" and it was estimated that if the U.S. army had effective tracking systems the savings could have potentially be $2 billion (Tsadikovich et al., 2016, p. 5798). To safeguard against waste and inefficiencies, *DoD Supply Chain Materiel Management Procedures: Operational Requirements* (2017) described guidelines for defense practitioners and how they should manage defense supply chains. Included in this guidance was to ensure best supply chain practices were implemented, develop relationships with supply partners, employ risk management strategies, and evaluate processes for optimization.

Another important issue Wilhite et al. (2014) emphasized concerning DoD supply chains was the main purpose of their systems. Private sector supply chains focus on profit margins and growth potential (Wilhite et al., 201; Haraburda, 2016). However, the DoD's goal is to ensure readiness of equipment and personnel are maintained at a rate sufficient to engage enemy combatants in both peace and war time (Wilhite et al., 2014). Keeping the warfighter at a high state of readiness is the main objective and design of the supply chains, while cost is a constraining factor professionals must manage and minimize (Wilhite et al., 2014; Haraburda, 2016). Tsadikovich et al. (2016) affirmed success in military supply chains are based on force readiness and not profitability.

A unique aspect to military supply chains is that they support complex weapon systems involving edge technology throughout the long life cycles of the weapon systems (Wilhite et al., 2014). Differing from private sector, these characteristics lend themselves to a closed-loop supply chain, one where the DoD capitalizes on repairable components (Wilhite et al., 2014). When parts malfunction or breakdown, the core component of that part is returned to a repair facility, whether organic to the military service or a private contractor (Wilhite et al., 2014). Wilhite et al. assessed that the DoD generates large savings in cost as well as producing quicker response times for those repairable items; avoiding supplier purchases that may decrease readiness. An additional method to ensure readiness is the process of cannibalization, where functioning parts are stripped from inoperative weapon systems and used in other weapon systems that require the item (Wilhite et al., 2014). Wilhite et al. stressed the point that this approach to a limited supply solution and complete cannibalizations would produce poor results. Okyere-Boateng (2015) performed a study assessing cannibalization rates of the MV-22 Osprey which resulted in no improvements to readiness.

A constant challenge the U.S. Marine Corps experiences as stated in the *Marine Corps Operating Concept (MOC) Overview* is the ability to respond to global instability (Department of the Navy [DoN], 2010b). Having to operate in a dynamic environment, the Marine Corps must be an agile force able to enhance Marine Air Ground Task Force (MAGTF) capability and maneuver in all domains, including sea, land, air, space, and cyber (DoN, 2016). Due to the distributed nature of current naval forces, challenges supporting individual elements has increased (Zhao, Gallup, & Kendall, 2016). Logistics structures centered on supporting the carrier strike group are becoming antiquated as forces operate in a more dispersed fashion, growing the number of elements needing logistical support (Zhao et al., 2016). Snow (2011) also discussed the requirement for defense agencies to enhance the agility of supply chains and logistical support to improve response times in a global capacity. Though specifically researching U.S. Army supply chains, Snow highlighted the fact that supply chain nodes must be distributed throughout the battle space and a reduction in larger inventories at few supply depots would be necessary to adequately support the end-user at the time and location required.

B. BIG DATA AND SUPPLY CHAIN MANAGEMENT

To optimize SCM, discover opportunities, and identify shortfalls, big data and business analytics (BDBA) can be applied to enhance supply chain processes (Wang, Gunasekaran, Ngai, & Papadopoulos, 2016). Fan, and Bifet (2013) stated in a journal article that the term BD was first mentioned by John Mashey, a computer scientist for Silicon Graphics, in 1998. As technology advanced and data continued to change and expand, both in size and variety, professionals applied a definition to the concept. For this research BD will be defined as "a vast amount of data generated very quickly and containing a large amount of content. The characteristics of BD is based on the rule of 4 V: volume (a large amount of data), variety (any type of data), velocity (high changeability, dynamic of data), and value (assessment expressed by verification)." (Kościelniak, & Puto, 2015). Though only using four "V's" to express what BD is, professionals have identified up to seven "V's," including variability (the change in data flow rates), veracity (the unreliability in data sets), and visualization (presenting the data in a relevant and comprehensive manner) (Sivarajah, Kamal, Irani, & Weerakkody, 2017; Gandomi & Haider, 2015). Additionally, the variety of this data, as defined earlier, can comprise both structured and unstructured such as "digital papers, audio recordings, text messages, photos, books and technical information" (Kościelniak et al., 2015, p. 1054).

Due to the challenges BD imposes, BDBA must employ complex methods to process and analyze the data to discover valuable information relevant to the organization. Wang et al. (2016) continued to discuss the importance of business analytics and the application of BD. The end-state of BDBA is to assist managers concerning decisions on all levels of an organization; strategic, operational, and tactical. In a 2014 survey, one third of business professionals recognized the employment of BDBA as a topic of interest regarding logistics and SCM (Wang et al., 2016). By implementing BDBA, organizations can "improve visibility, flexibility, and integration of global supply chains and logistical processes, effectively manage demand volatility, and handle cost fluctuations." (Wang et al., 2016, p. 99). Hazen, Boone, Ezell, and Jones-Farmer (2014) also argue that organizations data science, predictive analytics, and big data (DPB) to improve supply chain effectiveness. The key component of DPB Hazen et al. mentioned is the quality of data during the assessment. If the data is of low quality, the results of analysis will include high levels of inaccuracy or noise. This can be detrimental to organizations who would make decisions based on DPB. The quality of information flow throughout a supply chain is vital to enhance supply chain performance.

1. Big Data Justification

In 2010, the White House stressed the importance of BD by implying that it is a vital contributor to national security (Tan, Zhan, Ji, Ye, & Chang, 2015). Sivarajah et al. (2017) stated in their 2017 business journal that currently 2.5 quintillion bytes of data are created per day and of that 90% is unstructured. By 2020, Sivarajah et al. assessed that data generation will have increased to 40 zettabytes and analyzing this data will be time sensitive iterative process, with difficulty creating value. This is a massive increase in digital data, considering only three percent of data was digital in 1993 and by 2007, just fourteen years later 94% of data was digital (Kościelniak et al., 2015). The goal for organization will be to examine this data with the intent of making knowledge and wisdom for future use (Jifa & Lingling, 2014). It is important to note that it is not only significant for businesses to manage BD, but to be able to assess it for decision purposes (Ziora, 2015). As shown in Figure 3, the Data, Information, Knowledge, and Wisdom (DIKW) pyramid emphasizes why the application of BD is important to producing prudence and judgment when making business and supply chain decisions.

Figure 3. DIKW Pyramid. Source: Vaes (2013).

As BD is generated, organizations must have a means to collect and consolidate this data, whether structured or unstructured. Technology such as BD analytic tools then run algorithms to transform random data into information, determining relationships and interdependencies. Through analysis, information evolves into knowledge, correlating the information to the system it is affecting. The final action in the process is developing wisdom from the knowledge created to better make future decisions.

2. Mining and Extraction

Because of the digital nature of today's data, BD can be an asset, improving and supporting organizational decision making (Elgendy & Elragal, 2016; Ziora, 2015). Two critical components of the DIKW is to ensure organizations start with the most appropriate data as well as using the most beneficial BD analytic tools. Tan et al. (2015) stated that research must start with the right information, which will lead to the desired results. Also when examining data, one must understand that the recency of data is more important than the amount that is collected; more data introduced can cause false correlations and erroneous outcomes (Fan et al., 2013). However, Fan et al. continued to address that smaller data sets could also skew findings due to it not representing an entire population. Ziora further defended these notions when stating that BD creates value by through the collection of more accurate and timely performance data.

As corporations evaluate their data, they must view the quality from two perspectives, the inherent nature of the data and the contextual merit of that data. Hazen et al. (2014) described these categories as "Intrinsic" and "Contextual." Understanding the intrinsic qualities such as accuracy, recency, and consistency and the contextual qualities including relevancy, organizations can begin to shape their analytics (Hazen et al., 2014). Once the type of data is chosen, algorithms are then used to mine the data and prepare it for analysis. Tan et al. (2015) alluded to the amount of noise within the data than can be acquired, thus BD tools need to ensure the data cleansing, data integration, and data reduction is applied to remove any inconsistencies that may appear. Depending on noise accumulation, significant information may be overlooked or not emphasized, or spurious correlation may occur, falsely correlating items within the data due to the large size of the data sets (Gandomi & Haider, 2015).

3. Analytics and Decision

When data extraction is complete, BD analytic tools are applied to transform the raw data into valuable information. Wang et al. (2016) referenced numerous types of analytics including; descriptive, predictive, and prescriptive. Descriptive analytics are executed periodically or when necessary, they identify problems or opportunities within systems or processes (Wang et al., 2016). Predictive analytics use mathematical methods to find predictive patterns to project future outcomes and prescriptive analytics aim to improve business performance by determining and assessing alternative decisions (Wang et al., 2016; Gandomi & Haider, 2015). Wang et al. further described predictive and prescriptive as those types that assist with the strategic direction of an organization, while descriptive assists management with decisions, answering the questions "what happened and/or what is happening" (p. 100). From these techniques, extraction of information occurs through the uncovering of patterns and identification of relationships (Gandomi & Haider, 2015). Gandomi and Haider proceeded to state these relationships included with historical data can be extrapolated using statistical methods for future decision making. Sivarajah et al. (2017) presented in Figure 4 a process of data analysis and how it leads from data and information to providing understanding and awareness for decision making.

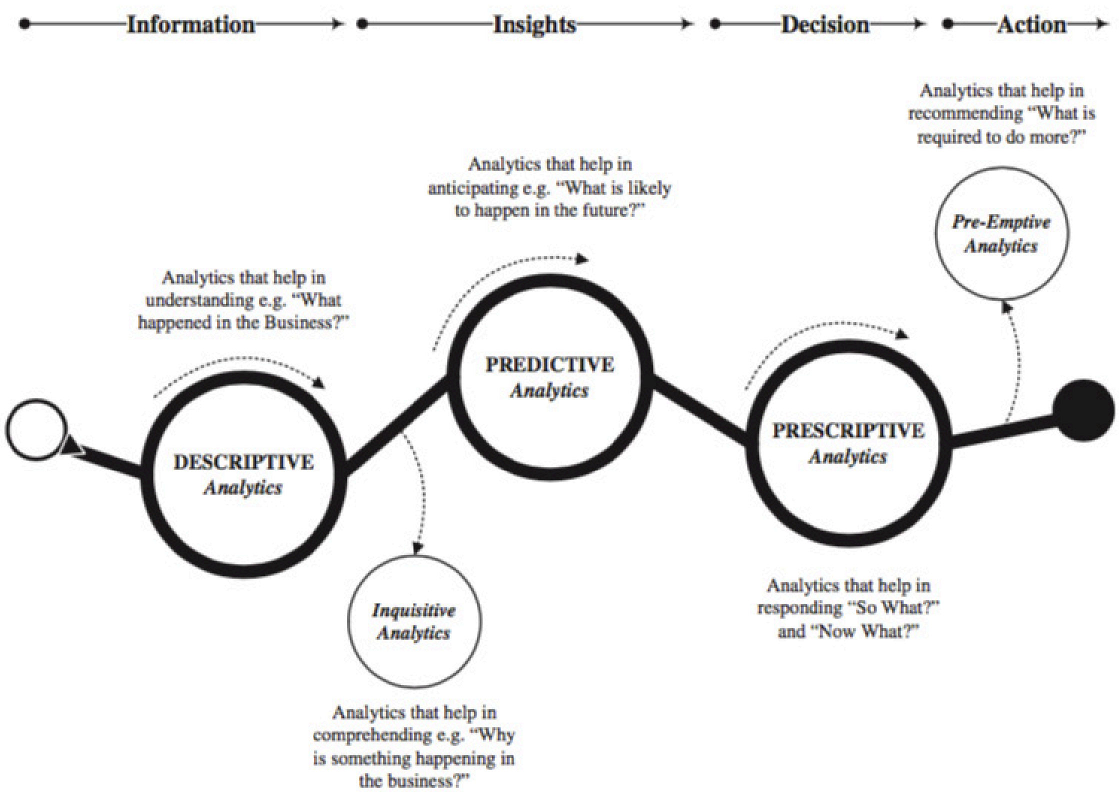

Figure 4. BD Analytical Methods. Source: Sivarajah et al. (2017).

This model first examines previous results and induces reasoning as to why those end-states occurred. Assessing that information, predictions can be formulated as to what might transpire in the future. Following those estimations, managers and professionals can then induce the purpose of the information and be better prepared to make organizational judgments and act on those decisions. This representation reflects BD aspects of the DIKW model and the methods needed to evolve BD into usable knowledge and wisdom.

4. Big Data Application to the Supply Chain

When concepts of BD are understood, organizations can identify opportunities for implementation. Waller and Fawcett (2013) recognized the importance of BD and SCM by providing examples of its value concerning the medical field, public policy, and informing business decisions. Their article, *Data Science, Predictive Analytics, and Big Data: A Revolution that will Transform Supply Chain Design and Management* stated that, "SCM data science is the application of quantitative and qualitative methods from a variety of disciplines in combination with SCM theory to solve relevant SCM problems and predict outcomes, taking into account data quality and availability issues” (p. 79) and believed that the use of DPB will revolutionize SCM. Incorporating BD tools into SCM can return benefits not otherwise visible. For example, they can illuminate market trends and customer habits, draw out vulnerabilities and inefficiencies, seek solutions for demand fluctuations and volatility, and can integrate logistic processes on a global scale (Wang et al., 2016). Previously, these advantages have been focused on strategic decision making, the technology today is assisting managers in the ability to make operational and tactical supply decisions such as with inventory management, procurement, and demand forecasting (Wang et al., 2016). Though many advantages can be discovered, Kitchin (2014) noted some challenges when employing big data, including the requirement for large computing power, the laborious management of the data, and potential expenses connected to such research. Applying these types of statistical tools is not common for businesses regarding SCM, thus organizations need to balance the rewards that can be obtained from BD and the difficulties they may experience employing techniques (Hazen et al., 2014). A 2014 survey completed by Wang et al. found that one-third of survey participants mentioned the employment of BD analytics as a topic of interest regarding business application, logistics, and SCM.

As discussed earlier, the quality of the data is vital to acquiring the results desired and is the first step to using BD analytic tools. As shown in Figure 5, professionals must view the creation of data similar to the manufacturing of physical products.

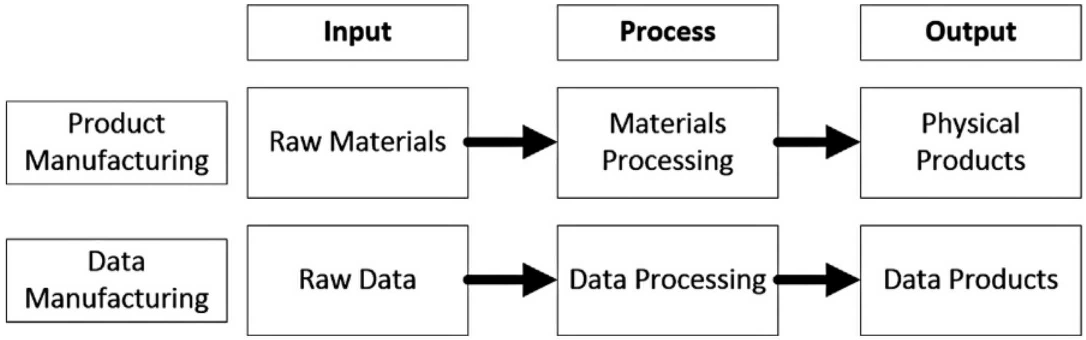

Figure 5. Data Manufacturing Processes. Source: Hazen et al. (2014).

Just as manufacturers impose standards on quality and the processes that produce high quality products, so to must IT professionals establish processes that allow corporations to leverage quality data when making supply chain decisions. If the data are poor then corresponding decisions will be made, negatively impacting business practices and potentially financial outcomes (Hazen et al., 2014).

a. Supply Chain Analytics

Due to competition evolving from individual organizations to encompass SCM, organizations should adopt DPB techniques to improve supply chain performance (Hazen et al., 2014). Analytics can be used to improve decision making, reduce risks, find information not readily visible and can be applied across a wide spectrum of organizations including financial, telecommunications, health care, and other industries with global capacity (Elgendy et al., 2016; Koscielniak & Puto, 2016). Koscielniak and Puto continued to state that supply chain analytics (SCA) and BDBA allow organizations to make more informed decisions which provide optimized solutions for supply chains and product production. Wang et al. (2016) defined SCA as the marriage between BDBA and Logistics SCM and it is based off of real-time information sharing which can assist in strategic decision making and provide accountability for business or government agencies.

Previously discussed was supply chain strategies and how they should be aligned with the overall business strategy. These strategies should account for SCA and BDBA, for these tools are another approach to supply chain performance improvement (Wang et al., 2016). Analytics should draw on data from a variety of supply chain network nodes to produce information that can potentially mitigate uncertainties, assist with scheduling and inventory problems, and reduce disruptions (Wang et al., 2016). However, assessing supply chain nodes can be complicated and complex depending upon the size of the supply chain and the locations of the individual participants. As depicted in Figure 6, the life cycle of data and some of the challenges associated with different phases of data transformation and management of the data when analyzing and comprehending the information.

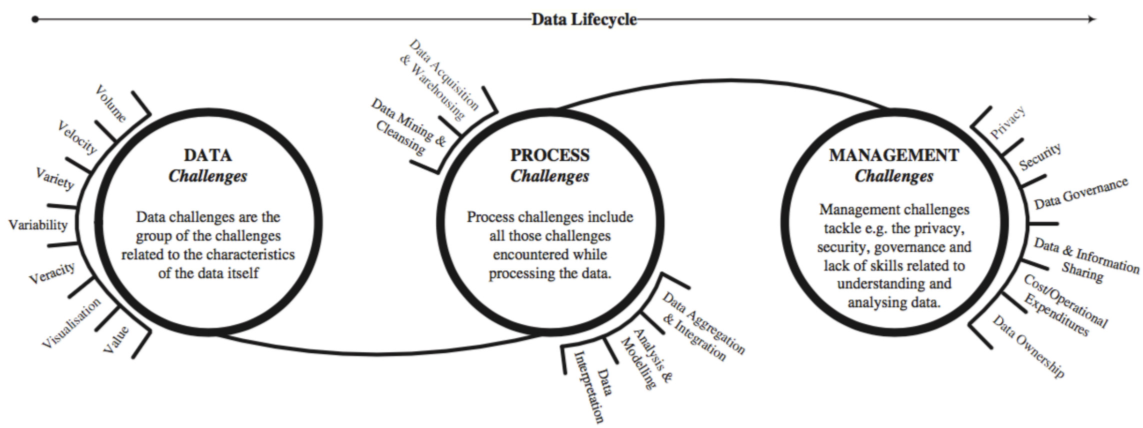

Figure 6. Big Data Challenges. Source: Sivarajah et al. (2017).

Supply chain managers must grasp BD concepts and the characteristics of the data to ensure the data is of correct variety, integrity, and size (Sivarajah et al., 2017). When the data set is defined, appropriate BDBA and SCA tools need to be employed to transform the data into the information desired. Lastly, management challenges deal with actual use of the information generated, including privacy, ownership, and security of the information. When challenges are understood and mitigated, SCA and BDBA can be a supply chain force multiplier, improving performance and enhancing supply chain visibility (Tan et al., 2015).

C. MV-22 OSPREY AND FORCE STRUCTURE

The *MCOC Overview* discussed how Anti-Access Area Denial (A2AD) has made it difficult for U.S. Marine Corps forces to conduct amphibious and expeditionary operations, as well as how gaining access foreign locations will become more challenging in the future (DoN, 2010b). To combat standoff distances required to project power from the sea as described in the *MCOC 1–5, Power Projection*, was the development and employment of the MV-22 Osprey aircraft; a platform that could provide logistical support for personnel, equipment, and effectively carry out the Range of Military Operations (ROMO) (DoN, 2010a). The MV-22 Osprey was developed to replace the CH-46E Sea Knight and CH-53D Sea Stallion helicopters necessary to conduct sea basing and expeditionary operations such as "expeditionary assault from land or sea, medium-lift assault support, aerial delivery (AD), tactical recovery of aircraft and personnel (TRAP), air evacuation, aerial refueling, and rapid insertion and extraction" (MV-22 Osprey, 2015; V-22 Osprey, n.d.-a). The Osprey's unique Short Take-Off/Vertical Landing, as well as its ability to rotate its nacelles, the engine and propeller housings, to fly like an airplane provides the Marine Corps with enhanced flexibility while conducting land and sea based operations at ranges otherwise not attainable from conventional helicopters (MV-22 Osprey, 2015). The tilt-rotor technology allows the MV-22 to cruise at a speed of 270 knots, to have a maximum troop capacity of 24 passengers, to carry an external load of 12,500 pounds, and to fly a combat radius of 428 nautical miles that can be extended to 2100 nautical miles if conducting refueling operations. ("Bell Boeing," n.d.; MV-22 Osprey, 2015; V-22, n.d.-b). MV-22s in airplane mode are displayed in Figure 7.

Figure 7. MV-22 Osprey in Flight. Source: https://DoDrams.com/programs/aviation/mv-22-osprey (2015).

Production and transition to the MV-22 took an incremental approach, incorporating aircraft upgrades as the aircraft aged and new models were incorporated into the Marine Corps (MV-22 Osprey, 2015). Initially, the V-22 program saw its beginning in the early 1980s, experiencing numerous challenges including cost, performance, and safety leading to one mishap in June of 1991 and a second in July of 1992, with seven fatalities (Gertler, 2011). Unfortunately, the program experienced two additional mishaps, one in April of 2000 with 19 fatalities and again in December of 2000 with four fatalities (Gertler, 2011). As testing and development continued, non-deployable Block "A" aircraft were finally delivered to the operating force until 2005 and replaced by deployable Block "B" aircraft that included maintainability and operability improvements. In 2010, Block "C" aircraft were placed into production with upgrades such as a weather radar, an improved ALE-47 self-protection system, and improved hover coupling features (MV-22 Osprey, 2015).

1. Employment of the MV-22 Osprey

The mission of the MV-22, defined in the MV-22B Training and Readiness (T&R) Manual is to "Support the MAGTF Commander by providing assault support transport of combat troops, supplies and equipment, day or night, under all weather conditions during expeditionary, joint, or combined operations" (DoN, 2010c, p. 1–3). The Marine Corps accomplishes this mission by fielding three Marine Medium Tiltrotor (VMM) squadrons under the 1st Marine Aircraft Wing (MAW) headquartered at Camp Foster, Okinawa Japan; six operational squadrons and one Fleet Replacement Squadron (VMMT) under the 2nd MAW headquartered at Marine Corps Air Station (MCAS) Cherry Point, North Carolina; seven squadrons under the 3rd MAW headquartered at MCAS Miramar, California; and one VMM detachment assigned to Marine Helicopter Squadron One (HMX-1), located in Quantico, Virginia (First, Second, Third MAW, Marine Helicopter Squadron 1, 2018). The table of organization as stated in the communities T&R Manual is that each squadron should have 12 MV-22 aircraft, 28 pilots, 20 crew chiefs, and 12 aerial gunners or observers (DoN, 2010c). Additionally, the T&R Manual delineated that the VMMT squadron, training new and refreshing pilots, should be assigned 17 aircraft with 20 pilots, 15 crew chief instructors, and 23 crew chiefs (DoN, 2010c). As stated earlier, but also outlined in the T&R Manual, the mission skills these squadrons' focus is on are expeditionary sea and shore-based missions, AD, combat assault transport, TRAP, Air Evacuation, and rapid insert and extraction (DoN, 2010c). The flexibility of the platform's tilt-rotor design allows for it to support any configuration of the MAGTF, being employed aboard numerous vessels at sea or from land based sites.

2. Marine Air Ground Task Force Framework

A smaller service than other military branches under the Department of Defense (DoD), the U.S. Marine Corps has designed a command structure that can adapt to any military operation it is responsible (Marine Air Ground Task Force, 2017). The MAGTF is the foundational structure of which the Marine Corps can change given any situation (Marine Air Ground Task Force, 2017). Whether employing the largest framework, a Marine Expeditionary Force (MEF) or organized into a Special Purpose MAGTF

(SPMAGF), the design of the force will be manipulated to optimize effects on the battlefield (Types of MAGTFs, 2015). Comprising every MAGTF are four scalable elements, including the Command Element (CE), Ground Combat Element (GCE), Air Combat Element (ACE), and Logistics Combat Element (LCE), as shown in Figure 8.

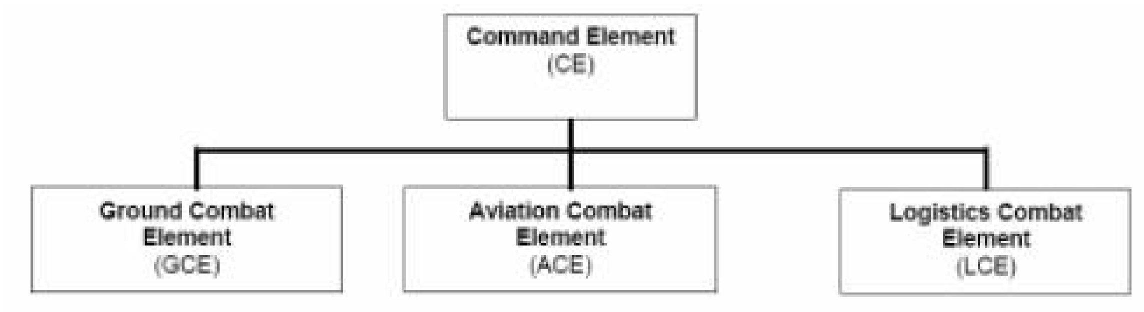

Figure 8. Elements of a MAGTF. Source: http://www.operational medicine.org/TextbookFiles/FMST_20008/FMST_1102.htm (2008).

The CE provides the communication backbone, integrated intelligence, and logistical support throughout the MAGTF (MAGTF Composition, 2015). The GCE is formed from ground combat arms occupations such as infantry, combat engineers, and armor assets (MAGTF Composition, 2015). The ACE provides air support for the MAGTF, including attack, assault support, electronic warfare, and reconnaissance platforms (MAGTF Composition, 2015). Lastly, the LCE furnish all logistical needs to sustain the MAGTF such as vehicles, support equipment, and sustenance (MAGTF Composition, 2015). Together these components cooperate to ensure the success of the combined force and as such become a force multiplier, massing combat power.

The strength behind the MAGTF force structure is its ability to be multi-mission (Types of MAGTFs, 2015). Whether embarked on naval vessels or land-based with foreign partners the customization of the structure provides flexibility and adaptability meeting the needs of the assigned commander (Types of MAGTFs, 2015). Overall tasks that the MAGTF can be responsible for include over-the-horizon crisis response, humanitarian and disaster relief, establishment of airfields and basing rights, theater security cooperation, integrate with special operations forces, and operate in urban and rural areas (Types of MAGTFs, 2015).

a. Marine Air Ground Task Force Configurations

Four Types of MAGTFs, MEF, Marine Expeditionary Brigade (MEB), Marine Expeditionary Unit (MEU), and SPMAGTF, with an additional Security Cooperation MAGTF (Types of MAGTFs, 2015). Changes in manpower, equipment, and capabilities can be implemented depending on the size and requirement of the force needed to project power and accomplish the assigned task. The MEF is the largest of MAGTFs, primarily established during peace time and crisis of long duration (Types of MAGTFs, 2015). Deploying approximately 45,000 Marines with a sustainment of 60 days, the MEF is capable of conducting spectrum-wide amphibious and sustained land-based operations (Joint Chiefs of Staff [JCS], 2014). Joint amphibious doctrine further states that composition of a MEF is a GCE of a Marine division, the ACE as a MAW, the LCE comprising of a logistic force serving all combat service support functions, and the CE established as a Joint Task Force headquarters (JCS, 2014).

The second largest MAGTF, the MEB, can accomplish similar tasks as the MEF, however sustainment of this force is 30 days vice the 60 days a MEF can provide (Types of MAGTFs, 2015). A tailorable mid-size force, the MEB is structured around a reinforced infantry regiment, a Marine Aircraft Group formed from fixed wing, rotary wing, and tilt-rotor aircraft, a LCE comprising of a logistic force serving all combat service support functions (JCS, 2014). A MEB may operate independently or as a forward element of a MEF, executing from an amphibious force of approximately 15 ships, strategic airlift, or from Maritime Prepositioning Force (MPF) assets (Types of MAGTFs, 2015). The MEU is a forward deployed sea based MAGTF consisting of approximately 2,400 Marines and Sailors (Types of MAGTFs, 2015; JCS, 2014).

