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Reconsidering Readiness for the Egyptian Navy

June 2025

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ABSTRACT

This thesis evaluates and compares two readiness reporting models for the Egyptian Navy: the traditional binary classification system and the proposed Operational Readiness Score Model (ORSM). The current system reports a ship as either fully operational (100%) or unavailable (0%), failing to capture partial mission capabilities. ORSM introduces a mission-based readiness framework, assigning readiness scores based on the percentage of missions a vessel can complete. A stochastic simulation implemented in Excel and R was employed to test these models across a representative sample of Egyptian Navy ships. Initial results suggest that ORSM provides a more accurate, data-driven, and operationally relevant assessment, reducing overestimation errors and improving fleet management. Findings emphasize the importance of transitioning to mission-based readiness evaluations for strategic decision-making, maintenance optimization, and resource allocation. The study offers actionable recommendations for fleet sustainment, modernization, and predictive maintenance strategies to enhance operational effectiveness.

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LIST OF ACRONYMS AND ABBREVIATIONS

AUV	Autonomous Underwater Vehicle
CBM+	Condition-Based Maintenance Plus
DAU	Defense Acquisition University
DOT&E	Office of the Director, Operational Test and Evaluation
DRRS	Defense Readiness Reporting System
EN	Egyptian Navy
EW	Electronic Warfare
GAO	Government Accountability Office
LHD	Landing Helicopter Dock
NADACS	Naval Autonomous Data Collection System
NATO	North Atlantic Treaty Organization
OCC	Operational Capabilities Concept
OCC E&F	Operational Capabilities Concept Evaluation and Feedback
ORSM	Operational Readiness Score Model
USV	Unmanned Surface Vehicle

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I. INTRODUCTION

A. BACKGROUND AND STRATEGIC IMPORTANCE

Egypt's geostrategic position at the intersection of Africa, the Middle East, and Europe has long been a defining factor in its regional and global security role. The country controls the Suez Canal, a key maritime chokepoint that facilitates a significant percentage of global trade and military logistics (International Maritime Organization, n.d.). As a crucial artery of international commerce, the canal's security is paramount, ensuring the uninterrupted flow of energy supplies and goods between Asia, Europe, and North America. With the Mediterranean Sea to the north and the Red Sea to the east, Egypt's expansive maritime borders make naval security a central pillar of its national defense strategy.

The evolving security landscape in the Mediterranean and Red Sea regions has introduced new challenges, including territorial disputes, competition over maritime resources, and the rise of asymmetric threats such as piracy, terrorism, and illicit trafficking. The North Atlantic Treaty Organization (NATO) Parliamentary Assembly (Krimi, 2021) highlights the Mediterranean's role as a contested maritime space, emphasizing the growing need for naval forces to address regional instability and external pressures. In this context, Egypt's ability to maintain a modern, well-equipped, and responsive naval force is critical to securing its maritime assets and upholding its strategic influence.

The Egyptian Navy (EN), the largest in the Middle East and Africa, has undergone significant transformation in recent decades. Originally centered on coastal defense, its modernization strategy has evolved to encompass maritime security, power projection, and regional stability. Technological advancements and strategic acquisitions have expanded its operational capabilities, yet readiness remains an ongoing challenge. Given Egypt's critical role in securing vital sea lanes and protecting offshore energy resources, ensuring the sustainability and preparedness of its naval forces is of utmost importance (Energy Information Administration, 2022).

A defining characteristic of the modern EN is its fleet diversity, comprising ships, submarines, and maritime vehicles sourced from various countries, including the United States, France, Germany, Italy, the United Kingdom, Russia, and China. While this diversification enhances strategic autonomy, reducing dependence on any single supplier, it also introduces significant logistical and technical challenges. The integration of multiple naval platforms requires extensive coordination in maintenance, supply chain management, and operational standardization, creating complex sustainment demands for Egypt's naval infrastructure.

Fleet diversity becomes particularly significant given Egypt's volatile security environment, where maintaining operational readiness is essential. Increasing geopolitical tensions over maritime resources in the Mediterranean and Red Sea, coupled with the imperative to safeguard national maritime assets, highlight the need for a robust naval readiness framework. Additionally, the Suez Canal remains a linchpin of Egypt's economy, generating substantial revenue while serving as a global trade artery. Ensuring the safe and uninterrupted passage of commercial and military vessels through this strategic corridor is vital for both national economic security and international maritime stability. Given these factors, an accurate and mission-oriented readiness assessment framework is essential for optimizing fleet availability and strengthening naval operations in an increasingly complex geopolitical landscape.

B. PROBLEM IDENTIFICATION

Despite significant advancements, the Egyptian Navy continues to rely on a traditional readiness reporting system that employs a binary classification designating ships as either fully operational (100%) or unavailable (0%). This model presents a fundamental limitation, as it fails to reflect the nuanced reality of mission capability (Government Accountability Office [GAO], 2023). A vessel classified as "operational" may still experience degraded systems that compromise its ability to execute critical missions, while a ship deemed "unavailable" may retain functionality for specific roles.

This oversimplified classification system leads to inefficiencies in resource allocation, maintenance prioritization, and fleet assessment accuracy. The challenges are exacerbated by the Egyptian Navy's diverse fleet composition, as different ships require specialized technical expertise, training programs, and tailored supply chains. Commanders and decision-makers relying on outdated readiness assessments risk strategic miscalculations that can impact fleet-wide operational effectiveness. These limitations highlight the necessity of transitioning to a more dynamic and mission-based readiness assessment model that provides a realistic and actionable measure of a ship's operational status.

C. RESEARCH OBJECTIVE AND METHODOLOGY

This study proposes the adoption of the Operational Readiness Score Model (ORSM), a mission-based readiness assessment framework designed to address the shortcomings of the current binary classification system. Unlike traditional models, ORSM evaluates a ship's readiness based on its ability to complete assigned missions rather than simply assessing whether it is capable of sailing. By introducing a percentage-based readiness scale, this approach provides a more precise and operationally relevant evaluation (Madusanka et al., 2023)

To validate this model, the research employs a comparative analysis of the existing binary readiness framework and ORSM. A stochastic simulation is used to test the performance of each model under varying fleet conditions, incorporating factors such as maintenance backlogs, system failures, and mission-specific requirements. This methodology aligns with contemporary best practices in naval readiness reporting, as demonstrated by NATO's Operational Capabilities Concept (OCC; NATO Allied Land Command, n.d.) and the U.S. Defense Readiness Reporting System (DRRS; Office of the Director, Operational Test and Evaluation [DOT&E], 2013). The study aims to enhance decision-making by providing a structured, data-driven assessment model that optimizes fleet management and ensures efficient resource allocation. The key objectives of this research are as follows:

1. Develop a mission-based readiness model that provides a more precise and realistic assessment of fleet capability
2. Improve fleet decision-making by introducing a data-driven approach to naval readiness evaluation
3. Optimize resource allocation and maintenance prioritization to enhance the long-term operational sustainability of the EN

D. STRUCTURE OF THE THESIS

This thesis is structured into six chapters, each contributing to the overall objective of improving the Egyptian Navy's readiness assessment framework:

1. Literature Review

Examines existing naval readiness frameworks, identifying their limitations and assessing their applicability to modern operational requirements. The chapter explores global best practices, including NATO and U.S. military readiness models, and contextualizes their relevance to the EN.

2. Methodology

Details the research methodology, explaining the comparative analysis framework, data sources, and simulation techniques used to evaluate the proposed readiness model. The chapter outlines the stochastic simulation process and key performance metrics.

3. Simulation Results

Presents the findings of the simulation, comparing the traditional binary readiness model with ORSM. The chapter includes statistical analysis, graphical data representations, and insights into operational efficiency.

4. Operational Insights and Actionable Recommendations

Analyzes the implications of the simulation results, offering strategic recommendations for optimizing fleet readiness, improving maintenance cycles, and enhancing operational planning.

5. Conclusion and Future Research

Synthesizes the research findings, emphasizing the contributions of ORSM to naval readiness assessment. The chapter also identifies potential areas for future study and practical implementation.

Each chapter builds upon the preceding one to ensure a logical and structured progression toward the thesis objective. By integrating a mission-based readiness assessment framework with data-driven analysis, this study aims to enhance the Egyptian Navy's operational readiness and fleet management capabilities.

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II. LITERATURE REVIEW

Ensuring naval fleet readiness is critical to maritime security, requiring advanced assessment frameworks to sustain operational effectiveness in dynamic threat environments. Therefore, a structured readiness assessment framework allows for efficient force allocation, proactive mission planning, and sustained operational agility. The U.S. Navy's Fleet Response Plan was designed to achieve this goal, aiming to maintain a high state of readiness to address evolving threats, as assessed by the GAO (GAO, 2005).

Similarly, the Navy Reserve underscores the necessity of preparedness, emphasizing its commitment to mission readiness from the outset (U.S. Navy Reserve, n.d.). However, real-world constraints, such as fluctuating fleet availability and sustainment limitations, highlight the limitations of traditional readiness models. Testimony from First Sea Lord Admiral Ben Key before the House of Commons Defence Select Committee (UK House of Commons, 2023) further reinforces this, as he highlighted readiness challenges faced by the Royal Navy due to maintenance bottlenecks. These challenges highlight the limitations of the Egyptian Navy's legacy readiness reporting, which relies on a binary evaluation of "ready" or "not ready," emphasizing the need to transition toward mission-based, real-time assessment frameworks.

This chapter examines the theoretical and empirical foundations of naval readiness reporting rather than summarizing existing models and explores their practical implications, gaps in current frameworks, and the need for adaptive readiness assessments tailored to modern naval challenges. By evaluating strategic planning, supply chain resilience, maintenance protocols, and technological advancements, this review establishes a foundation for the development of the Operational Readiness Score Model as an optimized readiness framework. It also situates ORSM within global military trends, comparing it to NATO's readiness models, and the U.S. Defense Readiness Reporting System (DOT&E, 2013).

A. STRATEGIC READINESS AND FLEET MANAGEMENT

As previously mentioned, traditional readiness models relied on rigid availability classifications, leading to inefficiencies in mission planning, force allocation, and strategic assessments. In response, modern systems such as the DRRS (DOT&E, 2013) have introduced real-time, mission-based evaluation mechanisms that assess unit capability based on operational effectiveness rather than static resource availability.

1. The Defense Readiness Reporting System

The DRRS revolutionizes military readiness assessment by replacing outdated static classifications with real-time, mission-focused evaluations. Unlike the legacy Global Status of Resources and Training System, which depended on fixed indicators, DRRS enables commanders to assess unit capability dynamically (DOT&E, 2013). Operating through a classified network, it integrates with the Global Combat Support System – Joint to enhance interoperability across service branches.

Despite its advantages, the DRRS has encountered cybersecurity vulnerabilities. During testing phases, several information assurance risks were identified, necessitating mitigation efforts before the system could be fully operationalized (DOT&E, 2013). Additionally, DRRS has faced integration challenges with external platforms, such as the Joint Operational Planning and Execution System, limiting its ability to provide comprehensive and actionable readiness assessments (DOT&E, 2013). These cybersecurity risks and interoperability issues highlight the need for enhanced data security measures and improved system integration within modern military readiness frameworks.

For the Egyptian Navy, transitioning from binary readiness classifications to mission-based evaluations, as demonstrated by DRRS, enhances fleet coordination and decision-making. Lessons from DRRS highlight the importance of structured implementation, cybersecurity resilience, and data-driven readiness tracking to ensure a smooth transition to more advanced readiness assessment models like the ORSM.

2. NATO's Operational Capabilities Concept

NATO's Operational Capabilities Concept Evaluation and Feedback (OCC E&F) provides a structured framework for assessing and improving the operational readiness of partner nations' forces. The program ensures that participating units meet NATO interoperability standards and can effectively integrate into multinational missions. Instead of relying solely on resource-based assessments, OCC E&F evaluates mission-specific capabilities to determine a force's ability to operate in coalition environments (NATO Allied Land Command, n.d.).

OCC E&F enhances force coordination, modernization efforts, and strategic alignment within a unified command structure. It includes rigorous readiness criteria—covering logistics, training, equipment sustainability, and operational effectiveness—to ensure that naval forces are technically prepared and strategically capable of joint operations. This mission-based assessment methodology also supports real-time adaptability in response to evolving security challenges (NATO Allied Land Command, n.d.).

For the Egyptian Navy, adopting key elements of OCC E&F would enhance fleet readiness evaluation and strategic force planning. By integrating NATO's mission-based assessment principles, the ORSM can create a more adaptive and responsive evaluation framework, improving interoperability with coalition forces and supporting naval modernization.

3. Addressing Readiness Gaps with ORSM

While DRRS and OCC E&F have significantly improved mission-based readiness assessments, they lack real-time predictive analytics for fleet sustainment. The ORSM model can be improved to fill this gap by integrating AI-driven maintenance forecasting, optimizing cross-service coordination, and enhancing interoperability with external operational platforms. This approach provides a proactive readiness optimization system, ensuring data-driven sustainment planning, improved fleet efficiency, and real-time readiness adaptation to enhance naval interoperability.

However, readiness assessment alone is insufficient without robust sustainment strategies. While DRRS and OCC E&F improve mission-based readiness assessments, their effectiveness depends on resilient supply chains and predictive maintenance frameworks. Without an integrated approach to sustainment, even the most advanced readiness models will struggle to support mission success. To ensure long-term fleet availability and operational efficiency, supply chain resilience and AI-driven maintenance strategies must be incorporated into readiness planning.

The following section explores how advanced supply chain resilience frameworks, AI-driven inventory management, and predictive maintenance solutions contribute to the effectiveness of ORSM, ensuring mission-ready fleets in dynamic operational environments.

B. SUPPLY CHAIN RESILIENCE AND MAINTENANCE FRAMEWORKS

1. Challenges in Fleet Sustainment

Naval fleet management relies on a resilient supply chain to maintain operational readiness. However, aging components, obsolescence of critical systems, and geopolitical instability impose significant logistical constraints. The COVID-19 pandemic and the Russia-Ukraine conflict have further exacerbated these challenges, delaying the procurement of essential materials, including propulsion systems and advanced weaponry. These challenges align with findings from Pournader et al. (2020), who emphasize that supply chain disruptions, particularly those caused by geopolitical instability and supplier concentration, pose significant risks to operational sustainment, necessitating robust risk management frameworks (Christopher & Peck, 2004). They further emphasize that resilience in supply chains is achieved through agility, adaptability, and risk-sharing strategies, which are essential to mitigating delays and sustainment gaps in high-risk environments. Additionally, overreliance on single-source foreign suppliers increases vulnerability to diplomatic tensions and trade restrictions, highlighting the need for diversification and strategic stockpiling.

2. Limitations of Traditional Readiness Evaluations

Traditional readiness evaluation systems often fail to capture the complexity of fleet sustainment needs. The U.S. Government Accountability Office (GAO, 2005) identifies that legacy readiness reporting tends to underestimate maintenance backlogs and inflate readiness scores, leading to strategic miscalculations and unscheduled downtime. The Egyptian Navy faces similar challenges, where reliance on static assessments has resulted in mission failures due to overlooked fleet degradation.

3. AI-Driven Maintenance and Digital Twin Simulations

An emerging solution to enhance fleet sustainment and readiness assessment is the use of digital twin simulations. A digital twin is a real-time virtual representation of a physical system, allowing naval planners to simulate performance scenarios, predict component failures, and optimize maintenance schedules before issues arise (Madusanka et al., 2023). By mirroring actual fleet conditions, digital twins provide continuous assessment of system vulnerabilities, complementing AI-driven diagnostics and maintenance planning programs like the Condition-Based Maintenance Plus (CBM+) framework, which emphasize predictive risk mitigation through real-time diagnostics and AI-driven sustainment strategies (Defense Acquisition University [DAU], n.d.). Unlike fixed-schedule maintenance models, ORSM will guide planners to prioritize operational needs and mission impact metrics, ensuring maintenance that need to be performed based on actual performance conditions rather than arbitrary timelines.

By incorporating CBM+ concepts, AI-based diagnostics, and predictive analytics, ORSM enhances mission-based readiness classification, reducing fleet sustainment gaps. These enhancements strengthen ORSM's ability to optimize maintenance prioritization and minimize unexpected failures, ensuring mission-ready fleets under dynamic operational conditions.

4. Enhancing Supply Chain Resilience through AI and Automation

Beyond maintenance challenges, the Egyptian Navy's reliance on single-source foreign suppliers heightens operational risks. This dependency increases vulnerabilities to diplomatic tensions, trade restrictions, and supply chain disruptions. To address these vulnerabilities, a multi-tiered sustainment strategy is essential. As highlighted by Pournader et al. (2020), supply chain resilience can be enhanced through a combination of supplier diversification, risk forecasting, and AI-driven analytics. Christopher and Peck (2004) emphasize that resilient supply chains must incorporate proactive risk management strategies, including early warning systems and multi-tiered inventory solutions, to withstand disruptions and maintain operational readiness. Their research underscores the importance of predictive risk assessment in mitigating procurement disruptions, aligning with AI-driven inventory management solutions currently transforming military logistics. Key measures include supplier diversification, the establishment of regional logistics hubs, and the integration of AI-driven inventory management to minimize procurement delays. According to the U.S. Department of Defense (Chief Digital and Artificial Intelligence Office, 2023), advancements in data analytics and artificial intelligence are reshaping military logistics by enhancing supply chain resilience, predictive maintenance, and inventory forecasting. AI-driven automation, as highlighted by Harper, (2023), plays a critical role in optimizing contested logistics environments by improving sustainment operations, reducing procurement inefficiencies, and ensuring real-time tracking of inventory and fleet sustainment needs.

