University of Southern Queensland

School of Engineering

Electric Power Load Analysis of a Naval Ship's Surveillance Radar System Using Stochastic Method

A dissertation submitted by

Mahesh Rajan

in fulfilment of the requirements of

ENP4111 Professional Engineer Research Project

towards the degree of

Bachelor of Engineering (Honours) (Electrical and Electronic)

Submitted: November, 2024

This page was intentionally left blank.

University of Southern Queensland

School of Engineering

ENP4111 Dissertation Project

(This is a 2-unit research project in the Bachelor of Engineering Honours Program)

Limitations of Use

CERTIFICATION

I certify that this dissertation's ideas, designs, experimental work, results, analyses and conclusions are entirely my effort, except where otherwise indicated and acknowledged.

I certify that the work is original and has not been previously submitted for assessment in any other course or institution except where specifically stated.

Student Name: Mahesh Rajan

Student Number: [redacted]

[redacted]

Signature

13 November 2024

Date

ABSTRACT

This thesis examines the application of stochastic methods to Electric Power Load Analysis (EPLA) for a surveillance radar system on a naval warship. Traditional deterministic methods of conducting EPLA, which typically use historical utilisation factors, often fail to accurately represent the complex and dynamic operating load patterns inherent in modern naval ships, particularly under varying (ship) operating conditions and environmental conditions. This research addresses the limitations of deterministic methods by integrating randomness and probability distributions into modelling the radar's operating load. The stochastic method enables the estimation of exceedance probabilities for critical operating load thresholds and the development of informed risk mitigation strategies. The research uses Monte Carlo simulation to account for variability and uncertainty in the radar's operating load by using three random variables influencing the operating load in real-world scenarios (radar operational state, environmental conditions, and deterministic utilisation factors). The findings emphasise the advantages of the stochastic methodology over deterministic methodology by providing a deeper understanding of the radar's operating load pattern and its implications for the ship's electrical system. The thesis intends to contribute to the naval (electrical) engineering domain by enhancing naval warship electrical system design and power management. The outcome of this work will ultimately contribute to improved efficiency, reliability and optimised power management on naval warships. This work aims to achieve the United Nations Sustainable Development Goals, SDG7 Affordable and Clean Energy, SDG9 Industry, Innovation, and Infrastructure and SDG13 Climate Action.

ACKNOWLEDGEMENTS

Swastika Rajan, my beloved wife, your unwavering support throughout my academic journey has made this thesis possible and shaped me into the person I am today. Your love and support have been a constant encouragement to me. Thank you for believing in my dreams, patiently enduring the long hours, sleepless nights and inevitable stress, and constantly reminding me of what really matters. I know we can overcome any challenge with you by my side.

My children, Vedh Rajan and Aahana Rajan, your presence in my life is the greatest gift. You are my sunshine, my greatest treasure, and the reason I strive to be the best version of myself. Thank you for being so understanding during the long hours of this research. Your smiles and hugs have been my constant reminders of what truly matters. I am eternally grateful for your love and patience, and I dedicate this accomplishment to the two most amazing children a father could ask for.

I am grateful to my supervisor, Zhi He, for suggesting this thesis topic and providing unwavering support. I am deeply grateful to my in-laws, Anjila Nadan and Shiu Nadan, for their invaluable support during my studies. Your willingness to care for my children gave me the time and peace to do this research. I appreciate your understanding and generosity.

Finally, I acknowledge the divine hand that has guided me through the challenges of my academic journey. When doubts dominated my consciousness, faith provided clarity. When obstacles seemed insurmountable, inner strength emerged. This thesis is a tribute to the power of perseverance and the unwavering belief in a guiding force that empowers us all to achieve our goals.

TABLE OF CONTENTS

PAGE

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

CDF	Cumulative Distribution Function
EPLA	Electric Power Load Analysis
MCS	Monte Carlo Simulation
PDF	Probability Density Function

DEFINITIONS

The following definitions, summarised from (Doerry 2012) and(BoveriD'Agostino, et al. 2018), are indispensable in understanding the content of this thesis.