The MEU consists of a CE and a GCE centered on a reinforced infantry battalion with supporting elements including a tank platoon, artillery battery, light armored reconnaissance platoon, combat engineer platoon, and an amphibious assault vehicle platoon (DoN, 2017a). The ACE is a reinforced aviation squadron composed of six AV-

8B Harriers or F-35 Joint Strike Fighters, 12 MV-22 Ospreys, four CH-53 Sea Stallions, four AH-1 Cobras, three UH-1 Hueys, and two KC-130J Hercules (DoN, 2017a). The LCE is organized as a combat logistics battalion including explosive ordinance disposal, general engineering, communications, supply, and medical units (JCS, 2014, DoN, 2017a). Additionally, the MEU sustainment is 15 days and can be rapidly deployed by amphibious shipping, airlift, and MPF resources (JCS, 2014). Because of its expeditionary capacity, the MEU is well suited for crisis response, raids, humanitarian assistance missions, limited contingency operations, and forward MAGTF operations (JCS, 2014; Types of MAGTFs, 2015).

Assigned as the naval component of a MEU, the Amphibious Ready Group (ARG), works in conjunction with the MEU to forward deploy forces in a rapid fashion (JCS, 2014). Typically, an ARG is composed of three naval vessels, an amphibious assault ship, a general purpose LHA or multi-purpose LHD; an amphibious transport dock, LPD; and a dock landing ship, LSD (JCS, 2014). The LHA and LHD are designed with a flight deck to support AV-8B Harrier, F-35 Joint Strike Fighter, MV-22 Osprey, and helicopter operations (JCS, 2014). A well deck, a submersible platform, was also constructed on these ships to execute amphibious operations from amphibious assault vehicles (JCS, 2014). The LPD incorporates a smaller flight deck for helicopter operations as well as a well deck for amphibious vehicles (JCS, 2014). Lastly, the LSD is only capable of amphibious operations with its well deck and submersible capabilities. Composition of the ARG/MEU team is shown in Figure 9.

Figure 9. MEU Components. Source: https://DoDrams.com/organizations/marine-air-ground-task-force/multi-mission-capable-magtf (2015).

The fourth type of MAGTF is a SPMAGTF, an organization that is structured for a very specific type of mission, one where a MEF, MEB, and MEU would be too large in size (JCS, 2014). The force can accomplish a wide variety of missions, however the scope and duration is short and well defined (JCS, 2014). Missions of a SPMATF include theater security cooperation, crisis and contingency response (Types of MAGTFs, 2015).

An additional configuration of a U.S. Marine Corps organizational force not known as a traditional MAGTF is the Marine Corps Security Cooperation Group (MCSCG). Initially established in late 2012, this organization focuses its capabilities around security assistance as well as training and advisory expertise. Composition is 203 troops structured into a headquarters element, liaison and assessment teams, and an instructor group (Types of MAGTFs, 2015). Objectives of the MCSCG is to grow partner capacity, build relationships and execute missions, including security advisory and support, and security cooperation training and education.

3. MV-22 Fleet Supply Effort

To support the MV-22 Osprey while conducting expeditionary and amphibious operations the Naval Aviation Maintenance Program (NAMP) provides structure and guidance to aircraft maintenance, delineating three levels of maintenance (DoN, 2017b). Organizational level (O-Level) maintenance is inherent to the aircraft squadron and perform basic maintenance capabilities including aircraft inspections, lubrication, and removal, replacement and repairs of components (DoN, 2017b). The intermediate level (I-Level) maintenance is an activity assigned to the Marine Aviation Logistics Squadron (MALS), an organization within a Marine Aircraft Group in support of operational squadrons (DoN, 2017b). I-Level maintenance conducts both supply and maintenance functions, providing technical assistance, conducts calibration, tests and repairs aircraft components and support equipment, and can manufacture various aircraft and support equipment parts, liquids and gases, and manages inventories and acquires parts (DoN, 2017b). The third layer of maintenance is the Depot Level (D-Level) assigned to Fleet Readiness Centers (DoN, 2017b). D-Level maintenance focus on aircraft integrity, conducting major overhauls, component reworks, and aircraft modifications (DoN, 2017b).

a. MALS Supply Structure and IS Interfaces

Naval aviation supply begins with the O, I, or D-Level activities and requests flow to the appropriate supply chain, depending on platform (DoN, 2017b). Operational MV-22 supply requests will begin at the O-Level and be transferred to the I-Level activity at MALS (DoN, 2017b). The NAMP dictates MALS supply responsibilities such as managing inventories of consumable and repairable components, replenishment of inventories and ordering of parts not on hand, provide delivery and pick-up of on station parts, and record customer demand and adjust for demand patterns (DoN, 2017b).

Within MALS, there are seven functional areas that comprise the Aviation Supply Department (ASD), Supply Personnel and Administrative Division (SPAD); Supply Accounting Division (SAD); Supply Management Division (SMD); Repairables Management Division (RMD); Supply Response Division (SRD); Consumables Management Division (CMD), and Squadron Support Division (SSD) (DoN, 2009). SPAD is responsible for all personal and administrative requirements of those assigned to the department; SAD maintains and reports all financial obligations; SMD is responsible for the overall operations of the supply department; RMD monitors the induction, storing, procurement, issue, and delivery of repairable items; SRD manages the research and requisition of material items not in the management information systems due to needing scrutiny; CMD is responsible for similar activities as RMD except those items that are consumable; and SSD is responsible for all equipment that is non-aeronautical, such as uniform items (DoN, 2009). These functional areas coordinate with the O-Level maintenance activity to ensure operational supply needs are met (DoN, 2017b). When requisitions are required and the supply demand extends beyond I-Level capabilities, Commander, Naval Supply Systems Command (COMNAVSUPSYSCOM) is responsible for aviation material for fleet squadrons (DoN, 2017b).

To manage supply requests and fulfillments, the I-Level activity employs the Naval Tactical Command Support System (NTCSS) and Optimized Naval Aviation Logistics Command Management Information System Intermediate Maintenance Activity (NALCOMIS IMA) while the O-Level activity uses Optimized Organizational Level Maintenance Activity (OOMA) NALCOMIS to provide real-time maintenance and supply information to improve decision making and the quality of data produced (DoN, 2017b). NALCOMIS IMA allows users to "collect, store, process, review, and report" information relevant to both the maintenance and aviation supply departments within MALS (DoN, 2017, p. 13-5). OOMA NALCOMIS, differs from I-Level NALCOMIS by which it tracks aircraft flight data as well as maintenance logs (DoN, 2017b). These management information systems interface with each other through work orders and requisitions produced by the O-Level activity (DoN, 2017b).

D. SUMMARY

SCM can produce numerous gains for organizations who collaborate with supply chain members. Information sharing is an important factor which leads to a competitive advantage achieved by aligning processes, policies, and integrating strategic activities (Zhou & Benton, 2007). Understanding the information required by supply chain participants can increase SCM performance and mitigate risks. Errors in inventory management and fluctuations in demand are a few of the challenges managers aim to minimize.

BD analytic tools are technologies that can reduce supply chain waste and improve supply chain performance. BDBA can discover relationships and associations within vast amounts of historical data and provide supply chain professionals with previously unknown information. This information then assists managers making future decisions and mitigating risk.

As in the private sector, the DoD can apply BDBA to supply chain data, unearthing strengths and potential vulnerabilities. In the following chapter, data mining methodologies and techniques will be discussed, including Lexical Link Analysis (LLA), a text mining tool used for this research.

III. METHODOLOGY

A. DATA MINING OVERVIEW

In Bahari and Elayidom's (2015) article concerning the framework of data mining, they define data mining "as a process that uses mathematical, statistical, artificial intelligence and machine learning techniques to extract and identify useful information and subsequently gain knowledge from databases" (p. 725). Building upon their definition, Ozyirmidokuz, Uyar, and Ozyirmidokuz (2015), added that data mining is the organization of large quantities of data into a structured model to visualize relationships and patterns. The Oracle Help Desk, (2018) described four principles concerning the concept of data mining; "the automatic discovery of patterns, prediction of likely outcomes, creation of actionable information, and the focus on large data sets and databases." Mining techniques can be beneficial to the discovery of previously unknown information, leading to the recognition of patterns and relationships that can improve quality and production (Ozyirmidokuz et al., 2015). An important aspect to note regarding data mining is that it is a process that seeks to ascertain implicit or unacknowledged information that can be useful in aiding to organizations during the decision making process (Shaw, Subramaniam, Tan, & Welge, 2001). Shaw et al., (2001) stated data mining "involves selecting, exploring, and modeling large amounts of data to uncover previously unknown patterns, and ultimately comprehensible information, from large databases" (p. 128). Because data mining and big data analytics focuses on hidden information, data mining is also referred to as Knowledge Discovery in Data (KDD) (Oracle Help Center, 2018). This discovery of knowledge can assist decision makers with such activities as the identification of process vulnerabilities or the prediction of future behaviors (Shaw et al., 2001).

1. Data Mining Process

Due to the large amount of data that needs to be examined, mining takes an automated approach when searching through vast data stores available to businesses and organizations (Oracle Help Center, 2018). Big data (BD) can be mined from a variety of sources and file types using mathematical algorithms to build models from the original data

(Oracle Help Center, 2018). Additionally, the massive quantity and variety of accessible data does not allow for humans to manually sift through and analyze it to draw meaningful conclusions (Gupta & Lehal, 2009). However, before an organization can begin applying automation and data mining techniques, it is critical that they understand the organization's goals, intentions, and most importantly the problem that requires resolution (Bahari & Elayidom, 2015). Narrowing down the problem set, enhances a manager's understanding of the requirements and objectives (Oracle Help Center, 2018).

Once the requirements are solidified and the desired outcomes are established, the data mining process flows through a logical method of application to ensure goals are achieved and the sought after knowledge is uncovered. As depicted in Figure 10, the data mining process as an iterative series of steps, beginning with raw data stored in databases and being complete when previously unknown knowledge is derived from the original data (Han & Kamber, 2000).

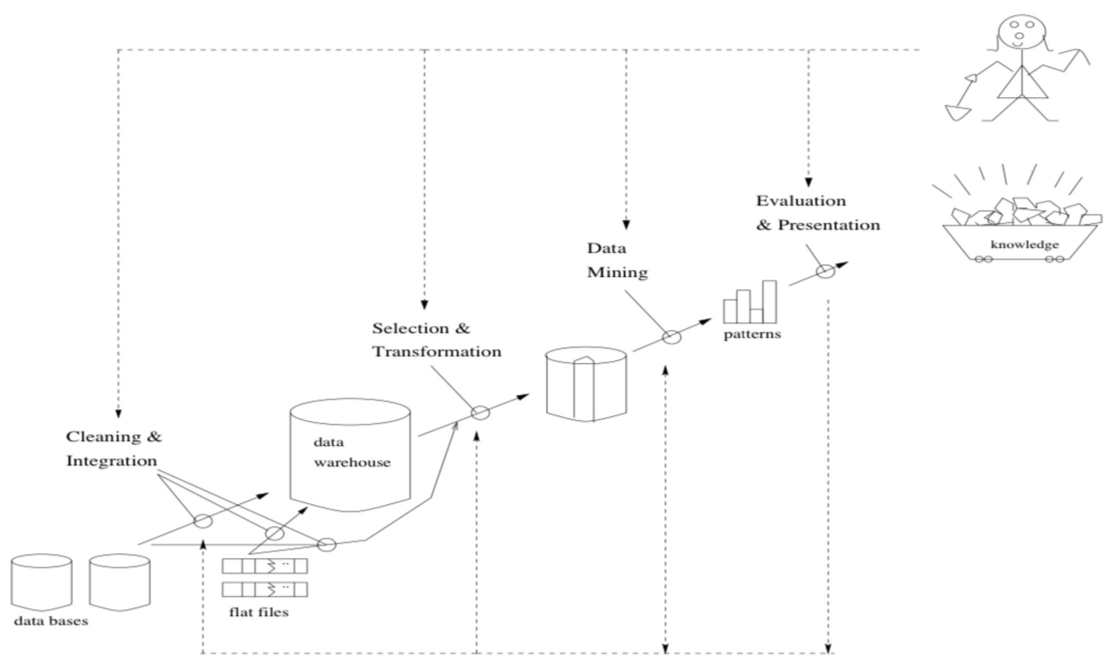

Figure 10. Data Mining Process. Source: Han and Kamber (2000).

1. Data Cleaning and Integration: “Removing noise and irrelevant data” (Han & Kamber, 2000, p. 6). Bahari and Elayidom (2015) called this step “data preparation or preprocessing” (p. 727)

2. Selection and Transformation: Retrieval of source data relevant to the problem and modifying the structure of the data to facilitate the mining process (Han & Kamber, 2000).

3. Data Mining: Application of algorithms to extract data and discover patterns and relationships (Han & Kamber, 2000).

4. Evaluation and Presentation: Identifying patterns of interest and creating visual and knowledge representations of the discovered information (Han & Kamber, 2000). Oracle Help Desk, (2018) similarly named this step “Model Building and Evaluation.”

Though straight forward as a visual depiction, Sivarajaj et al. (2017) however, described challenges related to each step throughout the data mining process.

1. Data Acquisition and Warehousing: The complex size and variety of data make it challenging for the mining of appropriate data (Sivarajaj et al., 2017). Algorithms are required to filter unnecessary data during collection, maximizing the value of the stored material and reducing storage cost and limitations (Sivarajaj et al., 2017).

2. Data mining and Cleansing: Before analysis, data pertaining to the problem set must be extracted from the stored collections (Sivarajaj et al., 2017). Cleaning data again, filters extraneous attributes and noise not needed during knowledge building (Sivarajaj et al., 2017). The Oracle Help Desk (2018) added that data can be transformed, modified, or cleaned, discarding attributes not relating to the problem. By consolidating appropriate data, desired results are more likely to occur (Oracle Help Desk, 2018).

3. Data Aggregation and Integration: Challenges again arise during data consolidation and integration due to the volume and variety of data generated (Sivarajaj et al., 2017). These complications are diminished through the use of appropriate algorithms and with a conscience effort of mining the most beneficial data.

4. Data Analysis and Modeling: This stage algorithms construct models or visual representations of relationships and patterns discovered from the chosen data set (Sivarajaj et al., 2017).

5. Data Interpretation: Visual representations and depictions of the data drive interpretations and impact decisions based off of the models employed (Sivarajaj et al., 2017).

When applying Han's and Kamber's (2000) iterative process, it must be stressed that a thorough understanding of the problem and knowing the desired outcome is vital to creating knowledge that adds value and enhances the decision making process (Bahari & Elayidom, 2015; Oracle Help Center, 2018)

2. Analytic Categories

Numerous analytic techniques can be employed to BD, however problem identification and requirements will drive which analytic tool to use, starting with descriptive, predictive, or prescriptive analytics (Wang et al., 2016). Descriptive analytics identifies problems, vulnerabilities, or opportunities with an existing process (Wang et al., 2016). Descriptive analytics looks at the past and describes what occurred, it is a "summation and description of knowledge patterns" (Sivarajaj et al., 2017, p. 275). Predictive analytics forecasts future behavior through mathematical algorithms and the discovery of patterns (Wang et al., 2016). It assesses historical and current data to develop conclusions about predictive behaviors (Elgendy & Elragal, 2016). Sivarajaj et al. (2017) added that predictive analytics use statistical models to express future possibilities. Lastly, prescriptive analytics, relates to both descriptive and predictive analytics, using algorithms to deduce and evaluate alternate solutions or possibilities (Wang et al., 2016). They "determine the cause-effect relationship among analytic results and business process optimization policies" (Sivarajaj et al., 2017, p. 276).

3. Machine Learning and Analytic Techniques

The category of analytics corresponds to a classification of learning employed. Descriptive analytics refers to unsupervised learning while predictive analytics applies to supervised learning, both derived from techniques used by machine learning and artificial intelligence (Oracle Help Desk, 2018). Techniques administered during BD analytics are highlighted in Figure 11.

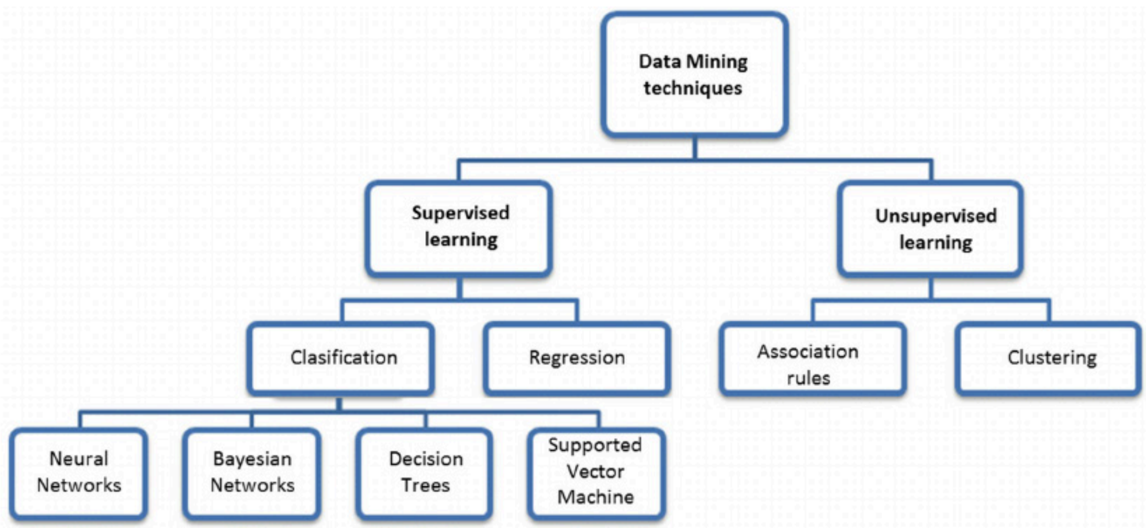

Figure 11. Data Mining Process. Source: Martin, Baena, Garach, and De Ona (2014).

Supervised learning seeks to explain behavior and involve training, "a process whereby the software analyzes many cases where the target value is already known" (Oracle Help Desk, 2018). Supervised approaches train and learn through assessment of historical data to make forecasts or classify new data (Hashmi & Ahmad, 2016). This technique uses models where attributes are known and analysis learns those attributes to make future predictions (Oracle Help Desk, 2018). Unsupervised learning recognizes patterns and clusters (Hashmi & Ahmad, 2016). This method is a process where attributes are unknown and there is no predetermined direction for the algorithm to follow when constructing a model (Oracle Help Desk, 2018). Supervised and unsupervised machine learning are applied in conjunction with traditional data mining techniques, such as "classification, clustering, regression, and association rules," as well as artificial intelligence including neural networks and decision trees to build desired models of knowledge and improve decision making processes (Elgendy & Elragal, 2016, p. 1075).

a. Classification

A supervised technique, classification consolidates data into groups or classes based on predefined categories (Oracle Help Desk, 2018). The algorithm sorts and organizes data, trying to predict which classification the target variable belongs (Oracle Help Desk, 2018). As an example, banks may categorize patrons by credit score class, high, medium, and low (Oracle Help Desk, 2018). Customer information such as previous credit score, employment history, salary, and debt will be used to predict which category a customer is classified (Oracle Help Desk, 2018). Apache Mahout, "scalable machine learning open source software," and Massive Online Analysis (MOA) are common classification software (Fan & Bifet, 2013).

b. Regression

Another supervised technique is regression, an algorithm that predicts an outcome using numerous variables (Oracle Help Desk, 2018). Relationships between variables are correlated to forecast an independent variable (Oracle Help Desk, 2018). Housing prices is an example of regression. Information pertaining to lot size, square footage, taxes, school districts, etc., are correlated to house value and used to predict the future value of homes (Oracle Help Desk, 2018). MOA is a software that can be used to apply regression models to data (Fan & Bifet, 2013).

c. Clustering

Similar to classification, clustering is an unsupervised learning approach to data mining (Oracle Help Desk, 2018). Cluster analysis classifies data by seeking "to maximize between-group variances and minimize within-group variances" (Ozyirmidokuz et al., 2015, p. 78). The difference between classification and clustering is that cluster analysis categories are not predefined (Oracle Help Desk, 2018). It uncovers organic collections and relationships that where potentially unknown (Oracle Help Desk, 2018). Apache Mahout and MOA can both be used with cluster analysis (Fan & Bifet, 2013).

d. Association Rule

A second unsupervised technique is the Association Rule. Association is a technique that discovers the "co-occurrence" between actions (Oracle Help Desk, 2018). The action against one variable relates to the impact on another (Oracle Help Desk, 2018). Yabing (2012) stated that the intent of Association Rule techniques is to uncover relationships and connections between various items within a large dataset. An example is the purchase of cereal at a grocery store and the likely occurrence milk is also purchased (Oracle Help Desk, 2018).

B. TEXT MINING

Text mining is a variation of data mining, where instead of searching large databases for patterns, it searches text and unstructured data for the creation of knowledge (Gupta & Lehal, 2009). Data mining examines a limited scope of all of the data generated by an organization (Dörre, Gerstl, & Seiffert, 1999). Dorre et al. (1999) alluded to about 90% of all the data an organization creates is never analyzed, such as "letters from customers, email correspondence, recordings of phone calls with customers, contracts, technical documents, and patients" (p. 398). Gupta and Lehal (2009) added ten years later, 80% of information is believed to be stored in text format and has high commercial potential. Furthermore 80% of the World Wide Web is in text format while only 20% is numerical, with unstructured text remaining the largest available source of knowledge (Gupta & Lehal, 2009). Text mining analyzes sources such as these to extract information, and identify links, patterns, and relationships between unstructured text sources (Gupta & Lehal, 2009). The basic process concerning text mining is shown in Figure 12.

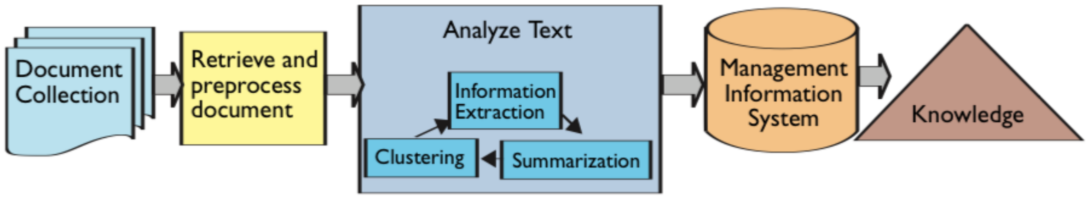

Figure 12. Text Mining Process. Source: Fan, Wallace, Rich, and Zhang (2006).

Just as with data mining, text mining begins with the consolidation of data pertinent to the problem requirements and objectives sought after (Fan et al., 2006). Employing a mining technique sources are retrieved by searching prewritten text and preprocessed by "checking for format and character sets" (Fan et al., 2006, p. 78; Gandomi & Haider, 2015). The data is then examined by specified algorithms for interpretation. Models are generated and representations are created to assist with understanding the material, leading to the development of knowledge and assisting with decision making processes (Fan et al., 2006).

a. Text Mining Analytics

Text mining is laborious and extensive due to the large amount and variety of text sources (Dorre et al., 1999). Thus, Gupta and Lehal (2009) stated that text mining algorithms require natural language processing (NLP) techniques while leveraging "statistics, machine learning, reasoning, information extraction, and knowledge management" (p. 60). Gandomi and Haider (2015) continued to assess that "text analytics involve statistical analysis, computational linguistics, and machine learning" (p. 140). Automation must recognize language patterns and rules to seek out and extract valuable information (Dorre et al., 1999). This recognition of language and patterns pose a challenge during the consolidation and extraction phases of the process (Dorre et al., 1999). Dorre, et al. mentioned that feature selection and extraction is difficult, where a feature is organized information from "single documents as well as the analysis of the feature distribution over whole collections to detect interesting phenomena, patterns, or trends" (p. 398). Feature extraction can be the selection and recognition of vocabulary terms, whether selected manually or completely automated and not predefined (Dorre et al., 1999).

Ensuring relevant features are selected will provide desired results from analysis and modeling of the extracted data.

b. Text Mining Techniques

As with data mining, the employment of numerous text mining tools can produce valuable information and assist with decision making. Again the critical element before mining data is to ensure the problem is fully understood and the method of extraction aligns with the organization's intent and goals (Bahari & Elayidom, 2015).

c. Information Extraction

Information extraction uses *pattern matching* predefined sequences within language and recognizes patterns and relationships through key phrases found (Fan et al., 2006). The algorithms then discover relationships and correlates key phrases with meaningful information (Gupta & Lehal, 2009). This technique generates structured data from unstructured text (Gandomi & Haider, 2015).

d. Topic Trackers

Using historical textual documents, topic trackers search for topics of interest and generate predictions of related documents to analyze (Fan et al., 2006; Gupta & Lehal, 2009). The benefits of this tool allow organizations to track information such as competitor figures, products, and medical advancements (Gupta & Lehal, 2009). Internet search engines are applications that use topic tracker techniques (Gupta & Lehal, 2009).

e. Summarization

Summarization uses algorithms to pull out important information from large documents, summarizing key elements for quick and easy understanding (Gupta & Lehal, 2009). This tool extracts information or themes from one or many source documents and consolidates it into a summary form of the original texts (Fan et al., 2006; Gandomi & Haider, 2015).

f. Categorization

"Categorization involves identifying the main themes of a document by placing the document into a predefined set of topics" (Gupta & Lehal, 2009, p. 63). It treats the document as a *bag of words* and categorizes the main themes, not processing the data itself (Gupta & Lehal, 2009).

g. Clustering

Similar to categorization, clustering finds relationships between keywords or themes autonomously, rather than using predefined topics (Fan et al., 2006; Gupta & Lehal, 2009). Clustering examines text as a string of words while "removing all stop words (pronouns, prepositions, conjunctions, etc.)" (Gupta & Lehal, 2009, p. 65).

h. Concept Linkage

Concept linkage discovers relationships between documents through shared themes and assists in locating information (Gupta & Lehal, 2009). As an example in the medical field, it allows professionals to browse medical information while creating links between documents that otherwise may have been unknown such as disease and treatment documentation (Gupta & Lehal, 2009).

i. Information Visualization

Information visualization maps large textual information into a visual representation for analysis of content (Gupta & Lehal, 2009).

C. LEXICAL LINK ANALYSIS (LLA)

This research uses a tool named LLA to conduct text mining (Zhao, MacKinnon, Gallup, & Billingsley, 2016). LLA is a software program which recognizes themes and relationships across a variety of data, then correlates and compares the data (Zhao, Gallup, & MacKinnon, 2015). Once relationships are identified, LLA will sort and rank the information of interest to enhance decision making processes (Zhao et al., 2015). Examining text sources, LLA autonomously discovers "word pairs or bi-grams and displays them as a network from data" (Zhao et al., 2016, p, 3). LLA's approach is similar to the *bag-of-words* approach used by algorithms such as Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Analysis (PLSA), WordNet...and Latent Dirichlet Allocation (LDA)" (Zhao et al., 2016, p, 6). Additionally, Zhao et al. stated that because LLA uses bi-grams instead of a *bag of words*, results may prove more meaningful. As depicted in Figure 13, a bi-gram network. Each word becomes a node and the link between two words is relationship uncovered during the mining process, forming a bi-gram (Zhao et al., 2016).

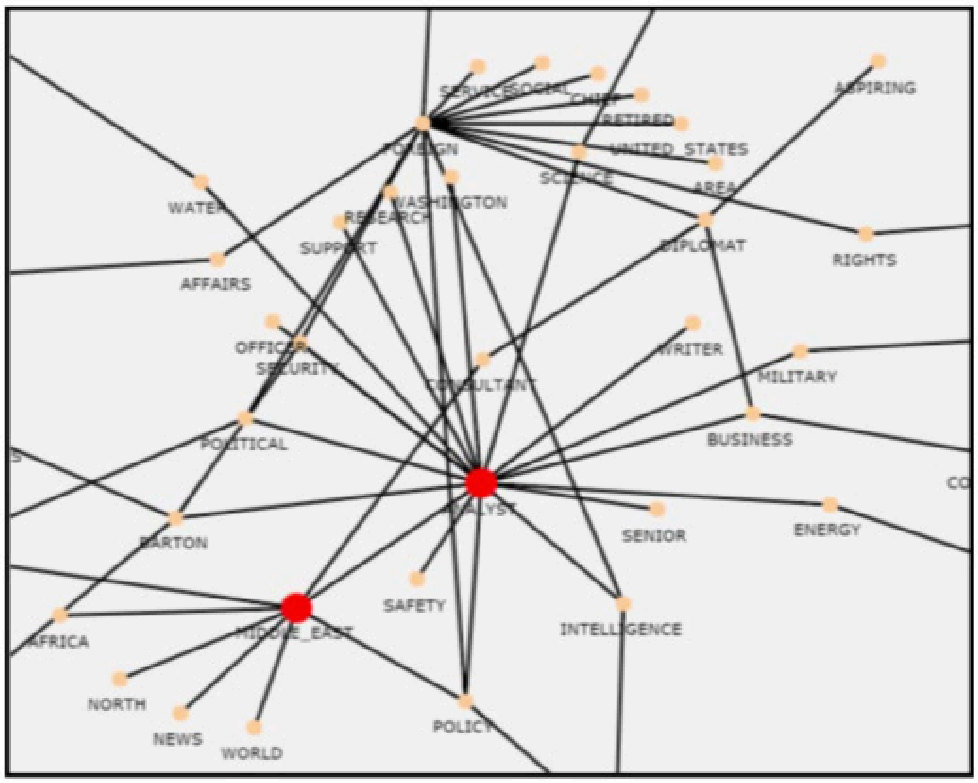

Figure 13. Bi-gram Network. Source: Zhao et al. (2016).