5. Optimizing Readiness with Data-Driven Sustainment Strategies

Data-driven sustainment strategies enable naval forces to shift from reactive maintenance to proactive AI-driven sustainment. Digital twin simulations and machine learning algorithms provide real-time assessments of system vulnerabilities, reducing failures and optimizing maintenance schedules (Madusanka et al., 2023). Additionally, the U.S. Naval Autonomous Data Collection System (NADACS) has demonstrated the effectiveness of RFID-based tracking and automated sustainment modeling in enhancing logistics efficiency (Stewart, 2021). Incorporating AI-driven logistics tracking and digital twin-based readiness modeling within the ORSM can streamline spare parts allocation, improve maintenance cycles, and increase operational flexibility, ensuring a more resilient and mission-ready fleet. AI applications in logistics, as demonstrated by the DoD's AI integration efforts (Harper, 2023), improve sustainment decision-making by utilizing real-time data analytics to mitigate logistical bottlenecks and enhance operational efficiency, particularly in high-tempo or contested environments.

C. ENHANCING ORSM THROUGH INTEGRATION AND FUTURE DEVELOPMENT

While ORSM represents a significant advancement in mission-based readiness assessment, its full potential lies in its ability to evolve alongside emerging technologies, multinational interoperability, and AI-driven sustainment planning. Enhancing ORSM through predictive maintenance, coalition readiness frameworks, and logistics integration would elevate its role beyond a readiness reporting tool, transforming it into a proactive fleet optimization system.

Future naval operations will increasingly depend on autonomous naval systems like unmanned surface vessels (USVs) and autonomous underwater vehicles (AUV), and for cyber-resilient infrastructure to become integral to modern naval operations, ORSM must evolve to incorporate advanced readiness assessments for both manned and unmanned assets. Future implementations should integrate AI-driven sustainment planning, cybersecurity risk analysis, and autonomous fleet diagnostics to enhance predictive maintenance and operational resilience. By leveraging cyber-defense metrics, automated fleet monitoring, and AI-enhanced sustainment modeling, ORSM can provide real-time risk assessments, optimize unmanned system deployment, and ensure fleet-wide mission readiness in contested environments.

By expanding ORSM's scope through technological integration, coalition-based standardization, and predictive sustainment planning, naval forces can optimize fleet resilience and mission effectiveness, reinforcing long-term modernization efforts.

D. THEORETICAL JUSTIFICATION

The ORSM integrates strategic planning, predictive analytics, and mission-based readiness evaluation, offering a modernized alternative to traditional frameworks. legacy models often rely on static classifications, failing to capture the fluid nature of naval operations. To address these shortcomings, ORSM applies 5 Ps of Strategy—plan, pattern, position, ploy, and perspective—ensuring a comprehensive approach to readiness optimization (Mintzberg, 1999).

Mintzberg's framework is particularly useful in dynamic military environments where adaptability and proactive decision-making are essential. ORSM leverages data-driven sustainment planning, real-time fleet assessments, and AI-enabled diagnostics to enhance operational effectiveness. By embedding these principles, ORSM facilitates strategic foresight, resource optimization, and mission resilience in high-tempo operations.

1. Plan: A Readiness Framework for Mission-Critical Demands

ORSM establishes a structured, mission-based assessment model that enables naval planners to allocate resources effectively. Moving beyond the binary classification of readiness, it incorporates real-time scoring, as seen in the DRRS and NATO's OCC E&F (DOT&E, 2013; NATO Allied Land Command, n.d.). This aligns with Mintzberg's concept of "Plan" by fostering a forward-looking strategy that enhances both immediate and long-term fleet readiness.

2. Pattern: Utilizing Historical Data for Predictive Readiness

By analyzing historical fleet data, ORSM identifies trends in maintenance efficiency, optimizing mission assignments and sustainment cycles. This approach aligns with the CBM+ framework, which emphasizes predictive diagnostics (DAU, n.d.). The integration of digital twin simulations further enhances forecasting accuracy (Madusanka et al., 2023). In this way, ORSM reflects Mintzberg's "Pattern," leveraging past data to refine future sustainment and readiness strategies.

3. Position: Enhancing Strategic Readiness through Interoperability

ORSM strengthens naval readiness by aligning with global defense frameworks such as NATO's OCC E&F and the U.S. DRRS (NATO Allied Land Command, n.d.; DOT&E, 2013). By integrating AI-driven logistics tracking and predictive maintenance analytics, it enhances multinational coordination and force sustainment. This supports

Mintzberg's "Position" concept by ensuring readiness strategies are aligned with broader defense objectives and geopolitical considerations.

4. Ploy: Proactive Readiness Optimization through AI

Through machine learning algorithms, predictive analytics, and real-time sustainment assessments, ORSM facilitates preemptive decision-making, reducing fleet downtime and optimizing maintenance resource allocation. AI-driven sustainment models, such as the U.S. Navy's NADACS, have already demonstrated the benefits of automation in fleet management (Stewart, 2021). ORSM builds upon these advancements, aligning Mintzberg's "Ploy" by enabling commanders to anticipate and mitigate sustainment risks before they impact operations.

5. Perspective: A Dynamic, Mission-Driven Readiness Model

ORSM transitions from rigid readiness classifications to a dynamic, mission-based evaluation framework. By incorporating AI-enhanced diagnostics, cyber-readiness assessments, and predictive sustainment, it fosters adaptability in response to evolving threats. This aligns with Mintzberg's "Perspective" by promoting a shift from reactive assessments to a forward-thinking, data-driven readiness paradigm that ensures continuous operational improvement.

E. CONCLUSION

This chapter underscores the limitations of traditional readiness models and highlights the necessity of real-time, mission-based assessment frameworks such as the ORSM. Unlike legacy systems like DRRS and NATO's OCC E&F, which improve mission-based assessments but lack real-time predictive analytics, ORSM integrates AI-driven sustainment planning, predictive maintenance, and strategic force deployment to enhance fleet readiness, efficiency, and adaptability. These advancements ensure that naval forces can respond dynamically to operational demands, rather than relying on static readiness classifications that fail to reflect real-world mission requirements.

By grounding ORSM in Mintzberg's 5 Ps of Strategy, this review establishes its theoretical validity as both a strategic planning tool and an operational readiness framework. ORSM's ability to analyze historical readiness trends, improve multinational interoperability, and implement AI-driven diagnostics enhances fleet sustainment resilience and mission effectiveness. By integrating mission-based assessments, AI-driven logistics, and predictive analytics, ORSM presents a modernized alternative to traditional naval readiness models. Future research should focus on testing ORSM's effectiveness in multinational naval operations, ensuring its applicability across diverse fleet structures.

III. METHODOLOGY

This chapter presents a comparative analysis of two readiness reporting models for the Egyptian Navy. The current approach employs a binary classification system, where a ship is considered either “available” or “unavailable,” depending solely on its ability to sail. This method assigns readiness as either 100% or 0%, which oversimplifies operational capability and fails to reflect mission-specific readiness. Furthermore, this binary approach creates a “perverse incentive” for commanders to prioritize getting a ship minimally operational rather than focusing on its full mission capabilities.

We propose an alternative model to address these shortcomings by providing a percentage-based measure of mission readiness. Our approach evaluates the ability of each ship to complete its assigned missions, offering a more nuanced and realistic picture of operational readiness.

To assess these models, we leverage a small-scale stochastic simulation, introducing variability in maintenance and mission requirements. The simulation evaluates the effectiveness of each model in depicting true operational readiness, with a particular focus on mission-specific performance. Given the policy and security restrictions, hypothetical data is used in this analysis, while future studies may incorporate real data for validation.

A. RESEARCH DESIGN

The research is structured as a comparative analysis of two readiness models, focusing on the evaluation of comparative readiness rates to determine which model more accurately reflects a realistic readiness picture for naval operations. By analyzing the outputs of each model, the study aims to assess their implications for operational readiness reporting.

The primary research tool is a stochastic simulation, chosen for its simplicity and ability to be rapidly replaced with real-world data. We replicate real-world dynamics, such as fluctuations in maintenance schedules, spare parts availability, and mission-specific requirements. By simulating diverse scenarios, the study provides a detailed comparison of the two readiness models, offering insights into their performance under different conditions.

B. DATA AND PARAMETERS

Due to the classified nature of EN readiness, the simulation relies on hypothetical data for comparison purposes. Sources include simulated lists of Egyptian Navy units, categorized by type, and hypothetical mission sets assigned to each ship based on typical operational roles. Additionally, assumptions about the availability of key systems are drawn from typical maintenance and supply conditions.

We rely on several key variables to model readiness accurately. Our mission set defines the range of tasks each unit is expected to perform, representing the operational responsibilities assigned to naval units. System availability captures the readiness of critical systems, including engines, propulsion, communication, and sensors, all of which are influenced by their technical condition.

The readiness score is calculated using two distinct approaches:

Legacy Method: This method evaluates readiness as a binary measure, assigning a score of either 0% (unavailable) or 100% (available for all missions).

Operational Readiness Score Model: This method provides a more detailed evaluation, measuring readiness as the proportion of missions a unit can accomplish based on the availability of its systems.

We operate under several important assumptions. Each ship is assigned a specific number of missions to perform as required, with the probability of mission accomplishment directly tied to the technical condition of its systems. For simplicity, all missions are considered equally critical to operational readiness. However, certain complexities are excluded from this analysis, including feedback effects, unscheduled maintenance during deployment, and varying readiness profiles for frequently deployed vessels.

C. SIMULATION DESIGN AND EXECUTION

The simulation process utilizes both Microsoft Excel and R programming language. These tools were selected because Excel is widely available and familiar to most users, making it an accessible option for organizing and reviewing data. On the other hand, R is a powerful open-source software globally available. These tools offer complementary strengths in data preparation and statistical modeling, providing a robust set of capabilities for efficient simulation and analysis. Unlike the legacy model, which classifies ships as either fully operational or non-operational, ORSM introduces a tiered readiness approach, ensuring that vessels undergoing maintenance or minor repairs still contribute to fleet operations.

To ensure accurate operational readiness assessments, each vessel is evaluated using two primary metrics: one reflecting real-world constraints (e.g., maintenance delays, system failures, and logistical challenges) and another serving as a standardized performance benchmark, moving beyond simplistic binary classifications to ensure that partial operational capabilities are accurately captured in readiness assessments. The first parameter, overall readiness, incorporates factors such as maintenance backlogs and system failures as a technical consideration. R employs a highly efficient random number generator, relying on the Mersenne Twister algorithm to generate values between 0 and 1 (Kinderman & Ramage, 1976). This stochastic approach simulates fleet variability, allowing for a more accurate representation of real-world readiness conditions.

The second parameter, fixed readiness, establishes a baseline operational capability of 0.9 across all ship classes, representing an ideal upper bound without external disruptions. This dual-parameter framework enables a more balanced and realistic assessment of fleet availability while accounting for potential logistical and mechanical constraints.

Additionally, the simulator includes a table categorizing mission types. Each mission is assigned a binary indicator (1 for assigned, 0 for not assigned) and is grouped under broader operational areas, reflecting technical and logistical conditions. This structured setup provides a clear foundation for analyzing readiness and mission execution across the fleet.

Step 1: The simulator evaluates each vessel's ability to sail by comparing the randomly generated overall readiness value with its fixed readiness value. If the random readiness is less than the fixed readiness, the vessel is deemed capable of sailing, represented as 1. Otherwise, it is recorded as 0. A fixed weight of 0.5 is applied to represent the readiness of vessels that are only capable of sailing without the ability to perform assigned missions.

Step 2: Each assigned mission is given a fixed weight based on expert opinion, ranging from 0.7 to 1, reflecting its significance and complexity. For example, a vessel assigned to reconnaissance (weight 0.7) has a lower operational complexity than a vessel designated for anti-submarine warfare (weight 1.0). This ensures that readiness scores properly reflect mission complexity, with ships assigned to high-intensity operations needing to meet higher readiness thresholds than those conducting routine patrols.

The total weight of all assigned missions is calculated, forming an adjustment factor. This factor refines readiness values, ensuring alignment with a vessel's mission responsibilities. It is computed as the ratio of a fixed weight of 0.5 (remaining vessel readiness weight) to the total mission weight. This weight highlights that even vessels with limited operational capacity can contribute to naval operations and ensures that operational readiness is evaluated within the context of both inherent capability and mission profile.

Step 3: Mission readiness is recalibrated by multiplying each mission's weight by the adjustment factor derived in Step 2. This calculation applies the adjustment factor to each mission weight, computing a vessel's mission readiness score based on its assigned responsibilities and available capabilities.

Step 4: The final step integrates the results from previous calculations to deliver a complete readiness assessment for each vessel in two metrics. The first assessment gives Binary Readiness (legacy method): This mirrors the traditional approach, categorizing readiness as either 1 (ready) or 0 (not ready) based solely on the ship's ability to sail. The second assessment gives mission-based readiness (ORSM). This advanced metric calculates readiness as the proportion of missions a vessel can successfully perform. It divides the total number of missions a vessel can perform by the total number of missions assigned to it (as the first portion of its readiness). Then it's added to the ship's ability to sail (the remaining portion of its readiness).

The simulator includes a detailed table to assess whether specific missions assigned to a vessel can be performed or not as one of the simulator's outcomes. This is determined by comparing a randomly generated value with the predefined mission area value. If the random value is less than the mission area value, the mission outcome is recorded as "mission performed" (indicated by 1). Otherwise, it is recorded as "mission not performed" (indicated by 0). This method accounts for variability, simulating real-world mission success rates. Also, these outcomes are visually represented using color coding as: the cell shading will change to a yellow color for the mission not assigned. The cell shading will change to a red color for the mission assigned but cannot be performed. The cell shading will change to a green color for the mission assigned and successfully performed as mentioned in Figure 1 and Appendix A.

An interactive "run" button allows users to engage with the simulator by selecting a specific vessel (row) and specifying the number of simulation trials to run. This feature enhances user engagement and supports dynamic analysis.

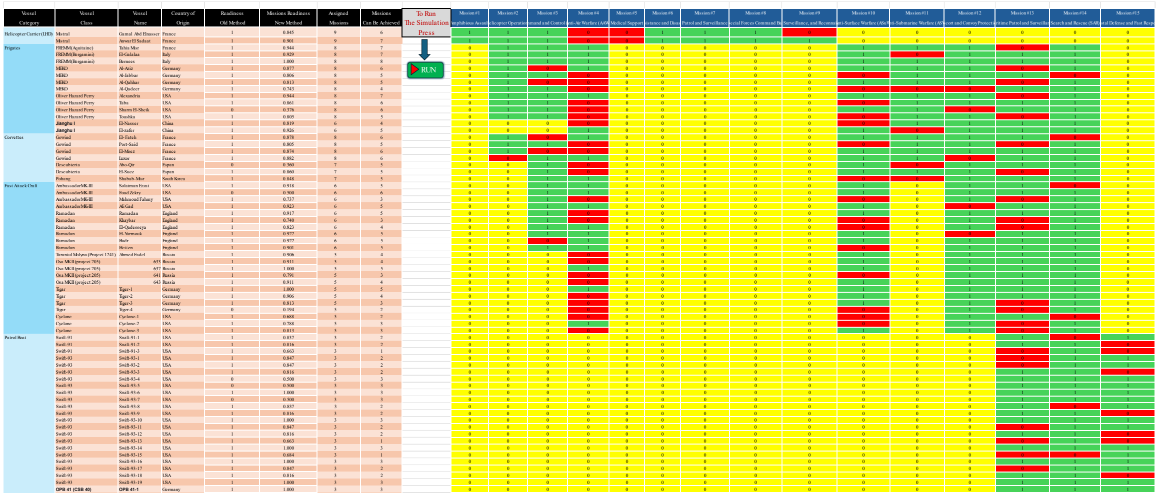

Figure 1. A Screenshot of the Simulation Main Page

To ensure a comprehensive evaluation, we randomly selected eight vessels from different classes for the simulation. These vessels represent a diverse range of operational profiles, with assigned missions varying from two to nine per vessel. To ensure statistical robustness, the simulation employs the Mersenne Twister algorithm—a widely used pseudo-random number generator—producing readiness scores over 1,000 trials each (Matsumoto & Nishimura, 1998). This allows for a thorough comparison of the legacy and ORSM methods while maintaining consistency across probabilistic assessments, generating statistical data to compare the traditional and mission-based readiness methods. Flawed statistical models can distort decision-making, leading to misguided conclusions and ineffective policies. This reinforces the necessity for a rigorous and validated readiness assessment model to avoid misinterpretations that could undermine operational planning.

The resulting dataset provides a robust basis for comparing the two models, offering insights into their effectiveness in capturing and representing operational readiness. By integrating Excel's foundational organization with R programming analytical power, the simulation process ensures a seamless and thorough evaluation of the models when comparing the impact of the legacy model and ORSM on fleet readiness and mission execution.

D. ANALYSIS AND VALIDATION

Building upon simulation's structured execution, this section focuses on interpreting the results through statistical analysis. By evaluating the stability and variance of readiness scores, we can determine the practical implications of the proposed models.

Our analysis evaluates and compares the performance of the readiness models by focusing on several key metrics. Average readiness scores are calculated across all simulation iterations, serving as a foundational measure for comparison; the variance and consistency of these scores are examined using standard deviation, providing insights into the stability and reliability of each model. Furthermore, the operational implications of the findings are assessed to determine how effectively each model represents actual mission capabilities.

To enhance this analysis, statistical tools such as confidence intervals and histograms are employed. These visualizations help to explore the distribution of readiness scores and to assess the consistency of the models across different scenarios.

The simulation results undergo cross-validation using hypothetical data sets designed to reflect realistic operational patterns. This approach verifies the alignment of simulation outcomes with expected performance.

