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ACQUISITION RESEARCH PROGRAM SPONSORED REPORT SERIES

Anticipating High Demand Class IX Supplies in the Western Pacific Area of Operations

December 2024

Capt Patrick D. Dosono, USMC
Capt William L. Meagher, USMC
GySgt Jeka D. Talaa, USMC

Thesis Advisors: Harrison C. Schramm, Senior Lecturer
Dr. Geraldo Ferrer, Professor

Department of Defense Management

Naval Postgraduate School

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ABSTRACT

The thesis focuses on predicting high-demand class IX items for MARFORPAC by analyzing maintenance and requisition data over multiple fiscal years. We apply a Markov chain model to examine failure patterns across subassembly systems of a specific assets; this model will provide a descriptive analysis to examine the maintenance history by identifying the primary defects that have caused failures within a given major end item. We will then apply this model to help us understand how the probabilities of one failure in a subassembly can lead to failures in another, allowing us to predict future breakdowns based on historical data. By identifying these failure sequences, we aim to provide a framework for MARFORPAC units to leverage predictive analytics in distributed and contested environments.

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LIST OF ACRONYMS AND ABBREVIATIONS

CBM+	condition-based maintenance plus
CEC	combat essentiality code
CFMC	Caterpillar Fleet Monitoring Center
CM	corrective maintenance
CMA	condition monitoring advisors
ETP	exception to policy
FMF	Fleet Marine Force
FSMAO	Field Supply and Maintenance Analysis Office
GCSS-MC	Global Combat Support System – Marine Corps
MAGTF	Marine Air-Ground Task Force
MARCORLOGCOM	Marine Corps Logistics Command
MARFORPAC	Marine Corps Forces, Pacific
MCO	Marine Corps Order
MCS	maintenance control systems
MCTP	Marine Corps Tactical Publication
MDR	mass data repository
NIIN	national item identification number
PM	preventative maintenance
SDN	standard document number
SME	subject matter expert
TAMCN	table of authorized materiel control number
TBM	time-based maintenance

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EXECUTIVE SUMMARY

Logistics is critical to sustaining the Marine Corps' operational readiness, especially in contested environments where supply chain disruptions are a constant threat. As a highly mobile force operating far from established supply lines, the Marine Corps faces significant challenges in maintaining equipment readiness amidst unpredictable demands. This research addresses the critical need to anticipate and prioritize high-demand Class IX repair parts by analyzing historical and maintenance requisition data. Through the application of Markov chain modeling, the study examines defect progression patterns in critical assets, offering actionable insights to inform proactive maintenance strategies and enhance supply chain resiliency.

The study emphasizes the value of Condition-Based Maintenance Plus (CBM+) as a framework for transitioning from reactive to predictive maintenance strategies. By leveraging data analytics and integrating CBM+ principles, the research highlights how the Marine Corps Forces Pacific (MARFORPAC) can better predict high-demand repair parts and optimize resource allocation. Current maintenance strategies often depend on time-based schedules, which may fall short in addressing the unpredictability of equipment failures. The application of CBM+ enables data-driven decision-making, ensuring the Marine Corps can adapt its logistics framework to meet the unique demands of expeditionary operations and enhance readiness in the Western Pacific.

This study analyzes 553,945 requisitions linked to 183,654 maintenance tasks across 127,190 service requests over four fiscal years. Data from Global Combat Support System – Marine Corps (GCSS-MC) is reconstructed into a time-based format, allowing the analysis of maintenance events relative to requisition dates. By focusing on defect occurrences and failure rates, the research employs a Markov chain modeling to quantify the likelihood of transition from one defect state to another. Transition matrices are generated for specific assets, capturing patterns in defect progression and providing insights into recurring failures.

The Markov chain analysis highlights critical patterns in defect progression. Figure 1 illustrates the transition dynamics for a specific Table of Authorized Materiel Control Number (TAMCN) we analyzed – D00157K. The figure was generated by aggregating transition matrices derived from the top 10% of D00157K assets with the highest maintenance and requisition counts. These matrices were normalized to ensure each row represented a valid probability distribution, creating a Markov chain representation. The visual captures the likelihood of transitions between defect states, providing actionable insights into defect behaviors and their potential progression over time.

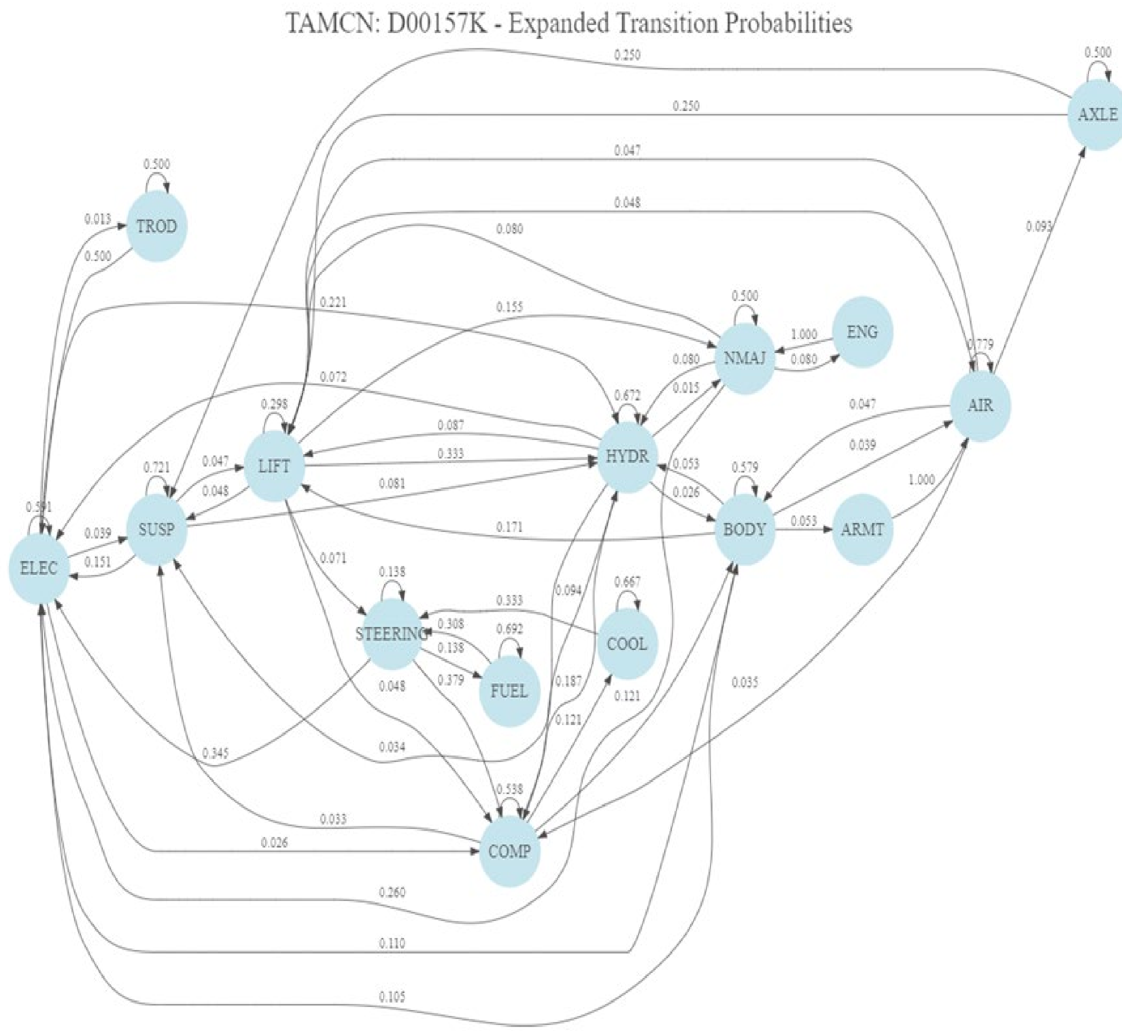

Figure 1. Markov chain analysis: Highlighting high-occurring and recurring defect failures to drive accurate demand for maintainers

Transforming maintenance and requisition data into actionable insights through a data-driven approach empowers planners to anticipate failures, generate more accurate demand signals, and prioritize resources effectively. By identifying defects with high transition probabilities using Markov chain analysis, the Marine Corps can adopt proactive maintenance strategies that enhance operational readiness, reduce downtime, and ensure mission-critical equipment is available when needed.

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I. INTRODUCTION

Logistics is a cornerstone of military operations, ensuring that forces remain ready capable in dynamic and contested environments. For the Marine Corps, the challenge lies in balancing agility with readiness, particularly in anticipating and meeting equipment maintenance and supply demands under uncertain conditions. This chapter provides an overview of the critical role logistics play in sustaining combat power, highlighting the importance of effective planning, supply chain integration, and data-driven approaches. A key challenge is determining how historical maintenance and requisition data can be used to predict demand for repair parts, ensuring equipment readiness and building supply chain resiliency in future conflicts.

A. BACKGROUND

The influence of logistics in the Marine Corps continues to evolve alongside changes in the global strategic environment and the need for the United States to remain a leader in peace and security. Increasing in prominence, logistics is essential for sustaining continuous military operations, signaling the Marine Corps' strength to respond to emerging problems. To maintain high levels of readiness, the Marine Corps must effectively supply its deployed units operating in contested environments far from home, and at a pace that deters adversaries and shapes global actions.

Generating and maintaining a competitive advantage in global security depends on effective logistics support. Particularly, high levels of material readiness and equipment availability are essential for leveraging total combat power. However, an uncertain operating environment demands a balance between operational necessity and logistical support. As a maneuver force by doctrine, Marine Corps planners can never be certain how frequently or intensively equipment will be operated to accomplish the mission. Furthermore, Marine units are organized to be highly mobile in order to operate quickly, limiting their capacity to carry a large footprint of repair parts needed to maintain equipment readiness. Therefore, logistics planners must find ways to accurately anticipate maintenance and supply needs, based on mission requirements and commanders' intent, while accounting for potential impacts by the adversary, environment, and uncertainty of operational tempo and equipment usage.

This imperative is distinct to an expeditionary fighting force where mission accomplishment takes precedence over all else. Planners must consider a wide variety of likely scenarios in uncertain environments and then apply methods and techniques to predict logistical requirements. For example, probabilistic models can help determine how many spare parts a unit should bring to an operation. The force must utilize its existing enterprise resource planning system and apply innovative thinking to anticipate the needs of warfighters on the ground.

When considering how units should maintain equipment readiness in austere environments, the current tactical practice is to establish a Class IX block of supplies, which are parts that are required to maintain or repair an item. When equipment breaks down, repair parts in the Class IX block are used to restore equipment back to an operating condition. Building a Class IX block begins in the planning phases of an operation but is often a challenging endeavor among key stakeholders including commanders, equipment owners, maintainers, and supply personnel due to the uncertainty of need and constrained resource capacity. Planners depend on past experience and historical usage data. However, with technological advancements, planners can leverage data analytics. Analytical approaches will help Marines bridge the gaps between historical usage data and future operational needs.