1. LLA Process

LLA applies a four step process, from searching through source data, to the creation of visual representations and models (Zhao et al., 2016). The four steps are as follows:

1. Filter out a list of pre-defined stop words; for example, the words "a," "the," "this" and "that," which do not convey meaning in English. Select word pairs in a sentence or paragraph level based on the bi-gram parameters of the following:

a. The probability of one word next to another word

b. The minimum frequency for each individual word

2. Apply a social network community finding algorithm, (*e.g.,* the Newman community detection method, to group the word pairs into *themes or topics*.) A *theme* includes a cluster or community of word pairs connected to each other.

3. Compute an importance measure for each theme.

4. Sort *theme importance* measured by time or other sequential parameters, and study the distributions of the discovered *themes.* (Zhao et al., 2016)

An example of bi-gram clusters and themes is shown in Figure 14. Once the bi-grams are identified, the community finding algorithm, groups the word pairs into themes showing relationships and links throughout sources of text (Zhao et al., 2016).

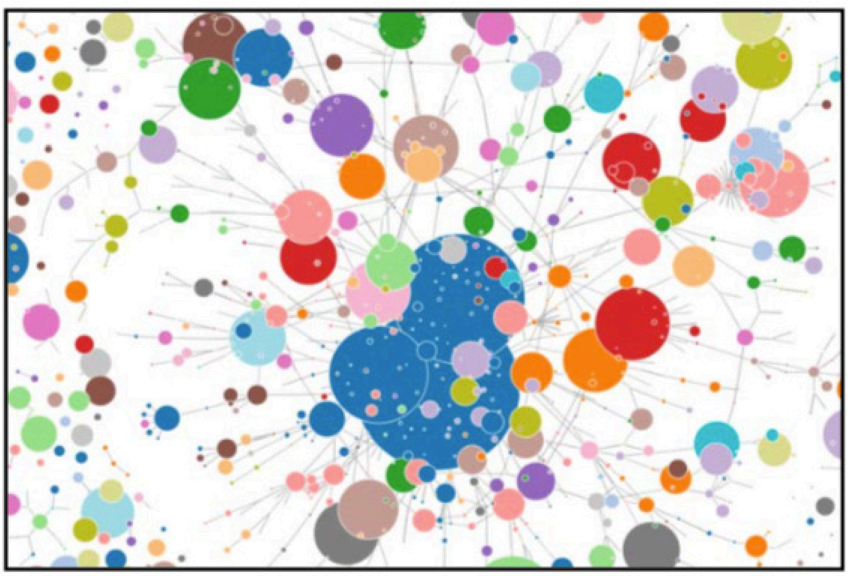

Figure 14. Word Pair Clusters and Themes. Source: Zhao et al. (2016).

When sorting and ranking word pair clusters, LLA classifies clusters into three categories, “authoritative or patterned features, emerging features, and anomalous features” (Zhao et al., 2016, p. 7). Authoritative features are those “clusters or themes containing the highest number of mutually connected word pairs or features” (Zhao et al., 2016, p. 7). Emerging features are an intermediate number of clusters or themes and may grow over time (Zhao et al., 2016). The last category is anomalous features, “clusters or themes with the lowest number of mutually connected word pairs” (Zhao et al., 2016, p. 7). Though minimal in comparison and lowest in priority, they may discover relationships which require further analysis (Zhao et al., 2016).

2. Collaborative Learning Agents

LLA is also employs deep learning to pattern recognition and intelligent text analysis through the use of collaborative learning agents (Zhao et al., 2016). These agents are applications that maintain an expertise or knowledge base focused on a specific domain or subject matter (Zhao et al., 2016). By assessing historical text data, they learn patterns of behavior and apply those patterns to new data (Collaborative Learning Agents [CLA], 2017 May 4). LLA takes advantage of these CLA’s to make insights toward discovered patterns and anomalies within the data (Zhao et al., 2015). An overview of LLA working in conjunction with CLA’s is described in Figure 15. Source data is processed by LLA and CLAs, recognizing themes, patterns, and anomalies for interpretation (Zhao et al., 2015).

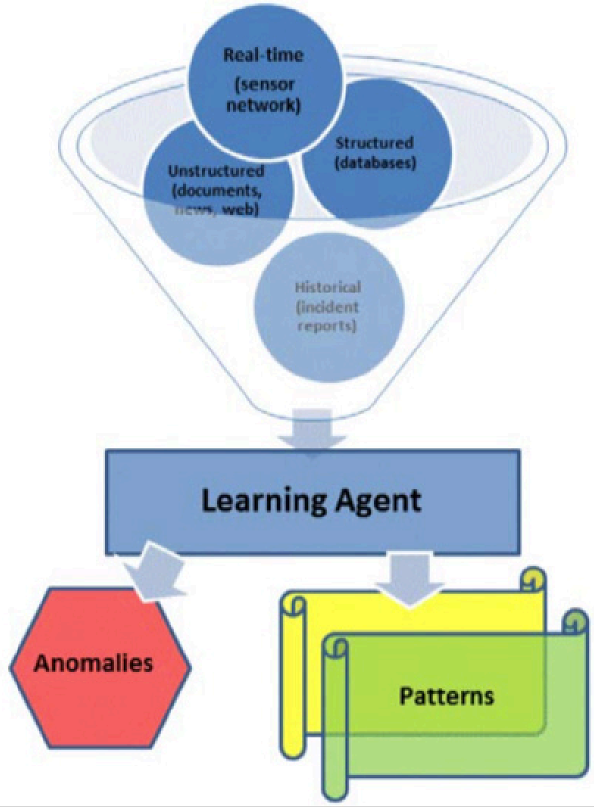

Figure 15. CLA Application. Source: Zhao et al. (2015).

D. RESEARCH COURSE OF ACTION

The focus of this research will be to assess the supply vulnerabilities or opportunities that present themselves between a MV-22 organizational level (O-Level) and intermediate level (I-Level) maintenance activities deployed on a MEU. The squadron examined will be Marine Medium Tiltrotor Squadron (VMM) 264 when assigned to the 22nd MEU in 2016. VMM-264 was embarked on the USS Wasp from 26 June 2016 to 21 December 2016 and assigned to support U.S. Africa Command, U.S. Central Command, Sixth Fleet, and Fifth Fleet operations (VMM-264, 2017a; VMM-264, 2017b). During the deployment VMM-264 participated in Operation ODYSSEY LIGHTNING and conducted operations in the Mediterranean and Red Sea areas of responsibility. Missions included TRAP, CASEVAC, and logistics support sorties such as troop and material transport (VMM-264, 2017a; VMM-264, 2017b). The squadron was co-located with the MALS-26 detachment aboard the USS Wasp the entire deployment.

This study will apply the LLA BD analysis tool previously described to various maintenance reports and documentation during VMM-264's deployment. One type of record of interest will be the daily supply documents created by I-Level Marines. The intent is to trace journey of individual components through the analysis of supply status updates. Comparing initial request dates to estimated, and arrival dates will provide information concerning the response and travel time of supply parts. The supply documents also include supply status codes and locations of the where the component is located. As the part moves through the supply chain a depiction of supply chain nodes will become apparent. The supply status codes will present the condition of part, including backorders, ready for shipment, and delay codes. The research expectation is that the data will illuminate a relationship between supply chain nodes and supply component statuses across VMM-264's MEU deployment.

Labeling of Not Mission Capable (NMC) and Partial Mission Capable (PMC) components is approved via the MV-22 Mission Essential Subsystem Matrix (MESM) (DoN, 2017). The Naval Aviation Maintenance Program (NAMP) (DoN, 2017b), described the MESM as a document that specifies aircraft maintenance readiness goals and categories aircraft systems that are essential for meeting mission objectives (DoN, 2017b). "The MESM lists subsystems required for specific missions and the impact of subsystem degradation or inoperability through Equipment Operational Capabilities (EOC). EOCs shall be documented only when the described subsystem, capability, function, or mode impacts the specific mission" (DoN, 2017b, p. 17-14). Furthermore, an "EOC code is a three-character alphanumeric code that identifies the degree of degradation to mission capability and the system responsible for the degradation" (DoN, 2017b, p. A-30). EOC alpha characters C, D, J, K, and L label aircraft readiness as PMC while an EOC character of Z will designate aircraft readiness as NMC (DoN, 2017b). PMC defined by the NAMP is a readiness condition which limits aircraft from flying all specified missions published in the MESM. NMC readiness is described as an aircraft that is not safe to fly and cannot carry out any of the MESM mission sets. If supply does not have the PMC or NMC component in stock, then the part is labeled as NCMS (supply) or PMCS until the part is received by the O-Level maintenance activity.

1. Measurement of Success

The NAMP (DoN, 2017b) described timelines for I-Level to O-Level supply chain success. Described in Table 1 is the timeline requirement for I-Level maintenance to provide the O-Level activity with requested components. All NMC and PMC components listed within the supply documents are Issue Priority Group (IPG) 1, thus should have been received by squadron maintenance within one hour of processing the defective part in OOMA (DoN, 2017b). However, due to delays, part requisition extends beyond IPG 1 processing time.

Table 1. I-Level Material Delivery Requirements. Source: DoN (2017b).

Issue Priority Group	Priority Designator	Processing Time
1	1-3	1 Hour
2	4-8	2 Hours
3	9-15	24 Hours

Repairable parts, those components where a carcass is accepted at I-Level, repaired, and restocked, also have a timeline known as a Turnaround Time (TAT) to facilitate expedient supply chain functionality (DoN, 2017b). The NAMP guideline for TAT is as follows:

1. Removal to Intermediate Maintenance Activity—1 day.
2. Scheduling time—3 days.
3. (Awaiting Parts) AWP time—20 days.
4. Actual repair time - 8 days. (DoN, 2017b, p. 9-34)

Additionally, the Joint Materiel Priorities and Allocation Board (JMPAB), acting under the Chairman of the Joint Chiefs of Staff, issues a Force/Activity Designator (F/AD) to expedite requisitions needed by designated organizations (DoN, 2018). The F/AD is an identification label that prioritizes the importance of activity, unit, or mission to accomplish objectives (DoN, 2018). F/AD I is only assigned to those activities of top national priority, F/AD II are assigned to all units and activities executing the Chief of Naval Operation's Optimized Fleet Response Plan and employment cycle "at commencement of the integrated phase, 30 days prior to deployment, or whichever milestone occurs first" (DoN, 2018, p. 5). F/AD III–V are those organizations determined to be of lowest precedence (DoN, 2018). F/ADs combined with Urgent Need Designators (UND) will set priorities for supply support, ensuring critical supply needs are met for the individual organization as well as meeting combatant commander requirements (DoN, 2018). Because the data for this research was during VMM-264's 2016 MEU deployment, the supply priority was designated F/AD II.

This research will determine success by evaluating the supply chain nodes and response times for components that trend beyond the specified TAT in the NAMP. The intent behind applying Microsoft Excel and LLA to VMM-264's supply documents and other provided documentation, is to discover unknown trends concerning MV-22 aircraft parts not meeting designated timelines, as well as those parts not managed appropriately in supply inventories while deployed on the USS Wasp. From Excel's and LLA's results, vulnerabilities may be ascertained, resolving issues pertaining to IPG-1 high priority parts listed on the supply documents and furnishing recommendations regarding deployed MEU supply chain efficiencies.

E. SUMMARY

Data mining is a process of searching through data to discover unknown patterns, relationships, and correlations. The information found can generate structured models and visual depictions of connections, links, and associations (Ozyirmidokuz, Uyar, & Ozyirmidokuz, 2015). Applying various analytic techniques to mined data will determine how information will best assist end-users. Techniques such as descriptive, predictive, or prescriptive analytics will produce results describing past occurrences, predict future behaviors, or determine alternative solutions or possibilities (Sivarajaj et al., 2017; Wang et al., 2016).

This project will employ LLA to structured and unstructured MV-22 supply documentation to unearth significant characteristics and features of interest. The following chapter highlights that analysis.

IV. ANALYSIS

A. DATA PREPROCESSING

Prior to conducting analysis, the data set was preprocessed to ease information extraction and support LLA's analytical requirements. The following steps are those actions used to modify the data.

(1) Group by Document Number

The original data set depicts each supply document update as one row in an Excel file. Numerous rows were needed to provide all of the information for one particular supply document. To eliminate redundancy, each supply document was compressed into one row of information. Thus, when searching, filtering, and sorting the data, the document number is reduced to one instance with all the updated information following. The initial supply document was chosen by the earliest Julian date annotated on each specific document number.

(2) Response Time Calculation

The data set provided two different dates to consider. The first was the Julian date when the supply document initially appeared in the data, or when it was first annotated on the Aircraft Maintenance/Supply Readiness Report (AMSRR). The second date was the Julian estimated delivery date (EDD). The preprocessed data took the latest EDD recorded in the supply document updates and subtracted it from the initial date. An estimated response time was then associated to the part within the supply document. This measurement was calculated, since no proof of delivery was annotated in the data. Because of this approximate calculation, estimated response time values may not reflect actual response times.

(3) Total Time

A "Total Time" column was added to show the response time calculation for each supply document.

(4) EDD Updates

EDD updates were counted to extract the number of times the supply document was updated concerning the response time.

(5) Comments

Comments were retained for all of the supply documents and placed in one string at the end of each supply document row.

(6) Null

All "Null" items within the data set were removed and left as empty cells. Empty cells were left empty.

(7) Supply Status

Columns were added for each supply status code and counted to reflect the updated supply status codes throughout the journey of the supply document's life.

(8) Routing Identification Code (RIC)

Columns were added for each RIC and counted to reflect the updated part location throughout the journey of the supply document's life. Conflicts between RICs were resolved through supply document analysis.

B. INFORMATION EXTRACTION

1. Overall Assessment

To achieve the measures of success for this project, examination of the data focused on five elements of the data set: individual high priority parts, project codes (criticality of component), response time, status codes (part supply status), and RIC (component location or sourcing activity). Additionally, to assess supply chain shortfalls, this research reduced the window of time from 1 August 2016 to 31 October 2016. During this period, VMM-264 was in a static geographic location off the coast of Libya conducting combat operations in support of Operation ODYSSEY LIGHTNING. This provided control to the squadron's location and emphasized attention toward the supply chain. The following examination highlights the overall assessment of the supply network. Microsoft Excel depictions are histograms associating frequencies or percentages to appropriate qualities. LLA diagrams are clustered discs with linked correlations. Green clusters are common or frequent, blue clusters are less common, and orange clusters are anomalies. LLA contractions concerning quantities are "lt," for less than; "bt," describing between; and "mt," expressing more than. It also must be stressed that Weapons System Support (WSS) NAVSUP Philadelphia, Pennsylvania (NRP), and Defense Logistics Agency (DLA) Fort Belvoir, Virginia (SMS) accounted for a large portion of the RICs listed on the supply documentation. However, these RICs are not supply locations; they are administrative activities used to forward supply requisitions to the most appropriate sourcing activity.

a. Parts

Over the 92-day period, VMM-264 ordered 2,262 discrete high priority components, a rate of 24.5 distinct parts per day. The number of parts and frequency of order is depicted in Figure 16.

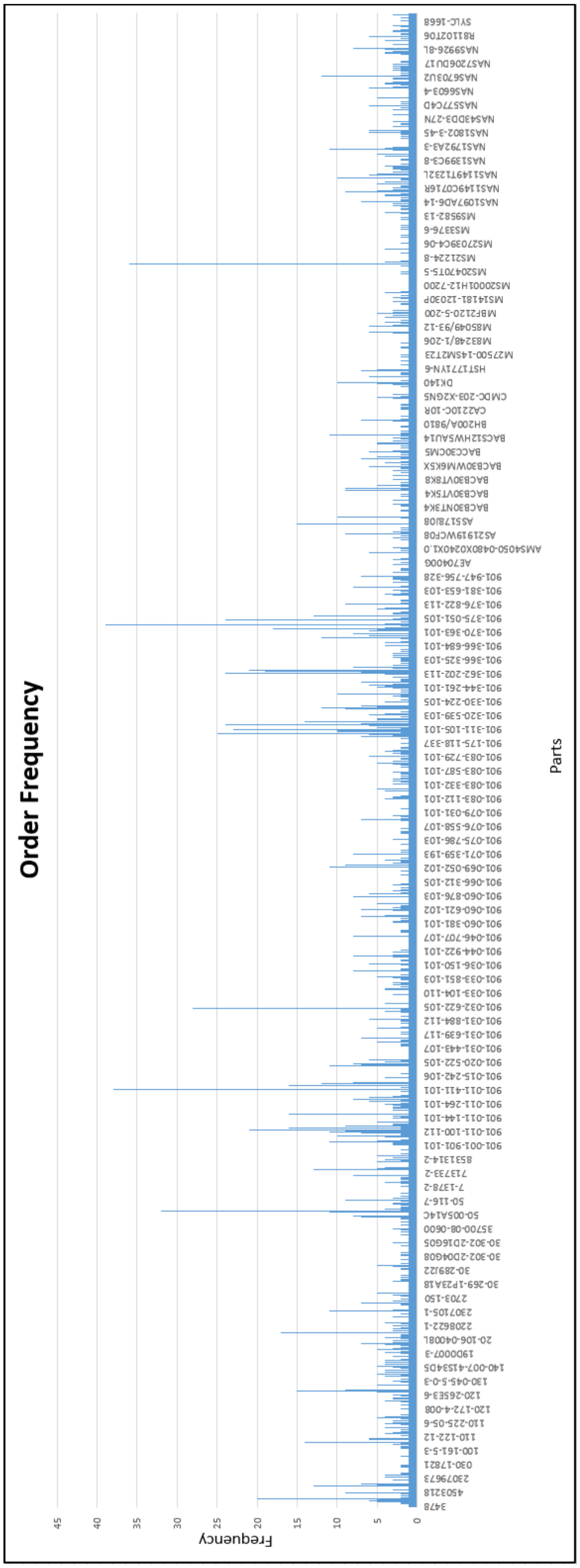

Figure 16. Order Frequency

Additionally, Table 2 shows the breakdown of the most frequently ordered parts in Figure 16.

Table 2. Order Frequency of High Priority Parts

Frequency of Discrete Parts Ordered	Number of Occurrences
10 times or greater	45
15 times or greater	21
20 times or greater	13
25 times or greater	6

For example, 45 different components were ordered 10 times or more during this period. Only 5.7% of the ordered components occurred at a frequency of six times or more. Of the 2,262 high priority parts ordered, 2,132 were demanded at frequency of five times or less, composing of 94.3% of the requisitions.

b. Project Code

To measure criticality of a part, a project code is given to the component based on the impact that part has to mission capability. NMCS designations encompassed 72.2% of the parts ordered and PMCS codes constituted 11.8% of the requisitions. As shown in Figure 17, a breakdown of all project codes ordered during this assessment.

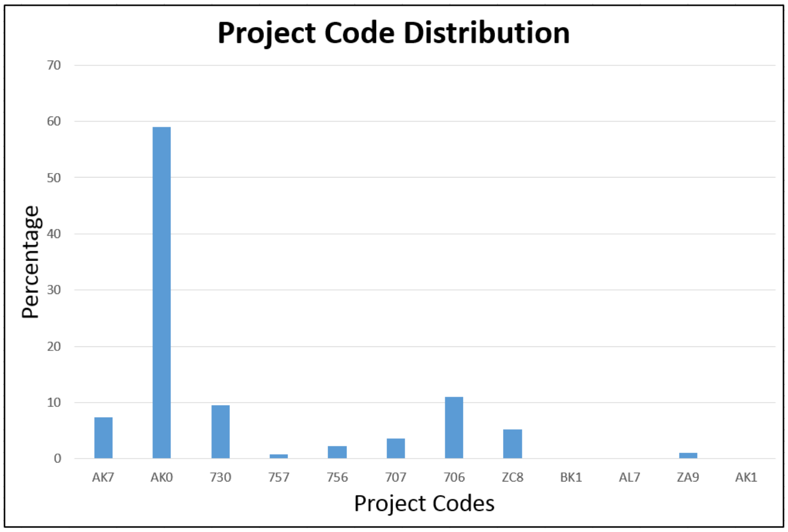

Figure 17. Project Code Breakdown

Table 3 in the Appendix gives definitions for all project codes displayed.

c. Status Code

Supply status codes were evaluated to understand the condition of the components and supply chain robustness. The codes analyzed were those identified on the earliest supply document within the data set, when they first appeared on the Aircraft Maintenance/Supply Readiness Report (AMSRR). This most likely indicates those parts available at the time of requisition. Of the components ordered, 30.9% were initially given a "BA" status code, i.e., items that were being processed for release and shipment. Additionally, the data indicates 9.9% were coded "AS," meaning those parts in shipping status. Initial codes of "BA" and "AS" are indications of availability. Conversely, 19.8% of the parts were labeled "BB," backordered and 11.7% were "BD," delayed. "BB" and "BD" demonstrate shortfalls within the supply system. As presented, Figure 18 is a breakdown of requisitions by status code when they are first documented on the AMSRR. Table 4 in the Appendix gives definitions for all status codes identified.

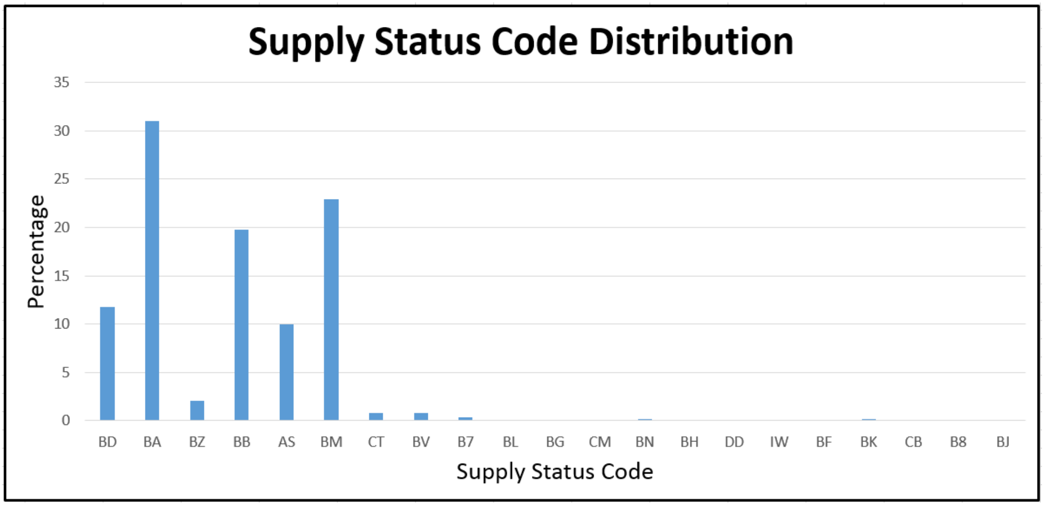

Figure 18. Supply Status Code Distribution

d. Response Time

Using the calculation as previously described, the estimated response times for requisitions of 15 days or less was 64.3%. The average estimated response time was 74.2 days from date of order, to the last known EDD. However, the median value for transit time was 15 days, with six days as the mode. As shown, Figure 19 displays the estimated response times over a 90-day period.

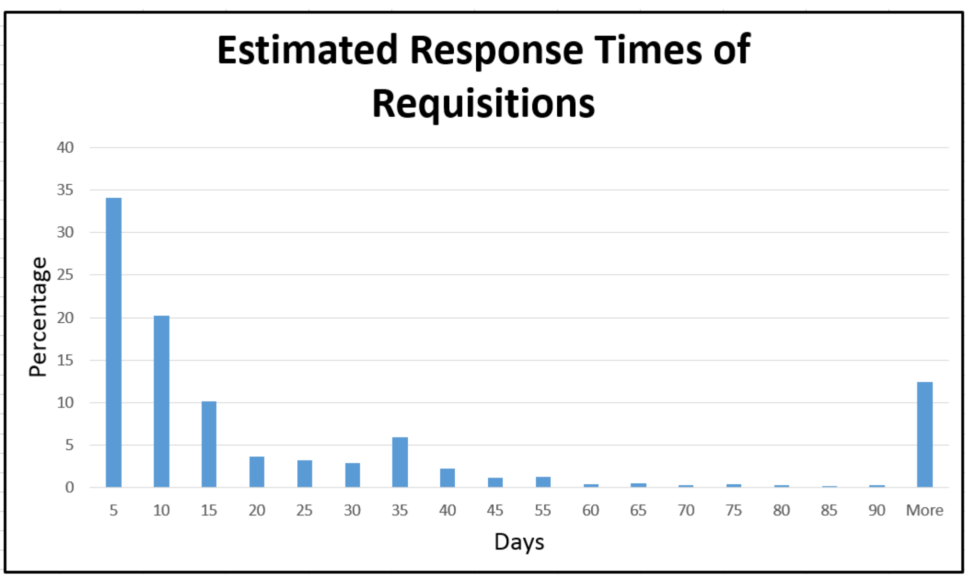

Figure 19. Estimated Response Times

2. “BA” Status Analysis

Isolating the “BA” supply status code focuses the research to assess those parts that were readily available at the time of requisition. Examining parts, project codes, response times, and RICs will highlight supply chain characteristics.

a. Parts

Of the 2,262 discrete high priority parts ordered, 505 were initially labeled with a status code of “BA.” This amounted to 22.3% of the parts. Only six parts were ordered at a frequency greater than five times. Thus, 98.8% of the parts demanded were ordered five times or less. Concerning the cognizance of material, 95.1% were consumable parts while 4.9% were repairable. The order frequency of the requested parts is highlighted in Figure 20.

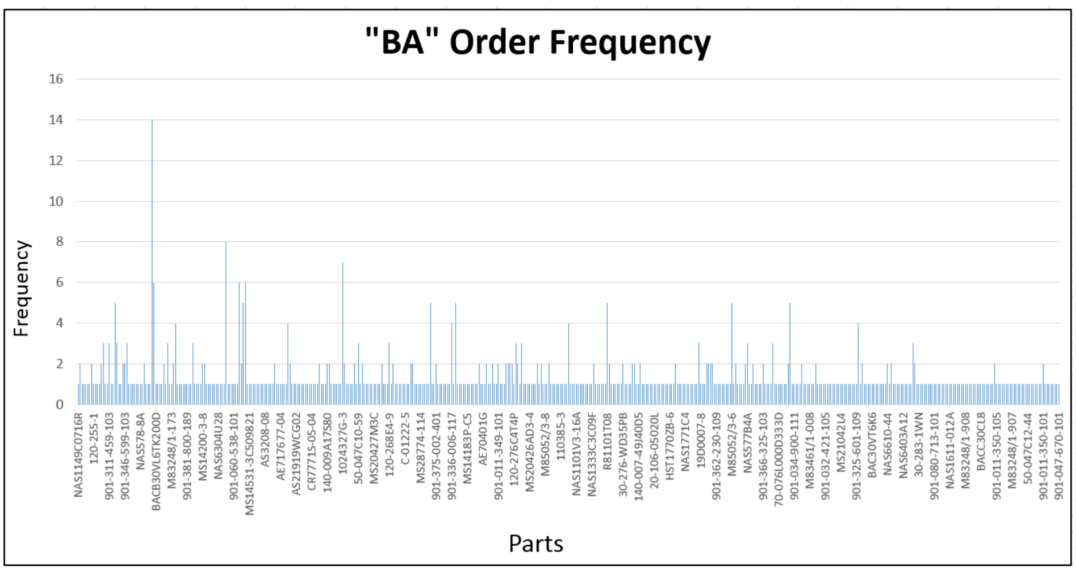

Figure 20. “BA” Order Frequency

b. Project Code

Concerning criticality, 79.2% of the parts were NMCS while 10.6% were PMCS. Project codes by percentage are depicted in Figure 21.