Several limitations must be acknowledged. The assumption that all missions carry equal importance may not fully represent real-world priorities. The reliance on hypothetical data, while necessary, constrains the ability to capture the nuances of actual operations. Additionally, the sensitivity of classified data limits the incorporation of real-world specifics into the analysis. Each of these issues may be addressed within the modeling construct when used in an appropriate classified environment for EN data.

The findings from this simulation will not only validate the ORSM model but also highlight key limitations in the current readiness classification system, shaping recommendations for future fleet management strategies. The following chapter will present and analyze the simulation results, comparing the impact of the legacy model and ORSM on fleet readiness assessments.

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IV. SIMULATION OUTCOMES AND RESULTS ANALYSIS

This chapter presents a detailed evaluation of the simulation outcomes for various classes of Egyptian Navy vessels. The simulation was conducted on a fleet of 150 vessels, with readiness scores determined by system availability and mission performance. Two models were compared: the Legacy Binary Readiness Model, which assigns ships either fully operational (100%) or non-operational (0%), and the ORSM, which introduces a tiered readiness framework reflecting partial mission capability. The primary goal of this simulation was to determine which model provides a more accurate and mission-relevant readiness assessment.

A. SIMULATION OUTCOMES AND ANALYSIS (FOR THE ENTIRE FLEET)

The simulation outcomes provide critical insights into the comparative effectiveness of the Legacy Readiness Model and the ORSM, particularly in scenarios where the limitations of the binary system are most pronounced. The binary readiness model fails to account for partial mission capability, classifying vessels as either fully operational or non-operational. This rigid classification misrepresents fleet potential by disregarding incremental readiness levels—a significant shortcoming in contemporary naval operations.

In contrast, ORSM employs a tiered readiness framework, recognizing graduated levels of mission capability and offering a more precise assessment of fleet readiness. As previously discussed, this approach aligns with modern defense strategies, ensuring a nuanced evaluation of operational capability. The relevance of ORSM is particularly evident in the Egyptian Navy, which operates a diverse fleet with varying levels of technological advancement and operational reliability.

By eliminating the overestimation biases inherent in the legacy model, ORSM provides a more realistic and data-driven evaluation of fleet readiness. This enhanced accuracy reduces the risk of resource misallocation and unrealistic deployment planning, leading to improved mission preparedness. The strategic implications of these findings, particularly their impact on mission planning and fleet management, are further examined in the next chapter, Operational Insights and Actionable Recommendations.

For a comparative visualization of fleet readiness distribution under the legacy method and ORSM, see Figure 2.

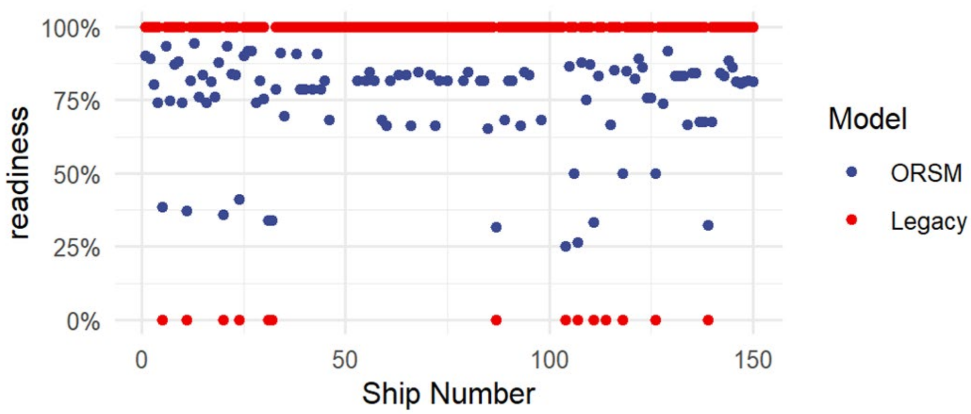

Figure 2. Fleet Operation Readiness Distribution in Both Legacy Method and ORSM. This plot shows how ORSM gives more actionable information than simply "ready" or "not ready."

1. Statistical Findings for the Entire Fleet

Statistical Parameter	ORSM	Legacy Model
Mean	**81%**	**91%**
Standard Deviation	**18.9%**	**29%**

Table 1. Simulated Fleet Statistical Data Outcomes. These show a lower mean, but less distribution, for ORSM than the legacy approach.

Table 1 and Figure 3 provide a comparative analysis of fleet readiness under the ORSM and the legacy model, highlighting key differences in how each method evaluates operational capability. A key advantage of ORSM is its ability to reflect actual operational readiness rather than relying on an all-or-nothing classification. By incorporating a tiered approach to mission capability, ORSM enables a more stable and reliable assessment of fleet availability. This distinction is evident in Table 1, which further demonstrates the difference in frequency distribution between the two models, and Figure 3, which illustrates the overall distribution of readiness scores,

These findings emphasize the need for a more nuanced readiness assessment framework, ensuring that naval planners and decision-makers base fleet management strategies on realistic operational capacity rather than inflated estimates. The implications of this shift—and how ORSM enhances strategic decision-making—are further explored in the next section.

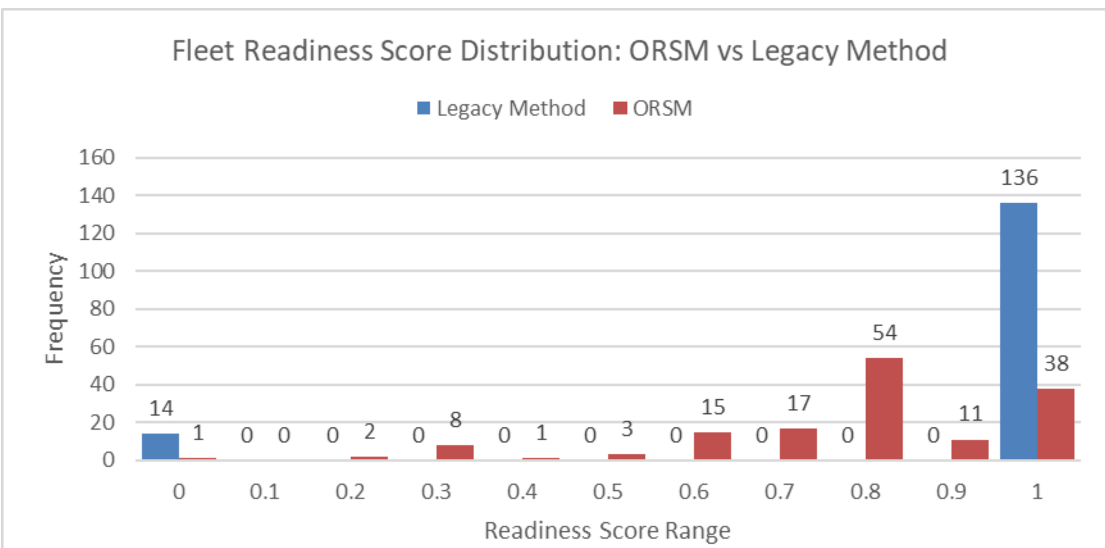

Figure 3. Simulated Fleet Readiness Score Distributed for ORSM model and Legacy Method. This plot—and ones like it—will help EN Leaders make better decisions for allocating maintenance to ships.

2. Interpretation of Results

The simulation results indicate that the Legacy Readiness Model systematically overestimates fleet availability, leading to strategic miscalculations and misallocated resources. The average readiness score under the legacy model was 90.67%, compared to 81.01% under ORSM, highlighting the risks of inflated fleet assessments (Figure 2). This overestimation is further reflected in the median readiness score of 100%, demonstrating the binary model's all-or-nothing classification. In contrast, ORSM accounts for incremental mission capability, providing a more precise and operationally relevant readiness evaluation.

A detailed statistical analysis reveals key flaws in the legacy model's readiness distribution. The high kurtosis (6.06) and extreme negative skewness (–2.82) suggest a strong clustering effect, with the binary system disproportionately labeling vessels as fully operational despite actual variations in readiness (Figure 3). The histogram shows that 136 vessels were classified as "fully operational" under the legacy model, whereas only 38 reached this status under ORSM. This overstatement can lead to flawed mission planning, misallocated resources, and operational gaps. Ships deemed "fully operational" in the legacy model may lack the capability to execute critical missions, leading to misplaced strategic confidence and inefficient fleet utilization In addition, denying needed data to create a robust predictive sustainment system.

The distribution of readiness scores in Figure 3 further reinforces the weaknesses of the legacy model. The overwhelming clustering at 1.0 readiness (136 ships) demonstrates a rigid binary assessment, while ORSM's more gradual distribution (spanning 0.3 to 1.0) provides a realistic view of readiness variation. This indicates that many vessels classified as "fully operational" under the legacy model may, in reality, have degraded mission capability, a critical flaw that could mislead strategic planners.

Variance analysis highlights a crucial distinction between the two models. The legacy model's variance (0.0852) is significantly higher than ORSM's (0.0358), indicating greater fluctuations in readiness scores. This inconsistency challenges fleet planning, increasing the likelihood of unexpected availability drops. In contrast, ORSM's lower variance ensures a stable and predictable readiness evaluation, supporting proactive mission planning and more efficient resource allocation. Greater fluctuations in the legacy model can lead to unforeseen operational gaps, forcing commanders into reactive, rather than proactive, decision-making.

ORSM also introduces an advantage in readiness threshold sensitivity. Unlike the legacy model, which categorizes ships as either "mission-ready" or "non-operational," ORSM allows for partial readiness scores (e.g., 0.7 or 0.8), ensuring that ships with minor limitations are not entirely excluded from operational planning. This provides commanders with more flexibility in tasking assets based on mission-critical requirements.

Ultimately, ORSM enhances deployment planning, minimizes fleet availability gaps, and supports proactive maintenance strategies. Its ability to provide a continuous and stable evaluation framework offers a distinct advantage over the rigid and often misleading assessments of the legacy model. The next chapter, "Operational Insights and Actionable Recommendations," will explore targeted solutions for readiness challenges and ORSM's role in mission-specific decision-making.

B. SIMULATION OUTCOMES AND ANALYSIS (FOR INDIVIDUAL VESSELS)

As discussed in the previous chapter, evaluating naval readiness requires a representative and diverse sample of vessels. To achieve this, eight ships were randomly selected from various classes, ensuring a balanced cross-section of Egypt's naval capabilities. These vessels span multiple operational roles, including amphibious assault, fast attack, undersea warfare, and logistical support, with assigned missions ranging from two to nine per ship. This selection provides a realistic and statistically robust foundation for the simulation.

At the forefront is Anwar El Sadaat, designated as the 1st Ship, a Mistral-class helicopter carrier landing helicopter dock (LHD) built in France and delivered to the Egyptian Navy in 2016. As one of the fleet's most formidable assets, this amphibious assault ship serves as a vital platform for power projection, facilitating the rapid deployment of troops, helicopters, and support equipment. With its expansive deck and sophisticated command infrastructure, Mistral-class LHDs play a pivotal role in humanitarian missions, amphibious operations, and naval task force coordination.

Complementing the carrier is Al-Jabbar, designated as the 2nd Ship, a Meko A-200-class frigate from Germany, commissioned into service in 2022. This multi-role frigate is a key defensive pillar of the fleet, equipped with advanced radar systems and an extensive weapons suite. Whether engaged in anti-air, anti-submarine, or surface warfare, Meko A-200-class frigates are an indispensable asset in Egypt's maritime defense strategy.

Adding to the fleet's versatility is El-Suez, designated as the 3rd Ship, a Descubierta-class corvette of Spanish origin, delivered to the Egyptian Navy in 1984. Though smaller than a frigate, this corvette is highly maneuverable and well-suited for coastal defense and escort missions. Patrolling territorial waters with agility and precision, Descubierta-class corvettes are equipped to counter both surface, underwater, and aerial threats, extending the Navy's operational reach.

For rapid strike and coastal engagement, the fleet includes two fast attack crafts. Foad Zekry, designated as the 4th Ship, is an Ambassador MK-III-class vessel from the United States, commissioned in 2014, and Tiger-2, the 5th Ship, is a Tiger-class attack craft from Germany, originally built in the 1970s and delivered to the Egyptian Navy in 2002. Both vessels are designed for speed and agility, making them highly effective in quick-response operations, precision missile strikes, and high-threat patrol missions. These attack crafts play a crucial role in disrupting enemy formations and conducting defensive maneuvers in littoral environments.

Operating beneath the waves is S-41, designated as the 6th Ship, a Type 209/1400-class submarine built in Germany and commissioned into service in 2017. With its diesel-electric propulsion system and stealth capabilities, the Type 209/1400-class submarine is a silent predator, executing reconnaissance, surveillance, and undersea warfare with formidable precision. Its presence serves as a strategic deterrent, reinforcing the Navy's ability to operate undetected while maintaining maritime superiority.

Navigating both coastal and open waters is El-Siddiq, designated as the 7th Ship. This Osprey-class mine hunter, built in 1997 and delivered to the Egyptian Navy in 2007, is specifically designed for mine countermeasures and maritime security operations. As a critical asset for naval defense, Osprey-class mine hunters enhance the Navy's ability to detect, identify, and neutralize underwater threats, ensuring safe passage for both military and commercial vessels. It contributes significantly to safeguarding strategic waterways and maintaining maritime security.

Ensuring sustained fleet operations is Abu-Simbel-1, designated as the 8th Ship, a Fort Rosalie-class support ship from England, originally built in 1978 and integrated into the Egyptian Navy in 2021. While lacking offensive capabilities, this logistics and replenishment vessel is indispensable for long-term naval missions. By providing fuel, ammunition, and critical supplies, these logistics and replenishment vessels ensure that frontline warships can maintain operational readiness without frequent port returns.

These vessels form a highly capable and strategically diverse fleet, integrating technological expertise from multiple nations. Each ship contributes uniquely to Egypt's maritime security, operational flexibility, and naval power projection. By incorporating assets from France, Germany, Spain, the United States, and England, the fleet reflects a blend of modern warfare capabilities and interoperability. This multinational composition ensures the Navy's ability to defend national interests, secure territorial waters, and uphold regional stability.

1. Statistical Findings for Individual Vessels

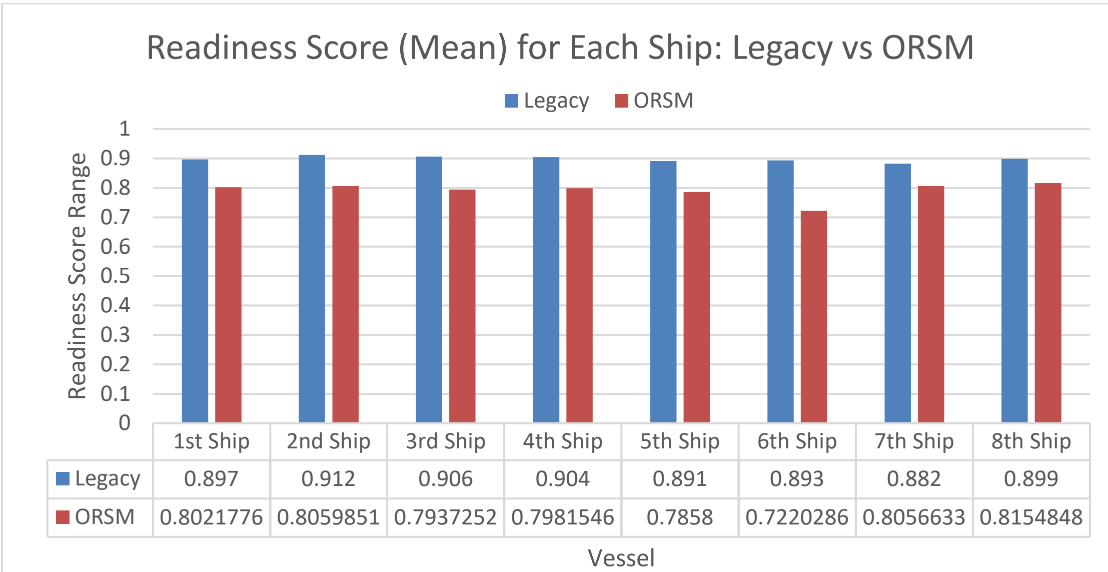

Figure 4. Simulated Ships' Readiness Scores Distributed for ORSM Model and Legacy Method. The difference in technique will allow EN decision-makers to strategically focus their maintenance effort.

Table 2 (Appendix B) compares ship readiness under the legacy model and ORSM, detailing key metrics like mean readiness scores, standard deviation, variance, and operational failures. This detailed analysis identifies vessels needing urgent maintenance or reassignment, illustrating performance differences and readiness patterns, which provides a clear basis for evaluating the proposed readiness metric's impact.

2. Interpretation of Results

As shown in Figure 4 and Table 2 (Appendix B), there are key differences between the Legacy Readiness Model and the ORSM in evaluating vessel readiness. The legacy model inflates readiness, with mean scores ranging from 0.882 (7th Ship) to 0.912 (2nd Ship), while ORSM provides more realistic assessments between 0.722 (6th Ship) and 0.815 (8th Ship), providing more precise evaluation of mission capability by considering partial readiness rather than assuming full operational status. The legacy model's binary classification tends to overestimate readiness, overlooking gradual performance declines. In contrast, ORSM incorporates partial functionality and mission-based scoring, delivering a more nuanced assessment. Unlike the legacy model, which categorizes ships as nearly fully operational, ORSM differentiates performance levels, enabling commanders to prioritize maintenance efforts and optimize fleet deployment. And, help with predictive supply analytics.

As illustrated in Figures 12 through 19 (Appendix B), the legacy model clusters readiness scores at 1.0, reinforcing their tendency to overstate operational capability. ORSM, however, distributes readiness scores across different levels, providing a more accurate reflection of a ship's ability to perform specific missions. Notably, ORSM highlights ships operating at 0.7 and 0.8 readiness levels, values absent from the legacy model's assessment. This underscores the necessity of transitioning to a mission-based readiness framework that captures partial functionality.