The Marine Corps has already taken steps to improve logistical readiness by implementing directive orders to enhance equipment maintenance. One such order is known as Condition-Based Maintenance Plus (CBM+), which utilizes data and predictive analytics to anticipate when equipment will require maintenance or replacement. The Marine Corps has yet to establish clear methods for using data analytics to predict requirements, directing the responsibility on individual units to develop policies that enable execution. Past studies have shown the effectiveness of CBM+, especially in civilian industries, yet the full adoption of leveraging data to plan and conduct equipment maintenance has seen resistance in operational fleet units. This thesis applies predictive data analytics in supply and maintenance practices, demonstrating how analytical techniques can be used to anticipate demand of repair parts in future conflicts.

1. Doctrinal Overview of Marine Corps Logistics

Doctrinal publications form the foundation of the role of logistics in enabling the Marine Corps' mission. The Marine Corps operates in uncertain, fluid, and friction-filled environments, particularly at the tactical level of war where decisions and actions unfold rapidly. Maneuver warfare, the service's core warfighting philosophy, focuses on seizing the initiative, maintaining speed, and concentrating combat power at decisive points to achieve desired outcomes (Department of the Navy [DON], 2023b). This approach to warfighting requires careful planning and equipping of the force to ensure combat readiness. Logistics support is vital in this process, ensuring that the resources necessary for mission accomplishment are available when and where they are needed.

Logistics, as both an art and a science, provides the foundation for supporting Marine Corps operations by integrating supply, maintenance, and other functions to sustain forces in contested environments. In maneuver warfare, logistics elements must be agile, responsive, and able to anticipate future requirements at all levels of warfare (DON, 2023a). Additionally, essential material readiness levels must be attained initially and sustained over the course of operations. As technology continues to advance, logistics planning has evolved to incorporate data-driven insights, improving prediction and responsiveness of sustainment needs. This is critical for anticipating those repair parts that are likely to be in high demand in protracted conflicts, such as those expected to arise in the Western Pacific Area of Operations. Additionally, the lines between the tactical, operational, and strategic levels of logistics will overlap, requiring closer integration and coordination of multiple supply chains across diverse sources, including the Department of Defense writ large, partner militaries, and the global defense industrial base (LaPlante & Lowman, 2024). As logistics continues to grow in importance, it is vital to leverage information and innovation, ensuring that the Marine Corps can sustain combat power against adaptive adversaries in increasingly contested and complex environments.

2. Tactical Overview of Marine Corps Logistics

The Marine Corps has developed publications for each of the six functions of logistics at the tactical level of war. For the purposes of this thesis, we will focus on two: supply and maintenance. Marine Corps Tactical Publication (MCTP) 3–40H outlines Marine Air-Ground Task Force (MAGTF) Supply Operations, while MCTP 3-40E focuses on Maintenance Operations. Both tactical publications emphasize that these logistics functions must be governed by responsiveness and flexibility, aligning with the principles of Marine Corps logistics.

Supply operations involve managing various classes of supply, with Class IX repair parts being particularly complex due to the uncertainty of demand for thousands of unique repair parts. This characteristic contrasts with other types of supplies such as Class I (subsistence), Class III (fuel), and Class V (ammunition). At the tactical level, supply operations focus on ensuring that units receive the necessary resources at the point of need to support mission execution and sustain operations (Department of the Navy [DON], 2019). Deployed units initially equip a Class IX block, and any shortfall of repair parts within the Class IX block are requested for procurement outside the using unit level. Class IX blocks are outfitted based on the equipment to be operated, and account for the specific repair parts that are expected to be in demand when failures occur. Information management has become increasingly critical in this process, enabling commanders, equipment owners, maintainers, and supply personnel to make data-informed decisions about Class IX sustainment. When Class IX blocks are properly planned, equipment downtime is reduced since repair parts are already on hand and available for immediate use. Effective logistics planning ensures the availability of the right repair parts at the right time, which directly impacts the readiness of equipment affected by both operational use and adversarial action.

Maintenance operations are inherently linked to MAGTF supply operations, as the procurement of repair parts is essential to performing equipment repairs. Sustaining equipment in a tactical environment involves two primary maintenance approaches: preventive maintenance, aimed at scheduling service, and corrective maintenance, which addresses issues after they occur (Department of the Navy [DON], 2020b). To oversee these actions, unit maintenance management personnel integrate command guidance, unit resources, maintenance production, and information to ensure that equipment is ready and available when needed. In an effort to improve maintenance programs, CBM+ builds upon tactical guidance, aiming to increase maintenance efficiency, enhance equipment availability, and reduce long-term costs (Department of the Navy [DON], 2020a). Furthermore, increased operational tempo and restricted availability of specialized maintenance facilities requires a shift from traditional Time-Based Maintenance (TBM) to responsive CBM. Thus, we make an inference about the viability of equipment in the next time horizon, and match maintenance events to both need and availability. Ultimately, planning for maintenance actions, such as building an effective Class IX block strategy, should leverage historical usage data, operational conditions, and commanders' guidance in an effort to optimize scarce material resources and time.

B. PURPOSE AND SCOPE

To address the challenges of sustaining equipment readiness and ensuring supply chain resiliency in contested environments, this thesis examines the intersection of logistics planning and data analytics. At its core is the effort to identify and predict high-demand repair parts critical to Marine Corps operations. Developing predictive models and framework is essential to enhancing operational capabilities and shaping a more agile, resilient logistics system to meet the demands of future conflicts.

1. Problem Statement

As Marine Corps logistics evolve together with advancements in technology and information, integrating data analytics and CBM+ will be crucial to predicting future demand for repair parts, streamlining both supply and maintenance processes. This shift is critical for adapting logistics operations to meet the challenges of the future operating environment, where adversaries in the Western Pacific Area of Operations will target global supply chains that connect the United States with its allies and partners, impacting the availability of mission-critical supplies. Furthermore, the use of data-driven methods in supply and maintenance operations is vital to informing a resilient sustainment framework in the region. This thesis focuses on predicting Class IX repair parts that will be in high demand for equipment critical to the mission of Marine Corps Forces Pacific (MARFORPAC). To sustain equipment readiness and build supply chain resiliency, MARFORPAC must identify these high-demand repair parts to ensure the readiness of its combat power in future conflicts.

2. Primary Research Question

The Marine Corps uses Global Combat Support System-Marine Corps (GCSS-MC) as its system of record to plan, execute, and track supply and maintenance actions on military equipment. Information in GCSS-MC includes maintenance activities performed to restore equipment conditions and the repair parts that were procured in the process. The primary research question is: How can planners use empirical data to calculate conditional probabilities of equipment failure given the previous occurrences of maintenance actions? What equipment defects drive the demand for critical repair parts based on usage data in GCSS-MC over the past four fiscal years?

3. Secondary Research Questions

1. Can classical and novel ideas in applied probability associate historical maintenance failures of a given component based on data entered into GCSS-MC?

2. What high-demand repair parts are common across equipment defects, and how can this information be used to improve readiness planning?

C. ORGANIZATION

This research project begins with a review of past studies on CBM+, particularly those conducted at the Naval Postgraduate School, where researchers assessed the impact of CBM-like methods in the civilian sector and the adoption of CBM+ within the Marine Corps. Following the literature review, the thesis introduces the methodology, focusing on the application of the Markov Chain model. This model will help us determine the probability of equipment failure based on historical defect codes. This model will also help us ascertain the repair parts that are likely to be needed based off the last known defect and as equipment degrades over time. The analysis section will focus on selected equipment sets provided by MARFORPAC, encompassing key equipment commodity types: communications (A), engineer (B), motor transport (D), and ordnance (E). Using data from GCSS-MC, we will apply the Markov Chain model to examine repair part demand across each commodity type, identifying patterns of high-demand parts common to multiple critical systems. The research will conclude with findings and recommendations, offering insights for future planners to enhance the accuracy of Class IX sustainment planning for any given set of equipment.

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II. LITERATURE REVIEW

This literature review begins with an understanding of Condition-Based Maintenance Plus (CBM+) as defined by the Department of Defense and the subsequent implementation of that policy within the United States Marine Corps. It then transitions to a review of how CBM+ concepts have been applied in the civilian sector, where industries like the military use data analytics and information technology to optimize industrial maintenance. Although these approaches may not be labeled as CBM+, they reflect the same principles of predictive maintenance. The final section focuses on the challenges and progress of CBM+ adoption within the Marine Corps, highlighting the barriers that have limited full implementation and the steps needed to overcome them. Understanding the development of CBM+ in both civilian and military contexts provides insight into where the approach has succeeded and where it has struggled. This foundation establishes the basis for our methodology, which will apply data analysis, probability models, and predictive maintenance techniques to determine how CBM+ can enhance the accuracy of repair part forecasting. These analytical techniques will bridge the gap between past equipment data and future sustainment needs, informing a more resilient logistics framework for the Marine Corps.

A. STRATEGIC GUIDANCE ON CONDITION-BASED MAINTENANCE

Our research builds upon the Marine Corps' ongoing efforts to implement a CBM+ strategy designed to integrate predictive maintenance capabilities that enhance operational availability and readiness across the MAGTF. Specifically, we're leveraging a data-driven approach to apply a predictive model, aiming to contribute to the Marine Corps' ability to proactively address equipment failures and identify critical repair parts that impact asset degradability.

Our first focus is on the DoD's CBM+ Guidebook (Department of Defense [DoD], 2008), which provides a foundational reference for our approach. Figure 1 highlights a comparative overview of the different types of maintenance approaches, ranging from reactive (left) to proactive (right). These approaches vary significantly, with reactive maintenance being the least efficient and proactive maintenance aiming to reduce failures and cost through predictive strategies. As defined in Condition—Based Maintenance Plus for Materiel Maintenance (DoD 4151.22, 2020):

> Condition-based maintenance is a maintenance practice based on monitoring the condition of equipment to assess whether it will fail during some period in order to take appropriate action to avoid the consequences of that failure. The objective of condition-based maintenance is to perform maintenance based on evidence of need while ensuring safety, reliability, availability, and reduced life-cycle cost. (p. 13)

This concept serves as a guiding principle for transitioning from reactive to proactive maintenance strategies to predictive approaches like CBM. The goal of this research is to move the Marine Corps towards the ‘right’ side of this chart, embracing more proactive approaches that improve operational readiness.

	Maintenance Approaches			
	Reactive	Proactive		
Category	Run-to-fail	Preventive	Predictive	
Sub-Category	Fix when it breaks	Scheduled maintenance	Condition-based maint.-diagnostic	Condition-based maint.- prognostic
When Scheduled	No scheduled maintenance	Maintenance based on a fixed time schedule for inspect, repair and overhaul	Maintenance based on current condition	Maintenance based on forecast of remaining equipment life
Why Scheduled	N/A	Intolerable failure effect and it is possible to prevent the failure effect through a scheduled overhaul or replacement	Maintenance scheduled based on evidence of need	Maintenance need is projected as probable within mission time
How Scheduled	N/A	Based on the useful life of the component forecasted during design and updated through experience	Continuous collection of condition monitoring data	Forecasting of remaining equipment life based on actual stress loading
Kind of Prediction	None	None	On- and off-system, near-real-time trend analysis	On- and off-system, real-time trend analysis

Figure 1. Maintenance approaches for large organizations. The overall goal for the Marine Corps is to move to the right on this chart. Source: DoD (2008).