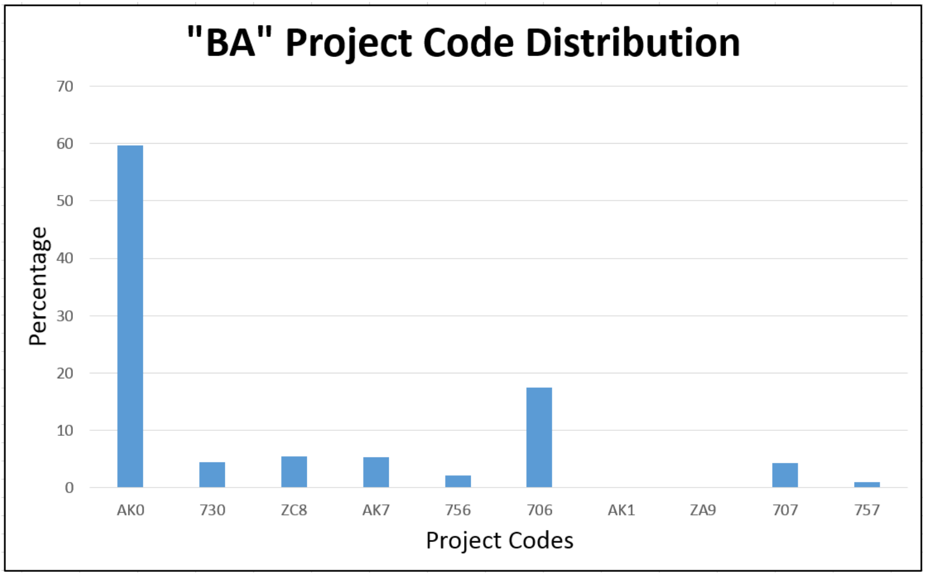

Figure 21. "BA" Project Code Breakdown

c. Response Time

Estimated response times for requisitions of 15 days or less was 85.3%. The average estimated response time was 15.6 days from date of order, to the last known EDD. However, the median value for estimated transit time was eight days, with six days as the mode. As highlighted, Figure 22 displays the response times over a 90-day period.

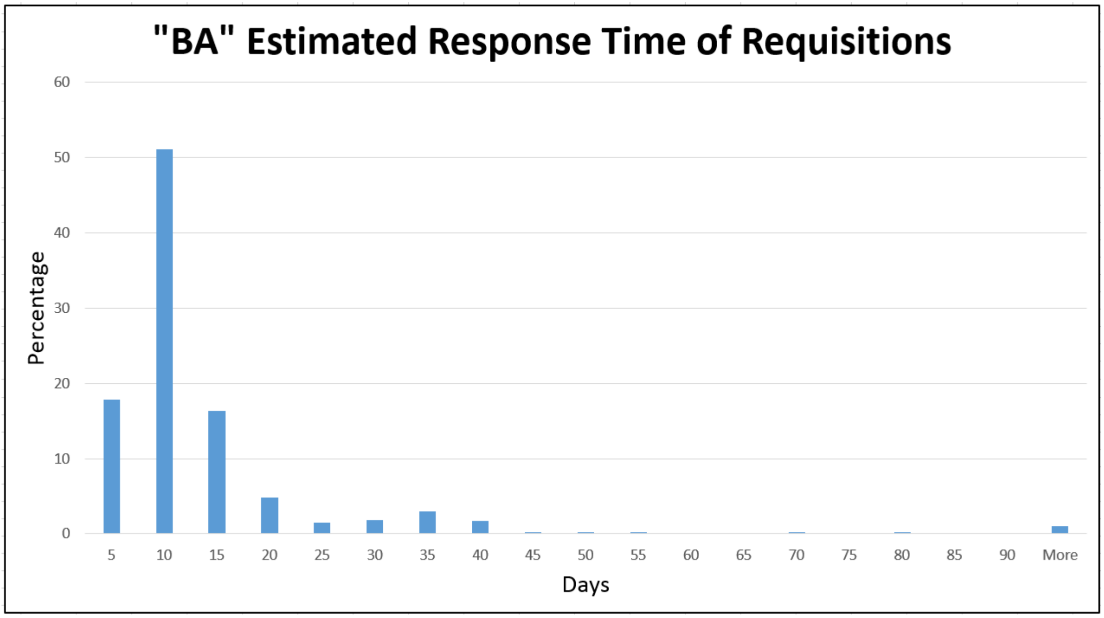

Figure 22. "BA" Estimated Response Times

d. RIC

The number of RICs discovered as sourcing activities was 37, a number which includes Weapons System Support (WSS) NAVSUP Philadelphia, Pennsylvania (NRP), and Defense Logistics Agency (DLA) Fort Belvoir, Virginia (SMS). Within VMM-264's area of operation (AO), DLA Europe, Germersheim, Germany (SDQ) was the only sourcing location uncovered. Thus, 73.1% of the sourcing activities were located in the continental United States, excluding WSS NAVSUP Philadelphia, Pennsylvania (NRP), and DLA Fort Belvoir, Virginia (SMS), activities. DLA Europe Germersheim, Germany (SDQ), constituted 0.15% of the sourcing. As shown, Figure 23 depicts the sourcing activities discovered and Table 5 in the Appendix lists all of the discovered routing identification codes.

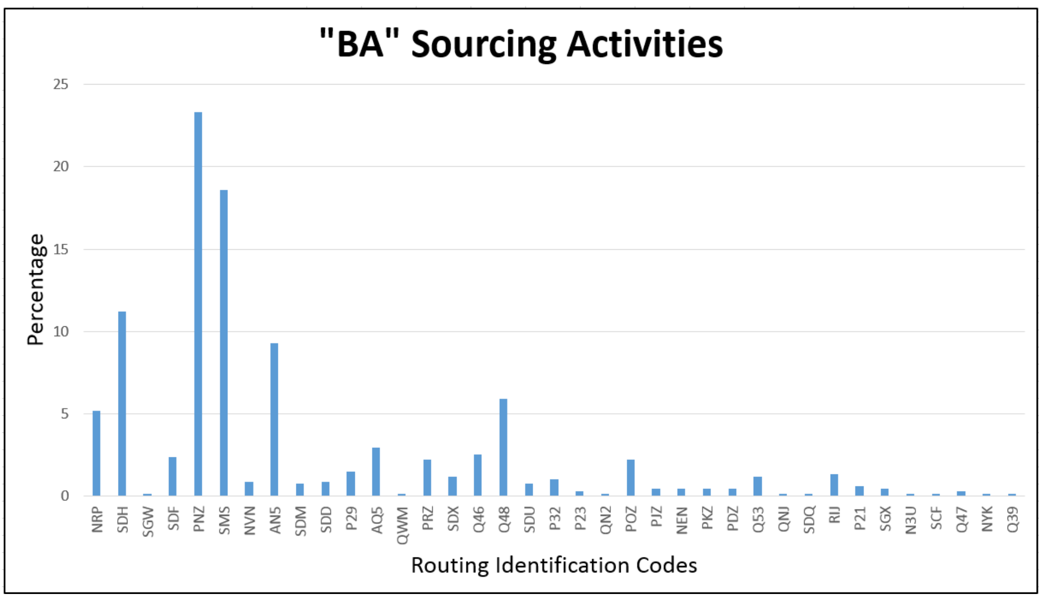

Figure 23. "BA" Sourcing Activities

3. "BA" Critical Component Examination (NMCS)

To assess available parts critical to aircraft readiness and combat capability, the research delved into Not Mission Capable Supply (NMCS) project codes. The intent was to discover which parts were most hindering to readiness while being accessible in the supply chain.

a. Parts

Of the 505 discrete "BA" parts ordered, 407 were identified as NMCS. This contributed to 80.6% of the parts. Only three parts were ordered at a frequency greater than five times. Thus, 99.3% of the parts demanded were ordered five times or less. Concerning the cognizance of material, again, 95.1% were consumable parts while 4.9% were repairable. The order frequency is displayed in Figure 24. Additionally, Figure 25 draws out characteristics of parts labeled with the "706" project code. The key point to highlight is that there were 15 distinct high priority parts ordered with a quantity between five and 22, and seven parts requested required a quantity greater than 22.

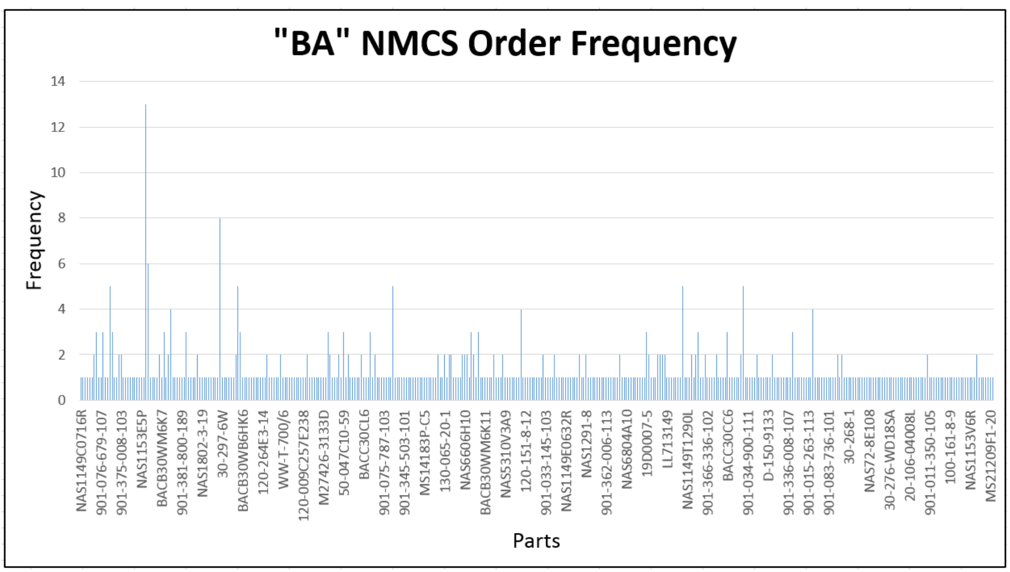

Figure 24. "BA" NMCS Order Frequency

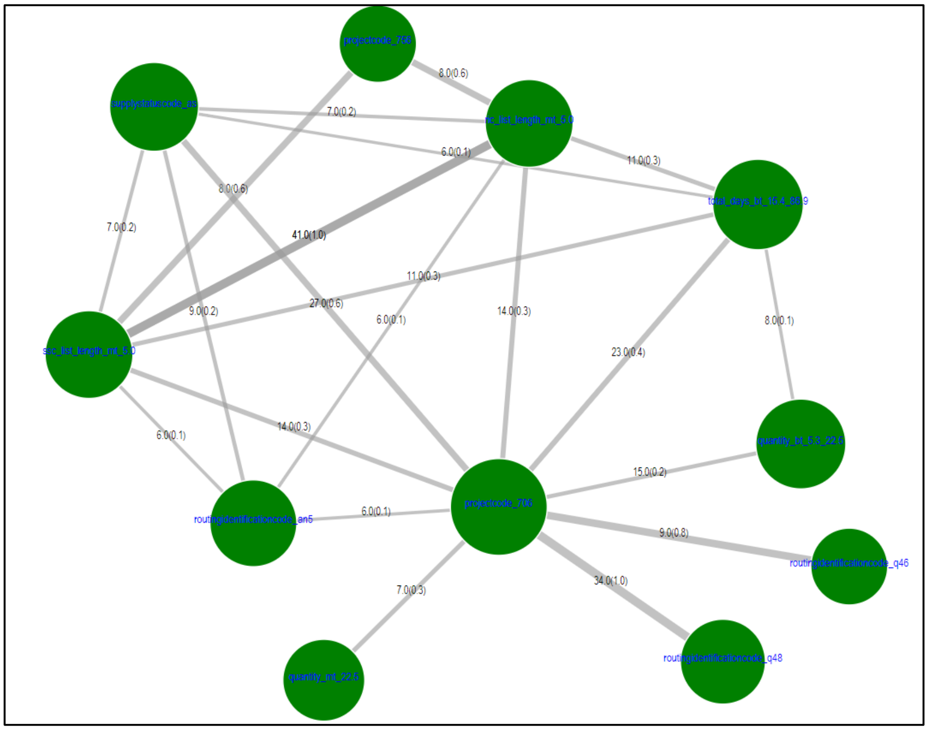

Figure 25. “BA” Project Code “706” Attributes

b. Response Time

Estimated response times for requisitions of 15 days or less was 83.6%. The average estimated response time was 20 days from date of order, to the last known EDD. However, the median value for transit time was eight days with six days as the mode. The response times over a 90-day period is shown in Figure 26. Furthermore, Figure 27 identified DLA San Joaquin, California (AQ5) as an anomaly. Though DLA San Joaquin, California (AQ5) accounted for 2.8% of the sourcing, all 14 orders had an estimated response time of 15 days or less.

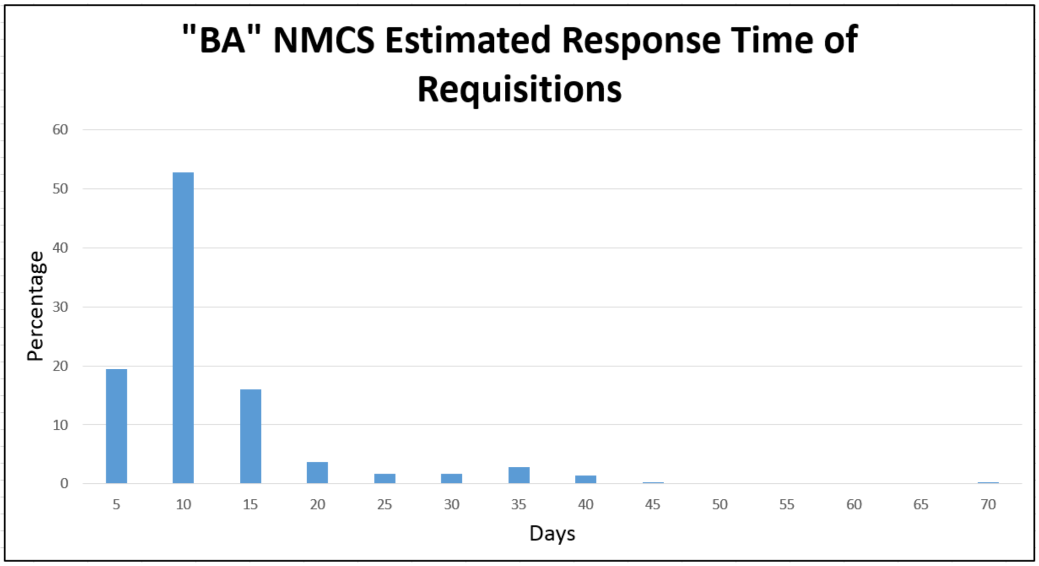

Figure 26. “BA” NMCS Estimated Response Times

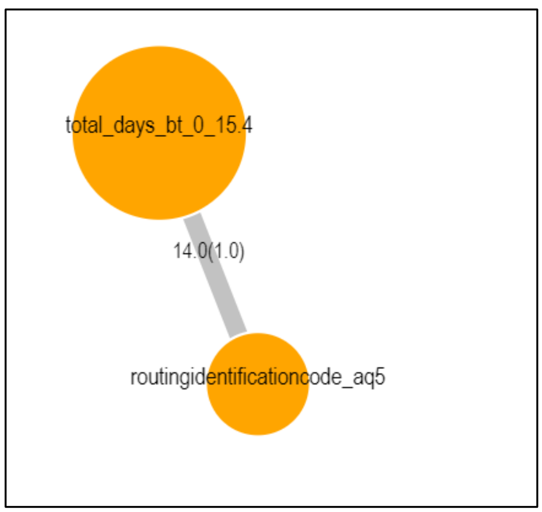

Figure 27. Estimated Response Times: DLA San Joaquin, California (AQ5)

Moreover, Figures 28 and 29 emphasize estimated response times between 15 and 86 days, and greater than 86 days respectively. Of note, seven discrete parts sourced from DLA Cherry Point, North Carolina (SDH) and 12 from DLA Fort Belvoir, Virginia (SMS) experienced estimated response times between 15 and 86 days, while DLA Fort Belvoir, Virginia (SMS) and Naval Air Station (NAS) Oceana, Virginia (PNZ) sourced two parts each with an estimated response time greater than 86 days.

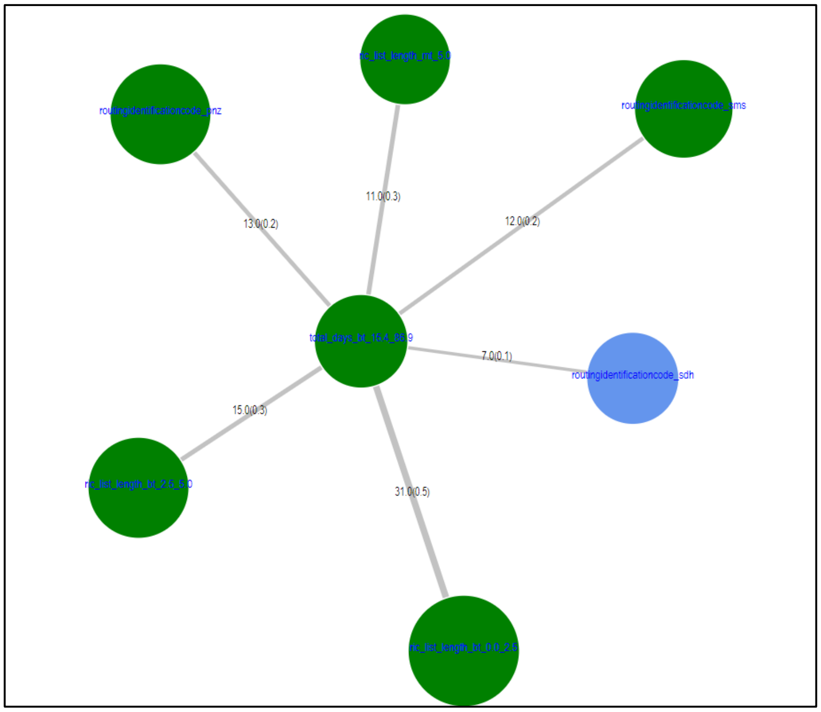

Figure 28. “BA” NMCS Estimated Response Times: 15–86 Days

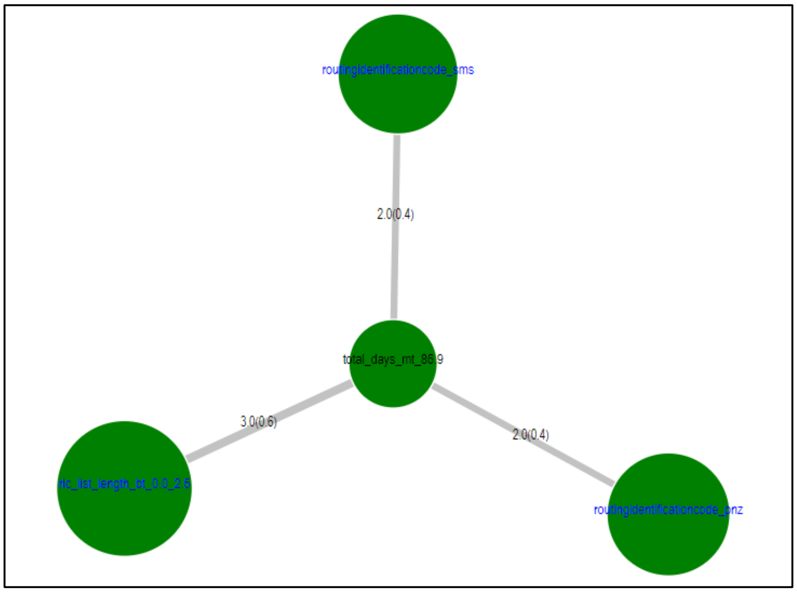

Figure 29. “BA” NMCS Estimated Response Times: Greater Than 86 Days

c. RIC

The number of RICs discovered were reduced from 37 to 35, a number which includes WSS NAVSUP Philadelphia, Pennsylvania (NRP) and DLA Fort Belvoir, Virginia (SMS). Again, DLA Europe, Germersheim, Germany (SDQ) was the only sourcing activity within VMM-264’s AO. Sourcing activities located within the continental United States accounted for 71.3% of the requisitions, excluding NAVSUP Philadelphia, Pennsylvania (NRP) and DLA Fort Belvoir, Virginia (SMS). DLA Europe, Germersheim, Germany (SDQ sourced 0.19% of the requests. As presented, Figure 30 depicts the sourcing activities identified.

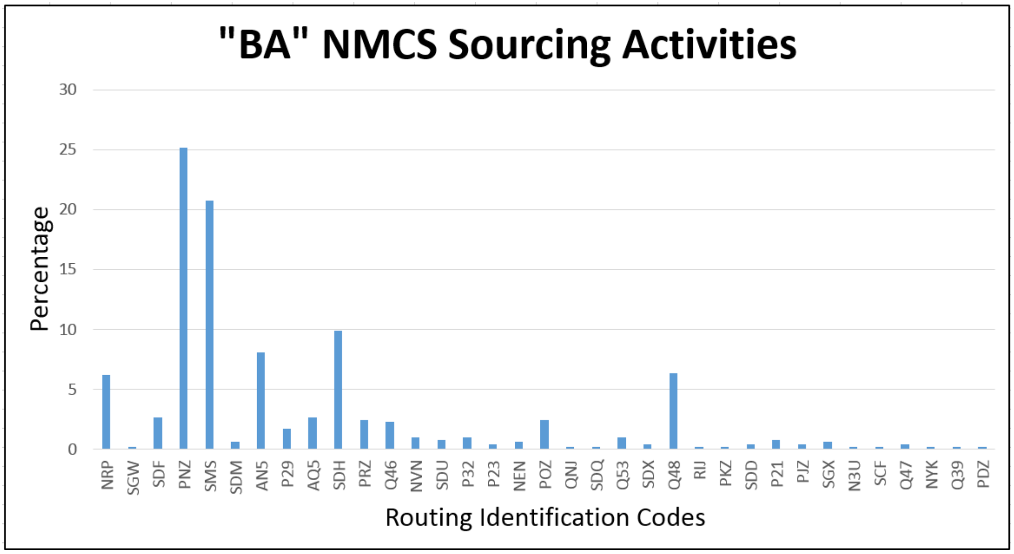

Figure 30. “BA” NMCS Sourcing Activities

Furthermore, Figure 31 shows order quantities between five and 22 items were sourced from DLA Fort Belvoir, Virginia (SMS), NAS Oceana, Virginia (PNZ), and U.S. Navy Mayport, Florida (P29).

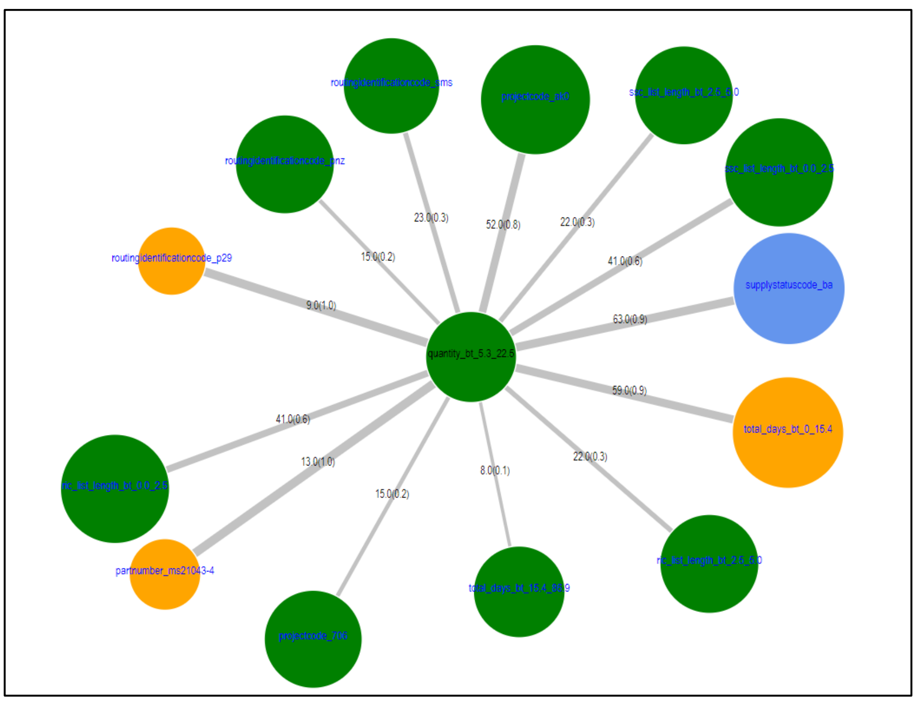

Figure 31. “BA” NMCS Sourcing Activities: Quantities Five to 22 Items

4. “BA” Critical Component Examination (PMCS)

The final dissection of information using the “BA” supply status code was to examine Partial Mission Capable Supply (PMCS) parts also critical to aircraft readiness and combat capability. Again, the intent was to determine which parts were most hindering to readiness while being readily available in the supply chain.

a. Parts

Of the 505 discrete “BA” parts ordered, 57 were identified as PMCS. This contributed to 11.3% of the parts. Only two parts were ordered at a frequency greater than three times. Thus, 96.5% of the parts demanded were ordered three times or less. Concerning the cognizance of material, 86.1% were consumable parts while 13.9% were repairable. As depicted, Figure 32 highlights the order frequency.

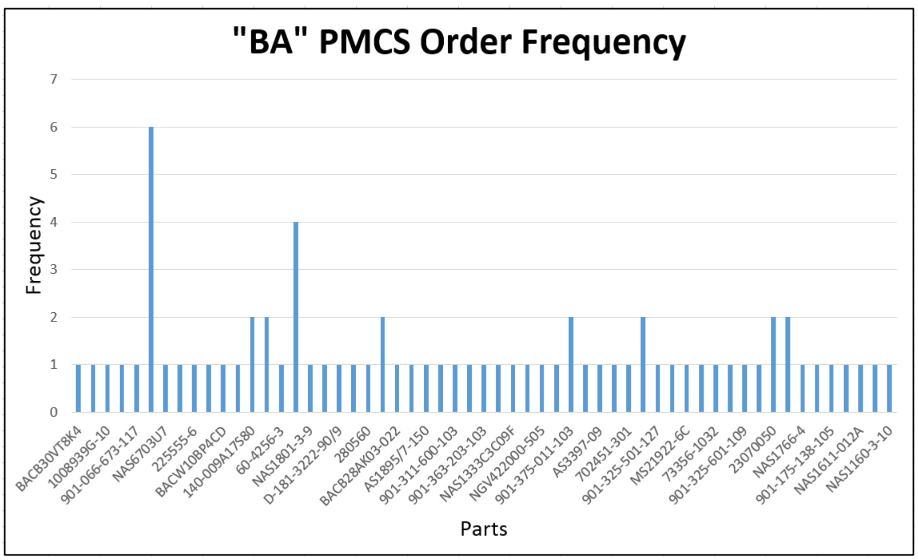

Figure 32. “BA” PMCS Order Frequency

b. Response Time

Estimated response times for requisitions of 15 days or less was 78.8%. The average estimated response time was 12.8 days from date of order, to the last known EDD. However, the median value for transit time was 8.5 days with seven days as the mode. The estimated response times over a 90-day period are described in Figure 33. Furthermore, Figures 34, 35, and 36 display characteristics of "BA" PMCS estimated response times. As shown in Figure 34, those orders experiencing an estimated response time less than 12.4 days were sourced from NAS Oceana, Virginia (PNZ); DLA Cherry Point, North Carolina (SDH); DLA Fort Belvoir, Virginia (SMS); and MALS-26 Support Element, Djibouti (RIJ). Additionally, part number 23055151 is highlighted in orange because all of those requisitions were presumed to be delivered under 12.4 days. The key elements discovered Figure 35 is that all components sourced from MALS-26 Jacksonville, North Carolina (Q48), and those orders with quantities less than 1.8 items exhibited an estimated response time between 12.4 and 24.2 days. Lastly, Figure 36 shows the characteristics of estimated response times greater than 24.2 days. The important trait is that the preponderance of parts were sourced from DLA New Cumberland, Pennsylvania (AN5), with quantities less than 3.4 items per supply document.