Connected Load	The term connected load pertains to the total electrical power a piece of equipment is designed to consume, typically indicated on its identification plate and expressed in kilowatts (kW). In instances where equipment specifies a rated current rather than rated power, it is imperative to convert the rated current into rated power. This conversion necessitates the application of an appropriate power factor, which is a numerical value that reflects the efficiency of power conversion.
Demand Power	Demand power is defined as the continuous electrical power that a specific component within a power system must be capable of supplying, given predetermined operating and ambient conditions. This concept is essential for assessing the reliability and performance of power system components, ensuring they can effectively meet the energy requirements. A thorough understanding of demand power is vital for the design, optimisation, and overall efficiency of power systems, particularly in adapting to fluctuations in usage and environmental factors.
Load Factor	The load factor is an important metric in assessing the efficiency of an electrical system. The actual operating load ratio represents the electricity consumed at any given moment to the total connected load.

This ratio is a valuable tool for evaluating energy utilisation and can provide insights into whether a system is operating at optimal capacity or experiencing underutilisation.

Operating Load In specific ambient and operating conditions, the operating load indicates the power demand from a load expressed in kilowatts (kW). When calculating the average load over a 24-hour period, this operating load is aligned with the long-term average. However, the operating load may be intentionally set higher than the average for scenarios like ship demand power assessments. This adjustment ensures that all equipment is sufficiently sized to manage potential fluctuations and power demand variations over extended durations. It is crucial to note that operating load does not encompass instantaneous power surges. These surges typically arise when large motors are started or during short-duration peak loads, which can lead to temporary spikes in power demand that differ from the sustained operating load.

Ship Demand Power Ship demand power is a fundamental measure of the electrical power that a ship's power system must consistently deliver, considering specific operational and environmental conditions. This assessment is critical for selecting and adequately sizing generator sets and, where applicable, energy storage modules, ensuring that the ship's energy needs are met across various operational scenarios. The calculation of ship demand power involves evaluating the total operating load and applying appropriate *margins* and *service life allowances*. This process ensures that the power system is adequately equipped to manage fluctuations and maintain reliability throughout its life cycle.

Utilisation Factor The utilisation factor is a critical metric that quantifies the average power consumption of a specific load over a predetermined time interval, typically set at two hours. This factor is calculated by dividing the total energy consumed by the load during this period by the maximum continuous power it can draw. By assessing the utilisation factor, one can gain valuable insights into the operational efficiency of the load in relation to its peak capacity. A higher utilisation factor signifies greater consistency and effectiveness in power use, while a lower factor may indicate periods of inactivity or suboptimal utilisation.

1 INTRODUCTION

Modern naval warships increasingly rely on complex electrical systems for propulsion, weaponry, sensing, and other critical functions. This electrification trend challenges ship demand power management, especially given the dynamic nature of naval operations and the variability of environmental conditions (Doerry & Amy 2011). Conventional Electrical Power Load Analysis (EPLA) methods, often deterministic, struggle to accurately capture these complexities, environmental variabilities and uncertainties. This thesis addresses the challenges by employing a stochastic method to EPLA, explicitly focusing on the operating load of a naval warship's surveillance radar system.

Surveillance radar systems are essential for naval operation’s situational awareness, threat detection, and weapon guidance. The operating load of the radar can vary significantly depending on radar operational states, environmental conditions and utilisation factors. Accurately estimating and analysing the operating load is crucial for ensuring the stability and reliability of the ship's electrical system.

This research utilises Monte Carlo simulation, a powerful stochastic technique (Boveri, Gualeni & Silvestro 2016), to model the radar's operating load under various environmental conditions and the radar’s operational states. By incorporating randomness and probability distributions, the simulation captures the inherent variability in the radar’s operating load and provides a more realistic assessment of the load pattern compared to conventional methods.