Table 2 (Appendix B) reveals greater fluctuations in the legacy model, with standard deviation values between 0.283 (2nd Ship) and 0.323 (7th Ship), compared to ORSM's more stable range of 0.160 (2nd Ship) to 0.214 (8th Ship). These variations indicate inconsistent assessments in the legacy model, leading to unpredictability in mission planning. ORSM mitigates these fluctuations, providing a stable framework that enhances readiness evaluations and long-term fleet sustainability. The higher variability in the legacy model increases the risk of last-minute operational shortfalls, whereas ORSM's consistency enables proactive maintenance scheduling.

Variance comparison further highlights a key difference between the two models. The legacy model exhibits significantly higher variance across ships, with values ranging from 0.0803 (2nd Ship) to 0.1042 (7th Ship), compared to ORSM's lower variance values, which range from 0.0256 (2nd Ship) to 0.0459 (8th Ship). This contrast underscores the inconsistency of the legacy model in readiness assessments. The higher variance in the legacy model means readiness scores fluctuate significantly, leading to unpredictable mission availability and increased risks of operational disruptions. In contrast, ORSM's lower variance, ranging between 0.0256 and 0.0459, provides a more consistent readiness evaluation, enabling better maintenance prioritization, resource allocation, and strategic mission planning. Ultimately, the variance analysis reinforces that ORSM offers a more dependable approach to fleet readiness management, ensuring a predictable and stable operational framework for mission planning.

A critical insight is the number of vessels classified as 'Unable to Sail.' Despite high-readiness ratings under the legacy model of 0.882, the 7th Ship recorded 118 operational failures, the most in the dataset. ORSM's lower score of 0.806 for the same vessel more accurately reflects its limitations, supporting informed maintenance and deployment decisions. The frequent 'Unable to Sail' instances in the legacy model reveal a significant flaw. It does not account for the underlying mechanical and operational constraints. ORSM aligns readiness scores with actual fleet conditions, improving predictive maintenance and mission planning.

Another key difference is seen in kurtosis values. The legacy model shows excessive kurtosis, reaching 6.50 (2nd Ship), compared to ORSM's 3.96 for the same vessel. This clustering at full operational status misrepresents mission reliability by failing to capture gradual wear and degradation. ORSM's lower kurtosis ensures a more balanced readiness distribution, incorporating incremental changes in ship performance rather than enforcing rigid classifications. The legacy model's extreme negative skewness and high kurtosis distort readiness perceptions, leading to misinformed decisions. ORSM's more evenly distributed skewness and lower kurtosis reflect gradual performance changes, providing a more accurate operational assessment.

By improving assessment accuracy, ORSM enhances resource allocation and reduces the risks associated with overestimating fleet availability. It provides several operational advantages. It enables precise mission assignments, improves maintenance prioritization for aging vessels, and optimizes asset utilization to enhance fleet-wide efficiency. This structured approach aligns readiness assessment with mission planning, strengthening strategic coordination and long-term sustainability.

The findings emphasize the need for a data-driven fleet management approach. The legacy model frequently overestimates operational availability, while ORSM offers a more precise readiness evaluation. By integrating ships with partial capabilities into mission planning rather than deeming them non-operational, ORSM promotes a more efficient deployment strategy. These results highlight the importance of proactive maintenance, contingency planning, and structured mission-based deployment. The next chapter explores operational insights and actionable recommendations, translating these findings into strategies that improve fleet sustainability, optimize resource allocation, and enhance mission effectiveness.

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V. OPERATIONAL INSIGHTS AND ACTIONABLE RECOMMENDATIONS

This study focused on simulation highlights the need for a structured, data-driven approach to fleet maintenance, mission planning, and modernization. While traditional binary readiness models provide clear assessments of fleet availability, they often fail to capture the complexities of mission effectiveness. Some defense analysts argue that these models simplify command decision-making, but their limitations become evident in modern naval operations. Commanders often prefer binary classifications for their decisiveness in crisis situations, as they eliminate ambiguity in deployment decisions. However, as naval operations grow more complex, such models fail to capture partial mission capability, potentially leading to underutilization of functional assets. As we previously discussed, the U.S. Department of Defense (DOT&E, 2013), NATO, and other allied forces have increasingly emphasized dynamic readiness frameworks that account for graded mission capability, ensuring optimal fleet utilization in multi-domain operations (NATO Allied Land Command, n.d.). ORSM mitigates the shortcomings of binary models while maintaining operational clarity. This framework enhances the Egyptian Navy's agility and ensures precise asset allocation for mission effectiveness.

A. FLEET MAINTENANCE AND READINESS STRATEGY

Given the findings from the ORSM model as presented in Figure 5, the following section examines targeted maintenance interventions aimed at optimizing fleet performance under mission-based readiness frameworks. A structured, data-driven maintenance strategy is essential for sustaining fleet combat effectiveness. Prioritizing maintenance efforts based on actual fleet conditions rather than generalized assumptions reduces inefficiencies in fleet management.

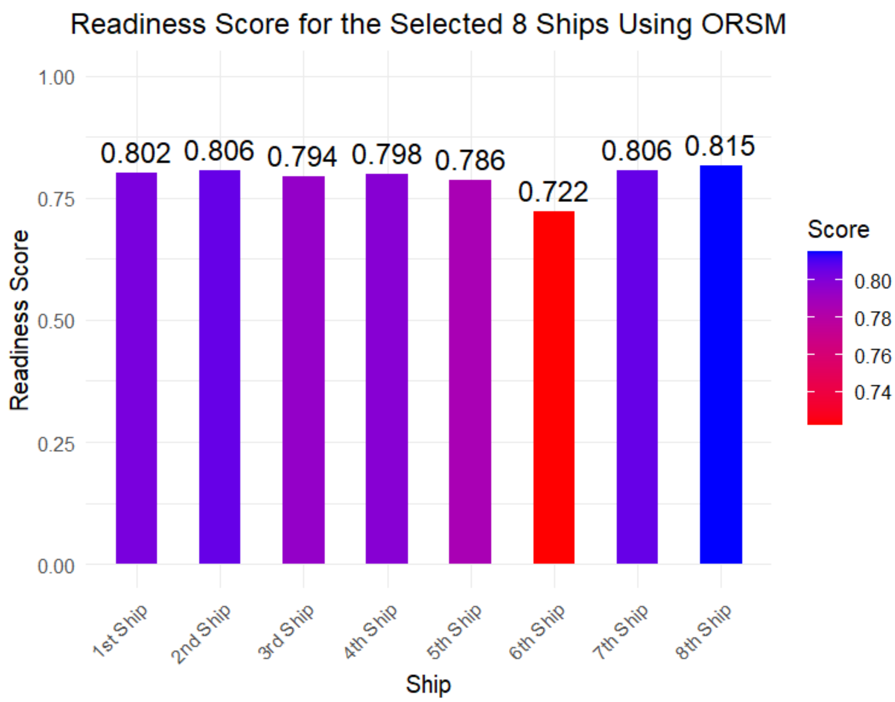

Figure 5. Readiness Score Using ORSM for the Selected Eight Ships

1. Critical Repairs for High-Risk Vessels

The 6th Ship exhibits severe operational challenges, making it a top priority for urgent repairs. With the lowest ORSM score across the fleet, this vessel faces critical mechanical and propulsion system failures, necessitating immediate overhauls to restore mission readiness.

The 7th Ship recorded the highest mission failure rate, further highlighting significant reliability concerns. Despite a moderate ORSM score, the high number of failed mission trials suggests persistent performance failures. Fleet-wide analysis indicates that vessels with ORSM scores approaching or below 0.80 frequently experience mission-critical breakdowns. Urgent interventions, including propulsion system overhauls and structural reinforcements, are necessary to restore operational dependability.

The 5th Ship also demonstrated recurrent mechanical failures. Although its ORSM score is slightly higher than the 6th Ship's, the ship remains in a borderline high-risk category, with significant failure probability in mission-critical operations. Immediate maintenance interventions are required to prevent further deterioration of its readiness status.

2. Moderate-Risk Vessels: Preventive Maintenance Required

Ships categorized as moderate risk require preventive maintenance measures to sustain operational readiness. The 2nd Ship demonstrated strong overall performance but suffered frequent availability failures. Scheduled maintenance is essential to stabilize performance and minimize downtime. Fleet-wide analysis supports this approach, as ships in the 80%-82% ORSM range experience intermittent downtime primarily due to minor technical issues rather than systemic failures.

The 1st Ship exhibited similar patterns, requiring proactive maintenance scheduling to mitigate availability issues and enhance long-term operational stability.

The 4th Ship faced readiness constraints linked to logistical inefficiencies rather than mechanical failures. This pattern was evident across multiple ships in the fleet, suggesting that maintenance scheduling improvements—rather than major repairs—could enhance fleet availability. By addressing both mechanical and logistical inefficiencies, fleet commanders can optimize resource allocation, minimize unexpected downtimes, and ensure mission continuity.

B. CONTINGENCY ROLES FOR MODERATE-READINESS SHIPS

As ORSM results indicate that moderate-readiness ships retain significant functional capability, despite being classified as "non-operational" under the legacy model. Not all vessels must be in peak operational condition to contribute to mission success. The ORSM model demonstrates that while these ships may not be suited for high-intensity missions, they remain valuable for logistics, reconnaissance, and auxiliary support roles. Rather than sidelining these assets, strategic reallocation based on readiness scores allows commanders to maximize fleet efficiency while preserving high-readiness assets for critical operations.

1. Strategic Reassignment of Moderate-Readiness Ships

ORSM reveals that ships classified as "ready" under the legacy model (but with ORSM scores between 72% and 82%) do not necessarily possess the mission-specific capabilities required. While these vessels are operational, ORSM analysis indicates they are best suited for secondary roles such as reconnaissance, logistics, and intelligence support. Simulations confirm that strategic reassignment of these vessels enhances fleet efficiency while preserving high-readiness assets for critical operations.

The 4th Ship and the 5th Ship excelled in auxiliary roles. Fleet-wide simulations found that ships in the 78%–80% ORSM range were 30% more effective in non-combat missions like supply delivery, search-and-rescue, and coastal defense. This indicates that while these vessels may not be fully mission-capable, they can support broader fleet objectives through strategic role assignments.

2. Enhancing Fleet Utilization through Role Optimization

Strategic role optimization ensures that even ships with moderate readiness contribute effectively to fleet operations. The 1st Ship and the 2nd Ship demonstrated high mission capability but suffered intermittent availability issues. ORSM fleet-wide analysis shows that ships with occasional readiness gaps can still be highly effective in logistical transport, communication relay, and support assignments.

Reallocating moderate-readiness ships to contingency roles ensures that high-readiness assets remain available for critical missions while optimizing fleet-wide resource utilization.

C. MANAGING AGING FLEET ASSETS AND MISSION REALLOCATION

The Egyptian Navy operates a diverse fleet that includes excess defense articles acquired from allied nations such as the United States. While these assets extend fleet capabilities, they also present significant logistical and operational challenges due to their age and potential obsolescence. Many of these vessels and systems are transferred only after being decommissioned by their original operators, making certain components difficult to maintain or replace.

Aging platforms often introduce logistical and operational challenges, including supply chain dependencies, sustainment difficulties, and system incompatibilities. In cases where obsolescence limits modernization feasibility, naval leadership must evaluate whether targeted upgrades can extend operational utility or if decommissioning is the optimal course. If full replacement is not viable, ORSM's mission-based reassignment ensures legacy vessels remain operationally effective without burdening critical fleet resources, thereby balancing sustainment priorities with force readiness requirements.

The GAO report on U.S. Navy sustainment has identified that aging naval platforms suffer from supply chain disruptions, maintenance difficulties, and compatibility issues with modernized naval systems. The Egyptian Navy faces similar constraints, where legacy systems require extensive modifications or complete replacements (GAO, 2023).

To address sustainment challenges, ORSM-driven reassignment ensures aging vessels remain strategically valuable without straining fleet resources, optimizing mission effectiveness while maintaining readiness. By aligning fleet sustainment with ORSM-based mission reassignment, the Navy enhances operational effectiveness while ensuring realistic readiness assessments. This data-driven framework strengthens force management, optimizes resource allocation, and improves overall fleet resilience.

D. MISSION PLANNING OPTIMIZATION USING ORSM

Effective fleet-wide mission planning must account for readiness variations to ensure vessels are deployed in roles that match their operational strengths. The simulation results provide clear fleet-wide readiness benchmarks, allowing commanders to optimize ship assignments.

The ORSM simulation categorizes fleet readiness into three operational tiers: high-readiness (80%–100%), moderate-readiness (60%–80%), and low-readiness (below 60%). This classification allows commanders to assign roles based on actual mission capability, enhancing efficiency and operational flexibility while ensuring long-term fleet sustainability.

1. High-Readiness Ships (80%–100% ORSM)

These vessels displayed exceptional stability across multiple trials, confirming their combat readiness and suitability for high-priority missions. As the primary assets for combat, rapid response, and high-stakes security operations, these ships should be strategically prioritized for critical engagements where full operational capability is essential.

2. Moderate-Readiness Ships (60%–80% ORSM)

While vessels in this category exhibited occasional fluctuations in readiness, they maintained consistent effectiveness in support roles, such as humanitarian aid, intelligence gathering, surveillance, and routine patrols. Simulation data revealed that ships within this range achieved an 85% success rate in non-combat missions, reinforcing their role in sustaining operational continuity while preserving high-readiness assets for more demanding operations. By strategically deploying these ships in auxiliary roles, fleet commanders can optimize fleet utilization and maintain mission flexibility while preserving the readiness of frontline vessels.

3. Low-Readiness Ships (Below 60% ORSM)

Ships with readiness scores below 60% exhibited inconsistent performance and were found to be unreliable for primary operational roles. Fleet-wide analysis indicated that these ships failed to complete missions in 65% of trials, making them unsuitable for immediate deployment in mission-critical assignments. Instead, they should be temporarily reassigned to reserve duties, maintenance cycles, or training operations until their readiness improves. By allocating these vessels to lower-priority roles, fleet leadership can ensure that available resources remain focused on operationally capable ships while allowing lower-performing vessels to regain mission readiness through scheduled maintenance and system upgrades.

As naval forces worldwide adopt mission-based readiness models, it becomes increasingly clear that binary classification systems are insufficient for modern operational planning. NATO, the U.S. Navy, and other allied forces emphasize readiness scalability, ensuring that partially mission-capable ships remain integrated into operational strategy (NATO Allied Land Command, n.d.; DOT&E, 2013). Similarly, regional navies, such as the Japan Maritime Self-Defense Force and the Republic of Korea Navy, have implemented tiered readiness approaches, balancing force availability with operational sustainability.

Drawing from global best practices, the ORSM model provides a strategic approach tailored to the Egyptian Navy's needs, ensuring efficient fleet utilization and effective asset management.

E. LONG-TERM FLEET IMPROVEMENT STRATEGY

Beyond short-term interventions, the ORSM simulation highlights long-term strategic areas requiring improvement, particularly in sustainment, logistics, and modernization. Sustaining long-term fleet readiness requires continuous improvement in maintenance, logistics, and modernization. A structured fleet improvement strategy will ensure greater mission sustainability, minimize downtime, and strengthen the fleet's long-term capabilities.

To ensure sustained fleet readiness, a proactive improvement strategy must address fleet-wide maintenance, logistics, and modernization challenges identified in the simulation.

1. Predictive Maintenance for High-Risk Ships

Unplanned maintenance remains a persistent issue, often leading to extended downtime and logistical constraints, particularly in resource-limited environments. Predictive maintenance solutions address these challenges by identifying system vulnerabilities before failures occur, ensuring fleet readiness is sustained through structured maintenance programs. By leveraging failure pattern assessments, fleet commanders can proactively detect system weaknesses, optimize maintenance scheduling, and enhance fleet-wide operational stability.

2. Inventory Optimization for Mission Sustainability

The analysis of fleet-wide readiness trends suggests that logistical delays in maintenance significantly impact operational efficiency, often sidelining vessels due to a lack of readily available spare parts. To mitigate this issue, a strategic inventory optimization plan is essential, with a focus on prioritizing the stockpiling of critical spare parts for vessels experiencing recurring system failures. By implementing a targeted supply chain strategy, fleet logistics teams can ensure that essential components are readily available, reducing delays and maintaining fleet-wide operational readiness. ORSM provides the data necessary to employ this logistic strategy

3. Fleet Modernization and System Upgrades

As naval forces modernize, integrating advanced maintenance technologies and supplier diversification will enhance fleet resilience. Phased system upgrades help reduce supply chain vulnerabilities, ensuring naval assets remain operational throughout the modernization process. ORSM provides a structured, data-driven framework for optimizing fleet readiness, ensuring that mission-based deployment and sustainment strategies are aligned with real-world operational capacity. By adopting structured maintenance programs and optimizing spare parts logistics, the Egyptian Navy can sustain fleet resilience and mission readiness without overextending modernization efforts.

The findings of this study reinforce the importance of transitioning from binary readiness classifications to a mission-capability-based approach, a shift that aligns with global best practices in naval operations. The U.S. Navy, NATO, and other allied forces have already embraced multi-tiered readiness assessment models, allowing for a more nuanced and realistic evaluation of fleet capability. By adopting a similar readiness framework, the Egyptian Navy can improve force management, sustainment planning, and mission effectiveness while ensuring optimal resource allocation.