The run-to-fail category is at the farthest reactive end of the maintenance approach matrix. This strategy involves unscheduled maintenance, where repairs are made only after a part or component has failed. As the sub-category suggests, no action is taken until the part requires replacement, meaning there are no advance schedules or predictive measures to anticipate potential breakdowns. When the failure occurs, the weapon system or asset is classified as non-mission capable, representing the worst status for a piece of equipment since it becomes inoperable due to the defect. Another condition within the unscheduled maintenance category is when an asset is operationally degraded. In this state, the equipment can still function, but its performance and safety are compromised, preventing it from operating at full capacity or optimal efficiency.

The proactive maintenance categories include preventative and predictive approaches. Preventative maintenance focuses on scheduled or planned tasks, such as changing oil at specific intervals based on mileage or timeframes like quarterly, semiannually, or annually. Because these actions are planned in advanced, they allow for better resource allocation and help minimize unexpected downtime.

On the other hand, the predictive maintenance approach involves strategies such as condition-based maintenance and prognostics, where historical data and trend analysis are used to forecast when failures are likely to occur. By leveraging real-time monitoring and predictive analytics, this approach reduces the risk of an asset becoming non-mission capable or operationally degraded, ultimately minimizing failures and ensuring higher operational readiness.

Aligning with the foundational framework from the CMB+ Guidebook, the Marine Corps Order (MCO) 4151.22, the Marine Corps' order on CMB+, underscores the importance of integrated data environments and metric=based management tools as enablers for improving decision-making and optimizing maintenance process (DON, 2020a). The MCO expands on the practical application of these concepts by detailing how maintainers can analyze defect issues as they arise, using the equipment health condition as a critical factor in forecasting maintenance needs (DON, 2020a). The MCO emphasizes that technology-driven data analysis tools can assist maintainers to track performance trends, identify early signs of equipment degradation, and predict failures, ensuring that equipment remains operationally ready (DON, 2020a). These approaches embody the core objectives of CBM+ by leveraging predictive analytics to drive maintenance decisions based on actionable data, enabling informed, proactive interventions rather than relying on reactive responses.

By synchronizing data from various sources into an integrated environment, the Marine Corps aims to improve equipment availability while reducing life-cycle costs. This proactive model shifts maintenance planning from a reactive stance—where repairs are made after a breakdown—to one where forecasted maintenance ensures optimal asset performance and minimizes downtime.

B. INDUSTRIAL PERSPECTIVE OF PREDICTIVE MAINTENANCE

To better understand how CBM strategies can enhance military logistics, it is useful to explore how these practices have been implemented across civilian industries. The study conducted by Stuetelberg and Thomas (2021) employed a multiple case study methodology to examine CBM practices in the mining, railroad, and heavy equipment industries. These industries face challenges similar to those encountered by the Marine Corps, such as managing diverse equipment from multiple manufacturers, strategically positioning maintenance resources, and relying on internal expertise to sustain performance. Each case study provides insights into advanced maintenance techniques, particularly in managing complex fleets, streamlining operations, and maintaining operational readiness. The Marine Corps can draw lessons from these civilian sectors by adopting comparable strategies, such as employing sensors and cloud-based platforms to manage data, dynamically deploying maintenance capabilities across networks, and empowering experts to drive data-informed decisions.

Stuetelberg and Thomas (2021) organized their research into five key themes: organizational structure, asset classification, information technology infrastructure, data management, and maintenance decision-making. They then conducted interviews and literature review to determine best practices, as shown in Figure 3. Their findings demonstrated that CBM strategies significantly improve asset availability, reduce maintenance costs, and enhance operational efficiency. The following case studies focusing on Freeport-McMoRan, Union Pacific, and Caterpillar provide practical examples of these strategies in action, offering insights that the Marine Corps can adapt to enhance its logistics and maintenance operations.

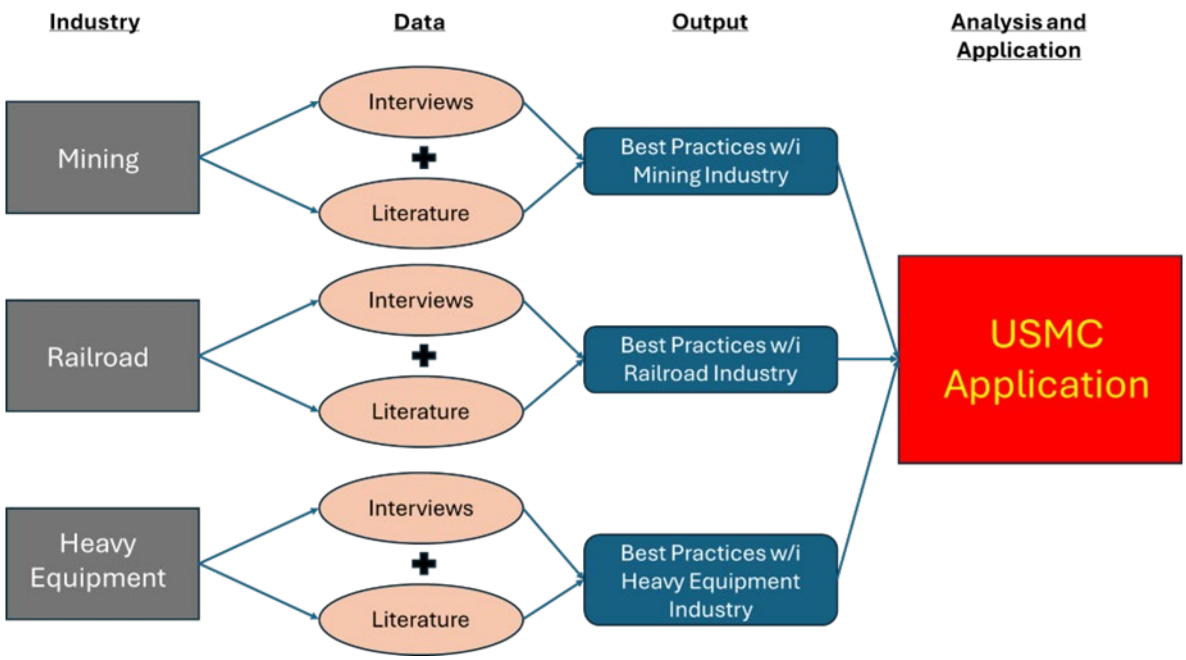

Figure 2. Process Flow Chart Detailing Case Study Construction as They Apply to the Marine Corps Application of CBM+. Source: Stuetelberg and Thomas (2021).

1. Mining Industry Case Study: Freeport-McMoRan

Freeport-McMoRan, based in Phoenix, Arizona, demonstrated the importance of having an organic data analytics department in employing CBM strategies. The company analyzed data on the throughput and maintenance of large mining trucks and other assets made by various manufacturers. To collect data, Freeport-McMoRan utilized a network of sensors on their equipment, monitoring usage via factory-installed sensors by the original equipment manufacturer, and even coupling those sensors with secondary and tertiary sensors to ensure operation and accuracy (Stuetelberg & Thomas, 2021). Data collected by these sensors were automatically transmitted to the cloud, which enabled real-time tracking of equipment status and maintenance health through Microsoft's Azure platform. Continuous data transmission from sensors to the cloud significantly improved asset visibility and, when paired with a software platform that visually presented the data, facilitated informed decision-making. This approach to CBM resulted in reduced costs, increased production, and allowed Freeport-McMoRan to refine equipment lifespans based on actual usage and environmental conditions rather than relying solely on manufacturer estimates.

2. Railroad Industry Case Study: Union Pacific

Union Pacific, based in Omaha, Nebraska, applied automated Maintenance Control Systems (MCS) as their version of CBM for its fleet of diesel-electric locomotives. Many rail companies such as Burlington Northern and Santa Fe assess cargo volume, train type, and environmental conditions to determine maintenance scheduling (BNSF Railway, 2019). In practice, Union Pacific adopted a hybrid maintenance strategy where they operated many locomotives to the point of failure because the practice of rebuilding and replacing components was more cost-effective than time-based maintenance (Stuetelberg & Thomas, 2021). Union Pacific leveraged “dynamic resource allocation,” strategically positioning repair parts and maintenance facilities along their rail network based on asset health and operational demand. This strategy aligns with Sanoubar et al.’s (2023) insights into the use of network models for managing maintenance routes and making decisions to repair or replace components. As a result, Union Pacific reduced its locomotive fleet size while still meeting operational requirements.

3. Heavy Equipment Case Study: Caterpillar Inc.

Caterpillar Inc., based in Irving, Texas employed an intricate CBM approach centered on its in-house Caterpillar Fleet Monitoring Center (CFMC) along with customer-facing Condition Monitoring Advisors (CMA). Like Freeport McMoRan and Union Pacific, Caterpillar Inc. installed sensors on their equipment, providing real-time diagnostics and prognostics data that were fed into user-friendly dashboards, allowing equipment owners to make informed decisions about maintenance. CMAs were assigned to equipment and were reputed as “medical doctors” for equipment because they employed a multidisciplinary approach using their own mechanical knowledge, equipment repair history, inspection results, and scheduled maintenance analyses to synthesize a plethora of data into actionable insights (Stuetelberg & Thomas, 2021). At the CFMC level, raw data was consolidated, cleaned, and analyzed with algorithms to identify trends across a fleet of various equipment types and operational uses. This combined approach empowered experts and operators at all levels to monitor trends and optimize maintenance decisions proactively.

In all of these case studies, a key feature of CBM has been the reliance on advanced data analytics and machine learning algorithms that predict potential failures based on patterns and historical data. Such reliance enabled each organization to optimize their maintenance schedules, reducing unnecessary resource consumption while preventing unexpected breakdowns. The application of CBM in these industries draws parallels with the military community. Similar to industry efforts, the U.S. Navy has already begun integrating CBM practices through initiatives led by the Naval Surface Warfare Center, Philadelphia Division, where they focused on increasing maintenance efficiency while reducing reliance on time-based schedules by monitoring the condition of critical shipboard systems. Specifically, the Navy is deploying an Enterprise Remote Monitoring platform to replace legacy systems and provide real-time visibility into ship health on their hull, mechanical, and electrical systems, feeding into algorithms to detect performance anomalies before they occur (Ell, 2023). Much like civilian industries, the Navy's operations can benefit from a CBM strategy that ensures ships remain mission-ready across deployment cycles, which is key to ensuring readiness at sea. By comparison, maintaining expeditionary readiness across any domain requires the Marine Corps to ensure that equipment availability directly influences mission success. Bagley et al. (2016) conducted an analytical study on Marine Corps amphibious assault vehicles, determining cost drivers of maintenance through a semi-automated model selection process, and finding that costs were primarily driven by the number of field repairs post depot-level maintenance and field down time since depot-level repair among other variables. By adopting CBM practices, the Marine Corps can move away from reactive maintenance, which is often triggered by unexpected failures, and instead shift toward predictive actions. This proactive stance could greatly enhance the management of class IX repair parts by reducing the number of emergency maintenance requests and reducing the lead time for ordering replacement parts.