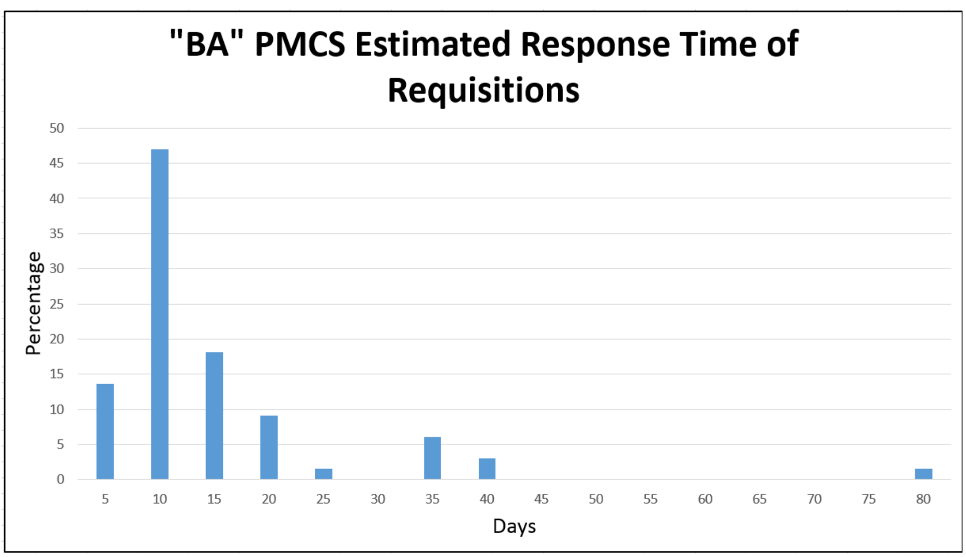

Figure 33. "BA" PMCS Estimated Response Times

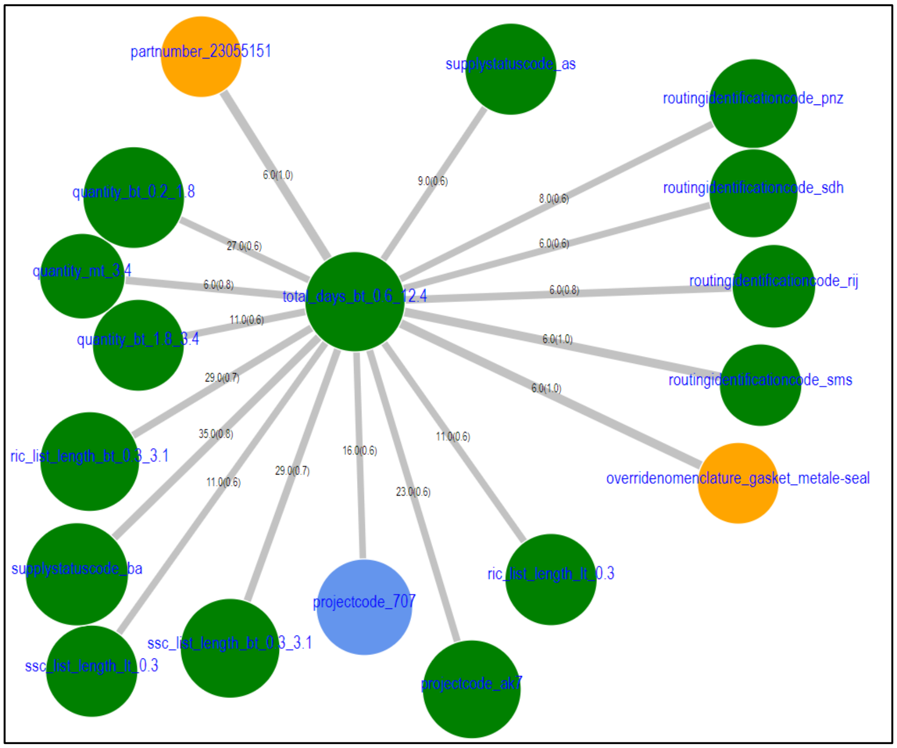

Figure 34. “BA” PMCS Estimated Response Times: Less Than 12.4 Days

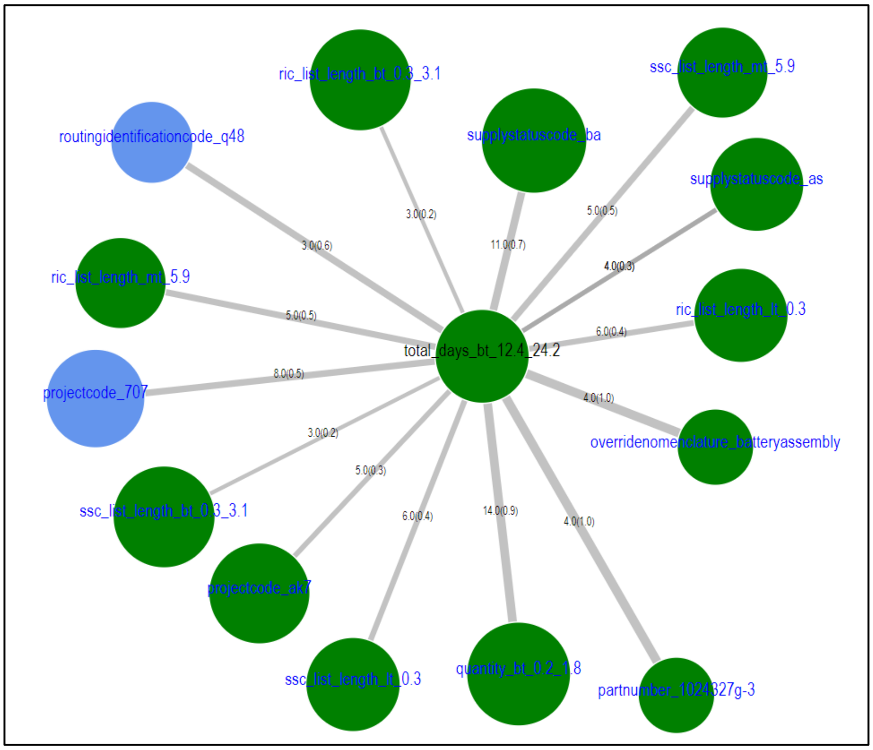

Figure 35. “BA” PMCS Estimated Response Times: 12.4 and 24.2 Days

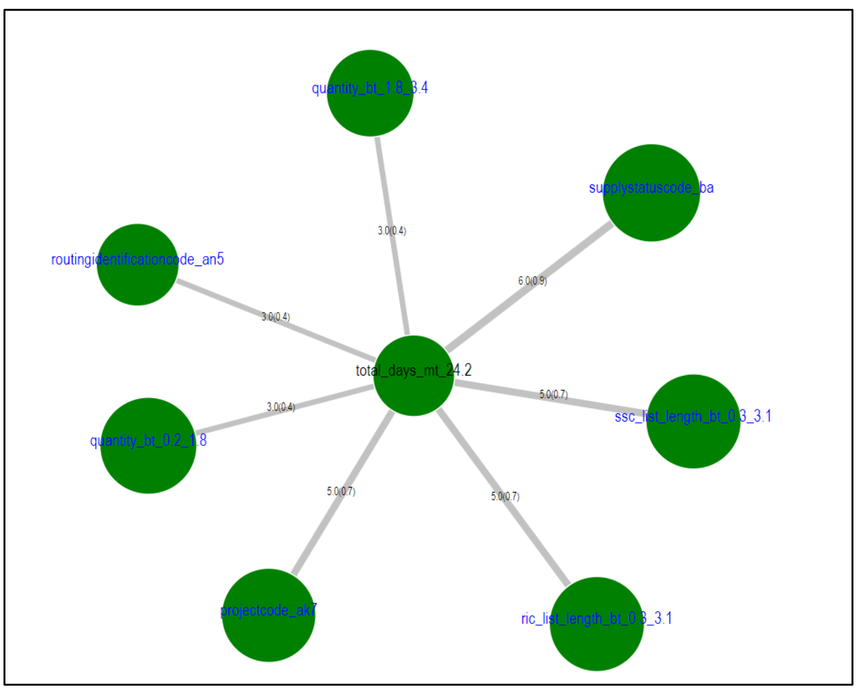

Figure 36. “BA” PMCS Estimated Response Times: Greater Than 24.2 Days

c. RIC

The number of RICs discovered were reduced from 37 to 19, a number which includes WSS NAVSUP Philadelphia, Pennsylvania (NRP) and DLA Fort Belvoir, Virginia (SMS). No requisitions were sourced from VMM-264's European AO. Sourcing activities located within the continental United States accounted for 73.6% of the requisitions, excluding NAVSUP Philadelphia, Pennsylvania (NRP), and DLA Fort Belvoir, Virginia (SMS). As displayed, Figure 37 depicts the sourcing activities identified. Additionally, supply documents that contained more than 3.4 items per order are shown in Figure 38. All such orders were sourced from DLA Cherry Point, North Carolina (SDH), and NAS Oceana, Virginia (PNZ).

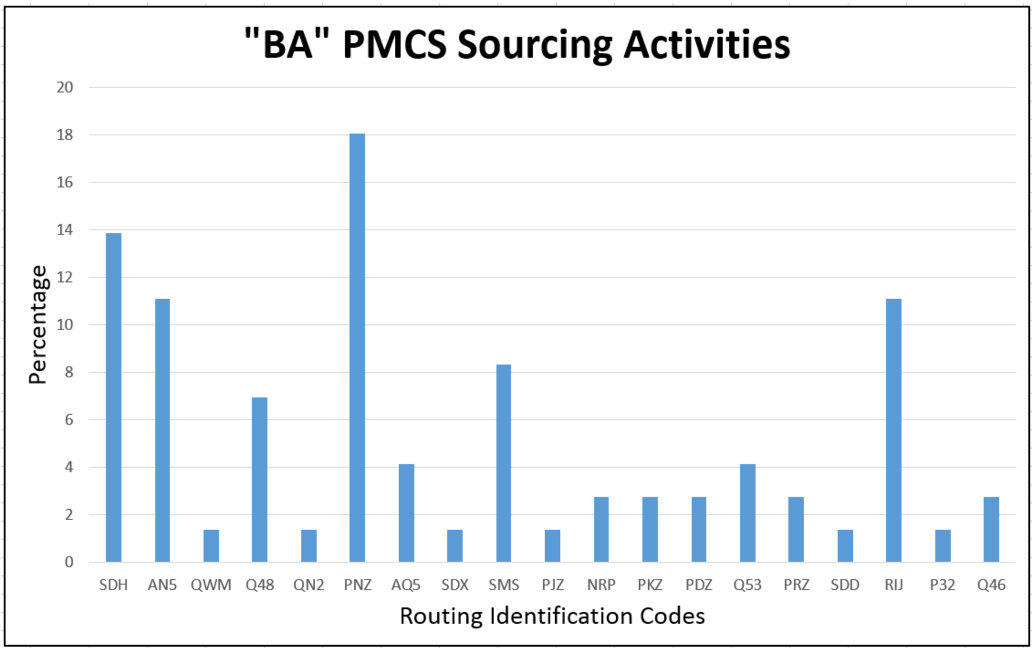

Figure 37. "BA" PMCS Sourcing Activities

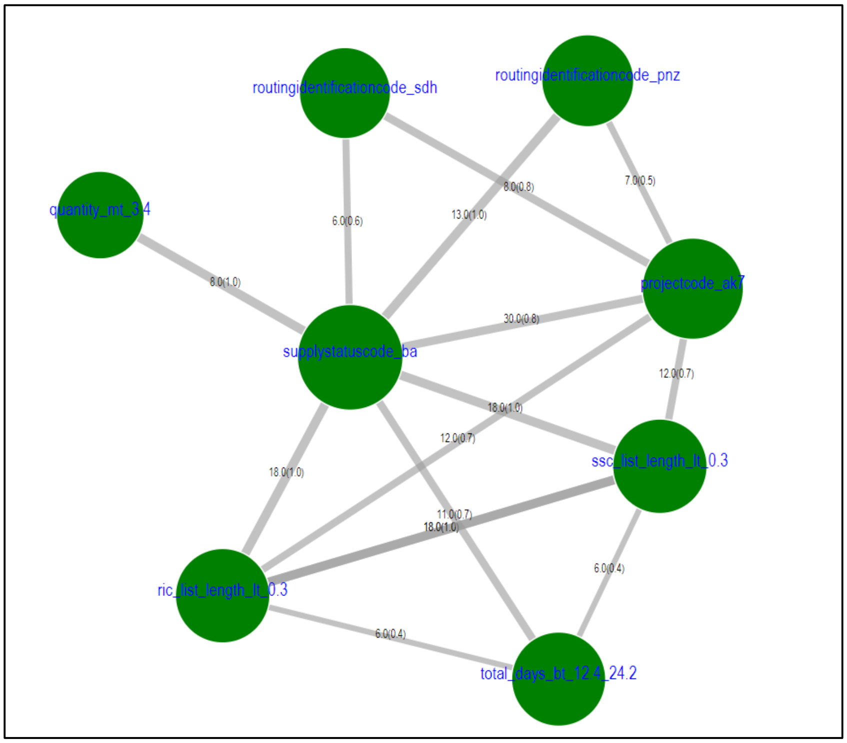

Figure 38. Order Quantities: Greater Than 3.4 Items

5. "AS" Status Analysis

Isolating the "AS" supply status code also focuses the study to assess those parts that were readily available at the time of requisition. As previously completed, examining parts, project codes, response times, and RICs will highlight supply chain characteristics.

a. Parts

Of the 2,262 discrete high priority parts ordered, 153 were initially labeled with a status code of "AS." This amounted to 6.8% of the parts. Only three components were ordered at a frequency of three times or greater. Thus, 98.0% of the parts demanded were ordered less than three times. Concerning the cognizance of material, 89.6% were consumable parts while 10.4% were repairable. The order frequency of the requested parts are highlighted in Figure 39.

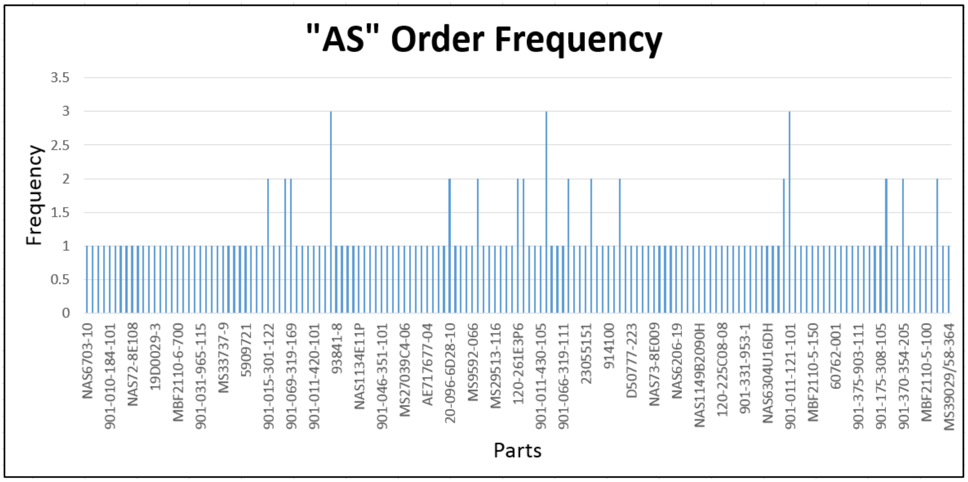

Figure 39. "AS" Order Frequency

b. Project Code

Concerning criticality, 68.8% of the parts were NMCS while 14.5% were PMCS. As presented, Figure 40 depicts project codes by percentage.

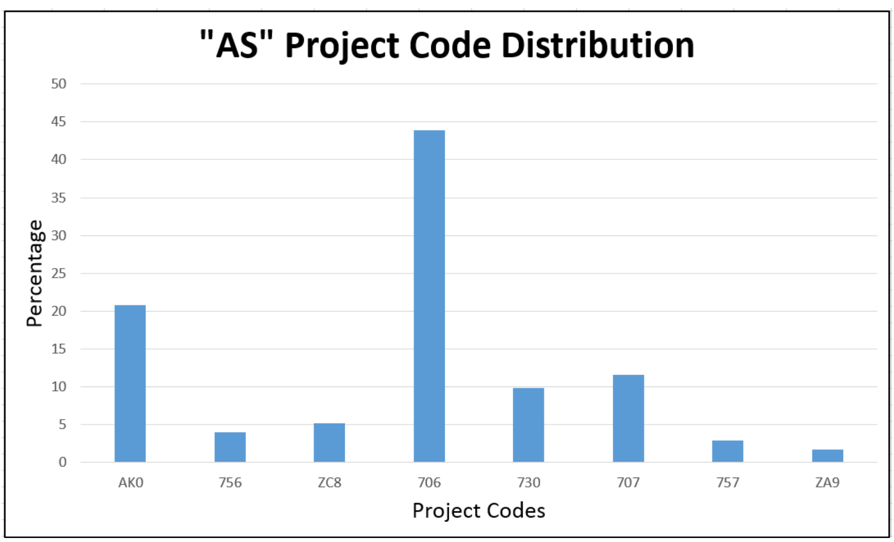

Figure 40. "AS" Project Code Breakdown

c. Response Time

Estimated response times for requisitions of 15 days or less was 81.7%. The average estimated response time was 12.5 days from date of order, to the last known EDD. However, the median value for estimated transit time was 10 days with 10 days as the mode. As displayed, Figure 41 shows the response times over a 90-day period.

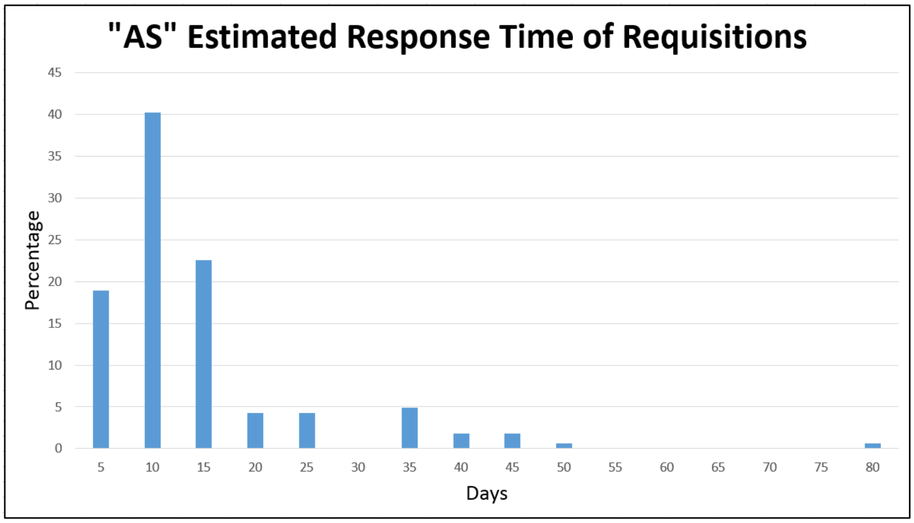

Figure 41. “AS” Estimated Response Times

d. RIC

The number of RICs discovered as sourcing activities were 25, a number including DLA Fort Belvoir, Virginia (SMS). No requisitions were sourced from VMM-264’s European AO. Sourcing activities located within the continental United States accounted for 74.0% of the requisitions, excluding DLA Fort Belvoir. The sourcing activities identified are depicted in Figure 42.

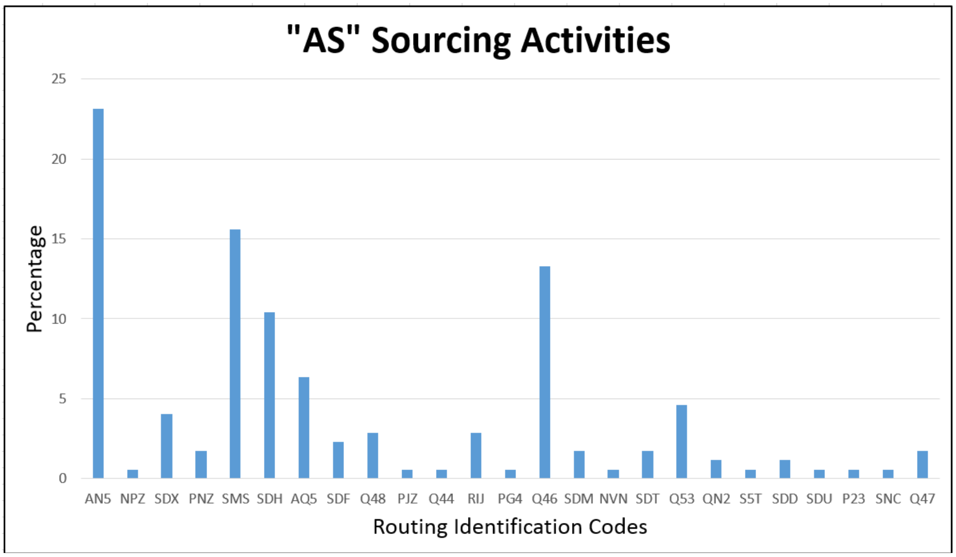

Figure 42. “AS” Sourcing Activities

6. "AS" Critical Component Examination (NMCS)

To assess available parts critical to aircraft readiness and combat capability, the research delve into Not Mission Capable Supply (NMCS) project codes. The intent was to discover which parts were most hindering to readiness while being accessible in the supply chain.

a. Parts

Of the 153 discrete "AS" parts ordered, 106 were identified as NMCS. This contributed to 69.3% of the parts. Only two parts were ordered at a frequency of three times or greater. Thus, 98.1% of the parts demanded were ordered less than three times. Concerning the cognizance of material, 92.4% were consumable parts while 7.6% were repairable. As described, Figure 43 highlights the order frequency.

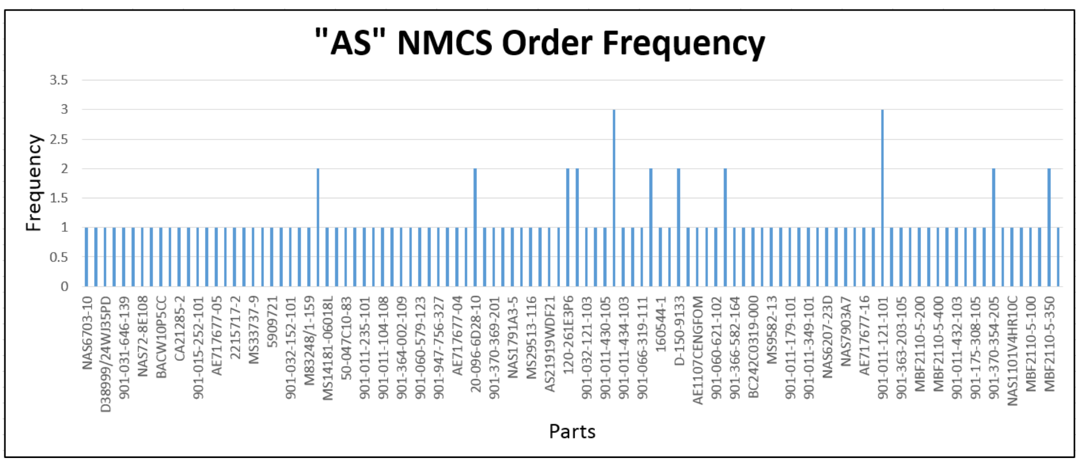

Figure 43. "AS" NMCS Order Frequency

b. Response Time

Estimated response time for requisitions of 15 days or less was 83.2%. The average estimated response time was 11.3 days from date of order, to the last known EDD. However, the median value for transit time was 10 days with 10 days as the mode. As shown, Figure 44 depicts the estimated response times over a 90-day period. Moreover, it was discovered that smaller supply document quantities potentially experienced longer delivery times. As discovered in Figure 45, 21 discrete parts ordered with a quantity up to 8.8 items potentially experienced an estimated response time of 11.3 to 19.5 days. While 13 discrete parts ordered with the same quantity range took more than 19.5 days. Conversely, Figure 46 identifies six discrete parts ordered with a quantity greater than 31.3 being delivered between 3.1 and 11.3 days.

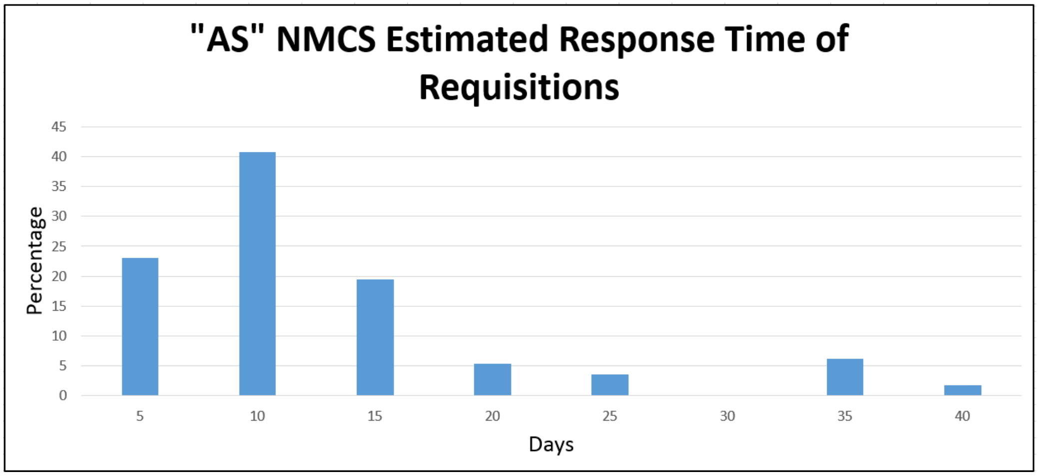

Figure 44. “AS” NMCS Estimated Response Times

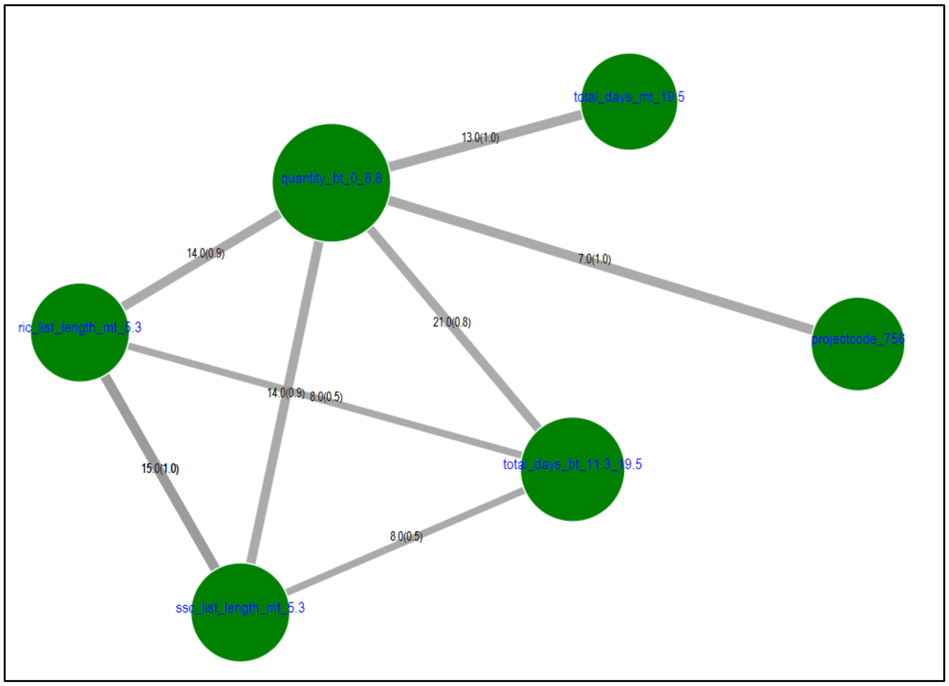

Figure 45. “AS” NMCS Estimated Response Times: Low Quantity

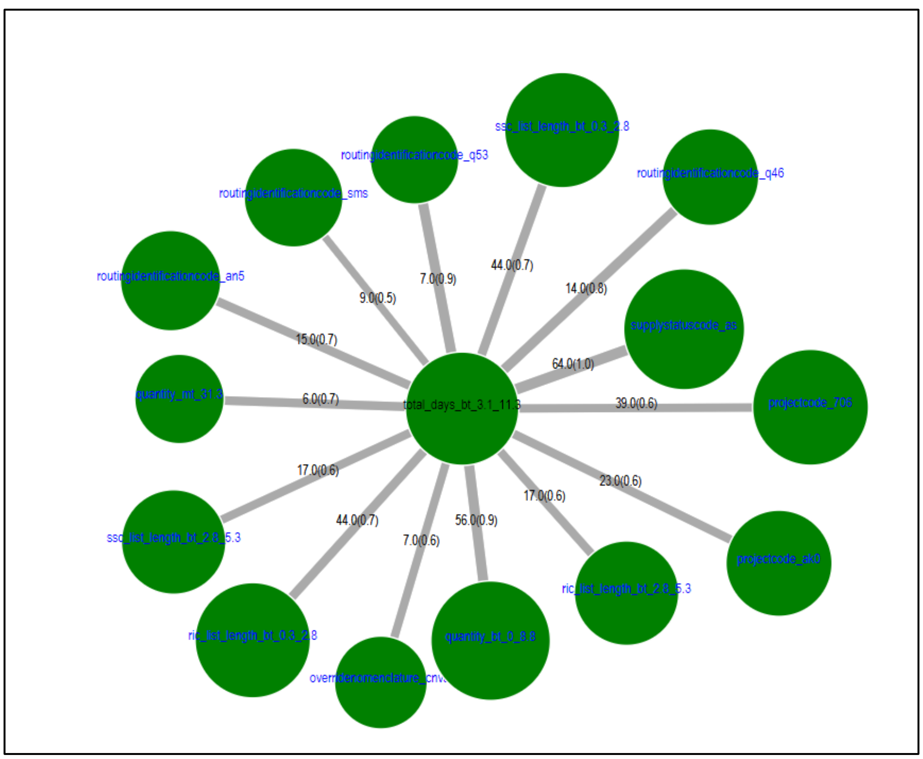

Figure 46. “AS” NMCS Estimated Response Times: High Quantity

c. RIC

The number of RICs discovered were reduced from 25 to 21, a number including DLA Fort Belvoir, Virginia (SMS). No sourcing activities within the squadron's AO were identified. Sourcing activities located within the continental United States accounted for 83.4% of the requisitions, excluding DLA Fort Belvoir. The sourcing activities identified are depicted in Figure 47. Additionally, Figures 48 and 49 provide examples of sourcing activities for both low quantity and high quantity requisitions. DLA Cherry Point, North Carolina (SDH), and MALS-36 Okinawa, Japan (Q53), were discovered as sourcing activities in Figure 48 with quantities less than 8.8 items. Likewise, Figure 49 distinguishes both low and high quantity sourcing activity characteristics. DLA San Joaquin, California (AQ5), and DLA New Cumberland, Pennsylvania (AN5), sourced quantities less than 8.8 items while MALS-16 San Diego, California (Q46), and MALS-36 Okinawa, Japan (Q53), sourced quantities of greater than 31.1 items.