F. ENHANCING ORSM THROUGH INTEGRATION AND FUTURE DEVELOPMENT

The ORSM marks a transformation in naval readiness assessment. To reach its full potential, it must integrate emerging technologies, AI-driven analytics, and multinational frameworks. This evolution will shift ORSM from a reactive tool to a predictive, mission-planning enabler, enhancing fleet-wide operational efficiency.

1. Foundations for AI-Driven Maintenance and Readiness Forecasting

To enhance fleet availability and reduce unplanned downtime, ORSM should evolve into a proactive readiness assessment tool by incorporating predictive maintenance approaches that can eventually support AI-driven decision-making. Rather than adhering to static maintenance schedules, it should employ machine learning algorithms that continuously analyze historical failure trends, operational stressors, and real-time system performance. This data-driven approach enables naval planners to optimize repair schedules and sustain fleet operations more efficiently.

A key advancement in this transformation is AI-powered readiness forecasting. By evaluating past failures and assessing the impact of mission demands on system longevity, ORSM can anticipate maintenance needs before breakdowns occur. This predictive capability allows decision-makers to address issues preemptively, reducing costs and preventing operational disruptions.

Additionally, transitioning from fixed maintenance intervals to condition-based servicing is essential. Maintenance actions should be triggered by real-time equipment degradation detected through onboard sensors and performance analytics, ensuring timely interventions while extending system lifespan.

Another critical upgrade involves digital twin modeling. Virtual replicas of naval vessels can simulate real-time conditions, allowing engineers to test maintenance strategies before implementation. These simulations provide valuable insights into system wear, component failures, and optimal intervention points, ultimately strengthening long-term fleet sustainability (Madusanka et al., 2023).

2. Integrating ORSM with Logistics and Supply Chain Systems

A fleet's ability to sustain operations depends not only on the capability of its vessels but also on the strength of its logistics and supply chain. Even the most advanced warship is ineffective without timely access to spare parts, fuel, and mission-critical equipment. To maintain readiness, ORSM must integrate seamlessly with logistics and inventory systems, enabling a real-time, data-driven sustainment strategy.

One way to enhance fleet sustainment is automated inventory monitoring. AI-powered inventory management (Pournader et al., 2020) allows ORSM to track spare parts usage, identify equipment failure trends, and anticipate maintenance needs. Predictive analytics can automate procurement, ensuring essential supplies are pre-positioned before shortages occur, reducing downtime and operational disruptions.

Furthermore, ORSM should incorporate supply chain risk assessment to detect potential disruptions before they affect fleet operations. By analyzing global supply chain trends, vendor stability, and geopolitical risks (Christopher & Peck, 2004), ORSM can issue early warnings about potential shortages, allowing planners to adapt procurement strategies and secure alternative sources. This proactive logistics approach ensures continuous fleet sustainment, even in dynamic operational environments.

3. Integrating ORSM with Risk Assessment and Threat Mitigation

To maximize its impact, ORSM should extend beyond traditional readiness assessments by embedding within advanced operational frameworks, predictive analytics, and risk management systems. Aligning ORSM with AI-driven risk assessment models enhances force distribution, predictive maintenance cycles, and real-time threat intelligence, ensuring a proactive approach to fleet readiness and decision-making.

Future developments should focus on multinational interoperability, digital twin technology, and unmanned systems analytics. Strengthening ORSM's collaboration with allied forces and strategic partners will enhance joint operations, intelligence sharing, and fleet coordination, reinforcing naval readiness in an unpredictable security environment.

4. Leveraging AI for Strategic Decision Support

ORSM should be integrated into AI-driven decision-support systems, enabling naval commanders to make data-informed strategic decisions with greater accuracy and efficiency. By combining ORSM's readiness assessments with advanced AI models, fleet planners can enhance mission planning, force deployment, and resource distribution, ensuring naval operations remain adaptable to evolving threats and logistical challenges.

By incorporating ORSM-generated readiness data into AI-powered command support tools, naval leaders can receive real-time recommendations for fleet management, mission assignments, and risk mitigation. These systems analyze historical trends, current readiness levels, and operational requirements to identify the most effective courses of action, ensuring optimal force utilization even in complex, dynamic environments.

5. Strengthening Operational Planning with ORSM Data

To fully realize ORSM's potential, it should be embedded into operational planning, ensuring that fleet deployments and resource distribution are both strategic and efficient. By integrating real-time readiness data into mission planning systems, naval commanders can enhance decision-making, optimizing force deployment while mitigating operational risks.

A key application of ORSM in mission planning is readiness-based deployment. Rather than relying on traditional availability metrics, vessel assignments would be determined by actual operational capability. This ensures that the most mission-capable ships are prioritized for high-risk or critical operations, while those requiring maintenance or resupply can be allocated to support roles or lower-intensity missions.

Additionally, ORSM strengthens risk-adjusted mission planning by integrating readiness data with intelligence reports and threat assessments. If vulnerabilities are detected in a ship's systems, ORSM can recommend alternative routes, revised engagement strategies, or reassignment to minimize risks and enhance mission success.

6. Adapting ORSM for Future Naval Modernization

As naval forces continue to modernize, ORSM should be adapted to integrate emerging technologies, evolving assets, and new threat landscapes. To remain effective, its scope should extend beyond traditional readiness metrics, encompassing cyber resilience and autonomous systems for a more comprehensive assessment of fleet capabilities.

A key area for future development is cyber resilience integration. With naval operations increasingly dependent on networked systems and digital infrastructure, cyber threats present a major risk to readiness. ORSM should incorporate electronic warfare (EW) and cybersecurity vulnerability assessments to gauge a vessel's ability to withstand cyberattacks and electronic disruptions (Richardson, 2025). Embedding cybersecurity metrics into ORSM enables commanders to evaluate the digital security of their fleet, ensuring compromised systems do not jeopardize mission success.

Another crucial enhancement is unmanned systems integration. As the naval force increasingly relies on USVs and AUVs for reconnaissance, mine countermeasures, and logistics, ORSM must evolve to assess their operational effectiveness, maintenance demands, and mission endurance. Incorporating these autonomous assets into readiness evaluations will provide a more complete and adaptive fleet readiness framework (Richardson, 2025).

7. Enhancing Training and Decision-Making through ORSM

a. War-Gaming and Decision Support Applications

To maximize ORSM's effectiveness, it should be fully integrated into naval training programs and war-gaming simulations. These readiness-based simulations immerse naval officers in high-pressure operational environments that replicate real-world constraints, such as logistics delays, equipment failures, and varying mission-specific readiness scores. This hands-on training approach helps commanders strengthen their strategic thinking, crisis response, and resource allocation skills. War-gaming with ORSM-based inputs allows leaders to simulate mission outcomes using realistic readiness data, improving the quality of operational planning and mission execution.

Incorporating ORSM into war-gaming also provides an opportunity for naval leadership to evaluate force distribution, test contingency strategies, and validate command decisions against probabilistic readiness forecasts. This integration ensures that decision-makers are equipped not only to respond to current operational conditions but also to anticipate and mitigate future risks through readiness-informed planning.

b. Integrating Manpower Qualification into Readiness-Based Training

Beyond simulating platform readiness, ORSM should account for the human element of mission success. Operational readiness depends equally on a ship's systems and the qualifications of its crew. To address this, ORSM should integrate a Crew Readiness Index, a metric that reflects personnel qualifications, recent training completion, operational experience, and physical or mental fitness. This concept aligns with the U.S. Navy's Ready Relevant Learning initiative, which emphasizes ongoing, tailored training to ensure sailors have the right skills at the right time (Naval Education and Training Command, n.d.).

Further, the RAND Corporation highlights how analyzing readiness and training data helps identify recurring human-error trends and qualification gaps (RAND Corporation, n.d.). Using ORSM data in this way allows naval leadership to design focused, competency-based training interventions. Likewise, NATO's education, training, exercise, and evaluation policy emphasizes the importance of continuous assessment to sustain personnel readiness across multinational operations (Pînzariu & Pînzariu, 2024).

Integrating personnel readiness metrics into ORSM ensures that training programs remain targeted, up-to-date, and responsive to real-world mission needs. It allows for a more comprehensive readiness model that aligns crew training cycles with mission demands, reducing operational risk while improving decision-making and fleet performance.

8. Expanding ORSM for Multinational Interoperability

To maximize its strategic value, ORSM should be adapted for interoperability with allied naval forces, ensuring readiness assessments align with coalition operational standards. The NATO Defense Planning Process and OCC E&F program focus on multinational readiness alignment, making ORSM a potential integration model for interoperability with allied fleets (NATO, 2025; NATO Allied Land Command, n.d.).

Collaboration between the Egyptian Navy and its partners would benefit from an upgraded ORSM-based readiness framework, integrating seamlessly with allied standards. Aligning readiness assessments across partner navies would enhance standardized mission planning, fleet coordination, and logistical support.

Beyond operational decision-making, AI-driven analysis of fleet readiness trends, equipment life cycles, and projected maintenance needs can provide acquisition teams with valuable insights, ensuring defense investments align with fleet sustainability and operational priorities. This data-centric approach enables naval leadership to modernize capabilities efficiently, allocate resources effectively, and prevent costly procurement inefficiencies.

By integrating ORSM with predictive analytics, logistics, multinational cooperation, and advanced training, naval forces can adopt a more intelligence-driven and adaptable readiness model. This transformation enables commanders to anticipate challenges, optimize sustainment planning, and improve fleet efficiency.

VI. CONCLUSION AND FUTURE RESEARCH

The results of the simulation highlight the ORSM as a transformative approach to assessing fleet readiness and mission capability. Unlike the traditional legacy method, which oversimplifies operational status, ORSM provides a granular, data-driven evaluation, enabling commanders to recognize partial readiness and optimize fleet deployment. By capturing the true operational potential of each vessel, ORSM ensures that even ships with limited functionality contribute effectively to naval missions.

This chapter consolidates key findings from the simulation, demonstrating how ORSM enhances fleet efficiency, mission success rates, and resource allocation by offering a more adaptive and data-driven readiness assessment framework. Additionally, it examines the model's practical applications for the Egyptian Navy, focusing on maintenance prioritization, mission planning, and long-term fleet sustainability. While ORSM presents clear operational advantages, its implementation introduces logistical and financial challenges that require careful management.

A. ENHANCING FLEET MANAGEMENT AND MISSION ADAPTABILITY WITH ORSM

The ORSM model enhances fleet management and operational effectiveness by providing comprehensive readiness scores that guide mission planning and resource allocation. Unlike the binary system, which often sidelines partially-ready ships, ORSM aligns with modern readiness frameworks such as the U.S. DoD's DRRS and NATO's OCC E&F program, ensuring that resources are deployed efficiently across mission-based categories (NATO Allied Land Command, n.d.; DOT&E, 2013). This approach aligns fleet management with real-world mission demands, increasing operational flexibility and strategic efficiency. Moreover, ORSM allows for the deployment of partially ready vessels in lower-risk or support missions such as patrols, humanitarian efforts, and logistical operations, while preserving high-readiness assets for critical engagements.

In high-stakes scenarios, such as regional conflicts, anti-piracy missions, and disaster response, ORSM ensures that partially-operational ships can still contribute effectively, avoiding fleet underutilization. In a regional crisis demanding swift naval mobilization, ORSM enables the efficient deployment of support and reconnaissance vessels, while ensuring that combat-ready ships remain prioritized for high-intensity engagements. This mission-based approach enhances overall fleet resilience and operational adaptability.

B. IMPLEMENTATION CHALLENGES AND STRATEGIC CONSIDERATIONS

While ORSM significantly enhances fleet readiness and operational efficiency, its successful implementation requires addressing key challenges, including financial constraints, supply chain risks, infrastructure development, and operational disruptions.

1. Financial and Logistical Investments

Integrating predictive maintenance and system upgrades demands substantial financial investments in advanced technologies, specialized training, and contractor support. To ensure that these enhancements provide long-term strategic value, it is crucial to implement cost-effective solutions that align with modern defense budget constraints and sustainment needs (GAO, 2023).

A cost-effective strategy involves leveraging domestic industrial capabilities, which reduces reliance on foreign suppliers while strengthening local defense sector resilience. By developing local partnerships for maintenance, upgrades, and technology transfers, the Egyptian Navy can gradually reduce reliance on foreign suppliers, making ORSM implementation more financially sustainable. Additionally, collaborative agreements with allied navies could allow for joint maintenance programs and technology-sharing, further offsetting operational costs

2. Supply Chain Constraints and Spare Parts Availability

Maintaining a steady supply of critical spare parts is a fundamental challenge, particularly for components sourced from foreign suppliers, where dependencies introduce vulnerabilities to supply chain disruptions. Procurement delays, fluctuating availability, and geopolitical risks further complicate fleet readiness, necessitating the adoption of strategic sourcing solutions, supplier diversification, and localized manufacturing partnerships to mitigate these risks (Christopher & Peck, 2004).

The establishment of regional logistics hubs plays a crucial role in enhancing supply chain resilience by expediting the procurement of essential components and minimizing dependency on external suppliers. Additionally, the integration of AI-driven predictive logistics systems allows for proactive inventory management by forecasting potential shortages, thereby ensuring continuous operational readiness These measures collectively strengthen the supply chain framework, optimizing fleet sustainment while reducing the risks associated with procurement uncertainties (Pournader et al., 2020).

3. Infrastructure and Inventory Management

Ensuring fleet readiness requires significant investment in infrastructure, including expanding inventory capacity, upgrading storage facilities, and employing skilled personnel to manage increasing logistical demands. For naval forces such as the Egyptian Navy, which often face delays in spare parts availability due to reliance on foreign manufacturers, establishing regional logistics hubs is an effective strategy to streamline supply chains and enhance fleet sustainability (Stewart, 2021). The U.S. Navy's implementation of the Naval Aviation Distributed Asset Visibility system demonstrates how improving asset visibility and integrating advanced logistics systems can optimize mission readiness and operational effectiveness.

Developing optimized inventory management systems is crucial for controlling stock levels efficiently, reducing shortages, and maintaining a steady flow of critical components, thereby reinforcing operational resilience. Integrating these systems with readiness assessment frameworks allows maintenance schedules to align with real-time operational demands, preventing supply bottlenecks before they disrupt fleet operations.

4. Operational Disruptions from System Upgrades

Implementing fleet-wide system upgrades and maintenance initiatives can lead to temporary reductions in fleet availability as vessels undergo installation, testing, and integration processes. To mitigate these disruptions, adopting a phased implementation strategy is essential. This approach involves rolling out upgrades incrementally across vessel classes, allowing for adjustments based on feedback and minimizing operational risks. By prioritizing ships with the highest operational demand for early upgrades, critical mission capabilities remain uninterrupted during the transition process. This method ensures a seamless modernization process, maintaining operational availability while effectively managing potential disruptions (Stiffler & Wells, 2024).

Additionally, designing systems with modular architecture enables software updates to be conducted during deployments without interrupting operations. This approach allows naval forces to adapt to emerging threats by deploying the latest algorithms and technologies seamlessly, much like how cloud service providers update systems without user disruption (Richardson, 2025).

By implementing these strategies, naval forces can achieve a balance between modernization and readiness, as demonstrated by recent naval sustainment initiatives within U.S. and allied forces.

5. Resistance to Change and Training Requirements

A potential barrier to ORSM adoption is the resistance from naval personnel and leadership accustomed to the traditional legacy method. Successfully transitioning to a mission-based readiness model requires a gradual shift in training, decision-making, and fleet management protocols. One motivator to change is for those ships who quickly adopt a realistic assessment under ORSM will receive more effective maintenance and logistics support.

A structured implementation plan, integrating ORSM into existing command structures via pilot programs and training exercises, will ensure a seamless transition and foster operational confidence in the system. Comprehensive hands-on training for fleet commanders and decision-makers will foster confidence in ORSM, ensuring a smooth transition and effective integration within existing naval workflows (Rosen, 1994).

While addressing current implementation challenges is crucial, the long-term success of ORSM depends on continuous enhancements, including the integration of predictive analytics, multinational interoperability, and logistics optimization. These opportunities, detailed in the "Operational Insights and Actionable Recommendations" chapter, will further strengthen ORSM's adaptability and strategic impact.

C. FUTURE RESEARCH DIRECTIONS FOR ORSM ENHANCEMENT

Future research should focus on refining ORSM's capabilities and expanding its integration within naval decision-making. Key areas for development include:

1. Standardizing Readiness Metrics and Risk Management

To enhance the accuracy and applicability of ORSM, a standardized readiness metric system should be developed to ensure that readiness assessments reflect real-time operational conditions. One critical aspect of this improvement is establishing standardized weighting mechanisms, allowing readiness scores to dynamically adjust based on ship system status, environmental conditions, and mission-specific demands. Instead of a static evaluation, these metrics would provide a more adaptable representation of a vessel's actual operational capability, aiding naval commanders in informed deployment and resource allocation decisions.

As modern warfare increasingly depends on cyber and EW capabilities, integrating cyber resilience metrics into readiness assessments is essential. ORSM should incorporate cybersecurity threats, EW disruptions, and system vulnerabilities to provide naval commanders with a comprehensive understanding of both physical and digital operational risks. By embedding cyber resilience into readiness assessments, naval forces can proactively identify vulnerabilities, implement defensive strategies, and improve overall fleet survivability.

Additionally, ORSM should be integrated into a readiness-based risk management framework that aligns readiness assessments with operational, maintenance, and mission-related risks. This integration would enable naval forces to proactively identify vulnerabilities, prioritize resources, and adjust deployment strategies to mitigate potential threats before they impact operations. A key enhancement would be linking ORSM with real-time threat intelligence, environmental hazard monitoring, and mission complexity assessments to anticipate external risks, such as geopolitical threats and extreme weather conditions. Furthermore, developing AI-driven risk mitigation strategies that align ORSM recommendations with fleet sustainment efforts and strategic contingency planning would provide automated, adaptive solutions for risk management.