C. IMPLEMENTATION OF CBM+ IN THE MARINE CORPS

The study conducted by Harding and Pennington (2022) employed a thematic analysis approach to explore CBM+ implementation in the Marine Corps. Their methodology involved identifying key Marine Corps maintenance community stakeholders, reviewing relevant policy documents, and interviewing subject matter experts (SME). Throughout their study, fifteen military and civilian maintenance and logistics experts were interviewed and selected from different organizational levels. The interview process was primarily focused on barriers and opportunities related to CBM+ adoption and using thematic analysis responses which were categorized into two themes: barriers and opportunities for change.

The authors of this study provide analysis which identified four key barriers to CBM+ implementation. First, there needs to be more consistent understanding of CBM+ across the Fleet Marine Force (FMF). Many personnel are unfamiliar with the technology and its potential benefits, which has led to slow implementation (Harding & Pennington, 2022). Second, existing Marine Corps maintenance policies conflict with the initiatives of CBM+. Many of the legacy policies are based on time-based or preventive maintenance strategies, which are making it difficult to integrate a predictive maintenance model (Harding & Pennington, 2022). Third, inspections conducted by the Field Supply and Maintenance Analysis Office (FSMAO) and Commanding General hinder the adoption of CBM+. This is due to the inspection team's primary focus on traditional maintenance metrics (Harding & Pennington, 2022). Lastly, competing priorities and resource constraints at the unit level reduce the capacity for leaders to focus on implementing new maintenance strategies (Harding & Pennington, 2022).

The team also identified multiple opportunities for CBM+ adoption. First, leadership and key personnel buy-in are crucial for successful CBM+ implementation. Leaders must advocate for CBM+ and ensure it is aligned with more significant strategic initiatives (i.e., *Force Design 2030* and *Talent Management 2030*) (Harding & Pennington, 2022). Additionally, they noted that exceptions to policy (ETP) can help accelerate the adoption of CBM+ by allowing units to bypass legacy maintenance processes (Harding & Pennington, 2022). The removal of non-value-added maintenance tasks is another opportunity to improve efficiency (Harding & Pennington, 2022). Finally, cross-training mechanics and operators to perform both roles also supports the integration of CBM+ and reduces operational bottlenecks (Harding & Pennington, 2022).

This study provides several recommendations to support the implementation of CBM+. First, aligning CBM+ with *Force Design 2030* and *Talent Management 2030* is recommended. By linking CBM+ to these strategic initiatives, leaders can create a sense of urgency for change. Second, they advise the establishment of a CBM+ guiding coalition. This coalition would be tasked with leading the implementation process and ensuring that all stakeholders are aligned with the vision of CBM+ (Harding & Pennington, 2022). Additionally, the study recommends resolving conflicts between maintenance policies by issuing interim exceptions to policies that conflict with CBM+ and conducting updates to maintenance orders as CBM+ evolves (Harding & Pennington, 2022). Lastly, developing CBM+ education programs for commanders and using FSMAO to support CBM+ integration are key recommendations to enhance organizational readiness for the transition (Harding & Pennington, 2022).

The implementation of CBM+ in the Marine Corps presents both challenges and opportunities. Organizational disinterest and policy conflicts pose significant barriers in the Marine Corps, but there can be a clear path forward with leadership advocacy and strategic alignment with initiatives such as *Force Design 2030*. The Marine Corps can achieve the required momentum for CBM+ to become an integral part of its ground maintenance strategy by focusing on early wins and emphasizing people and processes.

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III. METHODOLOGY

Data analysis through a managerial lens provides the foundation for this methodology, offering a structured approach to transform raw data from GCSS-MC into insights that inform decision-making. The challenge in today's data-abundant environment is not in collecting data but in refining vast amounts of information into concise and useful formats that drive operational readiness and resource management. The goal is to summarize data efficiently, enabling leaders to make informed decisions that improve maintenance performance and reduce waste. This process ensures that logistics operations, including supply and maintenance, are guided by insights derived from data, ultimately enhancing the Marine Corps' ability to anticipate and meet operational demands.

Probability will serve as the key analytical tool for our research. Specifically, conditional probabilities apply observed data to future outcomes by quantifying uncertainty. This is essential for understanding how defect codes and requisitions recorded in GCSS-MC relate to future demands. The methodology also draws on statistical analysis to project future needs. This structured approach ensures that data analysis directly supports identifying high-demand Class IX repair parts, aligning supply chain efforts with the realities of operational unpredictability. Through this framework, the Marine Corps can develop more responsive and data-driven logistics practices to sustain readiness across a range of missions and environments.

Our methodology takes place in three phases; the first is the ingestion and cleaning of raw GCSS-MC data. The size of the data, plus some of the nuances of formatting, creates a unique challenge. We analyzed 553,945 requisitions linked within 183,653 tasks, across 127,190 service requests over four fiscal years, from fiscal year 2021 through the current fiscal year. After the data is brought into the analytic environment and then prepared, formatted, and cleaned, the second stage can begin. This second stage is model building in which we utilize a Markov Chain. Our main reference for this work is Grimmett and Stirzaker (2001). Finally, the last phase aims to associate defect code probabilities to determine what parts will be in high demand.

A. PHASE I: GCSS-MC RAW DATA

Our analysis is centered explicitly around maintenance and requisition data, which will be explored in greater detail in this chapter. The data used in this analysis is sourced from the Marine Corps Logistics Command (MARCORLOGCOM) Master Data Repository (MDR). The MDR serves as a repository for a comprehensive collection of data from various logistics systems used by the Marine Corps and provides a centralized location to conduct data queries for research. GCSS-MC is the approved property system of record where maintenance and requisition transactions, among other logistics functions, are captured. Both maintenance and requisition data are accessed from the MDR, which consolidates information from GCSS-MC.

Table 1 highlights the key maintenance-related incident types critical to our research, which focuses on maintenance actions rather than supply or miscellaneous service requests. By concentrating on these incident types, which encompass actions such as corrective and preventative maintenance, our study aims to capture meaningful data directly related to maintenance activities. Other types of service requests, like supply or selective interchange, for example, are excluded as they do not reflect actual maintenance work performed via servicer requests. Including non-maintenance service requests would dilute the dataset, potentially obscuring insights necessary for a proactive maintenance analysis and undermining our ability to identify actionable patterns in maintenance demands.

Table 1. Example of service request types from GCSS-MC. Supply-related and other non-maintenance categories are excluded, as only maintenance-related actions are relevant. Source: USMC (2017).

Incident type	Description
Maintenance – CAL	Calibration
Maintenance – CM	Corrective Maintenance on PEI
Maintenance – MISC	Miscellaneous Maintenance
Maintenance – MOD	Modification Instructions
Maintenance – PM	Preventative Maintenance
Maintenance – SL3	Maintenance Stock List
Maintenance – SRP	Secondary Repairable Maintenance

The equipment's operational status is recorded in the service request under three classifications: Deadlined, Operational – Degraded, and Operational – Minor, with each status defined in Table 2. A more detailed description is provided in the problem summary module, which is user-generated. However, because this information is manually entered, there is no standardized way to ensure consistent or descriptive input. As a result, the problem summary module is not a reliable source of information for analysis.

Table 2. Operational Status Categories in GCSS-MC: Emphasis on Deadlined and Op-Degraded conditions. Source: USMC (2017).

Operational Status	Definition
Deadlined	Equipment requiring critical repairs
Operational – Degraded	Equipment requiring critical repair that does not deadline the equipment but does degrade equipment's operational capability
Operational – Minor	Equipment requiring non-critical maintenance

The problem code module is a required input from a list of values. The problem code is also commonly known as the defect code. A more comprehensive list of the defect codes is listed in Table 3. For our analysis, we will look at the defect code as the primary descriptive activity for which the equipment, or Table of Authorized Materiel Control Number (TAMCN), is undergoing repair.

Table 3. Defect codes used as transition nodes for analysis. Adapted from USMC (2017).

CODE	DESCRIPTION
A/C	Air Conditioner
AIR	Air Systems
ANEW	Ancillary Equipment
ANTL	Antenna/Transmission line
ARMT	Armament
AXLE	Axle System
BODY	Body, Frame or Hull
CANV	Canvas
COMP	Component
COOL	Cooling System
DAD1	Data/Digital Systems
ELEC	Electrical System
ENG	Engine
FCON	Fire Control System
FUEL	Fuel System
HYDR	Hydraulic System
IGNI	Ignition System
LIFT	Boom, Cable and Lift System

CODE	DESCRIPTION
LVTP	Landing Vehicle, Tracked, Personnel
MODM	Multiplex/Modulation-Demodulation
MTR	Meter
NMAJ	No Major Defect
PWRP	Power Pack
PWRT	Power Train
RCIC	Receiver/Input Circuitry
STEERING	Steering Components and Hardware
SUSP	Suspension System
TEDD	Test Equipment/Display devices
TEXT	Textiles
TRAC	Track Crawler System
TRAN	Transmission
TROB	Tire Rod
TURR	Turret System
WPNS	Weapons/Small Arms/Crew Served
XMOC	Transmitter/Output Circuitry

Tasks within a service request are required to document all actions performed during the maintenance cycle. USMC (2017) states “the requisition of repair parts, SL-3, documentation of labor hours, materials applied and reconciliations with supporting activities will be recorded via maintenance type tasks” (p. 521). The user manual further clarifies that “parts requirements for each defect will be requisitioned on the associated maintenance tasks for requisitioning parts requirements” (p. 522).

The parts requirements form, found within the task, captures the demand for repair parts necessary to initiate requisitions for corrective or preventative maintenance on degraded TAMCN. This form provides several key variables for our analysis, including the National Item Identification Number (NIIN), the source of supply, and the originating unit submitting the request. Each requisition links to a service request and task number, with the standard document number (SDN) serving as a unique 14-digit identifier; within the SDN, it contains a four-digit Julian date. We then convert the Julian date to a Gregorian date, which we use to track transitions between defect states in our Markov chain analysis.

B. PHASE II: MODEL BUILDING

We capture both scheduled (PM) and unscheduled (CM) maintenance actions by analyzing the service request type, which ideally indicates whether the action is preventative or corrective. However, inconsistencies in how users input data into GCSS-MC can lead to the misclassification of PMs and CMs. To address these inconsistencies, we rely on the problem summary field to clarify the nature of each maintenance action and ensure accurate associations with the relevant end items. This ensures we capture all corrective maintenance actions comprehensively, associate them with degraded assets, and effectively analyze transitions between defect states.