The objectives of this work are:

a. To develop a stochastic model of a naval surveillance radar's operating load using Monte Carlo simulation.

b. To analyse the impact of radar operational states, environmental conditions, and utilisation factors on the operating load of the surveillance radar.
c. To estimate the probability of exceeding critical operating load thresholds under defined environmental conditions.
d. To compare the stochastic method with conventional methods and highlight its advantages in EPLA for naval warships.

The thesis contributes to naval (electrical) engineering by demonstrating the value of stochastic methods in EPLA. The findings can inform design decisions, operational strategies, and power management for naval warships, ultimately enhancing the ship's operational effectiveness and resilience.

This dissertation is organised into seven chapters and appendices. This structured organisation guides the reader through the research process, from the initial context and background to the detailed methodology, results, and in-depth discussion, culminating in a concise conclusion that summarises the essential findings and contributions:

<u>Chapter 1: Introduction</u> - Provides an overview of the research topic, objectives, and contributions, setting the stage for the investigation. (This is the chapter you are currently reading).

<u>Chapter 2: Background</u> - Explores the context of EPLA in naval ship design, discussing the challenges of managing electric power loads on modern naval warships and the limitations of conventional methods.

<u>Chapter 3: Literature Review</u> - Examines prominent literature, similar works and recent literature relevant to stochastic EPLA, Monte Carlo simulation, and modern naval warship design, providing a foundation for the research.

Chapter 4: Methodology - Details the research methodology, including the deterministic and stochastic methods, implementation of the Monte Carlo simulation, tools and techniques used, method implementation, and testing and evaluation procedures.

Chapter 5: Results - Presents the findings of the Monte Carlo simulation, including visualisations and statistical analysis of the radar's operating load under influencing factors.

Chapter 6: Discussion - Discusses the implications of the simulation results, comparing the stochastic method with the deterministic method, highlighting key findings, and addressing limitations and future research directions.

Chapter 7: Conclusion - Summarises the essential findings and contributions of the research, emphasising the value of stochastic EPLA for naval warships and its potential impact on naval electrical system design.

Appendices – The appendices comprise supplementary materials, including detailed simulation code, data tables, additional visualisations, and relevant background literature on the concepts addressed in this thesis.

2 BACKGROUND

Electric Power Load Analysis (EPLA) is critical to naval warship design and operation (Doerry 2012). EPLA involves estimating and analysing the operating load of various shipboard systems to ensure the adequacy and stability of the ship demand power generation and distribution network. Traditionally, EPLA relies on deterministic methods, utilising fixed values and assumptions to calculate ship demand power. However, the increasing complexity of modern naval warships, coupled with the dynamic nature of their operating conditions, has exposed the limitations of these traditional approaches (Sievenpiper 2013). Deterministic EPLA typically employs the utilisation factor method, where a fixed utilisation factor is applied to the equipment's connected load (rated power) to estimate its operating load. This approach assumes constant and predictable load behaviour, which is often not the case in reality. Modern warships are equipped with a diverse array of sophisticated electrical systems, including:

a. High power radar systems with varying operational states and dynamic power demands.
b. Electric propulsion motors require significant and variable power depending on speed and maneuverability.
c. High energy weapon systems with pulsed power demands and rapid load fluctuations.
d. A wide range of sensors and electronic warfare systems with varying power requirements.
e. Auxiliary systems, such as essential support systems like HVAC, lighting, and galley equipment, contribute to the overall load.

These loads exhibit complex behaviours influenced by various factors, such as environmental conditions like “Tropical”, “Temperate”, and “Sub-Arctic”, which can significantly impact certain systems' performance and operating load. Different ship operating conditions (e.g., cruising, maneuvering, combat) have varying power demands from propulsion, weapon systems, and sensors (Doerry 2012). Individual systems and subsystems may have different operational states with distinct power requirements (e.g., the surveillance radar modelled in the thesis has operational states: “Available”, “Ready”, and “Radiate”)

The deterministic approach struggles to capture these complexities and variabilities accurately. It assumes constant load behaviour and fails to account for dynamic fluctuations and interdependencies between systems and subsystems. The fixed utilisation factors may not accurately reflect the power consumption under various ship operating conditions, leading to potential underestimation or overestimation of ship demand power. The deterministic method cannot effectively assess the risk of exceeding power system capacity or identify potential overload scenarios crucial for ensuring ship safety and operational effectiveness (Boveri 2018a).