2. Predictive Maintenance and Digital Twin Integration

To maximize fleet sustainability and operational efficiency, ORSM should integrate advanced predictive maintenance and digital twin technology. AI-driven predictive maintenance models can enhance ORSM's ability to anticipate system failures before they occur, reducing unexpected downtime and ensuring vessels remain mission-ready. These models analyze historical performance data, operational stress factors, and real-time sensor inputs to detect early warning signs of component degradation, allowing maintenance teams to address issues proactively rather than reactively.

Digital twin simulations can further enhance readiness by creating virtual representations of fleet assets, replicating their structural, mechanical, and performance characteristics. By integrating ORSM into these simulations, naval planners can dynamically predict fleet readiness under various operational conditions, anticipate potential vulnerabilities, and proactively adjust operational strategies. Beyond immediate readiness assessments, digital twin simulations can support long-term force structure optimization by analyzing readiness fluctuations over extended deployments and multiple operational scenarios. This approach allows decision-makers to evaluate how maintenance strategies, resource allocation, and mission tempo impact overall fleet sustainability.

Incorporating machine learning algorithms into ORSM's framework further refines its predictive capabilities. These algorithms can continuously learn from past maintenance records, failure trends, and operational conditions, improving the accuracy of failure predictions over time. This enables naval forces to optimize maintenance schedules, reduce unnecessary repairs, and allocate resources more efficiently, ensuring ships receive maintenance only when needed rather than adhering to rigid maintenance cycles.

3. AI-Driven War-Gaming and Training for Readiness Optimization

To enhance strategic decision-making and operational preparedness, ORSM should be incorporated into AI-driven war-gaming simulations, enabling naval forces to test force deployment strategies under realistic readiness constraints. By simulating various operational scenarios, commanders can evaluate how different fleet compositions, resource allocations, and mission strategies affect overall combat effectiveness. These AI-powered simulations allow for real-time adaptability, enabling naval leaders to refine their tactical approaches based on evolving mission dynamics and readiness fluctuations.

In addition to strategic planning, ORSM integration into readiness-based training exercises will significantly improve decision-making efficiency and risk mitigation. Training programs that reflect actual fleet readiness levels will provide officers with a more realistic operational environment, preparing them to make critical decisions under pressure. These exercises can help personnel develop adaptive thinking, crisis management skills, and resource optimization strategies, ensuring they are fully equipped to handle the complexities of modern naval warfare. By leveraging ORSM in both war-gaming and training, naval forces can cultivate a data-driven, readiness-focused approach to mission execution, ultimately enhancing combat readiness and operational effectiveness.

D. CONCLUSION

As ORSM continues to evolve, its integration with emerging technologies, supply chain systems, and multinational readiness frameworks will further enhance its strategic value. By providing a precise, adaptable, and mission-oriented framework, ORSM enables comprehensive fleet readiness assessments, aligning naval operations with real-world mission demands.

For the Egyptian Navy, adopting ORSM marks a strategic transformation, aligning readiness assessments with global best practices and improving interoperability with allied navies. This shift reduces reliance on foreign suppliers, enhances fleet resilience, and supports data-driven, mission-based decision-making. However, sustained effectiveness will require further research on ORSM's long-term impact on resource allocation, mission planning efficiency, and operational sustainability in a rapidly changing security environment.

By optimizing fleet sustainment, enhancing mission success rates, and strengthening rapid response capabilities, ORSM ensures long-term naval effectiveness despite resource constraints and global supply chain challenges. Its mission-based framework supports a systematic approach to aging fleet management, ensuring legacy vessels remain operationally viable or are strategically reassigned rather than prematurely decommissioned. This holistic approach reinforces fleet sustainability and aligns with evolving defense priorities in a dynamic maritime landscape.

APPENDIX A. SIMULATION AND SIMULATION OUTCOMES

Figure 6. A Screenshot of the Simulation Main Page

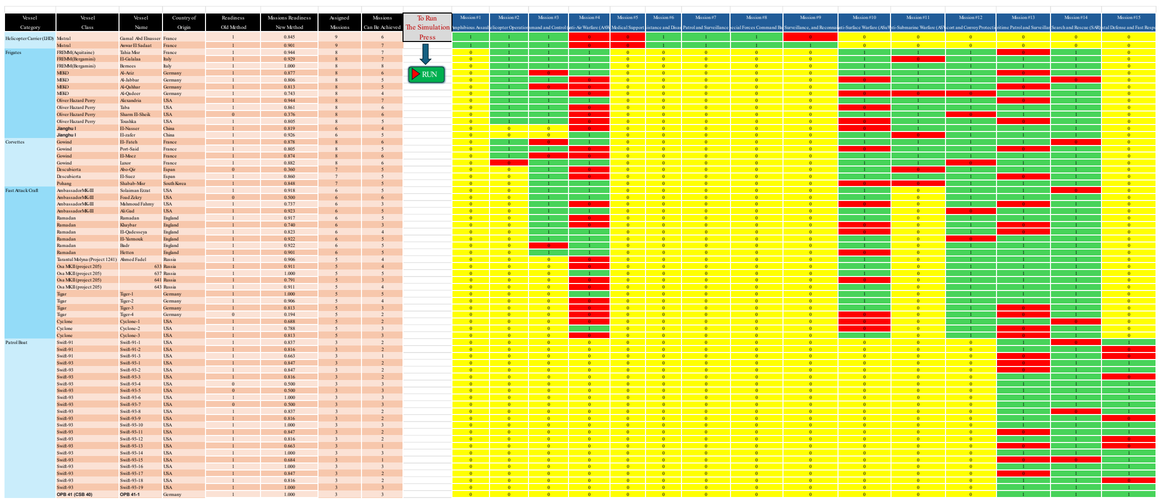

Figure 7. A Screenshot of the Simulation Page of Missions and Missions' Area Assigned for Each Ship

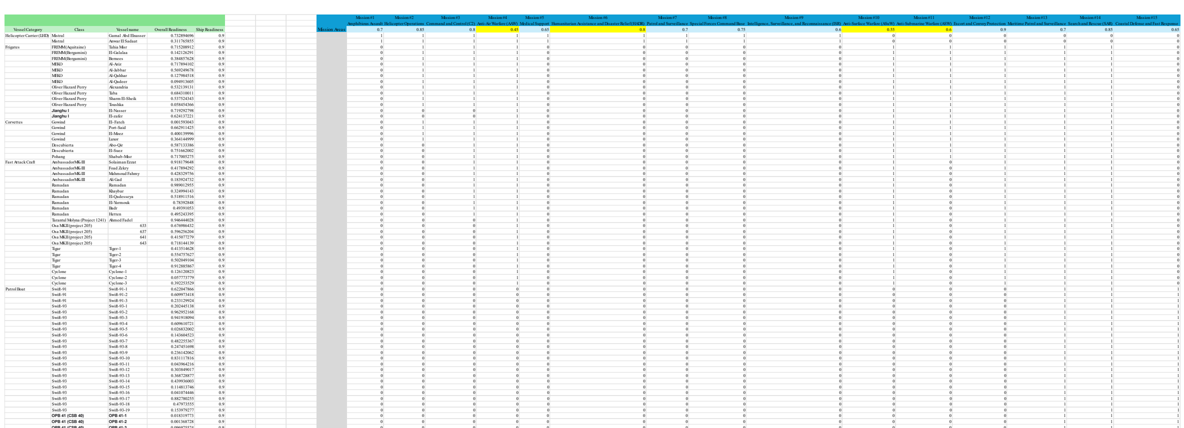

Figure 8. A Screenshot of the Simulation Page of Mission's Weights for Each Ship

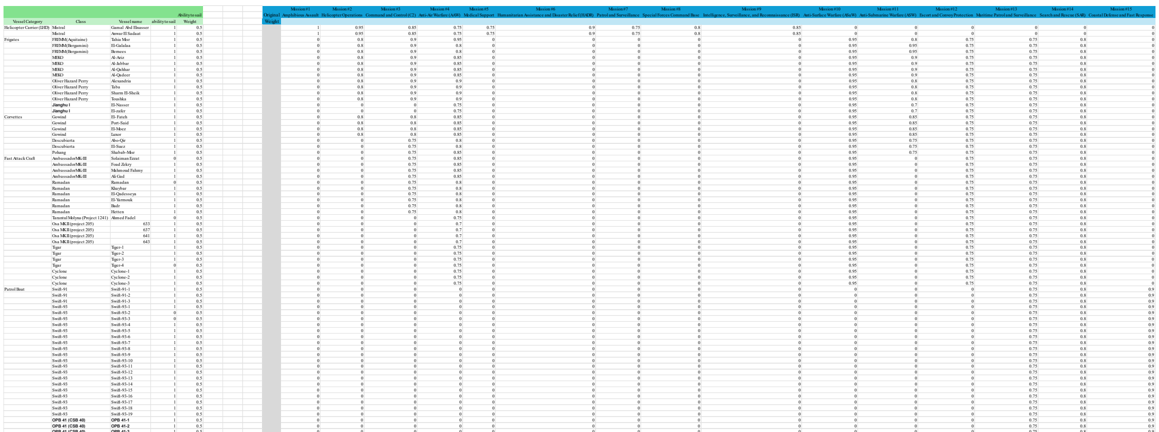

Figure 9. A Screenshot of the Simulation Page of Mission's Adjusted Weighted Values for Each Ship

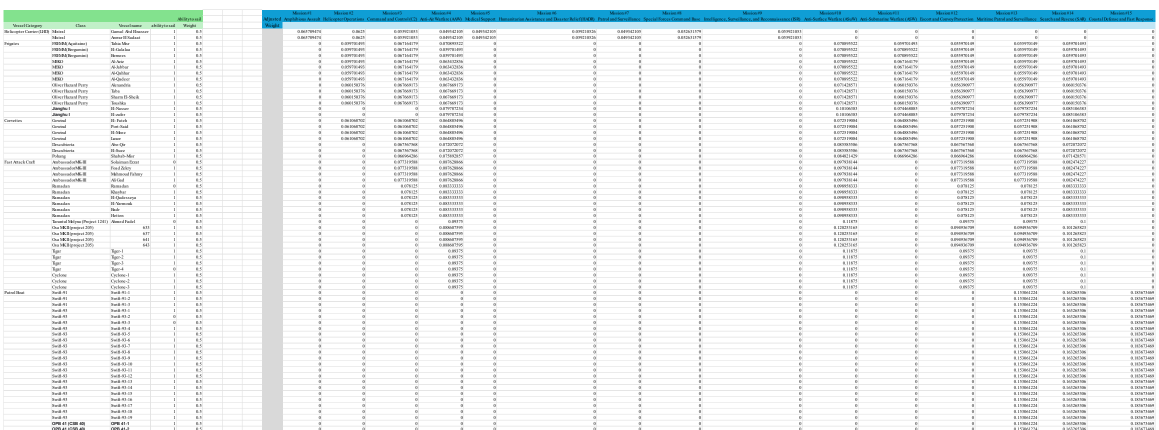

Figure 10. Sample of Simulation Outcomes Using Excel Random Number Generated for Ship Number 4 (20 Iterations)

Trial Number	Readiness - Old Method	Readiness - New Method	Assigned Missions	Missions Achieved	Mission #Mission #3 - Command and Control (C2)	Mission #Mission #4 - Anti-Air Warfare (AAW)	Mission #Mission #10 - Anti-Surface Warfare (ASuW)	Mission #Mission #12 - Escort and Convoy Protection	Mission #Mission #13 - Maritime Patrol and Surveillance	Mission #Mission #14 - Search and Rescue (SAR)
1	1	1	6	6	1	1	1	1	1	1
2	1	1	6	6	1	1	1	1	1	1
3	1	0.74742268	6	3	1	1	0	1	0	0
4	1	0.845360825	6	4	1	0	1	0	1	1
5	1	0.81443299	6	4	1	1	0	1	1	0
6	1	1	6	6	1	1	1	1	1	1
7	1	0.74742268	6	3	0	1	0	1	0	1
8	1	0.922680412	6	5	1	1	1	0	1	1
9	1	0.912371134	6	5	1	0	1	1	1	1
10	1	0.835051546	6	4	0	1	1	1	0	1
11	0	0.335051546	6	4	1	1	0	0	1	1
12	1	1	6	6	1	1	1	1	1	1
13	1	0.902061856	6	5	1	1	0	1	1	1
14	1	0.81443299	6	4	1	0	1	0	1	1
15	1	0.912371134	6	5	1	1	1	1	0	1
16	1	0.731958763	6	3	1	0	1	0	1	0
17	1	0.731958763	6	3	0	0	0	1	1	1
18	1	0.81443299	6	4	0	1	0	1	1	1
19	1	0.737113402	6	3	0	1	0	1	0	1
20	1	0.81443299	6	4	0	1	1	1	1	0

Figure 11. Sample of Simulation Outcomes Using R Programing Random Number Generated (the Mersenne Twister Algorithm) for Ship Number 4 (20 Iterations)

Vessel name	Mission #3	Mission #4	Mission #1	Mission #1	Mission #1	Mission #1	adjusted factor	Ability to sail Weight	ship readiness	random fo	random fo	random fo	random fo	random fo	random fo	random for		weighted	weighted	weighted	weighted	weighted	weighted			
	0.8	0.45	0.55	0.9	0.7	0.85				M1	M2	M3	M4	M5	M6	Legacy		M1	M2	M3	M4	M5	M6	trial numbe	Legacu Me	ORSM
Foad Zekry	0.07732	0.087629	0.097938	0.07732	0.07732	0.082474	0.103092784	0.5	0.9	0.914806	0.848293	0.989966	0.273792	0.59893	0.731494	0.246463		0	0	0	0.07732	0.07732	0.082474	1	1	0.737113
										0.937075	0.062746	0.438494	0.944197	0.968948	0.560953	0.530305		0	0.087629	0.097938	0	0	0.082474	2	1	0.768041
										0.28614	0.819845	0.699903	0.445983	0.390535	0.498188	0.213972		0.07732	0	0	0.07732	0.07732	0.082474	3	1	0.814433
										0.830448	0.53936	0.889077	0.541787	0.852815	0.841059	0.025849		0	0	0	0.07732	0	0.082474	4	1	0.659794
										0.641746	0.49902	0.834159	0.161754	0.042288	0.463644	0.342002		0.07732	0	0	0.07732	0.07732	0.082474	5	1	0.814433
										0.519096	0.022227	0.734421	0.693054	0.424722	0.198911	0.394135		0.07732	0.087629	0	0.07732	0.07732	0.082474	6	1	0.902062
										0.736588	0.554093	0.646903	0.797274	0.022391	0.655407	0.125346		0.07732	0	0	0.07732	0.07732	0.082474	7	1	0.814433
										0.134667	0.719898	0.842878	0.773587	0.032071	0.987299	0.824416		0.07732	0	0	0.07732	0.07732	0	8	1	0.731959
										0.656992	0.235715	0.159641	0.213289	0.098212	0.722036	0.867738		0.07732	0.087629	0.097938	0.07732	0.07732	0.082474	9	1	1
										0.705065	0.81188	0.363706	0.203604	0.942798	0.024533	0.183973		0.07732	0	0.097938	0.07732	0	0.082474	10	1	0.835052
										0.457742	0.421474	0.275093	0.633247	0.642757	0.493267	0.189577		0.07732	0.087629	0.097938	0.07732	0.07732	0.082474	11	1	1
										0.719112	0.564911	0.124795	0.761008	0.146892	0.152134	0.292156		0.07732	0	0.097938	0.07732	0.07732	0.082474	12	1	0.912371
										0.934672	0.151691	0.565627	0.807967	0.439513	0.662284	0.899608		0	0.087629	0	0.07732	0.07732	0.082474	13	1	0.824742
										0.255429	0.194792	0.67324	0.828922	0.405225	0.027335	0.901442		0.07732	0.087629	0	0.07732	0.07732	0.082474	14	0	0.402062
										0.462293	0.166783	0.001703	0.118571	0.231446	0.788355	0.072935		0.07732	0.087629	0.097938	0.07732	0.07732	0.082474	15	1	1
										0.940015	0.83511	0.800921	0.281343	0.687441	0.023689	0.339036		0	0	0	0.07732	0.07732	0.082474	16	1	0.737113
										0.978226	0.111078	0.198243	0.846821	0.217115	0.751714	0.80017		0	0.087629	0.097938	0.07732	0.07732	0.082474	17	1	0.92268
										0.117487	0.26807	0.666745	0.108489	0.83104	0.219657	0.232373		0.07732	0.087629	0	0.07732	0	0.082474	18	1	0.824742
										0.474997	0.798481	0.787734	0.017497	0.709377	0.904845	0.273183		0.07732	0	0	0.07732	0	0	19	1	0.654639
										0.560333	0.298929	0.952181	0.413415	0.523202	0.059825	0.109112		0.07732	0.087629	0	0.07732	0.07732	0.082474	20	1	0.902062

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APPENDIX B. READINESS SCORE DISTRIBUTION (FOR THE EIGHT SHIPS)