To gain a clearer understanding of the distribution of maintenance activities across MARFORPAC units, we grouped the TAMCN by its types: Type 1, Type 2, Type 3, and Special Item Equipment. Figure 3 gives an overview of the Table of Authorized Material Control Numbers types and categorizes assets across different commodity classes, including Communications-Electronics, Engineer, General Supply, Motor Transport, and Ordnance. Each commodity class contains TAMCNs segmented by type, which shows their operational roles. Type one assets are typically considered the most mission-critical, followed by types 2 and 3, and special item equipment.

TABLE OF AUTHORIZED MATERIEL CONTROL NUMBERS

Commodity	Type 1	Type 2	Type 3	Tactical Non-Standard Equipment (NS-E)*	Special Item Equipment (SIE)
Communications-Electronics	A0001-A9999	H0001-H9999	T0001-T9999	A0001-A9999 H0001-H9999 T0001-T9999	Q0001-Q9999
Engineer	B0001-B9999	J0001-J999	U0001-U9999	B0001-B9999 J0001-J9999 U0001-U9999	
General Supply	C0001-C9999	K0001-K9999	V0001-V9999	C0001-C9999 K0001-K9999 V0001-V9999	
Motor Transport	D0001-D9999	M0001-M9999	W0001-W9999	D0001-D9999 M0001-M9999 W0001-W9999	
Ordnance	E0001-E9999	N0001-N9999	X0001-X9999	E0001-E9999 N0001-N9999 X0001-X9999	
For HQMC Use	TAMCNs starting with F, R, Y and Z				
Not Used	TAMCNs starting with I, L, and O				
Garrison Mobile Equipment**	G0001-G9999				
Petroleum	P0001-P9999				
Subsistence	S0001-S9999				

Figure 3. Types of Table of Authorized Materiel Control Numbers (TAMCNs). Source: USMC (2016).

Figure 4 represents an overview of the count of distribution of each TAMCN type across the dataset; type 1 TAMCNs show a significantly higher maintenance activity compared to the other TAMCN types, underscoring their critical role and the frequency of maintenance they require. In our analysis, we will concentrate specifically on type 1 TAMCN, examining a subset of these assets identified by MARFORPAC as high priority. This targeted approach will allow us to explore the assets with the highest maintenance demands and delve into the factors that drive corrective maintenance activities.

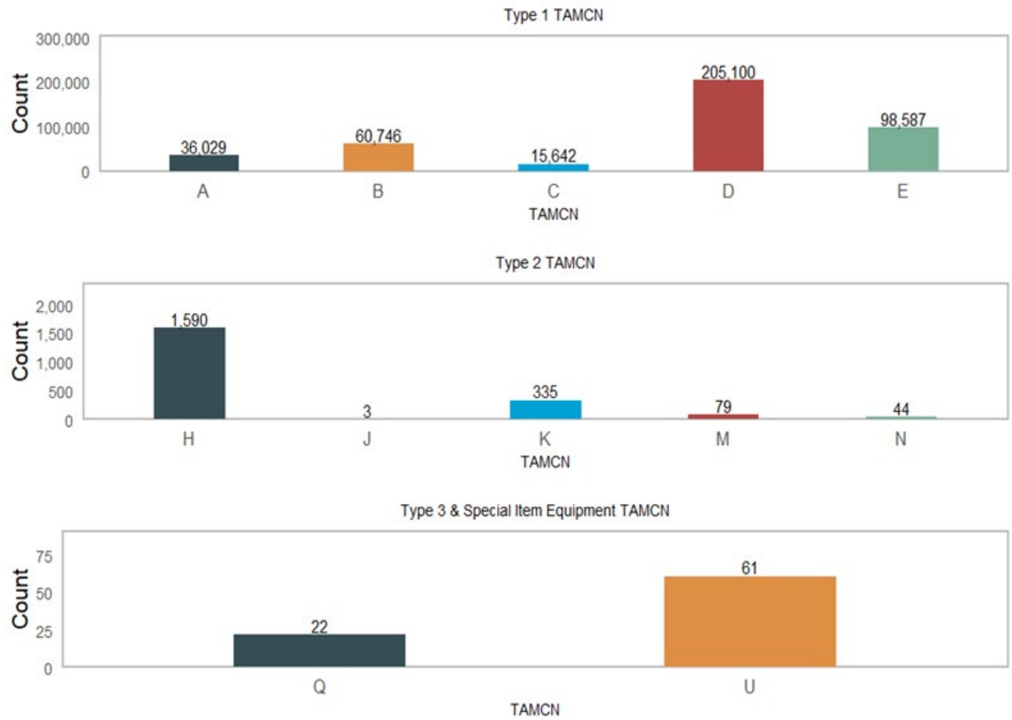

Figure 4. Comparison of TAMCN categories and Special Item Equipment.

To approach this analysis, we started with a list of type 1 TAMCNs prioritized by MARFORPAC (J. Ray, email to authors, October 15, 2024). Although our initial goal was to analyze a broad set of assets, we ultimately narrowed the scope to include ten TAMCNs: A00227G, A03367G, B00637B, B10217B, D00037K, D00487K, D00157K, D08867K. This selection represented an equitable sample across key commodity classes, with the intention of examining the two highest-maintenance TAMCNs within each category. However, due to limited maintenance activity associated with type 1 "Charlie" TAMCNs (General Supply), we substituted two high-requisition "Delta" TAMCNs – D08867K and D00487K – to ensure a comprehensive dataset that reflects assets with significant maintenance demands.

We then grouped maintenance actions by TAMCN and serial number to identify all unique requisitions associated with each individual asset. Since our objective is to analyze transitions from one defect to another, we focus on assets with the highest volume of maintenance events. Specifically, we filter for assets with more than 100 requisitions, as these assets may provide sufficient defect data to capture meaningful transitions between defect states.

For our analysis, we chose to analyze TAMCN D00157K as it has the highest requisition count. Filtering for the highest volume of maintenance actions, requisitions are then grouped by requisition date, along with the primary defect that caused the maintenance event. We then look to understand the defect transition over time by calculating the time difference between consecutive maintenance events; the goal is to understand how maintenance issues evolve throughout the life cycle of a particular asset. Table 4 represents the transition from one defect to another by illustrating the maintenance events in sequence, which are grouped by date of transaction and the primary defect; specifically, the table looks at the corrective maintenance issues regarding the D00157K, serial number 595793 from the start of fiscal year 2021.

Table 4. Transitions between different defect types for D00157K, SN: 595793

DOC_GREGORIAN_DATE	PRIMARY_DEFECT	count	TimeDiff	Next	Hist
2020-10-09	ELEC	1	NA	ELEC	ELEC -> ELEC
2020-10-22	ELEC	30	13	ELEC	ELEC -> ELEC
2020-11-24	ELEC	4	33	ELEC	ELEC -> ELEC
2020-11-25	ELEC	1	1	ELEC	ELEC -> ELEC
2020-12-01	ELEC	1	6	ELEC	ELEC -> ELEC
2020-12-02	ELEC	4	1	ELEC	ELEC -> ELEC
2020-12-04	ELEC	2	2	ELEC	ELEC -> ELEC
2020-12-10	ELEC	5	6	ELEC	ELEC -> ELEC
2020-12-15	ELEC	7	5	ELEC	ELEC -> ELEC
2020-12-17	ELEC	7	2	ELEC	ELEC -> ELEC
2020-12-18	ELEC	2	1	ELEC	ELEC -> ELEC
2020-12-29	ELEC	1	11	ELEC	ELEC -> ELEC
2021-03-11	ELEC	3	72	ELEC	ELEC -> ELEC
2021-03-24	ELEC	1	13	ELEC	ELEC -> ELEC
2021-04-01	ELEC	1	8	ELEC	ELEC -> ELEC
2021-04-23	ELEC	6	22	ELEC	ELEC -> ELEC
2021-06-22	ELEC	6	60	ELEC	ELEC -> ELEC
2021-06-25	ELEC	12	3	ELEC	ELEC -> ELEC
2021-06-28	ELEC	1	3	ELEC	ELEC -> ELEC
2021-07-09	ELEC	1	11	TROD	ELEC -> TROD
2021-07-15	TROD	29	6	TROD	TROD -> TROD
2021-07-16	TROD	1	1	ELEC	TROD -> ELEC
2021-08-13	ELEC	2	28	ELEC	ELEC -> ELEC
2021-08-19	ELEC	6	6	SUSP	ELEC -> SUSP
2021-10-21	SUSP	1	63	SUSP	SUSP -> SUSP
2022-02-07	SUSP	1	109	SUSP	SUSP -> SUSP
2022-03-25	SUSP	1	46	SUSP	SUSP -> SUSP
2022-06-16	SUSP	14	83	SUSP	SUSP -> SUSP
2022-07-14	SUSP	8	28	SUSP	SUSP -> SUSP
2022-12-08	SUSP	49	147	SUSP	SUSP -> SUSP
2023-02-09	SUSP	1	63	SUSP	SUSP -> SUSP
2023-04-18	SUSP	14	68	SUSP	SUSP -> SUSP
2024-01-08	SUSP	12	265	SUSP	SUSP -> SUSP
2024-02-23	SUSP	1	46	SUSP	SUSP -> SUSP

We utilize the concept of Markov chains to model the occurrence of unscheduled or stochastic vehicle maintenance events. Markov chains describe systems where the future state depends only on the current state and not on the sequence of previous events. This provides an effective framework for predicting maintenance events. In contrast to deterministic or scheduled maintenance, which occurs based on predictable factors like time intervals or mileage, stochastic maintenance events are less predictable. These events are not completely random, and with the right data, we can estimate the likelihood of future maintenance actions based on the vehicle's current condition. This approach allows us to anticipate better what kind of maintenance will occur next based on the vehicle's maintenance history.

In this model, the focus is on the sequence of maintenance events rather than the passage of time. We aim to compute the probability of the next maintenance event given the current state of a given asset's maintenance history. This approach follows the Markov property, where the future is conditionally independent of the past, given the present state. Mathematically, this is represented as $\Pr\{X_{(n+1)} = M \mid X_{n,n-1\ldots}\} = P$. This equation means that the probability (P) of the next maintenance action $\left(X_{(n+1)}\right)$ being a specific event (M) depends only on the current and immediate past maintenance states $\left(X_{n,n-1,\ldots}\right)$. By focusing on events rather than time, our model helps us predict unscheduled maintenance actions based on the vehicle's current state, allowing for more accurate maintenance planning and decision-making.

We use statistical tools such as Data Table and VizNetwork in the R programming language to implement the Markov chain model. These tools help us analyze the data and fit the Markov chain model, enabling us to evaluate the likelihood of different maintenance events. This method systematically estimates future maintenance needs, offering insights that support more effective maintenance strategies. The complete R code used in this analysis is provided in Appendix A, which allows for replication or further exploration of the methodology.