The limitations of deterministic EPLA highlight the need for a more sophisticated approach that can account for uncertainty and variability in operating load. Stochastic methods, such as Monte Carlo simulation, offer a solution by incorporating randomness and probability distributions to model the dynamic behaviour of modern warship electric loads (Orji et al. 2014). This approach provides a more realistic and comprehensive assessment of ship demand power, enabling better design, operation, and management of the ship's electrical power system.

3 LITERATURE REVIEW

3.1 INTRODUCTION

The literature review examines research on stochastic Electric Power Load Analysis (EPLA) for naval warships, encompassing deterministic and stochastic methods, Monte Carlo simulation, and modern naval ship design. The works cited represent a selection of prominent literature, similar works and recent literature that address the complexities of EPLA as applied to naval ships. These works provide a foundation for understanding the challenges and opportunities in EPLA for modern naval ships and power systems in general and support the application of stochastic methods like Monte Carlo simulation to overcome the challenges. To provide clarity and structure, the following definitions distinguish between the types of literature reviewed.

a. Prominent literature – are seminal works that have significantly influenced the field of EPLA for naval ships, establishing fundamental concepts, methodologies, and best practices. They often serve as authoritative references and provide a broad understanding of the subject. These publications are often cited by researchers and scholars and are considered essential reading within the context of electrical power load analysis of naval ships. The concepts, methodologies, analyses, and recommendations presented in these publications serve as the foundational basis for this thesis.
b. Similar works – are studies that closely align with the specific focus of this thesis, investigating stochastic EPLA for naval warships or similar maritime applications. They offer valuable insights into the challenges, methodologies, and findings relevant to this research.

c. Recent literature – category encompasses publications showcasing the latest developments, trends, and applications of stochastic methods in electrical power systems. They provide an up-to-date perspective on the field and highlight emerging research directions.

The literature review demonstrates the growing recognition of stochastic methods as essential in increasingly complex naval warships (Orji et al. 2014). The research presented in this thesis builds upon this foundation by developing and implementing a Monte Carlo simulation model to analyse the operating load of a surveillance radar system, contributing to advancing knowledge in this critical domain of naval (electrical) engineering.

3.2 PROMINENT LITERATURE

A prominent work in the field of naval electrical power load analysis is:

“Doerry, N 2012, Electric Power Load Analysis (EPLA) for Surface Ships, DoN, Naval Sea Systems Command, Washington Navy Yard, DC 20376-5124, viewed 10 February 2024, <.”

This document provides a comprehensive guide to conducting EPLA, outlining fundamental techniques for assessing power requirements and calculating endurance fuel. While its primary focus is on conventional fuel ships, the core principles and methodologies presented in “DDS 310-1 REV 1” remain highly relevant for modern hybrid and all-electric ship designs (Doerry 2012). This thesis draws significantly from this foundational work, particularly its approach to stochastic method implementation, Monte Carlo simulation algorithm, utilisation factor application and critical terms and definitions that are indispensable to understanding the content presented in this thesis.

Although "DDS 310-1 REV 1" predates the widespread adoption of hybrid and all-electric propulsion systems, its underlying principles remain valid and provide a valuable foundation for EPLA of modern warships. Despite the evolving landscape of naval propulsion technology, with the increasing prominence of hybrid and all-electric systems, the core principles of EPLA remain unchanged. The "DDS 310-1 REV 1" is a key resource that has retained relevance in this field. This thesis leverages the authoritative guidance of (Doerry 2012) in implementing the stochastic operating load model of the surveillance radar system. An overview of the stochastic method is presented in Error! Reference source not found..