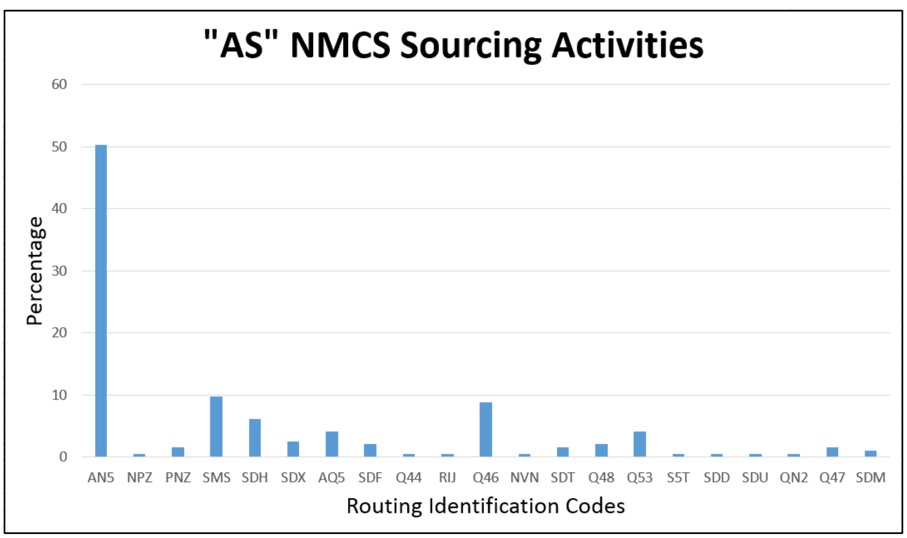

Figure 47. "AS" NMCS Sourcing Activities

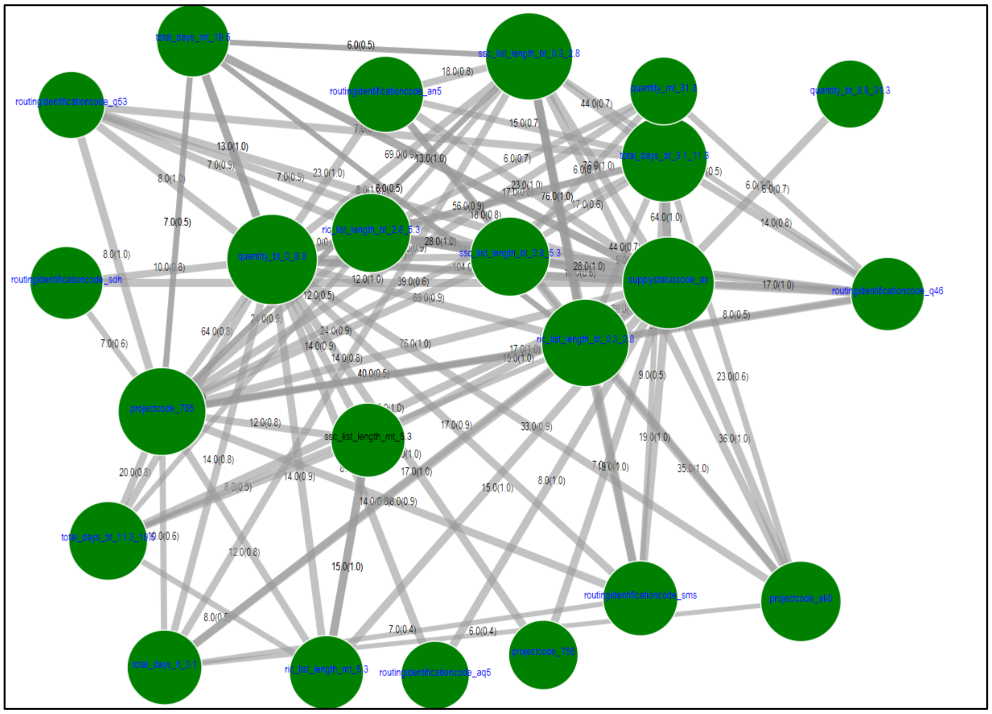

Figure 48. “AS” NMCS Sourcing Activities: Low Quantity

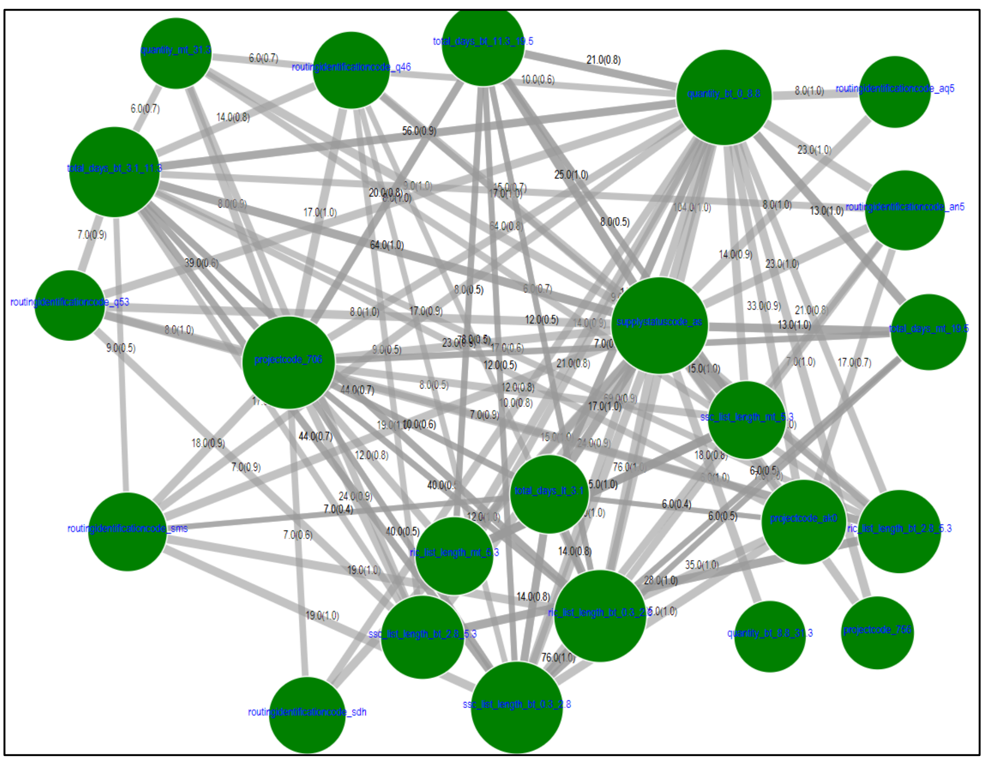

Figure 49. “AS” NMCS Sourcing Activities: Low and High Quantity

7. "AS" Critical Component Examination (PMCS)

The final dissection of information using the "AS" supply status code was to examine Partial Mission Capable Supply (PMCS) parts also critical to aircraft readiness and combat capability. Again, the intent was to determine which parts were most hindering to readiness while being readily available in the supply chain.

a. Parts

Of the 153 discrete "AS" parts ordered, 22 were identified as PMCS. This contributed to 14.4% of the parts. Only two parts were ordered at a frequency of two times or greater. Thus, 90.9% of the parts demanded were ordered once. Concerning the cognizance of material, 84.0% were consumable parts while 16.0% were repairable. The order frequency is displayed in Figure 50.

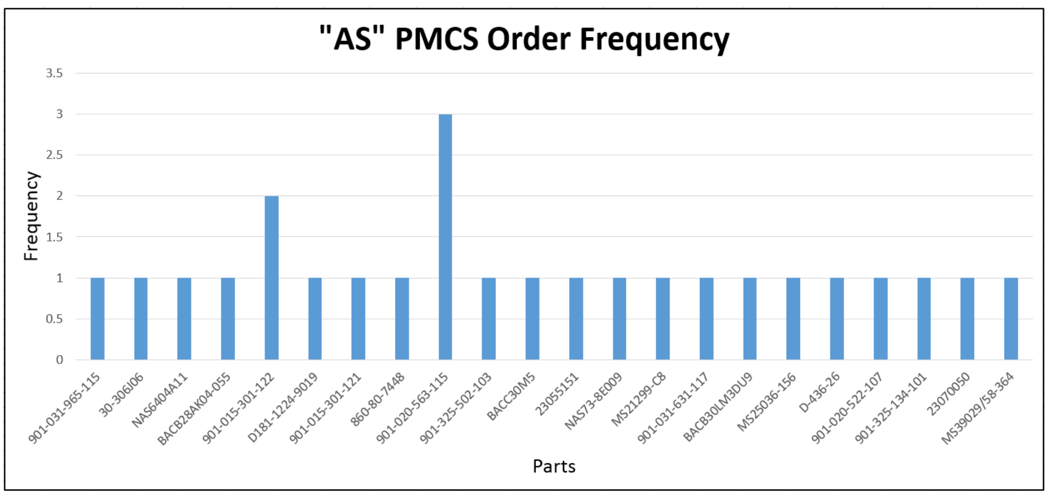

Figure 50. "AS" PMCS Order Frequency

b. Response Time

Estimated response times for requisitions of 15 days or less was 75.0%. The average estimated response time was 15 days from date of order, to the last known EDD. However, the median value for transit time was 10.5 days with six days as the mode. As shown, Figure 51 displays the estimated response times over a 90-day period. Moreover, Figure 52, highlights sourcing activity MALS-26 Support Element, Djibouti (RIJ) and estimated response times of six low quantity items. Three discrete parts with less than 1.6 items per order experienced estimated response times between 15 and 27.7 days, while three others incurred response times greater than 27.7 days. Similarly, Figures 53 and 54 emphasize longer estimated response times of low quantity requisitions sourced from DLA New Cumberland, Pennsylvania (AN5), and the USS Iwo Jima LHD 7, Kuwait (PG4), and MALS-26 Jacksonville, North Carolina (Q48) and MALS-26 Support Element, Djibouti (RIJ) respectively. Quantities less than 1.6 items per supply document were subject to transit times between 15 and 27.7 days and greater than 27.7 days correspondingly.

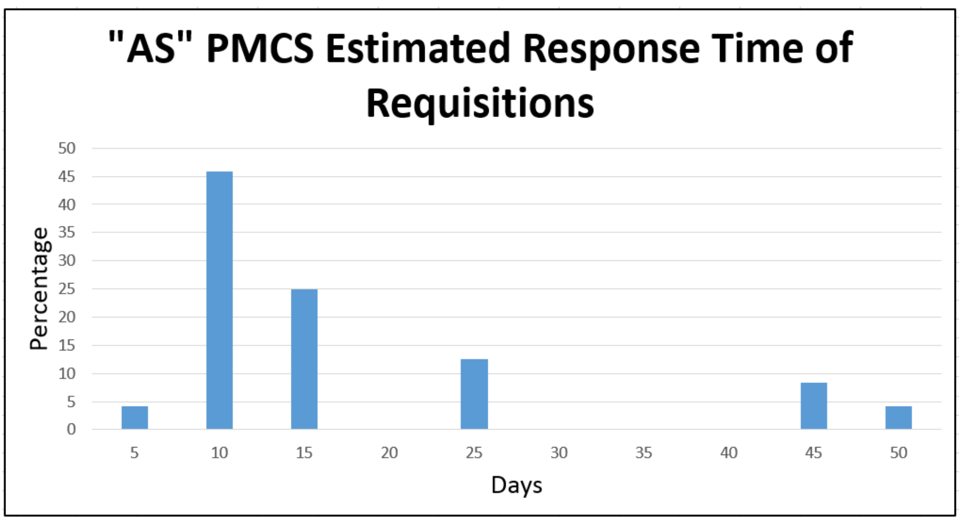

Figure 51. "AS" PMCS Estimated Response Times

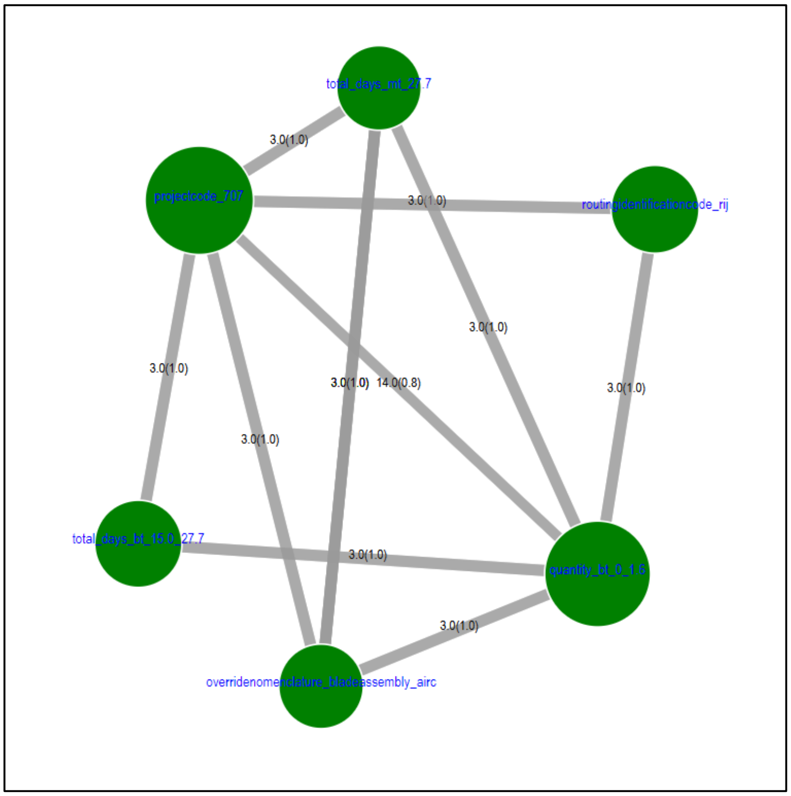

Figure 52. “AS” PMCS Estimated Response Times: MALS-26 Support Element, Djibouti (RIJ)

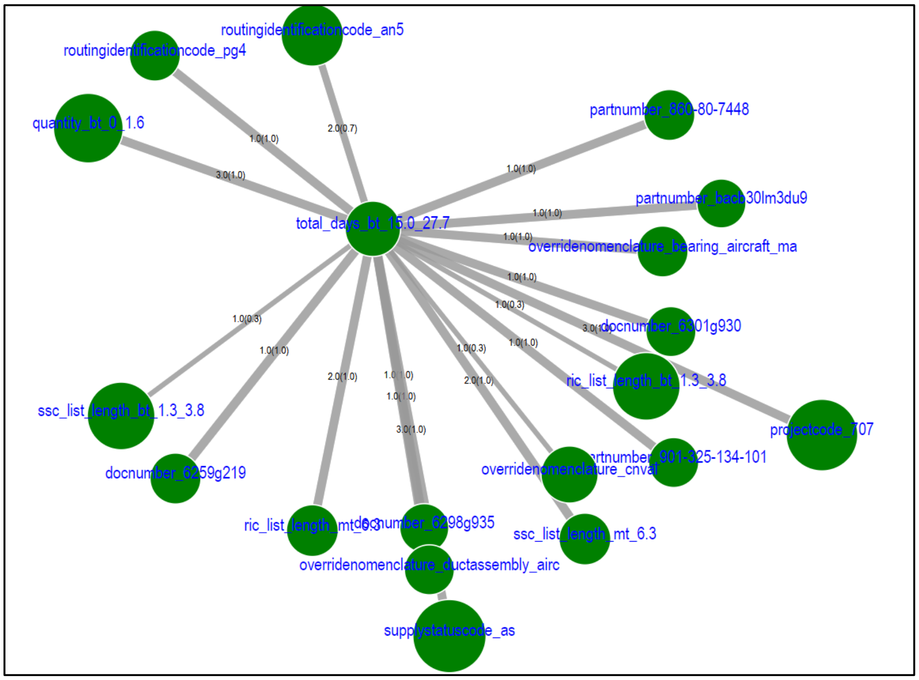

Figure 53. “AS” PMCS Low Quantity Estimated Response Times: 15 and 27.7 Days

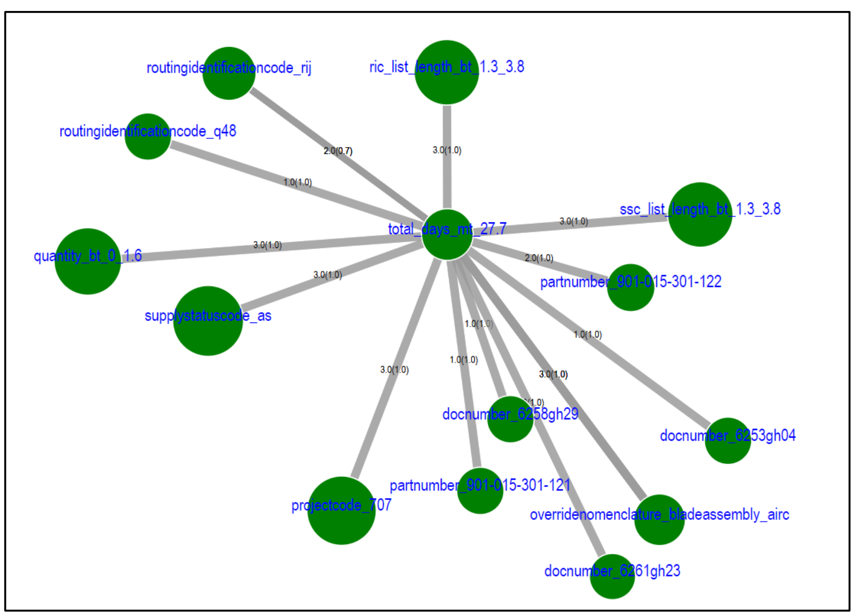

Figure 54. “AS” PMCS Low Quantity Estimated Response Times: Greater than 27.7 Days

c. RIC

The number of RICs discovered were reduced from 25 to nine, a number including DLA Fort Belvoir, Virginia (SMS). No requisitions were sourced from VMM-264's European AO. Sourcing activities located within the continental United States accounted for 72.0% of the requisitions, excluding DLA Fort Belvoir, Virginia (SMS). As depicted, Figure 55 displays the sourcing activities identified.

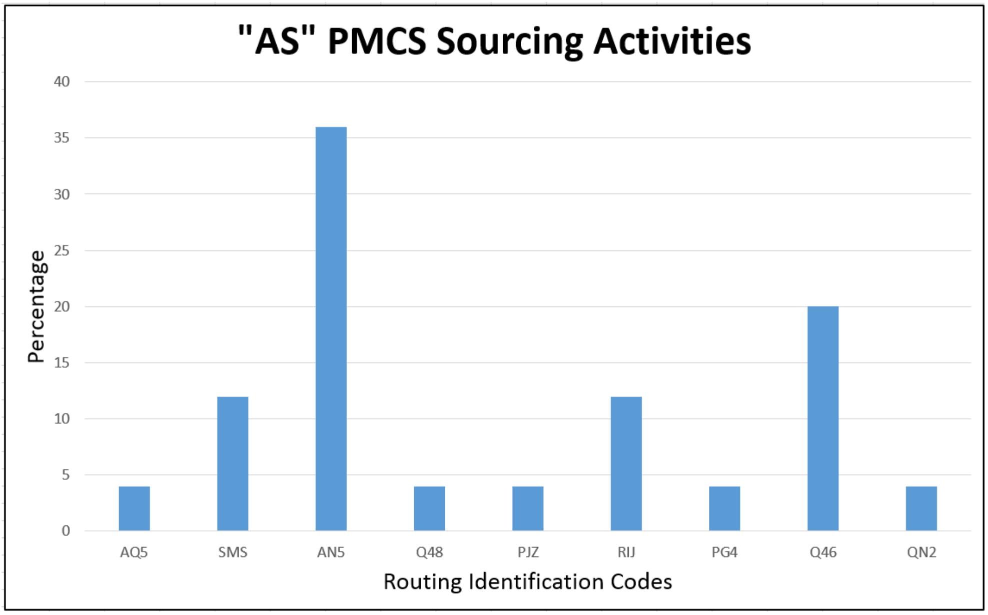

Figure 55. "AS" PMCS Sourcing Activities

Furthermore, Figure 56 illuminates, as did Figures 52 and 54, MALS-26 Support Element, Djibouti (RIJ) as a sourcing activity associated with long estimated response times.

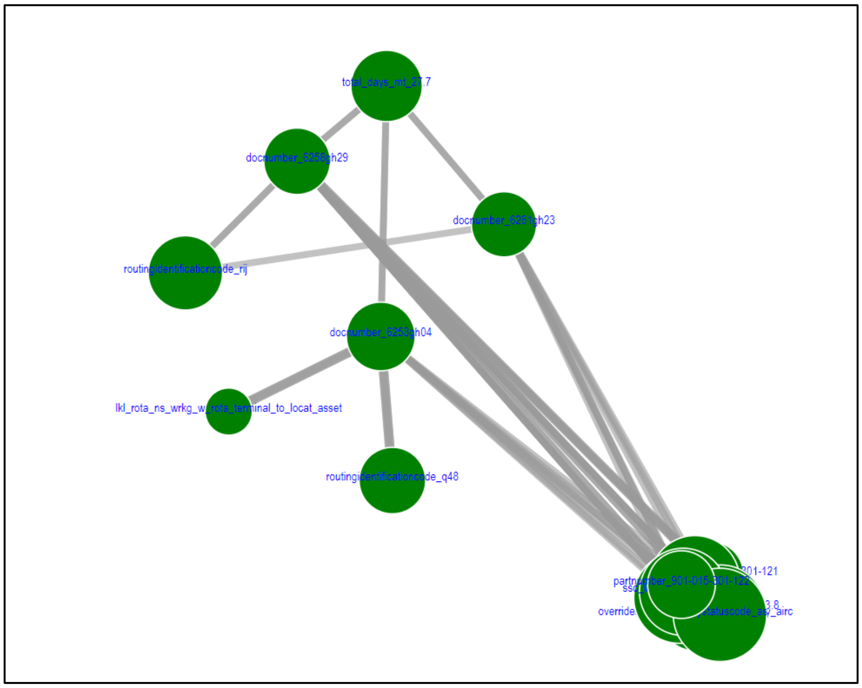

Figure 56. “AS” PMCS Sourcing Activities: MALS-26 Support Element, Djibouti (RIJ)

C. SUMMARY

Preprocessing the received data commenced the analysis phase of this research. To ensure smooth examination, the data was configured to maximize extraction of information from Microsoft Excel and LLA software. Refinement of the data underwent an iterative process until it materialized into an appropriate format for software requirements.

As mentioned previously, analysis of the data focused on five features within the data set: individual high priority parts, project codes (criticality of component), response time, status codes (part supply status), and RIC (component location or sourcing activity). Additionally, these characteristics were assessed during a time period when VMM-264 was in a static location off the coast of Libya. This restriction provided a control to the squadron’s location and accentuated attention toward supply chain performance.

The following chapter makes suggestions concerning the analysis conducted. Specifically, recommendations are presented in response to the research questions previously stated.

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V. RESULTS AND RECOMMENDATIONS

This project focused on two objectives: to assess how dynamic the supply chain was during a MV-22 Marine Expeditionary Unit (MEU) deployment; and discover potential opportunities to preposition MV-22 parts to maintain high aircraft readiness rates. To meet these goals the research centered on MV-22 Osprey squadron data when the 22nd MEU was in a static location off the coast of Libya supporting Operation ODYSSEY LIGHTNING from 1 August 2016 to 31 October 2016. Doing so eliminated possible supply chain vulnerabilities caused by ship relocation throughout the theater of operation. In this sense, the supply system was static, with the expectation that gaps would surface as data were examined. Additionally, supply documents initially annotated on the Aircraft Maintenance/Supply Readiness Report (AMSRR) with status codes of "BA" (parts in inventory and being ready to ship), and "AS" (parts that were shipping) were isolated for investigation. If supply documents possessed other status codes prior to being published on the AMSRR, they were not considered. Concentrating the research solely on these components, again allowed for detailed scrutiny of supply chain efficiency, and removed those parts that experienced specific component shortfalls and thus were not readily available, such as contractual agreements or life expectancy inconsistences. It is important to note that focusing on AMSRR documentation during this research was critical because it is a document used by commanders when making operational decisions.

A. FINDINGS

Overwhelmingly, the supply chain did not behave as an agile network, adjusting and adapting to the needs of VMM-264. After analyzing a 92-day period, the supply documents reported on the AMSRR conveyed a supply network that was reliant on supply nodes located within the continental United States. Highlighting "BA" Not Mission Capable Supply (NMCS) parts the research showed that 71.3% of the requisitions were sourced from the continental United States, while DLA Europe Germersheim, Germany (SDQ), sourced only 0.19% of the requests. Furthermore, those parts with higher quantities, between 5 and 22 items, were sourced from DLA Fort Belvoir, Virginia (SMS), NAS

Oceana, Virginia (PNZ), and U.S. Navy Mayport, Florida (P29). “BA” Partial Mission Capable Supply (PMCS) displayed similar sourcing rates from the United States, accounting for 73.6% of the components. None of the PMCS parts were sourced from DLA Europe or other European distribution centers. “AS” coded parts shared comparable results. “AS” NMCS and PMCS sourcing activities accounted for 83.4% and 72% of the components forwarded from the United States. None of the parts initially given a status code of “AS” were sourced within the European theater of operation.

Though identifying the sourcing activities of critical components was important to understanding supply chain efficiency, this research also assessed expected delivery date data to ascertain an estimated response time from order date to potential arrival of the component. As with previous results, the focus of effort was on NMCS and PMCS parts labeled as “BA” and “AS.” Estimated response times of 15 days or less for “BA” NMCS and PMCS components were 83.6% and 78.8%, respectively. However, the average NMCS time was 20 days, with a median of eight days and a mode of six days. Common “BA” NMCS sourcing activities experiencing longer estimated response times were DLA Cherry Point, North Carolina (SDH), DLA Fort Belvoir, Virginia (SMS) and Naval Air Station (NAS) Oceana, Virginia (PNZ). An example is shown in Figure 57. This depiction highlights two “BA” coded parts sourced from DLA Cherry Point, North Carolina (SDH). One estimated response time was 26 days while the second was 31 days. Comments annotated as both waiting on shipping and tracking information. DLA Cherry Point, North Carolina (SDH), may have experienced shipping challenges concerning these two parts.