C. PHASE III: ASSOCIATING DEFECT CODE PROBABILITIES

In this phase, we transition from analyzing historical defect data to constructing a predictive framework that leverages defect probabilities to map out a Markov chain. By examining the frequency and progression of defects, we can quantify how often each defect recurs or transitions into another, offering valuable insights into maintenance trends and defect behaviors. This approach not only highlights which defects are more likely to reoccur or escalate but also establishes the probabilistic foundation for building a Markov chain model. Through this model, we aim to translate these transition probabilities into a predictive tool, ultimately guiding a proactive maintenance strategy.

As mentioned previously, Table 4 provides the summary of the probabilities of each defect transition, which captures all possible unique transitions observed in the dataset for one specific asset. Table 5 considers the total occurrences of each unique defect transition event. By adding up the counts of each transition (e.g., ELEC → ELEC, ELEC → SUSP), we can calculate the probability of each transition within our dataset. This is done by dividing the count of each transition by the total number of transitions, resulting in a set of transition probabilities that reflect the likelihood of each defect either recurring or transition into another defect.

Table 5. Defect transition probabilities at a glance: From history to prediction.

Hist	count	Diff	Prob
ELEC -> ELEC	20	NA	0.588
ELEC -> SUSP	1	6.0	0.029
ELEC -> TROD	1	11.0	0.029
SUSP -> SUSP	10	91.8	0.294
TROD -> ELEC	1	1.0	0.029
TROD -> TROD	1	6.0	0.029

This transition probability table is foundational to our Markov chain analysis, capturing the frequencies and probabilities associated with defect transitions over time. By quantifying these transitions, we build a probabilistic model capable of predicting future maintenance requirements based on observed defect behaviors. This methodology moves us beyond a retrospective view of our data, enabling us to leverage historical patterns in defect occurrences to anticipate future maintenance needs. The transition probabilities not only indicate how often a defect reoccurs or evolves but also serve as indicators of where maintenance efforts might be prioritized to mitigate potential system failures. Ultimately, this predictive model transforms historical data into actionable insights, guiding more proactive maintenance strategies.

Upon successfully determining the probabilities of upcoming defect codes, the next step is to identify which repair parts are most likely to be in high demand. The objective is to anticipate potential failures and determine which parts correspond to those defects. Since a single defect can lead to the need for multiple parts, we will focus on the top 10 most frequently required parts associated with each defect. This framework provides practical insight into what should be included in a unit's Class IX block, which serves as a pre-planned supply cache for deployment.

In contested environments, units must operate with limited logistical capacity, making it impractical to carry every possible repair part. By prioritizing the top 10 repair parts based on usage frequency, units can increase their operational flexibility. Alternatively, some units may opt to prioritize parts based on their Critical Essentiality Code (CEC), focusing on mission-critical items. The selection strategy will depend on how the MAGTF organizes itself—frontline units might prioritize critical parts, while intermediate maintenance units could focus on high-demand items. Regardless of approach, the central theme driving demand is understanding the likely defect patterns. From this insight, units can build a tailored Class IX block that ensures they carry the right parts to maintain operational readiness throughout the mission.

IV. ANALYSIS

In this analysis, we explore the evolution of defect states within the D00157K, examining both individual asset transition and broader trends across multiple assts within MARFORPAC. The transition matrices will serve as the foundation of this analysis, which will capture the likelihood of a defect persisting or transition to another defect within a single asset, and then aggregating these behaviors to identify high-frequency defect patterns across a fleet of D00157K. We then normalize the transitions to apply a Markov chain model to enable a probabilistic view of defect progression over time, which will be valuable for forecasting maintenance demands. The Markov chain diagram illustrates the varying transition dynamics, highlighting both the recurring defects and potential escalation paths, supporting a comprehensive understanding of maintenance trends and requisition needs. Ultimately, applied across various D00157K assets, the pattern will reveal high-maintenance areas and helps pinpoint subassemblies that may require targeted maintenance strategies. This approach captures unique defect behaviors within a specified TAMCN asset and can provide a data-driven model for maintenance forecasting across similar assets.

A. TRANSITION MATRIX FOR INDIVIDUAL ASSET

Table 6 shows a transition matrix for a subset of defects a particular D00157K. This matrix was derived from the transition probabilities in Table 5, where each row represents a starting defect state, and the probability column represents the probability of moving from one defect to another. The transition matrix in Table 6 captures the basic transition dynamics for these defects, which shows the relative frequency with which each defect either persists or transitions to another defect.

Table 6. Conditional, partial transition matrix for D00157K, SN: 595793.

ELEC	TROD	SUSP
0.588	0.029	0.029
0.029	0.029	0.000
0.000	0.000	0.294

It is important to note that the defects represented in this transition matrix reflect the unique maintenance history of a single D00157K asset. Other assets may exhibit different sets of defects or transition probabilities depending on their operational conditions, usage patterns, and maintenance histories. Some assets might not display the three defects shown in Table 6, while others could include additional defect states. Examining multiple assets individually reveals that defect patterns and probabilities vary, underscoring the value of studying a broad sample of assets to capture a more comprehensive picture of transition dynamics across the D00157K fleet. The matrix in Table 6 provides a snapshot, but a more holistic analysis across multiple assets could yield deeper insights into high-demand defects and parts.

B. NORMALIZED TRANSITION MATRIX AND THE MARKOV CHAIN MODEL

Table 7 represents the normalized version of the transition matrix in from Table 4. Here, each row sums to 1, ensuring that each defect state has a complete probability distribution across its possible next states. This normalization is essential for creating a valid Markov chain model, as it provides a probabilistic interpretation of defect progression. For example, an ELEC defect now has a 0.91 probability of recurring, while TROD transitions to ELEC or itself with equal likelihood (at 0.5 each). This step allows us to interpret the transition matrix with the Markov framework, providing a probabilistic view of defect progression that helps in forecasting maintenance needs.

Table 7. Normalized matrix for D00157K, SN: 595793 reveals that suspension issues for this vehicle are absorbing.

	ELEC	TROD	SUSP
ELEC	0.91	0.045	0.045
TROD	0.50	0.500	0.000
SUSP	0.00	0.000	1.000

Figure 5 is the visual representation of the normalized transition matrix in the form of a Markov chain diagram. This diagram highlights the transition probabilities between states, with arrows indicating the direction of transition and labels showing the probabilities of each transition. For example, ELEC transitions back to itself with a probability of 0.9091. The probably of an ELEC issue to TROD is 0.0455, and the probability of a TROD to ELEC issue is 0.5.

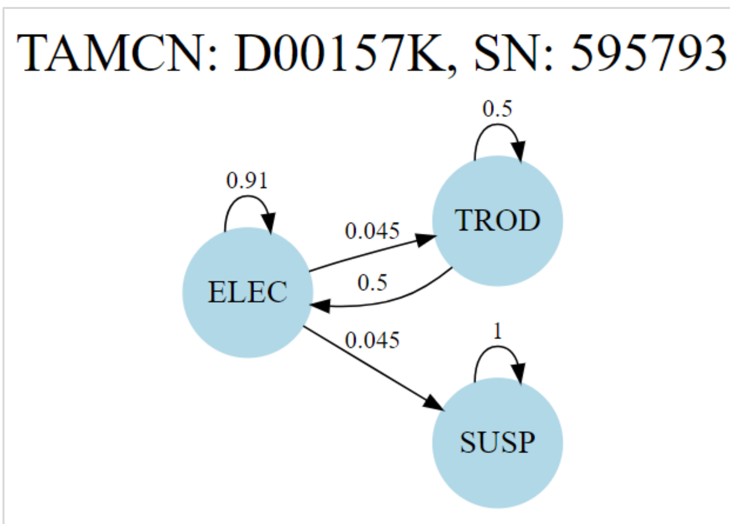

Figure 5. Markov chain, D00157K, SN: 595793.

C. ANALYSIS ACROSS MULTIPLE ASSETS

To expand on the Markov chain matrix for the D00157K, we aim to analyze transition probabilities across multiple D00157K assets within MARFORPAC. This approach will allow us to capture a broader view of transition patterns, providing insights that reflect trends across various assets rather than being influenced by the behavior of a single asset. We begin by selecting the top 10% of D00157K assets with the highest requisition counts from our dataset to focus on the most active and maintenance-intensive assets.

Table 8 shows the consolidated list of selected assets, including the matrix dimensions and associated defects for each asset. Each asset's matrix dimensions (row x columns) reflect the number of unique defects observed in that asset, representing the possible states in the Markov chain for that asset. The "Associated Defects" column lists the specific defects included in the matrix for each asset, showing which defect contributes to the transitions tracked in the Markov chain. By including all defects observed across the assets, which helps build a foundation for constructing transition matrices that capture behavior across multiple assets.

Table 8. Matrix dimensions for 10% highest counts of requisitions.

Serial Number	Matrix dimensions [rows x columns]	Associated Defects
595793	3x3	ELEC, TROD, SUSP
596705	3x3	LIFT, HYDR, ELEC
622364	3x3	BODY, ELEC, SUSP
596530	5x5	AIR, AXLE, LIFT, COMP, HYDR
596700	5x5	HYDR, LIFT, NMAJ, ELEC, BODY
596508	7x7	NMAJ, ENG, HYDR, LIFT, SUSP, ELEC, COMP
596630	7x7	STEERING, FUEL, ELEC, BODY, ARMT, AIR, HYDR
596599	5x5	HYDR, LIFT, STEERING, ELEC, COMP
596536	5x5	SUSP, LIFT, HYDR, BODY, ELEC
596346	5x5	AIR, COMP, SUSP, HYDR, BODY
594563	4x4	HYDR, SUSP, ELEC, COMP
596191	6x6	AIR, AXLE, SUSP, HYDR, NMAJ, LIFT
596461	5x5	HYDR, COMP, COOL, STEERING, BODY

D. AVERAGED AND NORMALIZED TRANSITION MATRIX

Appendix B presents the averaged transition matrix for the D00157K, representing the consolidated transition probabilities between defects across the 13 assets listed in Table 8. In order to do this, we calculate this matrix by first adjusting each asset's individual transition matrix to include all possible defect states, ensuring consistency across assets. By doing so, we make sure that even if certain defects are absent from some assets, their absence is represented as zero values in the matrix, aligning the dimensions of each matrix.

Once all matrices have consistent dimensions, we compute the average transition matrix by summing each cell across all matrices and then dividing by the total number of matrices. This averaging process results in a matrix that reflects the overall likelihood of transition from one defect state to another, averaged across all selected assets.

After obtaining the average transition matrix (as shown in Appendix B), the next step is to normalize the matrix, which ensures that each row in the matrix forms a complete probability distribution where the sum of each row equals 1. Without normalizing the probabilities, the values in the average matrix would only represent raw transition frequencies rather than probabilities, making it incomplete to interpret them in a Markov chain context. Appendix C shows the normalized average transition matrix for the 13 assets analyzed in a 15 x 15 dimension.