3.3 SIMILAR WORK

This body of literature encompassing EPLA of ships, in general, offers a wealth of insights and methodologies that can significantly contribute to developing and optimising EPLA systems within naval space. This section draws comparisons, highlights similarities, and identifies the application of key works by (Boveri 2018b), (BoveriD'Agostino, et al. 2018), (Boveri et al. 2017), (Boveri, Gualeni & Silvestro 2016), (Boveri, Silvestro & Gualeni 2016), (BoveriSilvestro, et al. 2018),(Orji et al. 2014), (Sievenpiper 2013) and (Wolfe & Roa 2016), (Wolfe & Fanberg 2013) in the context of this thesis.

"Boveri, A, D'Agostino, F, Gualeni, P, Neroni, D & Silvestro, F 2018, 'A stochastic approach to shipboard electric loads power modelling and simulation', 2018 IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC), IEEE, pp. 1-6."

“Boveri, A, Gualeni, P, Neroni, D & Silvestro, F 2017, 'Stochastic approach for power generation optimal design and scheduling on ships', 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), IEEE, pp. 1-6.”

“Boveri, A 2018, 'Approaches to Shipboard Power Generation Systems Design and Management', Thesis for the degree of Philosophiae Doctor thesis, University of Genoa, Genoa, Italy.”

“Boveri, A, Silvestro, F & Gualeni, P 2016, 'Ship electrical load analysis and power generation optimisation to reduce operational costs', 2016 international conference on electrical systems for aircraft, railway, ship propulsion and road vehicles & international transportation electrification conference (ESARS-ITEC), IEEE, pp. 1-6.”

“Boveri, A, Gualeni, P & Silvestro, F 2016, 'Stochastic electrical plan load Analysis for increasing flexibility in electrical ship system'.”

In addition to drawing heavily from the prominent work of (Doerry 2012) this thesis also takes into account the significant contributions of (Boveri, Gualeni & Silvestro 2016) in their study titled *"Stochastic Electrical Plan Load Analysis for Increasing Flexibility in Electrical Ship Systems".* This work provides a comprehensive analysis of stochastic methods to enhance the flexibility and efficiency of electrical systems on ships, which is closely related to the topics addressed in this thesis.

Methodologies provided by (Boveri, Gualeni & Silvestro 2016) for incorporating stochastic methods based on *load factors* are critical for the approach to radar operational state and ship environmental condition modelling. Noting the difficulty in accessing relevant data of naval ships, (Boveri, Gualeni & Silvestro 2016) method was beneficial. Their approach to stochastic analysis provided a robust framework for managing uncertainties in data availability and quality. By employing their methodologies, this research navigated the challenges of incomplete or imprecise data, ensuring that the ship's environmental condition modelling remained appropriate and adaptable. By integrating their advanced stochastic techniques, this thesis aims to improve the adaptability and resilience of naval electric power systems under varying operating conditions. This alignment underscores the relevance of Boveri et al.'s work to this thesis and demonstrates how this thesis extends their findings to address new challenges.

Boveri's extensive research, particularly in (Boveri 2018b), offers a foundational perspective on the design and management of shipboard power systems. The author's work emphasises the integration of stochastic methods for load analysis, as seen in the collaboration between Gualeni and Silvestro (Boveri, Gualeni & Silvestro 2016). This approach aligns well with the methodologies explored in this thesis, which also leverages stochastic models to increase the flexibility and reliability of EPLA.

(BoveriD'Agostino, et al. 2018) further delve into power modelling and simulation, providing empirical data that can be used to validate theoretical models. As discussed in the paper, applying stochastic approaches for electric load power modelling mirrors the empirical strategies employed in this thesis to ensure the practical applicability and reliability of EPLA in naval settings.

"Orji, U, Sievenpiper, B, Gerhard, K, Leeb, SB, Doerry, N, Kirtley, JL & McCoy, T 2014, 'Load modeling for power system requirement and capability assessment', IEEE Transactions on Power Systems, vol. 30, no. 3, pp. 1415-23."