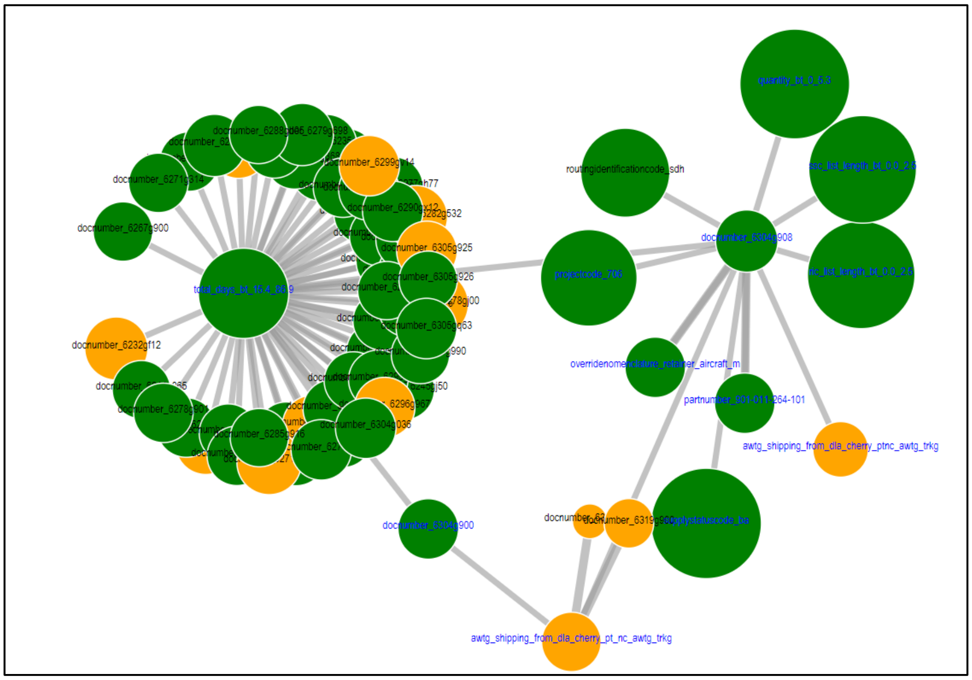

Figure 57. Shipping: DLA Cherry Point, North Carolina (SDH)

The average PMCS time was much less, at 12.8 days, yet with a similar median of 8.5 days and a mode of seven days. Though above the calculated average, "BA" PMCS components exhibiting two to three weeks of estimated response times are highlighted in Figure 58. This figure shows NAS North Island, California (PDZ), and Navy Materiel Oak Harbor, Washington (PKZ), as the sourcing activities for various supply documents. Supply document comments allude to "awaiting tracking information" and "in process for shipment." As alluded to before, shipping challenges may have been experienced.

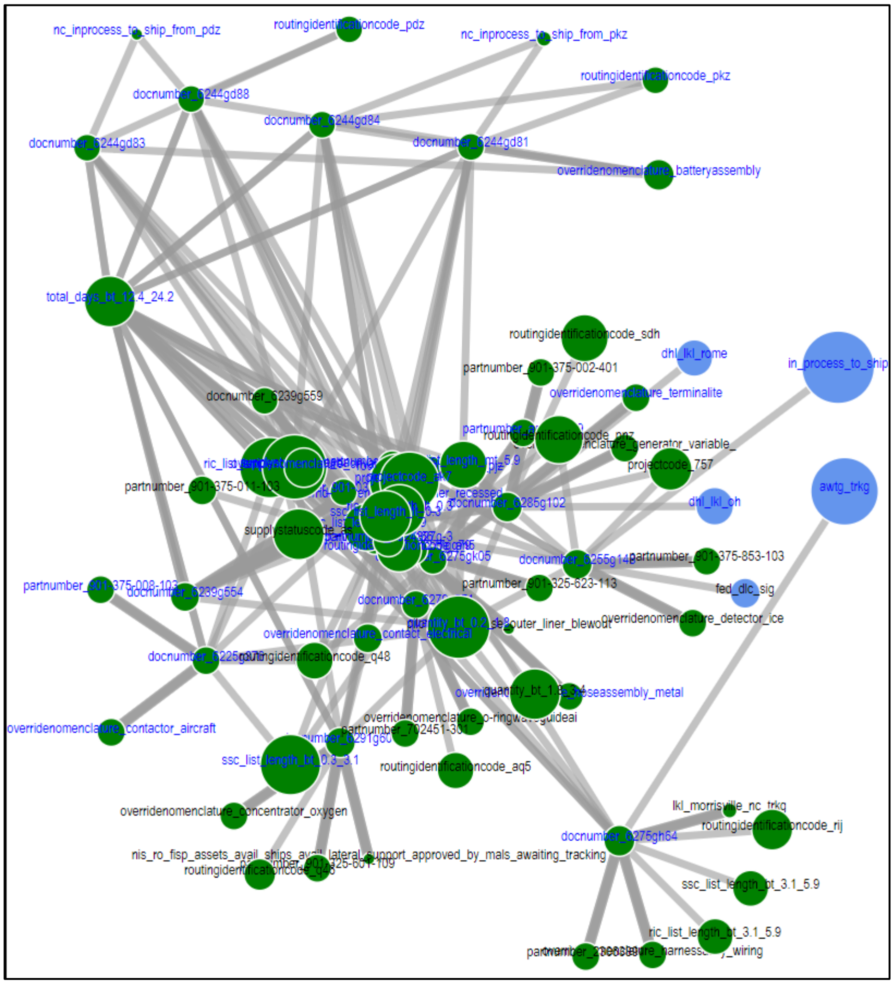

Figure 58. Estimated Response Times: Two to Three Weeks

However, based on estimated delivery dates, it was revealed the preponderance of "BA" critical components reached VMM-264 within two weeks of order.

Estimated response times of 15 days or less for NMCS and PMCS "AS" identified parts were discovered to be 83.2% and 75.0%, respectively. The average NMCS time was 11.3 days with a median and mode of 10 days. Likewise, the average PMCS time was 15 days, with a median of 10.5 days and a mode of six days. An example of "AS" PMCS estimated response times is highlighted in Figure 59. This figure shows the preponderance of parts sourced from MALS-16 San Diego, California (Q46), taking 2.3 and 15 travel days.

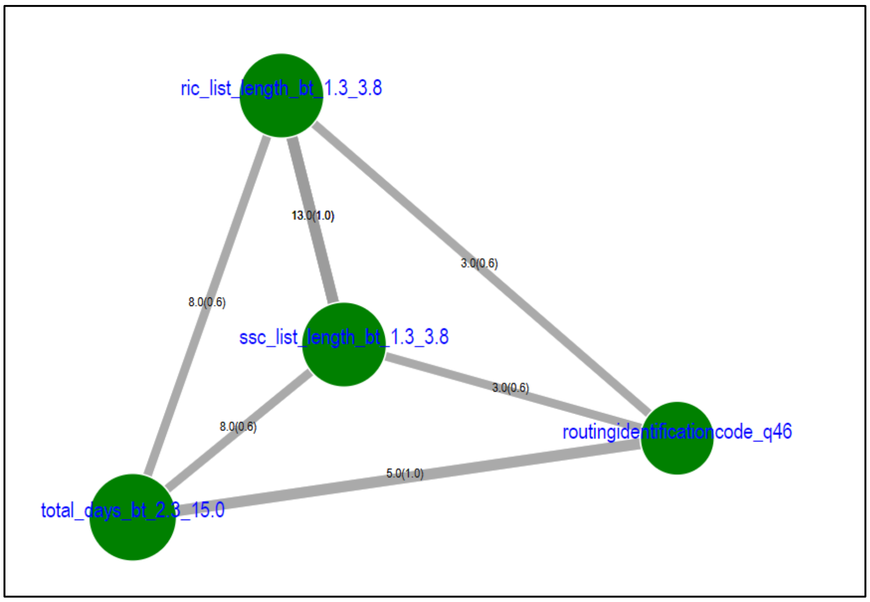

Figure 59. Estimated Response Times: MALS-16 San Diego, California (Q46)

Again, as with "BA" coded parts, the majority of parts immediately labeled "AS" arrived within two weeks from the order date with one exception. Sourcing activity MALS-26 Support Element, Djibouti (RIJ), trended to be long, greater than two to three weeks.

The quantity of items requested within each supply document and the cognizance of Navy material also highlighted an area of interest. Correlation within the data identified potentially longer estimated response times for lower quantity orders, while conversely, larger quantity items experiences faster estimated response times. Another example of "AS" NMCS low quantity orders is depicted in Figure 60. Supply document 6263GH68 had one item ordered and document 6297G904 had four items ordered. Sourced from

MALS-24 Marine Corps Base Hawaii (MCBH) Kaneohe Bay, Hawaii (Q47), comments reflected these discrete parts shipping commercially through FedEx requiring more than 19.5 days to transport. Though this example reflects a sourcing activity distant from VMM-264's AO, this is not routine. As previously discussed, DLA Cherry Point, North Carolina (SDH), MALS-36 Okinawa, Japan, DLA San Joaquin, California (AQ5), and DLA New Cumberland, Pennsylvania (AN5), were all activities sourcing quantities less than 8.8 items.

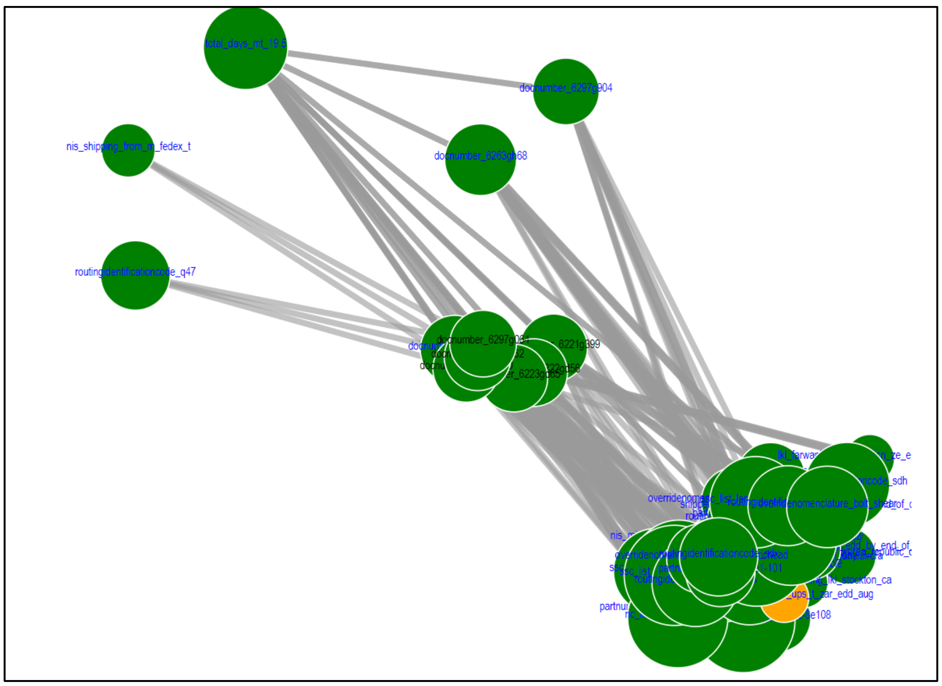

Figure 60. "AS" NMCS Estimated Response Times: Low Quantity II

Similar results were discovered concerning the quantity characteristics of "AS" PMCS labeled supply documents. Numerous requisitions requiring less than 1.6 items per order experienced estimated response times of two weeks or greater. As shown in Figure 61, order quantities of less than 1.6 items had response times between 15 and 27.7 days, and were sourced from DLA New Cumberland, Pennsylvania (AN5), and the USS Iwo Jima (LHD 7), Kuwait (PG4). All three supply documents, 6301G930, 6259G219, and 6298G935 each had one item requested.

Requisitions of fewer items per supply document and discrete part may be a vulnerability within the supply system. Because “BA” and “AS” supply status components were examined, lengthy estimated response times might be due to shipping methods, whether it be the size or quantity of component.

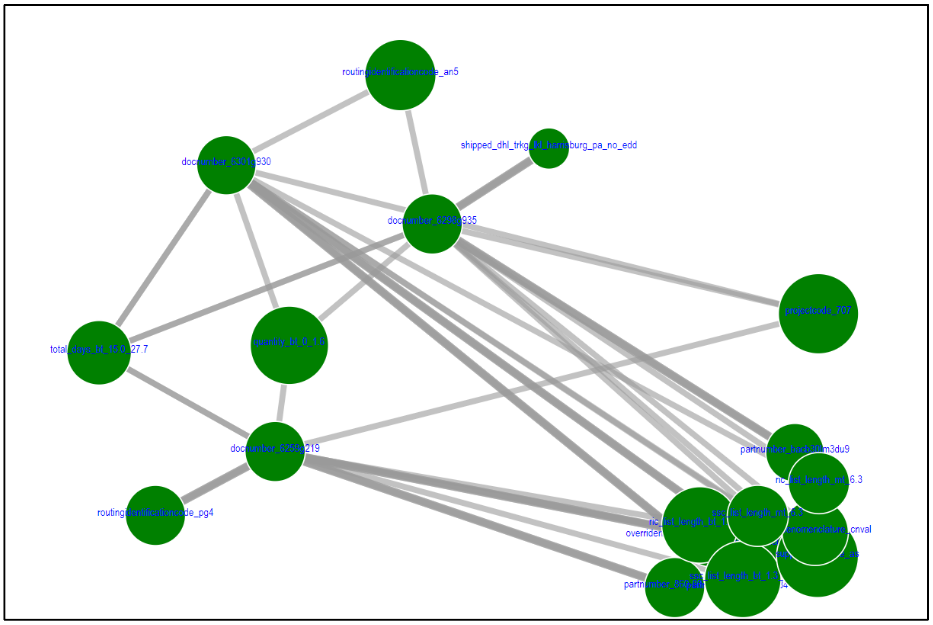

Figure 61. “AS” PMCS Estimated Response Times: Low Quantity

Cognizance of Navy material strongly indicated a high percentage of consumable parts were demanded when compared to repairable items. Overall, consumables accounted for greater than 89.6%, and repairables accounted for less than 10.4% of the discrete parts ordered. However, “BA” PMCS and “AS” PMCS were instances when these percentages differed noticeably. Repairable percentages increased to 13.9% for “BA” PMCS and to 16.0% for “AS” PMCS. These results may allude to challenges when restoring PMCS components at the I-Level maintenance activity.

B. PREPOSITIONING OPPORTUNITIES

To identify and recommend parts with possibilities to preposition, this project determined that outlier parts that were ordered at a higher frequency than the preponderance of the components demanded. Emphasizing parts that were originally categorized as "BA" and "AS" on the AMSRR, the research could presume those parts were maintained in the supply system and had the opportunity to be pushed to optimal supply chain locations based on mission requirements. The following nine components are parts that were retained within the supply system and demanded at higher frequencies.

1. MS21043-4—Nut, Self-Locking, Ex

Ordered at the highest discovered frequency of 13 times, this part was a "BA" coded NMCS item. Its nomenclature, "Nut, Self-Locking, Ex" was sourced from three different activities, all within the United States: U.S. Navy Mayport, Florida (P29), accounted for 69.2% (nine) of the requisitions; and NAS Oceana, Virginia (POZ) and (PNZ), accounted for 15.4% (two) of the requisitions at each location. This consumable component was ordered against seven different aircraft and exhibited an estimated response time of 15 days or less for 83.3% of the requests. Quantity ranged from eight to 16 items per order. Characteristics of this part are shown in Figure 62.

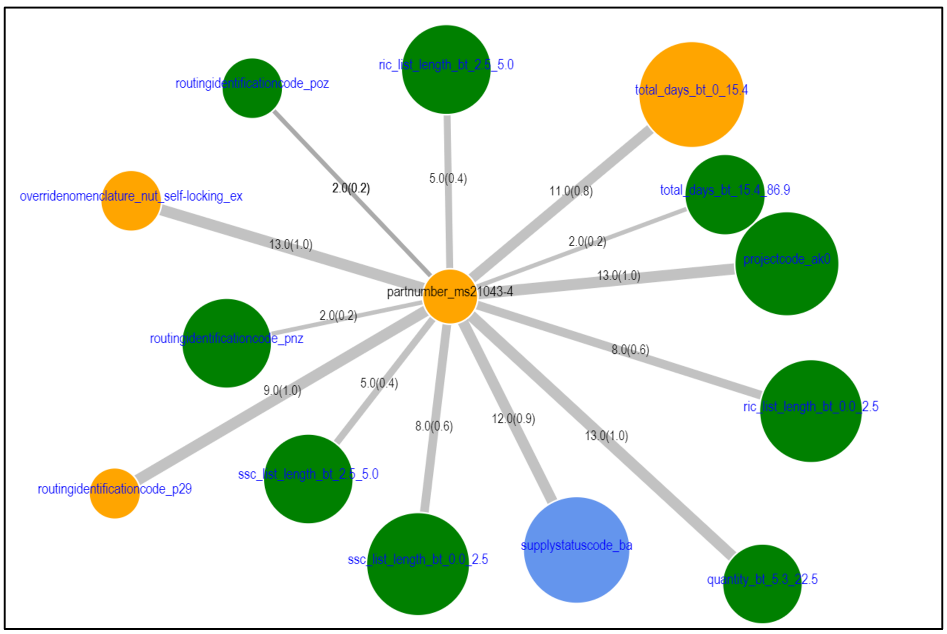

Figure 62. Part Number MS21043-4 Characteristics

2. 4866112-101—Radio, Set

Ordered at the second highest frequency of eight times, this part was a "BA" coded NMCS item. Its nomenclature, "Radio, Set" was sourced from one activity: DLA Norfolk, Virginia (SDF). This repairable component was ordered against one aircraft and 100% of the requests took an estimated response time of 10 days or less. Unfortunately, the supply documentation does not provide information concerning why this component was ordered for one aircraft only. Quantity was one item per order. Features of this part are depicted in Figure 63.

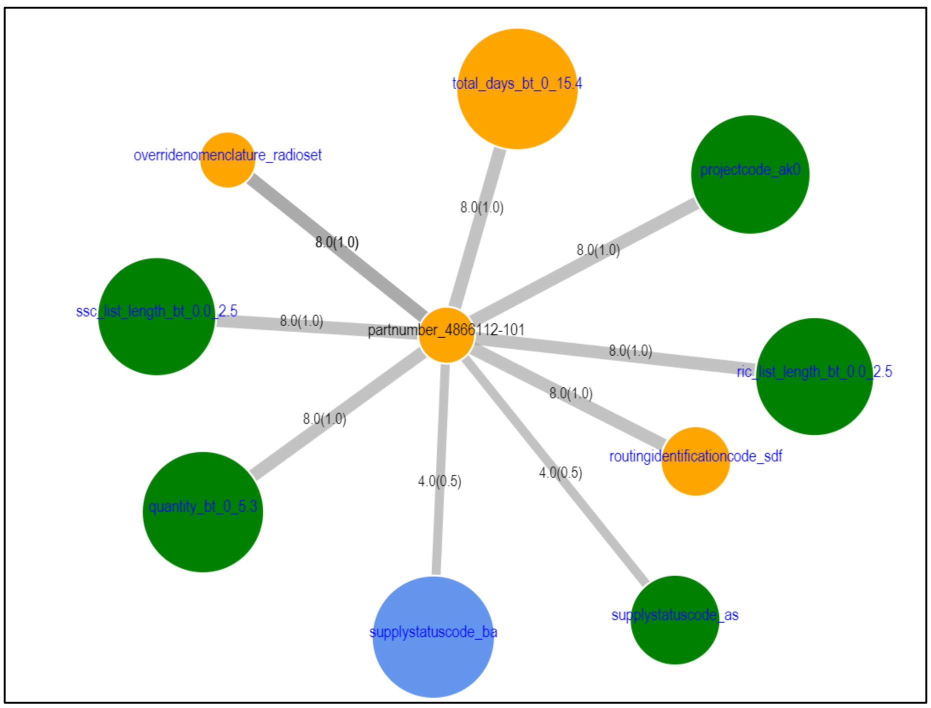

Figure 63. Part Number 4866112-101 Characteristics

3. AS21919WCG07—Clamp, Loop

Ordered at a frequency of six times, this part was a "BA" coded NMCS item. Its nomenclature, "Clamp, Loop" was sourced from potentially two different activities: DLA New Cumberland, Pennsylvania (AN5); and DLA Fort Belvoir, Virginia (SMS). Both AN5 and SMS accounted for 50% (three) of the requisitions. Unfortunately, the supply documentation listing DLA Fort Belvoir, Virginia (SMS) does not annotate the actual sourcing location. DLA Fort Belvoir, Virginia (SMS) is not a storage facility; it is an administrative activity. This consumable component was ordered against two different aircraft and revealed an estimated response time of 15 days or less for 66.6% of the requests. Quantity ranged from one to three items per order. Attributes of this part are highlighted in Figure 64.

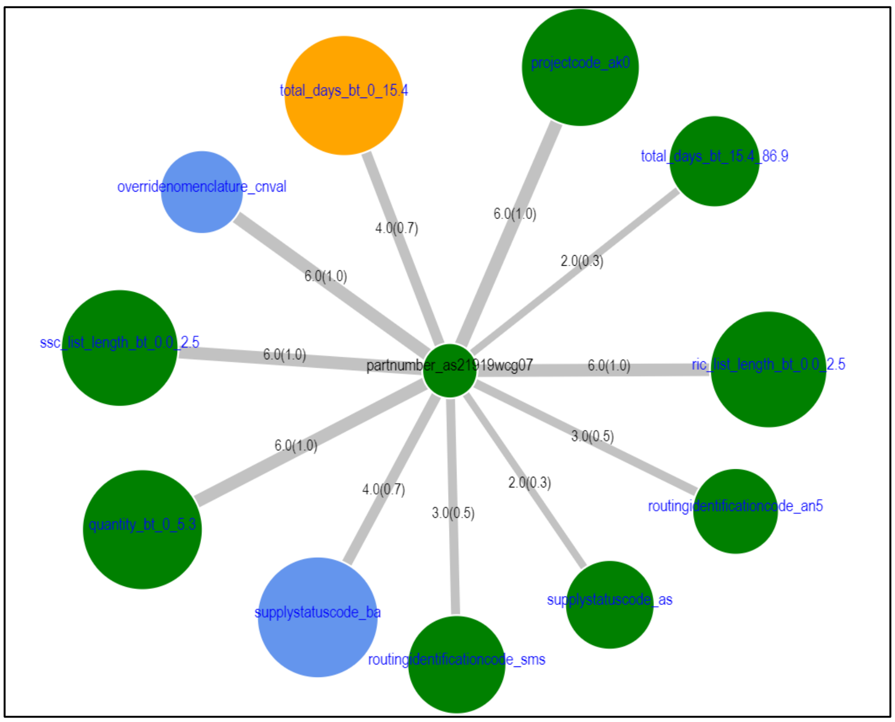

Figure 64. Part Number AS21919WCG07 Characteristics

4. 23055151—Gasket, Metal E-Seal

A "BA" PMCS coded component, this part was ordered at the highest discovered PMCS frequency of six times. Its nomenclature, "Gasket, Metal E-Seal" was sourced from three different activities: Rolls Royce Allison Indianapolis, Indiana (QN2) accounted for 16.6% (one) of the requisitions; MALS 36 Okinawa, Japan (Q53), accounted for 50% (three) of the requisitions; and MALS-26 Support Element Djibouti (RIJ) accounted for 33.3% (two) of the requests. This consumable component was ordered against five different aircraft and 100% of the requests took an estimated response time of 15 days or less. Quantity was two items per order. Characteristics of this part are shown in Figure 65.

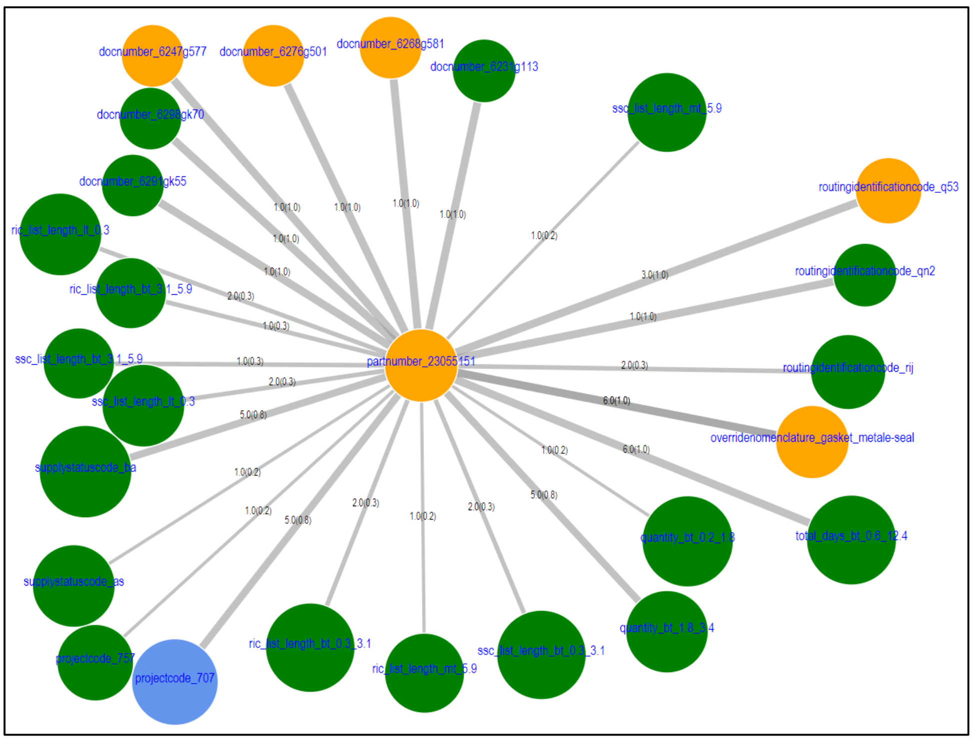

Figure 65. Part Number 23055151 Characteristics

5. 1024327G-3—Battery Assembly

Ordered at the frequency of four times, this part was a "BA" coded PMCS item. Its nomenclature, "Battery Assembly" was sourced from two activities: Navy Materiel Oak Harbor, Washington (PKZ); and NAS North Island, California (PDZ). Both locations constituted 50% (two) of the requisitions. This consumable component was ordered against four aircraft with an estimated response time between 10 and 20 days from the order. Quantity was one item per order. Features of this component are displayed in Figure 66.

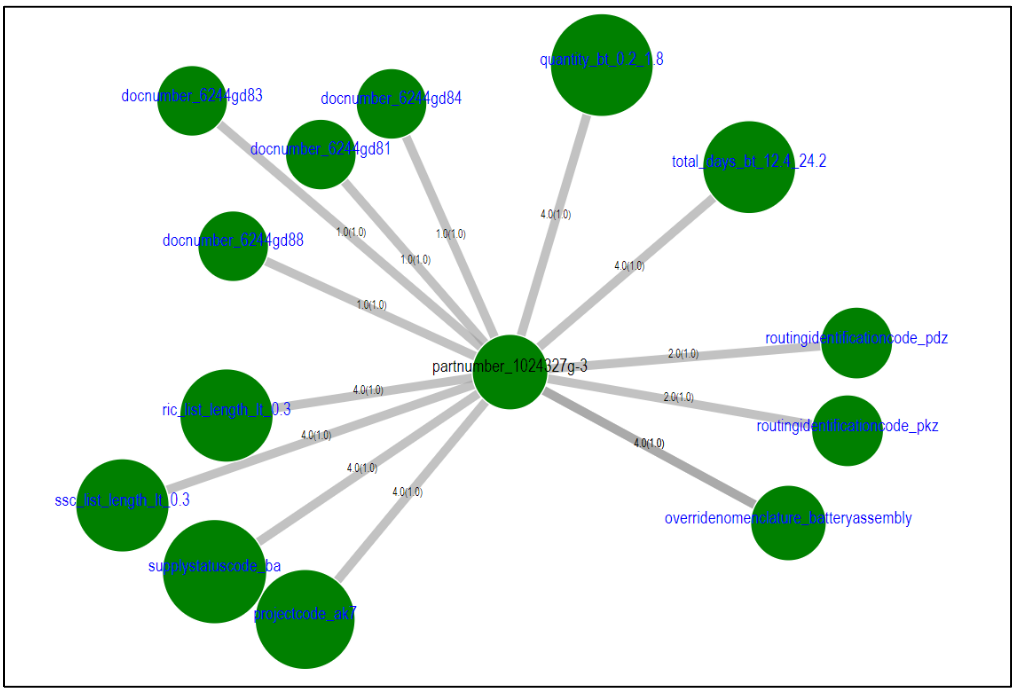

Figure 66. Part Number 1024327G-3 Characteristics

6. 901-011-121-101—Bolt, Eccentric Head

An "AS" NMCS coded component, this part was ordered at a frequency of three times. Its nomenclature, "Bolt, Eccentric Head" was sourced from one activity: MALS-24 Marine Corps Base Hawaii, Keneohe Bay, Hawaii (Q47). This consumable component was ordered against one aircraft on the same day, resulting in an estimated response time of 32 days. Quantity was one item per order. Attributes of this component are displayed in Figure 67.