E. EXPANDED TRANSITION PROBABILITIES AND DEFECT PATHWAYS

With the normalized average transition matrix (Appendix C) established, we can now represent these probabilities visually through a Markov chain diagram, as shown in Figure 6. The idea behind analyzing the expanded transition probabilities in a Markov chain framework is to gain a deeper understanding of defect progression patterns with the D00157K assets. The analysis reveals pathways of defect escalation and provides critical data points for improving maintenance strategies.

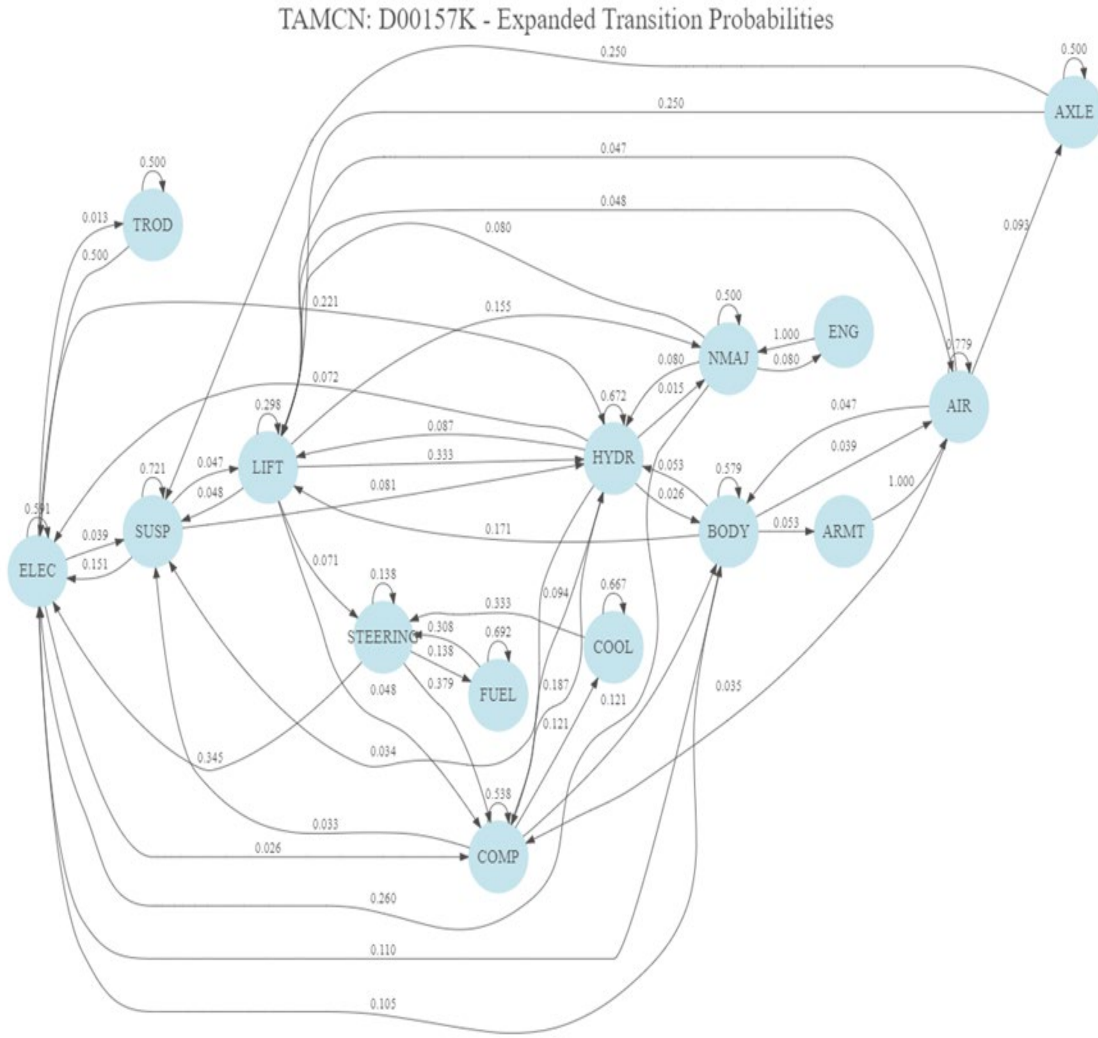

Figure 6. Markov chain analysis: Highlighting high-occurring and recurring defect failures to drive accurate demand signals for maintainers.

By analyzing the likelihood of transitioning from one defect to another, patterns in maintenance demand and areas of high requisition needs can be identified. High self-transition probabilities, such as AIR (0.779), SUSP (0.721), and HYDR (0.672), points to components that are prone to recurring failures. These probabilities highlight maintenance-intensive areas that demand frequent attention and timely requisitions of associated repair parts. By addressing these frequent problem areas proactively, maintainers can reduce equipment downtime, extend the operational lifespan of critical components, and ensure that key assets remain functional in high-demand environments. This data-driven approach enables better resource allocation, streamlining supply chain operations and reinforcing the overall readiness of mission-critical systems.

The Markov chain diagram further reveals pathways of defect escalation, illustrating how issues in one component may trigger secondary failures in interconnected systems. For instance, LIFT transitioning to HYDR (0.333) suggests the issues in the lift system can lead to problems in the hydraulic system failures. Such escalation pathways suggest that closely linked components should be inspected or repaired simultaneously to prevent cascading failures. This underscores the importance of understanding system interdependencies driven by empirical evidence, which not only enhances the efficiency of maintenance cycles but also minimizes the risk of broader system degradation. By focusing on defect escalation patterns, maintainers can implement more comprehensive maintenance strategies that reduce operational vulnerabilities and improve equipment reliability.

Extending this analysis across multiple D00157K assets provides measurable insights into systemic issues across the fleet. Determining whether certain defects are confined to specific operational conditions or indicative of broader design flaws directly informs maintenance protocols and equipment modifications, driving long-term operational efficiency.

V. CONCLUSION

A. SUMMARY

This research highlights the critical role of empirical data in optimizing maintenance and supply chain strategies for the Marine Corps. By examining historical defect patterns and leveraging Markov chain modeling, we developed a predictive framework for identifying high-demand repair parts and understanding defect progression. This approach not only empowers maintenance and supply teams to anticipate future requirements but also ensures operational readiness by addressing recurring and escalating defects with more precision.

Transition probabilities derived from maintenance records provide actionable insights into the behavior of defective components over time. By focusing on defects with high-self transition rates or those prone to cascading failures, maintainers can prioritize critical repair parts, streamline inventory strategies, and reduce equipment downtime. This aligns seamlessly with the principles of CBM+, offering a proactive, data-driven approach to enhance resilience and mission-critical readiness.

B. ADDRESSING THE RESEARCH QUESTION

The study was based on the following primary and secondary research questions:

1. Primary Research Question

(1) How can planners use empirical data to calculate conditional probabilities of equipment failure given the previous occurrences of maintenance actions? What equipment defect drive the demand for critical repair parts based on usage data in GCSS-MC over the past four fiscal years?

The study demonstrates that conditional probabilities of equipment failures can be calculated using Markov chain modeling, which analyzes transitions between defect states. By identifying defects with high transition probabilities, we pinpoint components that drive the demand for critical repair parts. This insight allows planners to prioritize maintenance actions to address high-demand parts effectively.

2. Secondary Research Questions

(1) Can classical and novel ideas in applied probability associate historical maintenance failures of a given component based on data entered into GCSS-MC?

Yes, the application of Markov chain modeling bridges classical probability with empirical maintenance data, revealing patterns in defect transition. This association provides a structed method for understanding historical failures and predicting future maintenance needs.

(2) What high-demand repair parts are common across equipment defects, and how can this information be used to improve readiness planning?

High-demand repair parts are identified by analyzing defects with high self-transition and escalation probabilities. These insights allow planners to include these parts in Class IX supply blocks, improving readiness and minimizing equipment downtime.

C. RECOMMENDATIONS

To fully capitalize on the insights gained from this research, the Marine Corps should consider the following actions:

- Integrate predictive maintenance frameworks, such as Markov chain models, into operation practices to enable maintainers to anticipate high-demand parts and proactively address recurring defects and reduce downtime.
- Leverage the transition probabilities identified in this research to pinpoint maintenance-intensive components and ensure their prioritization in Class IX supply blocks.
- Expand this methodology to additional Marine Corps assets, including aviation equipment, to uncover broader maintenance patterns and refine predictive models for enterprise-level application.
- This analysis is constrained by lack of operational context as it does not combine operational and maintenance histories. Addressing the disconnect

between these elements by developing an integrated dataset would provide a comprehensive resource for future studies and improving the ability to sustain readiness in contested environments. conclusion

D. CONCLUSION

This framework is not confined to a single TAMCN, such as the D00157K analyzed in this research. It is adaptable to other high-priority equipment with sufficient maintenance histories, offering a scalable and versatile solution for optimizing supply chain strategies. This research represents a transformative shift from reactive to predictive maintenance in military logistics. By converting historical maintenance and requisition records into actionable insights, the Marine Corps can allocate resources with greater precision. Leveraging data-driven models and predictive analytics, the Marine Corps is well-positioned to address the challenges of future conflicts with enhanced efficiency and resilience.