Figure 12. Readiness Score Distribution for the 1st Ship

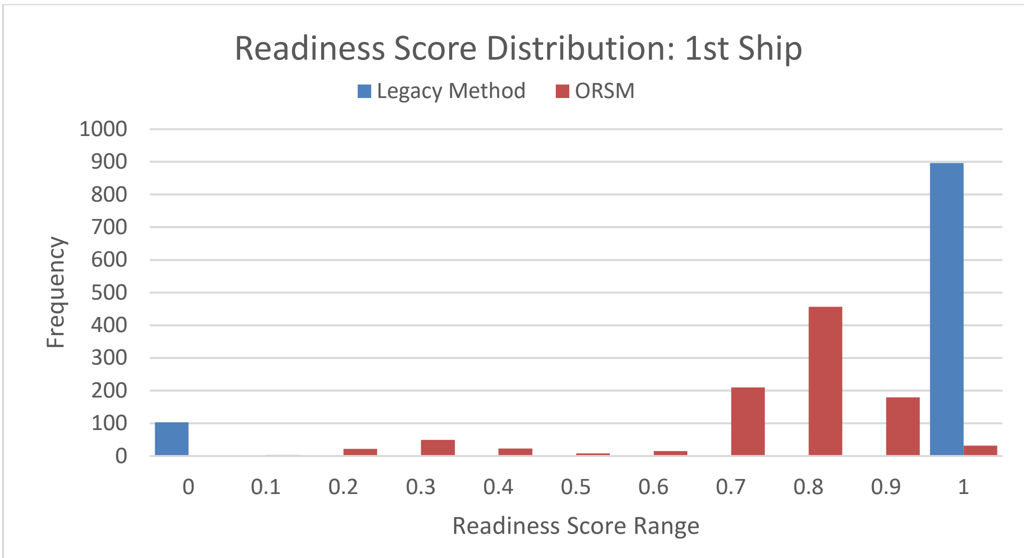

Figure 13. Readiness Score Distribution for the 2nd Ship

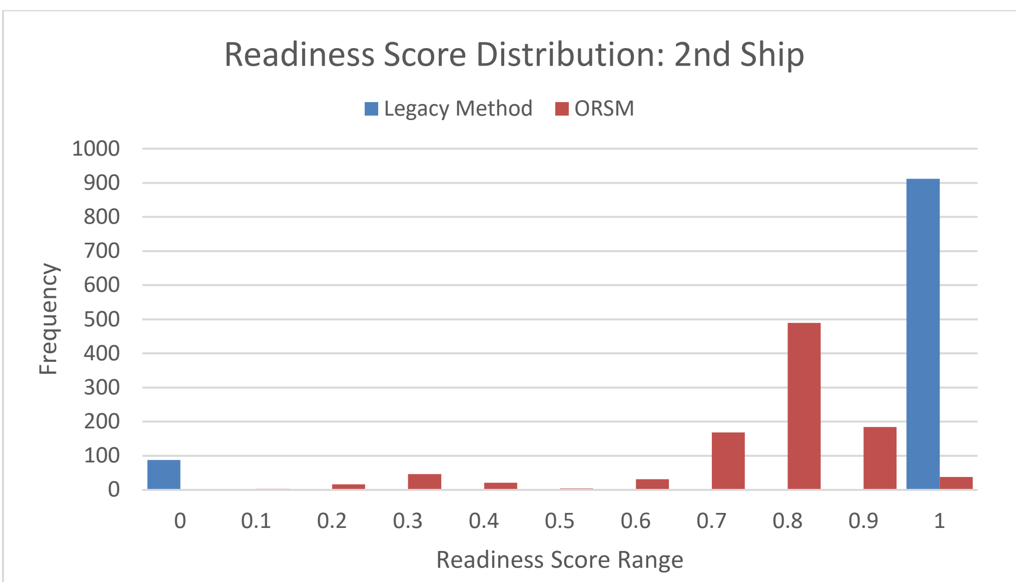

Figure 14. Readiness Score Distribution for the 3rd Ship

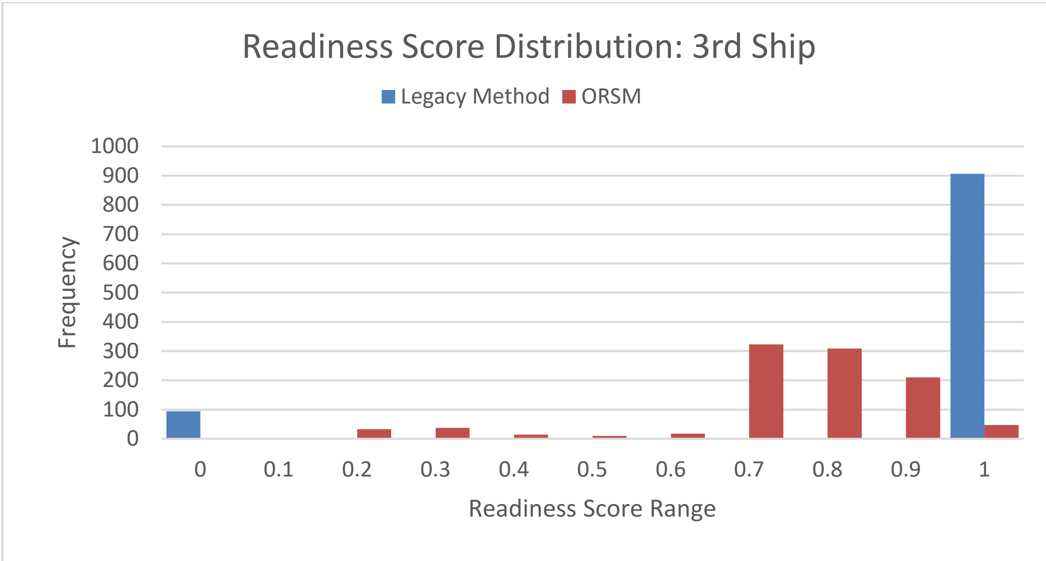

Figure 15. Readiness Score Distribution for the 4th Ship

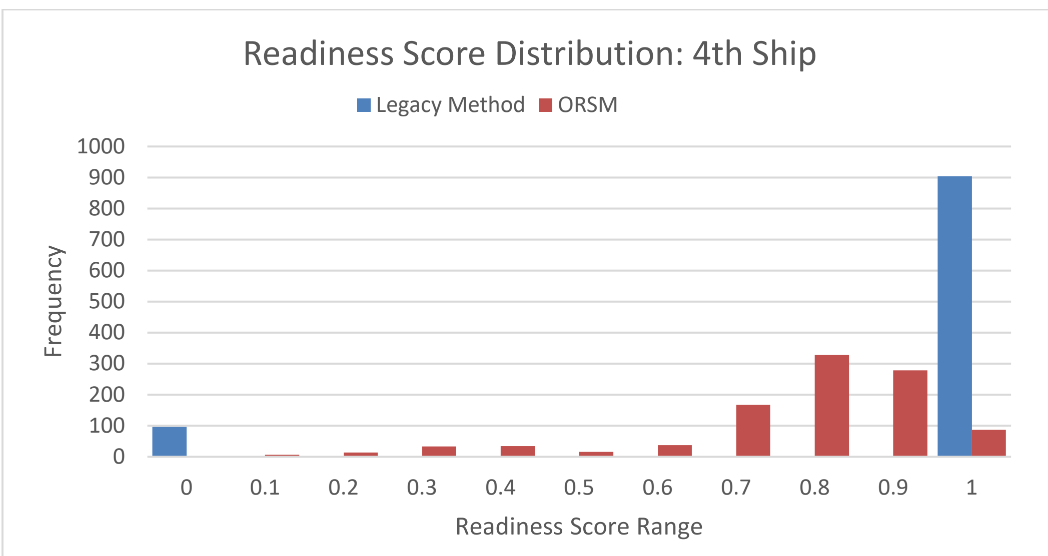

Figure 16. Readiness Score Distribution for the 5th Ship.

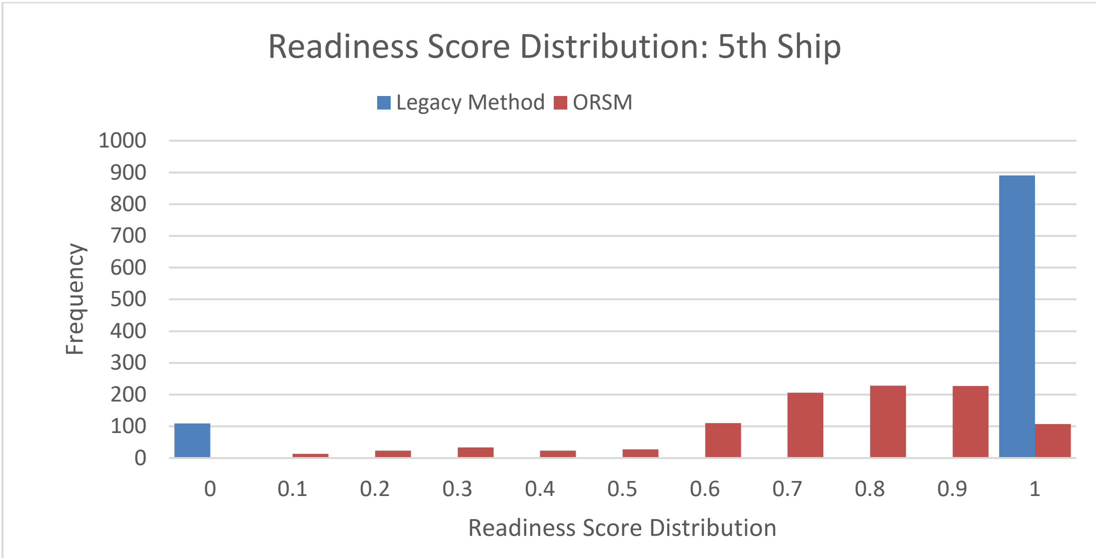

Figure 17. Readiness Score Distribution for the 6th Ship

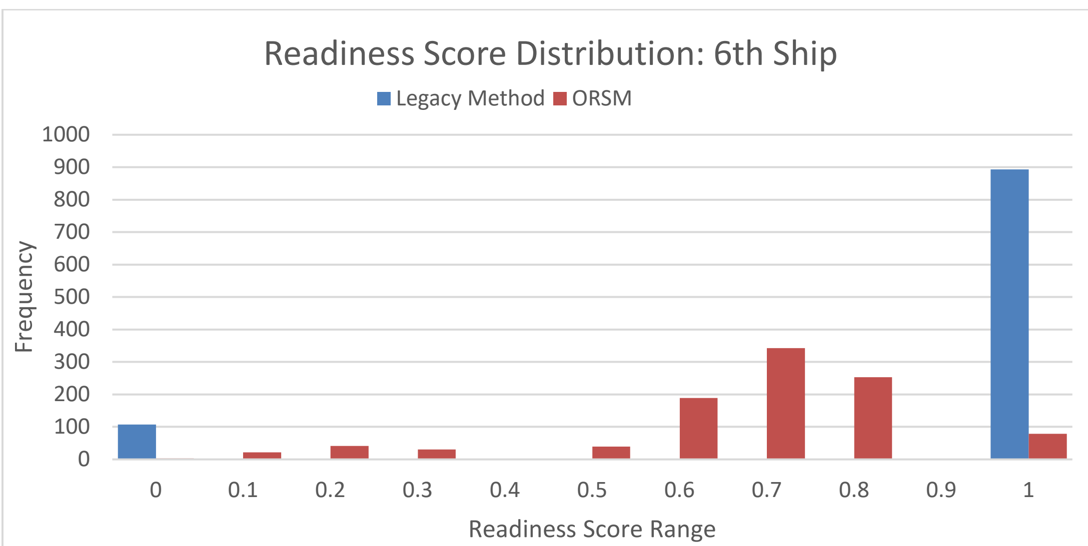

Figure 18. Readiness Score Distribution for the 7th Ship

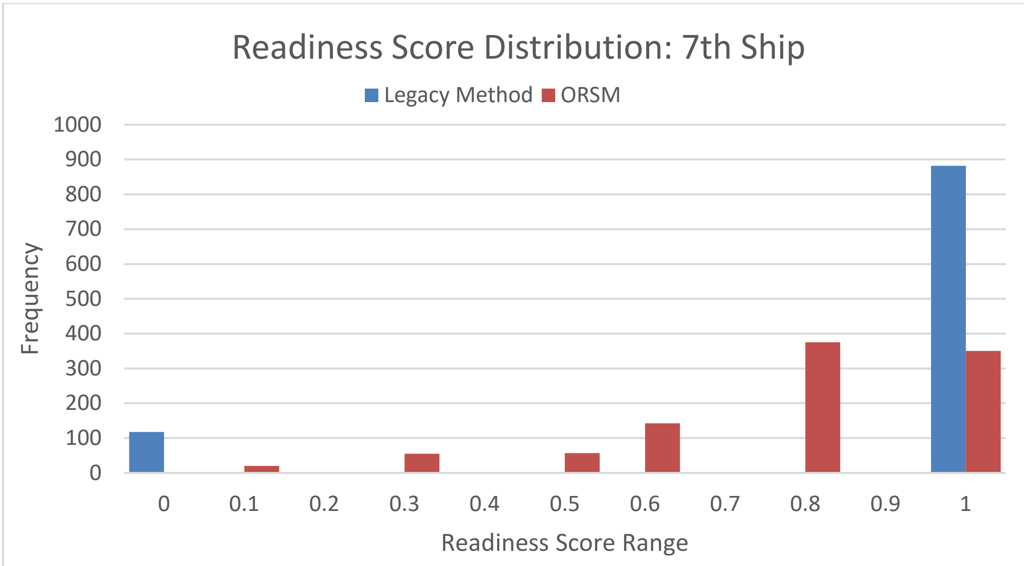

Figure 19. Readiness Score Distribution for the 8th Ship

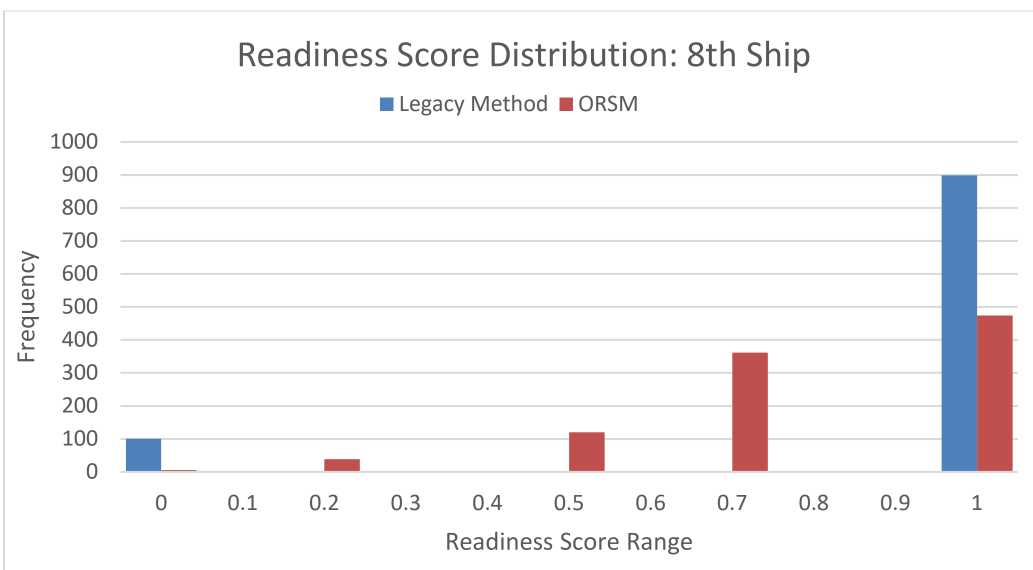

Table 2. Simulated 8-Ships Statistical Data Outcomes

Statistical Parameter	Assigned Missions	Mean		Median		Standard Deviation		Sample Variance		Kurtosis		Skewness		Unable to Sail
Ship		ORSM	Legacy	ORSM	Legacy	ORSM	Legacy	ORSM	Legacy	ORSM	Legacy	ORSM	Legacy	
1st Ship	9	0.802	0.897	0.8421	1	0.167	0.304	0.0279	0.0925	3.2521	4.8538	−1.9381	−2.6161	103
2nd Ship	8	0.806	0.912	0.8619	1	0.160	0.283	0.0256	0.0803	3.9566	6.4986	−2.0436	−2.9130	88
3rd Ship	7	0.794	0.906	0.8423	1	0.166	0.292	0.0276	0.0852	3.2324	5.7769	−1.8485	−2.7866	94
4th Ship	6	0.798	0.904	0.8299	1	0.170	0.295	0.0290	0.0869	2.9610	5.5566	−1.7525	−2.7469	96
5th Ship	5	0.786	0.891	0.8125	1	0.183	0.312	0.0335	0.0972	2.1642	4.3242	−1.5666	−2.5131	109
6th Ship	4	0.722	0.893	0.75	1	0.196	0.309	0.0384	0.0956	1.6185	4.4940	−1.2339	−2.5466	107
7th Ship	3	0.806	0.882	0.8367	1	0.207	0.323	0.0430	0.1042	1.1630	3.6325	−1.2522	−2.3718	118
8th Ship	2	0.815	0.899	0.7576	1	0.214	0.301	0.0459	0.0909	0.9643	5.0445	−1.1319	−2.6523	101

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APPENDIX C. CODE

A. Microsoft Excel VBA Script for the Simulation

```
Sub RunSimulationWithEquations()
  Dim wsData As Worksheet, wsOutput As Worksheet, wsMissions As Worksheet
  Dim selectedVesselRow As Long
  Dim trialCount As Long
  Dim oldMethod As Double, newMethod As Double
  Dim assignedMissions As Double, achievedMissions As Double
  Dim i As Long, col As Long, outputCol As Long
  Dim baseName As String
  Dim sheetIndex As Integer

  ‘ Step 1: Set the source worksheets
  On Error Resume Next
  Set wsData = ThisWorkbook.Sheets(“Vessels-Readiness”)
  Set wsMissions = ThisWorkbook.Sheets(“Vessels-Missions”)
  On Error GoTo 0

  ‘ Check if the source worksheets exist
  If wsData Is Nothing Or wsMissions Is Nothing Then
      MsgBox “Required sheets (‘Vessels-Readiness’ or ‘Vessels-Missions’) not found.
Please check the sheet names.,” vbCritical
      Exit Sub
  End If

  ‘ Step 2: Prompt the user to select a vessel row
  selectedVesselRow = Application.InputBox(“Enter the row number of the chosen vessel
(excluding header):,” _
                                   “Select Vessel,” Type:=1)

  ‘ Validate the row input
  If selectedVesselRow <= 3 Or selectedVesselRow > wsData.Cells(wsData.Rows.Count,
1).End(xlUp).Row Then
      MsgBox “Invalid row number selected.,” vbCritical
      Exit Sub
  End If
```