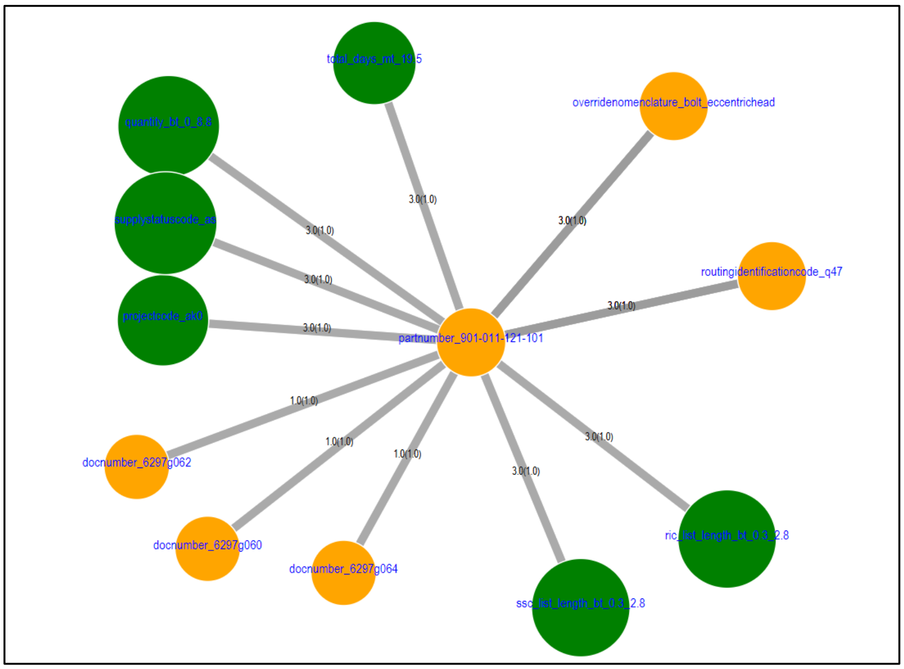

Figure 67. Part Number 901–011-121-101 Characteristics

7. NAS1291-10—Nut, Self-Locking, Ex

An "AS" NMCS coded component, this part was ordered at a frequency of three times. Its nomenclature, "Nut, Self-Locking, Ex" was sourced from three activities: NAS Oceana, Virginia (PNZ); MALS-26 Jacksonville, North Carolina (Q48); and DLA New Cumberland, Pennsylvania (AN5). All locations constituted 33.3% (one) of the requisitions. This consumable component was ordered against two aircraft resulting in estimated response times between 10 and 15 days. Quantity ranged from one to three items per order. Features of this part are highlighted in Figure 68.

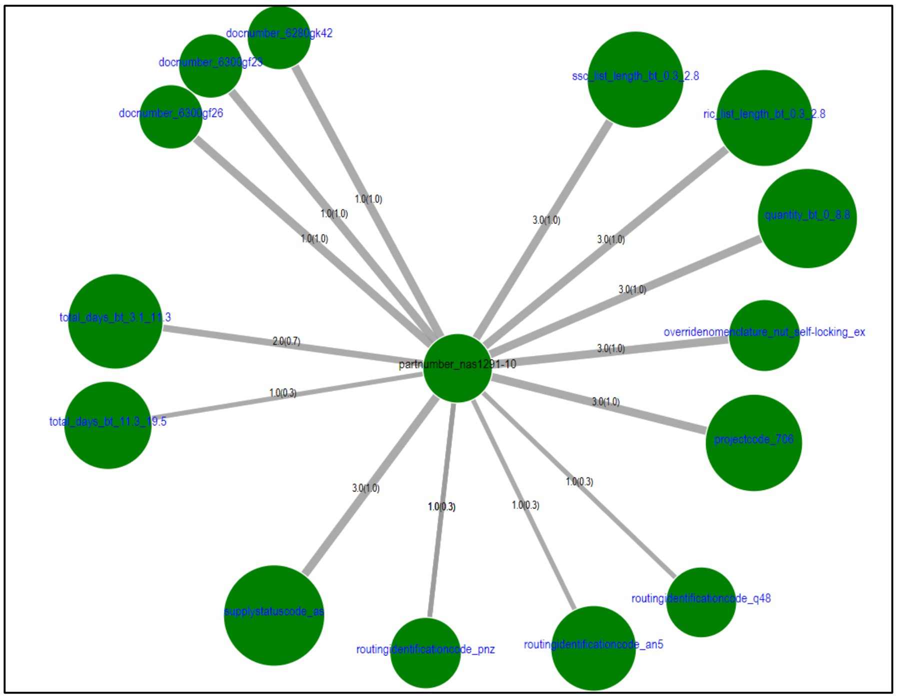

Figure 68. Part Number NAS1291-10 Characteristics

8. 901-020-563-115—Wire Rope Assembly

Ordered at the frequency of three times, this part was an “AS” coded PMCS item. Its nomenclature, “Wire Rope Assembly” was sourced from one activity: DLA New Cumberland, Pennsylvania (AN5). This consumable component was ordered against two aircraft with an estimated response time under 10 days. Quantity ranged from one to two items per order. Attributes of this component are displayed in Figure 69.

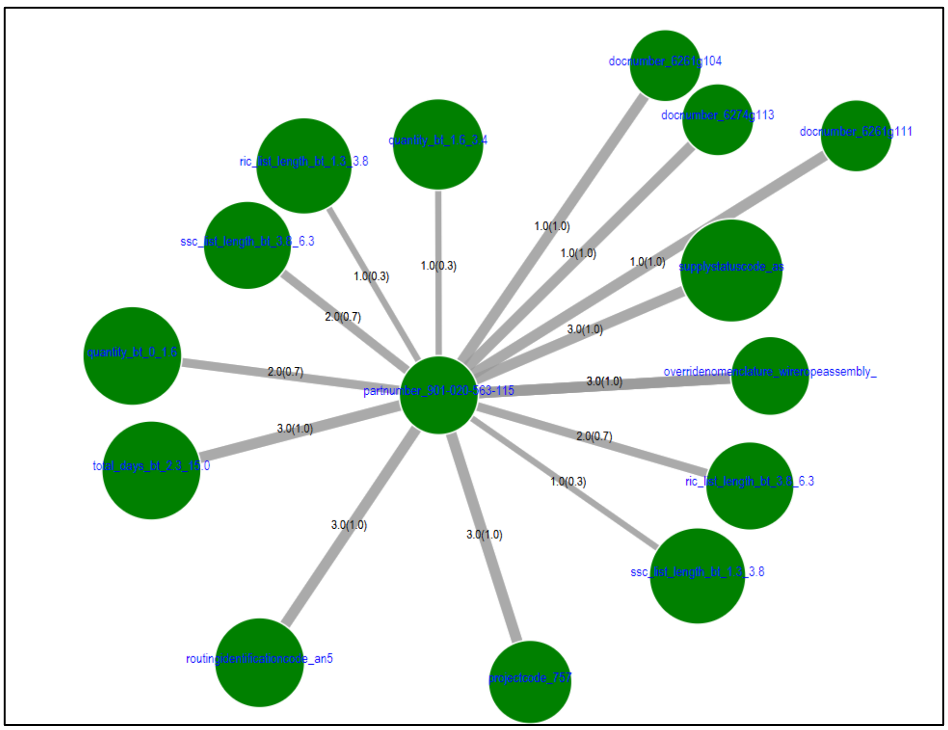

Figure 69. Part Number 901–020-563-115 Characteristics

9. 901-015-301-122—Blade Assembly, Aircraft

An “AS” PMCS coded component, this part was ordered at a frequency of two times. Its nomenclature, “Blade Assembly, Aircraft” was sourced from two activities: MALS-26 Jacksonville, North Carolina (Q48); and MALS-26 Support Element Djibouti (RIJ). Both locations were responsible for 50% (one) of the requisitions. This repairable component was ordered against two aircraft with an estimated response time between 40 and 50 days. Quantity was one item per order. Characteristics of this part are depicted in Figure 70.

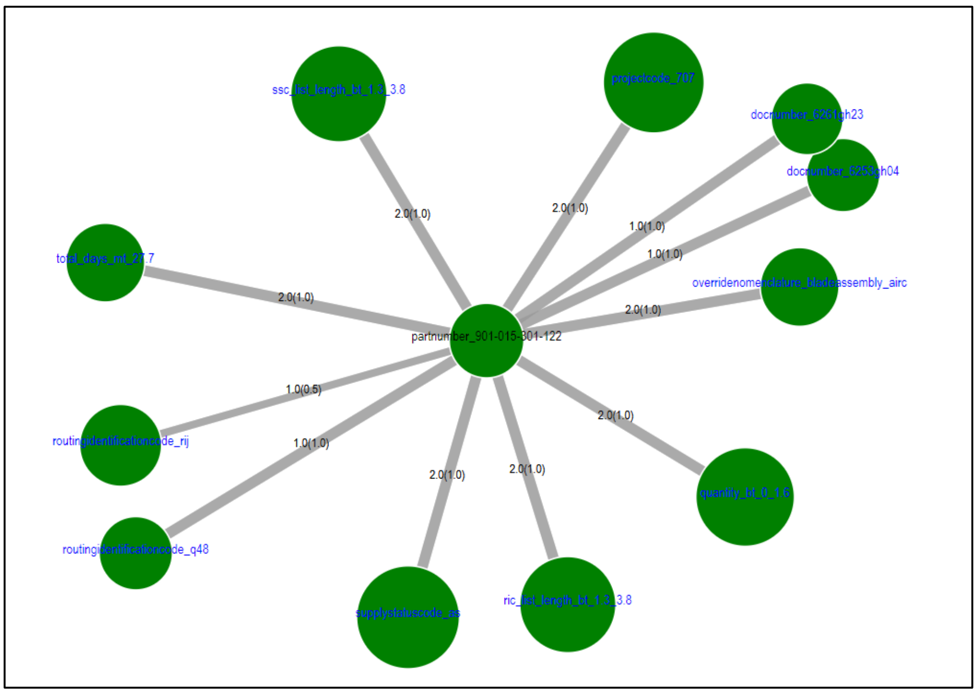

Figure 70. Part Number 901–015-301-122 Characteristics

C. SOURCING ACTIVITY ANALYSIS

Though not a research requirement, assessing estimated response times of the most frequently realized sourcing activities can provide additional insight to supply chain professionals. As previously stated, the estimated response time was calculated from estimated delivery dates and not a proof of delivery. Because of this approximate calculation, response time values may not be truly accurate. As an example, Figures 71 and 72 demonstrate how errors or flaws in the data can impact results. In Figure 71, 16 “BA” NMCS labeled supply documents, have an estimated response times less than zero days due to erroneous estimated delivery dates recorded on supply documents. All documents were sourced from NAS Oceana, Virginia (PNZ).

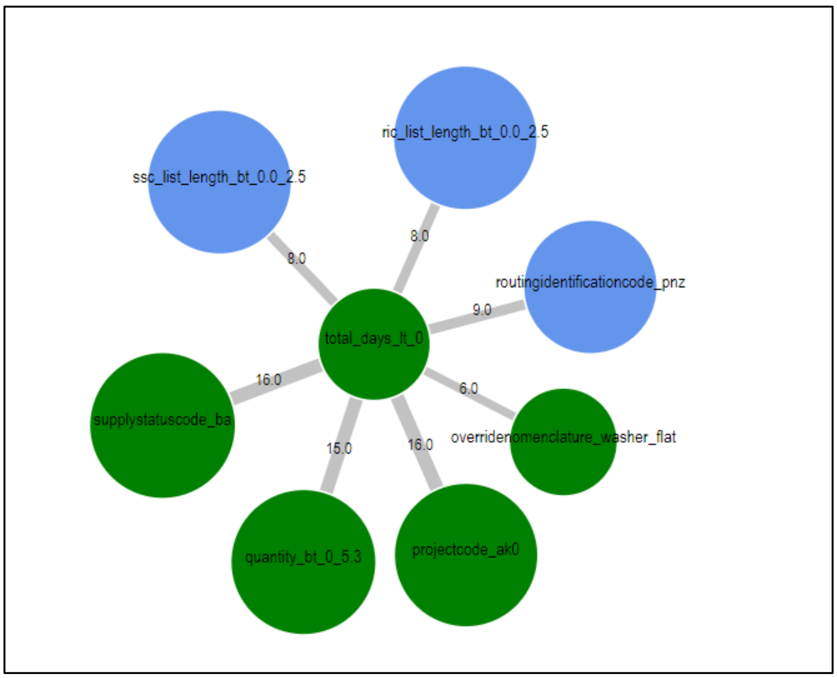

Figure 71. “BA” NMCS Erroneous Estimated Response Times

Likewise, Figure 72 shows one “AS” PMCS labeled supply document having an estimated response times less than 2.3 days, sourced from DLA Fort Belvoir, Virginia (SMS). Potentially, this document could have been sourced from DLA facility in Europe, resulting in a quick estimated response time. However, due to poor annotation of the sourcing activity, DLA Fort Belvoir, Virginia (SMS), it cannot be confirmed if the estimated response time is erroneous or accurate.

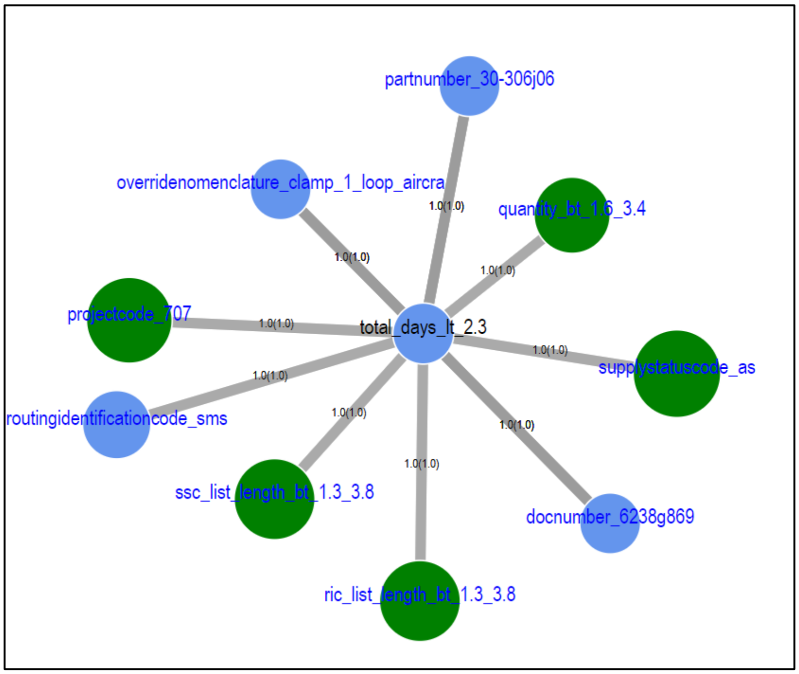

Figure 72. "AS" PMCS Data Flaw

When assessing "BA" NMCS coded parts, the top three RICs identified were NAS Oceana, Virginia (PNZ); DLA Fort Belvoir, Virginia (SMS); and DLA Cherry Point, North Carolina (SDH). Estimated response times for NAS Oceana, Virginia (PNZ), resulted in 87.3% of the parts arriving 15 days or less with an average of 30 days transit time, and a median and mode of 10 and seven days respectively. Though DLA Fort Belvoir, Virginia (SMS) is not a supply location, supply documentation that listed this RIC throughout the components' transit times resulted in 87.0% of estimated response time of 15 days or less with an average transit time of 14.4, and a median and mode of seven days each. Lastly, 81.0% of the parts sourced from and DLA Cherry Point, North Carolina (SDH) resulted in an estimated response time of 15 days or less with an average transit time of 12.2 days, and a median and a mode of six days each.

Analysis of "BA" PMCS coded parts, the top three RICs identified were NAS Oceana, Virginia (PNZ); DLA Cherry Point, North Carolina (SDH); and DLA New Cumberland, Pennsylvania (AN5). Estimated response times for NAS Oceana, Virginia (PNZ) resulted in 90.9% of the parts arriving 15 days or less with an average of 11 days transit time, and a median and mode of seven and six days respectively. DLA Cherry Point, North Carolina (SDH) components' transit times resulted in 75.0% of estimated response time of 15 days or less with an average of 11.1 days, and a median and mode of 7.5 and six days correspondingly. Lastly, 50.0% of the parts sourced from DLA New Cumberland, Pennsylvania (AN5) resulted in an estimated response time of 15 days or less with an average of 19.1 days, and a median of 15 days.

When assessing "AS" NMCS coded parts, the top three RICs identified were DLA New Cumberland, Pennsylvania (AN5); DLA Fort Belvoir, Virginia (SMS); and MALS-16 San Diego, California (Q46). Estimated response times for DLA New Cumberland, Pennsylvania (AN5) resulted in 90.0% of the parts arriving 15 days or less with an average of 9.1 days transit time, and a median and mode of 7.5 and four days respectively. As previously stated, DLA Fort Belvoir, Virginia (SMS) is not a supply location, however, supply documentation that listed this RIC throughout the components' transit times resulted in 89.5% of estimated response time of 15 days or less with an average transit time of 7.5, and a median and mode of four and two days correspondingly. Lastly, 100.0% of the parts sourced from MALS-16 San Diego, California (Q46) resulted in an estimated response time of 15 days or less with an average transit time of 10.2 days, and a median and a mode of 10 days each.

Analysis of "AS" PMCS coded parts, the top three RICs identified were DLA New Cumberland, Pennsylvania (AN5); MALS-16 San Diego, California (Q46); and MALS-26 Support Element, Djibouti (RIJ). Estimated response times for DLA New Cumberland, Pennsylvania (AN5) resulted in 77.7% of the parts arriving 15 days or less with an average of 11 days transit time, and a median and mode of seven and six days respectively. MALS-16 San Diego, California (Q46), components' transit times resulted in 100.0% of estimated response time of 15 days or less with an average of 10.6 days, and a median and mode of 10 and 12 days correspondingly. Lastly, 33.3% of the parts sourced from MALS-26

Support Element, Djibouti (RIJ) resulted in an estimated response time of 15 days or less with an average of 32.6 days, and a median of 41 days.

This examination depicts the preponderance of estimated transit times from the most used sourcing activities within a two-week window. The only significant outlier was MALS-26 Support Element, Djibouti (RIJ), with an estimated response time of six to seven weeks.

D. FUTURE RESEARCH

Follow on research to assess and increase supply chain management (SCM) efficiency can be broken down into three subject area: parts, locations, and inventory management. Focusing efforts to understand shortfalls and limitations with demanded components, supply warehouse locations, and methods of managing inventories will position supply chain professionals in a manner that will cultivate supply chain agility. Fostering agile SCM strategies will create a proactive rather than reactive supply chain response, resulting in improved readiness and increased combat capability.

Due to the robust nature of naval aircraft and equipment, an intimate knowledge of component lifespans and proper diagnosis of faulty parts and subsystems is a critical element to any supply system. Studies concerning failure rates of parts and engineering expectations may uncover additional supply chain vulnerabilities. Parts that are not identified or perceived as challenges will put un-due burden on the supply chain and decrease SCM effectiveness. This research could also consider maintenance actions repairing and diagnosing inoperative components. Assessing personnel habits and techniques to repair aircraft may unearth training deficiencies that negatively impact supply systems. Parts can also be grouped into subcomponents and subsystems to assess categories of parts and find inconsistencies or obstacles that may be occurring due to a specific subsystem rather than discrete components. A final evaluation regarding parts would be to scrutinize additional supply chain databases and tracking systems. A comparison of findings between AMSRR and other SCM systems may expose report weaknesses that could be rectified.

Another aspect to conduct research on would be to measure the efficiencies of each supply node. Analyzing each supply warehouse location and routing identification codes could provide additional insight to evaluate efficient locations. Through comparisons, research could uncover valuable information about location productivity, available space for stock, and shipping/transportation responsiveness. This could unearth reasons for the use of supply distribution originating from the continental U.S. Furthermore, information regarding host nation requirements, such as customs obligations, must be considered to ensure impediments are mitigated and do not add to supply chain delays. Making informed decisions regarding supply nodes and locations, supply chain professionals could real-time optimize the supply network depending on mission requirements.

Lastly, researching inventory management techniques and tools for supply warehouses and stockpiles could be beneficial to enhancing SCM effectiveness. Whether information technology systems are implemented to track and manage inventories, or locations manually account for inventories, various approaches to accountability could be assessed to determine the most resourceful. Again, supply professionals could modify inventory management methods to best fit each supply location, thus benefiting the entire supply network.

E. RECOMMENDATIONS

Given operational tasks and dynamic changes in location, SCM recommendations are to levy sourcing activities within a squadron's and MEU's area of operation. Pushing inventories of readily available parts to theater DLA facilities or U.S. Navy supply points may be beneficial in reducing response times of components critical to aircraft readiness. In this situation, DLA Sigonella, Italy, DLA Sigonella at Rota, Spain, may have been more advantageous. An end-user evaluating these results would have based their operational decisions on a one-to-two-week impairment in combat capability for specific components. As rigorously shown, a reduction in response time and strengthening of aircraft readiness may be achieved by prepositioning critical, frequently demanded, and low quantity components.

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APPENDIX. DATA CODE DEFINITIONS

The following tables describe the various codes recorded in the Aviation Maintenance/Supply Readiness Report data received for this project. As listed, Table 3 defines the project codes labeled within the supply documentation to determine readiness criticality of components.

Table 3. Project Code Definitions. Adapted from: DoN (1997).

Project Code	**Definition**
706	“Tiger Tom Priority-I Group NMCS COMNAVAIRPAC”
707	“Tiger Tom Priority-I Group PMCS COMNAVAIRPAC”
730	“NMCS/PMCS of an aircraft in an ‘Out’ of material condition reporting status”
756	“BOBCAT Priority-I Group NMCS COMNAVAIRLANT”
757	“BOBCAT Priority-I Group PMCS COMNAVAIRLANT”
AK0	NMCS requirement
AK1	Aircraft support equipment in unscheduled repair causing a work stoppage
AK7	PMCS requirement
AL7	Aircraft support equipment in scheduled repair impaired by a lack of parts
BK1	I-Level work stoppage due to unscheduled repair of in-use equipment
ZA9	Forced “High Time” removal of a primary weapon system of which the A/C will become NMCS within 20 days of removal
ZC8	I-Level to requisite material to “stop an ‘Awaiting Parts’ condition on components and aircraft engine undergoing repair.”

Various supply status codes are defined in Table 4. Of note, this research focused on “BA” and “AS” codes as they first appeared on the AMSRR, a likely indication of their availability in the supply system.

Table 4. Supply Status Code Definitions. Adapted from DoN (1997).

Status Code	Definition
AS	Shipping Status
B7	"Unit price change."
B8	"Quantity requested for cancellation…was not accomplished."
BA	"Item is being processed for release and shipment" on a requisition
BB	"Item is back ordered against a due-in to stock."
BD	"Requisition is delayed due to a need to verify requirements relative to authorized application, item identification, or technical data."
BF	"No record of your document…or cancellation request was submitted."
BG	Change in order documentation; stock number, unit of issue, part number ID, NIIN.
BH	"Service coordinated/approved substitute…will be supplied."
BJ	"Quantity changed to conform to unit pack"
BK	Requisition documentation was modified; data elements, priority, required delivery date, etc.
BL	"Notice of availability was forwarded to the country representative or freight forwarder"
BM	Requisition documentation was forwarded to a different activity
BN	"Requisition being processed as free issue. Adjust local fund obligation records."
BV	"Item procured and on contract for direct shipment to consignee."
BZ	"Requisition being processed for direct delivery procurement."
CB	"Initial requisition requested rejection of that quantity not available for immediate release."
CM	"Rejected. Item is no longer free issue."
CT	"Rejected. FMS requisition contains a 'U' or 'V.' " Correct documentation and resubmit.
DD	Processing a termination/drawdown requisition. "This quantity will not be delivered."
IW	In Work

A list of all the routing identification codes and their corresponding locations is provided in Table 5.

Table 5. Routing Identification Code Locations. Source: https://www.transactionservices.dla.mil/DAASINQ/ric.asp?cu=d (2018).

RIC	**Locations**
AN5	DLA New Cumberland, Pennsylvania
AQ5	DLA San Joaquin, California
B16	W4GV USA Aberdeen, Maryland
B56	W4GV ACTV CECOM Tobyhanna, Pennsylvania
DKV	FB4417 16 LRS LGSA Hurlburt Field, Florida
DYB	USAF Cannon AFB, New Mexico
F01	Lockheed Martin Fort Worth, Texas
FGZ	FD2020 OO ALC Hill AFB, Utah
GSA	GSA Federal Acquisition Arlington, Virginia
N32	NAVSUP Weapon Support Sys Philadelphia, Pennsylvania
N3U	Consolidated HAZ REUT IVEN MGMT Pro Groton, Connecticut
NEN	COMACCLOGWING DET AIMD Point Mugu, California
NGU	PEO Integrated Warfare Systems 3 Arlington, Virginia
NPR	Naval Air Pacific Repair Facility Atsugi, Japan
NPZ	NAVSUP Pearl Harbor, Hawaii
NRP	NAVSUP WSS Philadelphia, Pennsylvania
NSL	USS Essex LHD 2
NVM	Navy Uniform Support Center Chesapeake, Virginia
NVN	Aviation Support Dept. Fort Worth, Texas
NYK	NAVAIR ISS Residual Facility Beaufort, South Carolina
P21	Aviation Support Dept. Belle Chasse, Louisiana
P23	NAS Lemoore, California
P24	SRF and JRMC Yokosuka, Japan
P28	NAS Fallon, Nevada
P29	US Navy Mayport, Florida
P32	Aviation Support Dept. Fort Dix, New Jersey
PDW	ATAC Agent Air Cargo Terminal Sigonella, Italy
PDZ	NAS North Island, California
PG4	USS Iwo Jima LHD 7, Kuwait
PJZ	NAS Jacksonville, Florida
PKZ	Navy Materiel Oak Harbor, Washington
PNZ	NAS Oceana, Virginia
POZ	NAS Oceana, Virginia
PRZ	Naval Air Warfare Center Patuxent, Maryland
Q39	MALS-29 Jacksonville, North Carolina

RIC	Locations
Q43	MALS-13 Yuma, Arizona
Q44	MALS-14 Cherry Point, North Carolina
Q46	MALS-16 San Diego, California
Q47	MALS-24 MCBH Kaneohe Bay, Hawaii
Q48	MALS-26 Jacksonville, North Carolina
Q49	MALS-31 Beaufort, South Carolina
Q53	MALS-36 Okinawa, Japan
Q6C	FRC East Cherry Point, North Carolina
QD4	Bell Boeing Amarillo, Texas
QJM	ALFA Laval Inc. Chesapeake, Virginia
QJN	Bell Boeing Amarillo, Texas
QN2	Rolls Royce Allison Indianapolis, Indiana
QNJ	Raytheon Company McKinney, Texas
QWM	CMIO Aviation Norfolk, Virginia
R65	MALS-39 Camp Pendleton, California
R3K	USS Kearsarge LHD 3
R3W	USS Wasp LHD 1
RIJ	MALS-26 Support Element, Djibouti
S5T	DLA Philadelphia Pennsylvania
SCF	DLA Yokosuka, Japan
SDD	DLA Warner Robins AFB, Georgia
SDF	DLA Norfolk, Virginia
SDH	DLA Cherry Point, North Carolina
SDM	DLA Jacksonville, Florida
SDQ	DLA Europe Germersheim, Germany
SDT	DLA Hill AFB, Utah
SDU	DLA Tinker AFB, Oklahoma
SDX	DLA San Diego, California
SEX	DLA Groton, Connecticut
SGA	DLA Wright Patterson, Ohio
SGW	Industries in the Blind, Greensboro, North Carolina
SGX	Arizona Industries for the Blind Phoenix, Arizona
SMS	DLA Fort Belvoir, Virginia
SNC	DLA Susquehanna New Cumberland, Pennsylvania
SRR	DLA Richmond, Virginia

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