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APPENDIX A. R CODE

```
library(ggplot2)
library(ggsci)
library(reshape2)
library(dplyr)
library(magrittr)
library(data.table)
library(lubridate)
library(DiagrammeR)
library(visNetwork)

TRNormalizer = function(TRMatrix){
  x = TRMatrix/rowSums(TRMatrix)
  x [is.nan(x)] = 0
  return(x)
}

MF = fread("MARFORPAC_classIX_dmd.txt")


Tamcns = c("D00037K",
"D08867K",
"D00157K",
"D00487K",
"B00637B",
"E09477M",
"B10217B",
"E15007M",
"A03367G",
"A00227G"
)

MF %<>% filter(TAMCN %in% Tamcns)
MF %<>% filter(ENV_TYPE == "Non-Stationary")

MF$DOC_GREGORIAN_DATE %<>% mdy_hms()

filtered_MF <- MF %>% filter(TAMCN == "D00157K")
```

```
serial_number_counts <- filtered_MF %>%
 group_by(SERIAL_NUMBER) %>%
 summarize(count = n()) %>%
 arrange(desc(count))

top_serial_numbers <- serial_number_counts %>%
 slice(1:13) %>%
 pull(SERIAL_NUMBER)


transition_matrices <- list()
for (sn in top_serial_numbers) {

 Z <- filtered_MF %>% filter(SERIAL_NUMBER == sn) %>%
  group_by(DOC_GREGORIAN_DATE, PRIMARY_DEFECT) %>%
  summarize(count = n())

 Z$TimeDiff <- c(NA, diff(Z$DOC_GREGORIAN_DATE))
 Z$TimeDiff <- round(Z$TimeDiff, digits = 3)

 Z$Next = c(Z$PRIMARY_DEFECT[-1], NA)

 Z$Hist = paste(Z$PRIMARY_DEFECT, "->," Z$Next)

 Z <- Z %>% filter(!is.na(Next))

 q <- Z %>%
  group_by(Hist) %>%
  summarize(count = n(), Diff = mean(TimeDiff))

 q <- q %>%
  mutate(
   Diff = round(Diff, digits = 3),
   Prob = round(count / sum(count, na.rm = TRUE), digits = 3)
  )
```

```
 states <- unique(c(Z$PRIMARY_DEFECT, Z$Next))
 transition_matrix <- matrix(0, nrow = length(states), ncol = length(states),
                             dimnames = list(states, states))

 for (i in 1:nrow(q)) {
   transition <- unlist(strsplit(q$Hist [i], " -> "))

   if (length(transition) == 2) {
     from_state <- trimws(transition [1])
     to_state <- trimws(transition [2])

     if (from_state %in% states && to_state %in% states) {
       transition_matrix [from_state, to_state] <- q$Prob [i]
     }
   }
 }
   transition_matrices [[sn]] <- transition_matrix
}

adjust_matrix_dimensions <- function(mat, all_states) {

 complete_matrix <- matrix(0, nrow = length(all_states), ncol = length(all_states), dimna
mes = list(all_states, all_states))

 common_states <- intersect(rownames(mat), all_states)
 complete_matrix [common_states, common_states] <- mat [common_states, common
_states]

 return(complete_matrix)
}


normalize_matrix <- function(mat) {
 row_sums <- rowSums(mat)
 mat_normalized <- sweep(mat, 1, row_sums, FUN = "/")
 mat_normalized [is.nan(mat_normalized)] <- 0

return(mat_normalized)
}
```

```
adjusted_matrices <- lapply(transition_matrices, adjust_matrix_dimensions, all_states =
all_states)

adjusted_matrices <- lapply(adjusted_matrices, round, digits = 3)

sum_transition_matrix <- Reduce("+," adjusted_matrices)
average_transition_matrix <- sum_transition_matrix / length(adjusted_matrices)

average_transition_matrix <- round(average_transition_matrix, digits = 3)

normalized_average_transition_matrix <- round(normalize_matrix(average_transition_m
atrix), digits = 3)


generate_graph_code <- function(transition_matrix) {
 graph_code <- "
 digraph markov_chain {
  rankdir=LR;

  label = 'TAMCN: D00157K – Expanded Transition Probabilities';
  labelloc = 't';
  fontsize = 30;
  fontname = 'bold';

  node [shape = circle, style=filled, color=lightblue, fontsize=18, width=1.0, fixedsize=tru
e];
 "

 for (from_state in rownames(transition_matrix)) {
  for (to_state in colnames(transition_matrix)) {
   prob <- transition_matrix [from_state, to_state]

   if (prob > 0) {
    graph_code <- paste0(
     graph_code,
     "   \"," from_state, "\" -> \"," to_state, "\" [label = \"," round(prob, 3), "\"];\n"
```

```
      )
    }
  }
 }

 graph_code <- paste0(graph_code, "  }")

 return(graph_code)
}

graph_code <- generate_graph_code(normalized_average_transition_matrix)


grViz(graph_code)
```

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APPENDIX B. AVERAGED TRANSITION MATRIX, D00157K

	ELEC	TROD	SUSP	LIFT	HYDR	BODY	AIR	AXLE	COMP	NMAJ	ENG	STEERING	FUEL	ARMT	COOL
ELEC	0.091	0.002	0.006	0.000	0.034	0.017	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.000	0.000
TROD	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SUSP	0.013	0.000	0.062	0.004	0.007	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LIFT	0.000	0.000	0.004	0.025	0.028	0.000	0.004	0.000	0.004	0.013	0.000	0.006	0.000	0.000	0.000
HYDR	0.019	0.000	0.009	0.023	0.178	0.007	0.000	0.000	0.025	0.004	0.000	0.000	0.000	0.000	0.000
BODY	0.008	0.000	0.000	0.013	0.004	0.044	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000
AIR	0.000	0.000	0.000	0.004	0.000	0.004	0.067	0.008	0.003	0.000	0.000	0.000	0.000	0.000	0.000
AXLE	0.000	0.000	0.004	0.004	0.000	0.000	0.000	0.008	0.000	0.000	0.000	0.000	0.000	0.000	0.000
COMP	0.000	0.000	0.003	0.000	0.017	0.011	0.000	0.000	0.049	0.000	0.000	0.000	0.000	0.000	0.011
NMAJ	0.013	0.000	0.000	0.004	0.004	0.000	0.000	0.000	0.000	0.025	0.004	0.000	0.000	0.000	0.000
ENG	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.000
STEERING	0.010	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.000	0.004	0.004	0.000	0.000
FUEL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.009	0.000	0.000
ARMT	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
COOL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.000	0.022

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APPENDIX C. NORMALIZED AVERAGE TRANSITION MATRIX

	ELEC	TROD	SUSP	LIFT	HYDR	BODY	AIR	AXLE	COMP	NMAJ	ENG	STEERING	FUEL	ARMT	COOL
ELEC	0.591	0.013	0.039	0.000	0.221	0.110	0.000	0.000	0.026	0.000	0.00	0.000	0.000	0.000	0.000
TROD	0.500	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00	0.000	0.000	0.000	0.000
SUSP	0.151	0.000	0.721	0.047	0.081	0.000	0.000	0.000	0.000	0.000	0.00	0.000	0.000	0.000	0.000
LIFT	0.000	0.000	0.048	0.298	0.333	0.000	0.048	0.000	0.048	0.155	0.00	0.071	0.000	0.000	0.000
HYDR	0.072	0.000	0.034	0.087	0.672	0.026	0.000	0.000	0.094	0.015	0.00	0.000	0.000	0.000	0.000
BODY	0.105	0.000	0.000	0.171	0.053	0.579	0.039	0.000	0.000	0.000	0.00	0.000	0.000	0.053	0.000
AIR	0.000	0.000	0.000	0.047	0.000	0.047	0.779	0.093	0.035	0.000	0.00	0.000	0.000	0.000	0.000
AXLE	0.000	0.000	0.250	0.250	0.000	0.000	0.000	0.500	0.000	0.000	0.00	0.000	0.000	0.000	0.000
COMP	0.000	0.000	0.033	0.000	0.187	0.121	0.000	0.000	0.538	0.000	0.00	0.000	0.000	0.000	0.121
NMAJ	0.260	0.000	0.000	0.080	0.080	0.000	0.000	0.000	0.000	0.500	0.08	0.000	0.000	0.000	0.000
ENG	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.00	0.000	0.000	0.000	0.000
STEERING	0.345	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.379	0.000	0.00	0.138	0.138	0.000	0.000
FUEL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00	0.308	0.692	0.000	0.000
ARMT	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.00	0.000	0.000	0.000	0.000
COOL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.00	0.333	0.000	0.000	0.667

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LIST OF REFERENCES

Bagley, B., Huntley, B., DeGrange, W., DeZwarte, C., Reitter, N., Schramm, H., & Vinyard, B. (2016). Cost drivers in vehicle maintenance: An analytic perspective. *Phalanx, 49*, 38–41. https://www.jstor.org/stable/26296337

BNSF Railway. (2019, June 26). *Making the grade: How BNSF maintenance is planned and performed*. https://www.bnsf.com/news-media/railtalk/service/maintenance-planning.html

Department of Defense. (2008, May). *Condition-based maintenance plus DoD guidebook*. https://www.dau.mil/guidebooks/Shared%20Documents% 20HTML/Condition%2 0Based%20Maintenance%20Plus%20(CBM+)%20 Guidebook.aspx#toc8

Department of Defense Instruction. (2020, August 14). *Conditioned-Based Maintenance Plus For Material Maintenance*. https://www.esd.whs.mil/Portals/54/Documents/DD/issuances/dodi/415122p.pdf

Department of the Navy. (2019). *MAGTF supply operations* (MCTP 3-40H). https://www.marines.mil/Portals/1/Publications/MCTP%203-40H.pdf?ver=2B8tvA-ZgNgCXSR0DrEEcQ%3d%3d

Department of the Navy. (2020a). *Condition-based maintenance plus order* (MCO 4151.22). https://www.marines.mil/Portals/1/Publications/MCO%204151.22.pdf

Department of the Navy. (2020b). *Maintenance operations* (MCTP 3-40E). https://www.marines.mil/Portals/1/Publications/MCTP%203-40E.pdf?ver=2020-02-06-091753-840

Department of the Navy. (2023a). *Logistics* (MCDP 4). https://www.marines.mil/Portals/1/Publications/MCDP%204%20(SECURITY).pdf?ver=R5KC9FF-AVoNQB4m75kbZQ%3D%3D

Department of the Navy. (2023b). *Marine Corps logistics* (MCWP 3-40). https://www.marines.mil/Portals/1/Publications/MCWP%203-40.pdf?ver=hMYkljDLfDdfptjUrr_Zgw%3d%3d

Ell, G. (2023, November 16). *NSWCPD engineers spearheading condition based maintenance program for U.S. Navy*. Naval Sea Systems Command. https://www.navsea.navy.mil/Media/News/Article-View/Article/3590550/nswcpd-engineers-spearheading-condition-based-maintenance-cbm-program-for-us-na/

Grimmett, G., & Stirzaker, D. (2001). *Probability and random processes* (3rd ed.). Oxford University Press.

Harding, B. J., & Pennington, L. H. (2022). *Implementing condition-based maintenance plus as a ground maintenance strategy in the Marine Corps* [Master's thesis, Naval Postgraduate School]. NPS Archive: Calhoun. https://hdl.handle.net/10945/71580

LaPlante, W. A., & Lowman, C. J. (2024). *Regional sustainment framework*. https://www.acq.osd.mil/asds/docs/RSF-9MAY24.pdf

Sanoubar, S., De Jonge, B., Maillart, L. M., & Prokopyev, O. A. (2023). Optimal condition-based maintenance via a mobile maintenance resource. *Transportation Science, 57*(6), 153–167. https://doi.org/10.1287/trsc.2021.0302

Scott, S. L. (2024, January 17). Bayesian Structural Time Series. R package version 0.9. https://cran.r-project.org/web/packages/bsts/bsts.pdf

Stuetelberg, M. B., & Thomas, J. R. (2021). *Incorporating predictive maintenance best practices into Marine Corps training and operations* [Master's thesis, Naval Postgraduate School]. NPS Archive: Calhoun. https://hdl.handle.net/10945/68794

United States Marine Corps. (2016, June 13). *Management of property in the possession of the Marine Corps, Volume 3: Retail Supply Management*. https://www.marines.mil/Portals/1/Publications/MCO%204400.201%20VOL%203.pdf?ver=2016-07-22-081614-970

United States Marine Corps. (2017, August 11). *Retail Supply and Maintenance Execution Procedures*. Marine Corps User Manual 4000–125. UM 4000–125 (GCSS-MC User Manual)v3dated11AUG2017.pdf

Acquisition Research Program
Naval Postgraduate School
555 Dyer Road, Ingersoll Hall
Monterey, CA 93943

www.acquisitionresearch.net