‘ Step 3: Prompt the user for the number of trials
trialCount = Application.InputBox(“Enter the number of trials to run:,” “Number of Trials,” Type:=1)

‘ Validate the trial count input
If trialCount <= 0 Then
    MsgBox “Invalid number of trials entered.,” vbCritical
    Exit Sub
End If

‘ Step 4: Create a unique results sheet
baseName = “Simulation Results”
sheetIndex = 1

Do While WorksheetExists(baseName & IIf(sheetIndex = 1, “,” “ “ & sheetIndex))
    sheetIndex = sheetIndex + 1
Loop

‘ Create the results sheet
Set wsOutput = ThisWorkbook.Sheets.Add
wsOutput.Name = baseName & IIf(sheetIndex = 1, “,” “ “ & sheetIndex)

‘ Add headers for general simulation information
wsOutput.Cells(1, 1).Value = “Trial Number”
wsOutput.Cells(1, 2).Value = “Readiness – Old Method”
wsOutput.Cells(1, 3).Value = “Readiness – New Method”
wsOutput.Cells(1, 4).Value = “Assigned Missions”
wsOutput.Cells(1, 5).Value = “Missions Achieved”

‘ Step 5: Identify assigned missions and add headers dynamically
outputCol = 6 ‘ Start outputting from column F (6th column)

For col = 10 To 47 ‘ Columns J to AU (numerical index 7 to 44)
    If wsMissions.Cells(selectedVesselRow, col).Value = 1 Then ‘ Check if mission is assigned
        ‘ Combine “Mission #” from row 1 and mission name from row 2 in “Vessels-Missions”

```
        wsOutput.Cells(1, outputCol).Value = "Mission #" & wsMissions.Cells(1,
col).Value & " – " & wsMissions.Cells(2, col).Value
        outputCol = outputCol + 1 ' Move to the next output column
      End If
  Next col

  ' Step 6: Run the simulation by recalculating equations
  For i = 1 To trialCount
      ' Simulate recalculation logic for Old Method and New Method
      oldMethod = wsData.Cells(selectedVesselRow, 5).Value ' Column E: Old Method
      newMethod = wsData.Cells(selectedVesselRow, 6).Value ' Column F: New Method

      ' Get assigned and achieved missions
      assignedMissions = wsData.Cells(selectedVesselRow, 7).Value ' Column G:
Assigned Missions
      achievedMissions = wsData.Cells(selectedVesselRow, 8).Value ' Column H:
Missions Achieved

      ' Output general simulation information
      wsOutput.Cells(i + 1, 1).Value = i ' Trial number
      wsOutput.Cells(i + 1, 2).Value = oldMethod ' Recalculated Old Method
      wsOutput.Cells(i + 1, 3).Value = newMethod ' Recalculated New Method
      wsOutput.Cells(i + 1, 4).Value = assignedMissions ' Assigned Missions
      wsOutput.Cells(i + 1, 5).Value = achievedMissions ' Missions Achieved

      ' Output mission statuses for assigned missions
      outputCol = 6 ' Reset to column F for each trial
      For col = 7 To 44 ' Columns G to AR
        If wsMissions.Cells(selectedVesselRow, col).Value = 1 Then ' Check if mission is
assigned
            wsOutput.Cells(i + 1, outputCol).Value = wsData.Cells(selectedVesselRow,
col).Value ' Output mission status from "Vessels-Readiness"
            outputCol = outputCol + 1 ' Move to the next output column
        End If
      Next col
  Next i

  ' Notify the user
```

```
  MsgBox "Simulation complete. Results saved in '" & wsOutput.Name & "' sheet.,"
vbInformation
End Sub

' Helper function to check if a worksheet exists
Function WorksheetExists(sheetName As String) As Boolean
  Dim ws As Worksheet
  On Error Resume Next
  Set ws = ThisWorkbook.Sheets(sheetName)
  On Error GoTo 0
  WorksheetExists = Not ws Is Nothing
End Function
```

B. R Script for Simulating Naval Vessel Readiness and Mission Capability Using Mersenne Twister Algorithm (Entire Fleet)

```
# Load required libraries

library(readxl)
library(writexl)
library(dplyr)
library(ggplot2)

# Load Excel file
file_path <- "simulation rstudio.xlsx"
df <- read_excel(file_path, sheet = "Sheet1")

# Ensure data types are correct
df <- as.data.frame(df)

# Set the seed for reproducibility
set.seed(123)

# Readiness Legacy (Column 45)
# Generate random values using Mersenne Twister and compare with Column 3 (Ship
Readiness)
df$Readiness_Legacy <- ifelse(runif(nrow(df), min=0, max=1) < df [[3]], 1, 0)

# Legacy 50% (Column 46)
```

```
# Calculate 50% of Column 42
df$Legacy_50 <- df [[42]] * 0.5

# Adjusted Mission Values (Columns 47 to 84)
# Multiply Columns 4–41 (mission weights) by Column 46 (Legacy 50%)
df [, 47:84] <- df [, 4:41] * df$Legacy_50

# Mission Capability with Random Check (Columns 85 to 122)
# Generate new random values
set.seed(456)
random_values <- matrix(runif(nrow(df) * 38, min=0, max=1), nrow=nrow(df), ncol=38)

# Apply the condition: If random value < row 2 value, keep adjusted weight, else 0
df [, 85:122] <- ifelse(random_values < df [2, 4:41], df [, 47:84], 0)

# Compute Mission Capability (Column 123)
# Sum Columns 85 to 122
df$Mission_Capability <- rowSums(df [, 85:122], na.rm=TRUE)

# Create Empty Column (Column 124)
df$Empty_Column <- NA

# Compute “Mission + Sailing” (Column 125)
# Sum Column 46 (Legacy 50%) and Column 123 (Mission Capability)
df$Mission_Sailing <- df$Legacy_50 + df$Mission_Capability

# Copy Readiness Legacy to Column 126
df$Column_126 <- df$Readiness_Legacy

# Save Updated Data to Excel
output_file <- “simulation_updated_results_r.xlsx”
write_xlsx(df, output_file)

# Display completion message
print(paste(“Processing complete! The updated file is saved as:,” output_file))

# Display the first few rows of the updated dataset
head(df)
```

```
# Load necessary libraries
library(ggplot2)
library(readxl)

# Create a ship number column (assuming data starts from row 2 as valid ships)
df$Ship_Number <- seq(1, nrow(df))
# Create a scatter plot for ORSM and Legacy Readiness
ggplot() +
geom_point(data = df, aes(x = Ship_Number, y = `mission + sailing`, color = “ORSM”),
size = 2) +
geom_point(data = df, aes(x = Ship_Number, y = `Readiness Legacy Method.1`, color =
“Legacy”), size = 2) +
scale_color_manual(values = c(“ORSM” = “blue,” “Legacy” = “red”)) +
labs(x = “Ship Number,” y = “Readiness,” color = “Model”) +
theme_minimal() +
theme(legend.position = “right”)
```

C. R Script for Simulating Naval Vessel Readiness and Mission Capability Using Mersenne Twister Algorithm (Selected 8 Vessels)

```
library(readxl)
library(writexl)
library(dplyr)

# Set file path
file_path <- “simulation rstudio.xlsx”

# Load the Excel file
df <- read_excel(file_path, sheet = “Sheet1”)

# Define the selected vessel row numbers
selected_rows <- c(4, 10, 24, 27, 41, 60, 111, 127)

# Define the mission columns (Columns 47 to 84 in the original dataset)
mission_start_col <- 47
mission_end_col <- 84

# Define the number of trials
```

```
num_trials <- 1000

# Loop through each selected vessel
for (row_num in selected_rows) {

# Extract vessel name
vessel_name <- as.character(df [row_num, 1])

# Extract assigned missions (where weight > 0)
mission_weights <- df [row_num, mission_start_col:mission_end_col]
assigned_missions <- colnames(mission_weights)[which(mission_weights > 0)]

# Extract mission areas from row 2
mission_areas <- df [2, assigned_missions]

# Create a new data frame for the output
df_new <- data.frame(matrix(ncol = length(assigned_missions) + 4, nrow = num_trials +
3))

# Define column names
colnames(df_new) <- c(“Vessel Name,” assigned_missions, “Ability to Sail,” “Ship
Readiness,” “ ,” “Readiness Legacy,” “Readiness ORSM”)

# Insert vessel name in row 1
df_new [1, 1] <- vessel_name

# Insert mission names and mission areas
df_new [1, 2:(length(assigned_missions) + 1)] <- assigned_missions
df_new [2, 2:(length(assigned_missions) + 1)] <- as.numeric(mission_areas)
df_new [3, 2:(length(assigned_missions) + 1)] <- as.numeric(df [row_num,
assigned_missions])

# Set fixed values for Ability to Sail and Ship Readiness
df_new [1, (length(assigned_missions) + 2)] <- “Ability to Sail”
df_new [3, (length(assigned_missions) + 2)] <- 0.5
df_new [1, (length(assigned_missions) + 3)] <- “Ship Readiness”
df_new [3, (length(assigned_missions) + 3)] <- 0.9

# Generate random values using Mersenne Twister
```

```
set.seed(123)
random_values <- matrix(runif(num_trials * (length(assigned_missions) + 1), min = 0,
max = 1),
                nrow = num_trials,
                ncol = length(assigned_missions) + 1)

# Apply comparison logic for mission success/failure
mission_results <- ifelse(random_values [, 1:length(assigned_missions)] <
as.numeric(mission_areas),
                 as.numeric(df [row_num, assigned_missions]), 0)

# Compare last column (random values) with Ship Readiness (0.9)
readiness_results <- ifelse(random_values [, length(assigned_missions) + 1] < 0.9, 1, 0)

# Append trial results to the dataframe
df_new [4:(num_trials + 3), 2:(length(assigned_missions) + 1)] <- mission_results
df_new [4:(num_trials + 3), (length(assigned_missions) + 2)] <- 0.5
df_new [4:(num_trials + 3), (length(assigned_missions) + 3)] <- 0.9

# Insert an empty column
df_new [, " "] <- ""

# Add Readiness Legacy column
df_new [4:(num_trials + 3), "Readiness Legacy"] <- readiness_results

# Compute Readiness ORSM
df_new [4:(num_trials + 3), "Readiness ORSM"] <- (readiness_results * 0.5) +
rowSums(df_new [4:(num_trials + 3), 2:(length(assigned_missions) + 1)], na.rm=TRUE)

# Define output file name
output_file <- paste0("simulation_results_," gsub(" ," "_," vessel_name), ".xlsx")

# Save as Excel file
write_xlsx(df_new, output_file)

print(paste("File created:," output_file))
}

print("Processing complete! 8 Excel files generated.")
```

```
# Load necessary libraries
library(ggplot2)
library(scales)  # For color scaling

# Readiness scores for 8 ships with three decimal places
ships <- c("1st Ship," "2nd Ship," "3rd Ship," "4th Ship," "5th Ship,"
        "6th Ship," "7th Ship," "8th Ship")

readiness_scores <- c(0.802, 0.806, 0.794, 0.798, 0.786, 0.722, 0.806, 0.815)

# Create a data frame
df <- data.frame(Ship = ships, Score = readiness_scores)

# Create a bar chart with y-axis extending to 1.0 and score labels with 3 decimal places
ggplot(df, aes(x = Ship, y = Score, fill = Score)) +
geom_bar(stat = "identity," width = 0.5) +  # Adjust width (default is 0.9, reduce it for
thinner bars)
scale_fill_gradient(low = "red," high = "blue") +  # Color scale (Red = low, Blue = high)
ylim(0, 1.0) +  # Set y-axis range from 0 to 1.0
geom_text(aes(label = sprintf("%.3f," Score)), vjust = -0.5, color = "black," size = 5) +  #
Display 3 decimals
labs(title = "Readiness Score for The Selected 8 Ships Using ORSM",
    y = "Readiness Score") +
theme_minimal() +
theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

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LIST OF REFERENCES

Chief Digital and Artificial Intelligence Office. (2023). 2023 *analytics, and artificial intelligence adoption strategy* [Fact sheet]. https://media.defense.gov/2023/Nov/02/2003333301/-1/-1/1/DAAIS_FACTSHEET.PDF?utm_source=chatgpt.com

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management*, *15*(2), 1–14. https://doi.org/10.1108/09574090410700275

Defense Acquisition University. (n.d.). *Condition Based Maintenance Plus (CBM+)*. Retrieved March 7, 2025, from https://www.dau.edu/acquipedia-article/condition-based-maintenance-plus-cbm

Energy Information Administration. (2022, November 16). *Eastern Mediterranean*. https://www.eia.gov/international/analysis/regions-of-interest/Eastern_Mediterranean

Government Accountability Office. (2005). *Military readiness: Navy's fleet response plan would benefit from a comprehensive management approach and rigorous testing* (GAO-06-84). Government Accountability Office. https://www.gao.gov/products/gao-06-84

Government Accountability Office. (2023). *Weapon system sustainment: Navy ship usage has decreased as challenges and costs have increased* (GAO-23-106440). Government Accountability Office. https://www.gao.gov/products/gao-23-106440

Harper, J. (2023, June 20). *Four ways DoD can leverage AI for contested logistics*. DefenseScoop. https://defensescoop.com/2023/06/20/four-ways-dod-can-leverage-ai-for-contested-logistics/

International Maritime Organization. (n.d.). *Maritime Security*. Retrieved March 24, 2025, from https://www.imo.org/en/OurWork/Security/Pages/GuideMaritimeSecurityDefault.aspx

Kinderman, A. J., & Ramage, J. G. (1976). Computer generation of normal random variables. *Journal of the American Statistical Association*, *71*(356), 893–896. https://doi.org/10.1080/01621459.1976.10480965

Krimi, S. (2021). *NATO and the mediterranean security agenda* (No. 021 PCNP 21 E). NATO Parliamentary Assembly. https://www.nato-pa.int/download-file?filename=/sites/default/files/2021-11/021%20PCNP%2021%20E%20rev.%201%20fin%20-%20NATO%20AND%20THE%20MEDITERRANEAN%20SECURITY%20AGENDA.pdf

Madusanka, N. S., Fan, Y., Yang, S., & Xiang, X. (2023). Digital twin in the maritime domain: A review and emerging trends. *Journal of Marine Science and Engineering*, *11*(5), Article 5. https://doi.org/10.3390/jmse11051021

Matsumoto, M., & Nishimura, T. (1998). Mersenne twister: A 623-dimensionally equidistributed uniform pseudo-random number generator. *ACM Transactions on Modeling and Computer Simulation*, *8*(1), 3–30. https://doi.org/10.1145/272991.272995

Mintzberg, H. (1999). *The rise and fall of strategic planning* (7. [Dr.]). Prentice Hall.

NATO Allied Land Command. (n.d.). *Operations capabilities concept—evaluation and feedback programme*. Lc.Nato.Int. Retrieved March 7, 2025, from https://lc.nato.int/operations/military-partnership/the-partnership-for-peace/occ-ef.aspx

Naval education and training command NETC. (n.d.). *Ready relevant learning*. Retrieved April 7, 2025, from https://www.netc.navy.mil/RRL/

North Atlantic Treaty Organization. (2025). *Defence Planning Process*. NATO. https://www.nato.int/cps/en/natohq/topics_49202.htm

Office of the Director, Operational Test and Evaluation. (2013). *Defense Readiness Reporting System*. https://www.dote.osd.mil/Portals/97/pub/reports/FY2013/dod/2013drrs.pdf

Pînzariu, S., & Pînzariu, A.-I. (2024). Operational efficiency through optimization of education and training processes in NATO missions. *International Conference KNOWLEDGE-BASED ORGANIZATION*, *30*(1), 136–142. https://doi.org/10.2478/kbo-2024-0019

Pournader, M., Kach, A., & Talluri, S. (2020). A review of the existing and emerging topics in the supply chain risk management literature. *Decision Sciences*, *51*(4), 867–919. https://doi.org/10.1111/deci.12470

RAND Corporation. (n.d.). *Personnel, readiness, and health program*. Retrieved April 7, 2025, from https://www.rand.org/nsrd/prh.html

Richardson, J. (2025, February). *The future is here: Thoughts on warship design and acquisition*. U.S. Naval Institute. https://www.usni.org/magazines/proceedings/2025/february/future-here-thoughts-warship-design-and-acquisition

Rosen, S. P. (1994). *Winning the next war: Innovation and the modern military*. Cornell University Press.

Stewart, R. (2021, July 7). *NAVSUP applies tech to accelerate inventory management*. United States Navy. https://www.navy.mil/DesktopModules/ArticleCS/Print.aspx?PortalId=1&ModuleId=523&Article=2687895

Stiffler, W., & Wells, B. (2024, November 25). *Capability updates, upgrades, and modernization*. SEBoK. https://sebokwiki.org/wiki/Capability_Updates%2C_Upgrades%2C_and_Modernization

UK House of Commons. (2023, November 14). *Oral evidence: Armed forces readiness, HC 26*. https://committees.parliament.uk/oralevidence/13790/html/

U.S. Navy Reserve. (n.d.). *Navy Reserve Strategic Advantage*. Retrieved March 7, 2025, from https://www.navyreserve.navy.mil/Links/Navy-Reserve-Strategic-Advantage/

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