The work by (Orji et al. 2014) on load modeling for power system requirement and capability assessment provides a detailed analysis of load behaviour and its impact on power system performance. This research is crucial for understanding the dynamic nature of shipboard power requirements, a central theme in this thesis. The methodologies proposed by (Orji et al. 2014) are instrumental in refining the load analysis techniques used in this research, thereby enhancing the accuracy and reliability of EPLA for naval applications.

"Sievenpiper, BJ 2013, 'Electrical ship demand modeling for future generation warships', Massachusetts Institute of Technology, Cambridge, Massachussetts."

(Sievenpiper 2013) thesis on electrical ship demand modeling for future generation warships offers a forward-looking perspective on the evolving power needs of naval warships. The author's work underscores the importance of accurately predicting and managing electrical demand to ensure the operational readiness of warships. This focus on demand modelling is directly applicable to this thesis, which aims to develop EPLA capable of adapting to varying operational conditions and operating scenarios in naval space.

"Wolfe, J & Roa, MJ 2016, 'Advanced methods for tabulation of electrical loads during special modes of marine vessel operation', IEEE Transactions on Industry Applications, vol. 53, no. 1, pp. 667-74."

"Wolfe, JM & Fanberg, MM 2013, 'Statistical analysis for shipboard electrical power plant design', SNAME Maritime Convention, SNAME, p. D011S05R08."

(Wolfe & Roa 2016) research on advanced methods for tabulating electrical loads during special modes of marine vessel operation provides valuable insights into the specific challenges faced during peak operational periods. Their statistical analysis techniques, as discussed in (Wolfe & Roa 2016), offer robust tools for optimising the design of shipboard electrical systems. These methodologies are highly relevant to this thesis, which seeks to enhance the efficiency and reliability of EPLA systems through advanced load analysis and optimisation.

Integrating these similar works into this thesis strengthens the theoretical and empirical foundations of EPLA for naval applications. By drawing on the stochastic methods proposed by Boveri et al., the load modelling techniques of Orji et al., the demand modelling insights of Sievenpiper, and the advanced statistical methods of Wolfe et al., this research addresses key challenges in the design and implementation of reliable EPLA. Key applications of similar work include:

a. Stochastic methods utilising Boveri et al.'s stochastic approaches to enhance the flexibility and reliability of EPLA.
b. Load modelling adopted Orji et al.'s load modelling techniques to refine the analysis of dynamic power requirements.
c. Demand prediction leveraging Sievenpiper's demand modelling insights to develop adaptive EPLA.
d. Statistical analysis implements Wolfe et al.'s advanced statistical methods to optimise electrical power systems.

Furthermore, (Boveri, Gualeni & Silvestro 2016) exploration of flexibility in a ship's electrical systems directly informs the theoretical frameworks employed in this thesis. Their emphasis on flexibility has been pivotal in shaping this thesis, particularly in developing system optimisation strategies (future work). By leveraging their insights, this thesis seeks to enhance the robustness and efficiency of naval electrical power systems in ways that build upon and expand the scope of Boveri et al.'s research.

In summary, while (Doerry 2012) work provides the seminal foundation for the thesis, the similar work of Boveri, Gualeni, and Silvestro offers additional critical perspectives and methodologies that have significantly influenced and enriched this thesis. This dual reliance on prominent and similar works ensures a comprehensive and well-rounded approach to advancing a naval ship's stochastic electric power load analysis. These similar works offer valuable theoretical and empirical insights and highlight the importance of addressing limitations such as maturity, operational testing, long-term performance, and technological readiness.

3.4 RECENT LITERATURE

This section examines recent literature on stochastic EPLA, demonstrating advancements and trends in applying stochastic methods to power system analysis. While this thesis focuses on naval applications, it's important to consider broader developments in the field. For naval applications, it is imperative to rely on robust, mature technologies that have been rigorously tested and validated for the demanding environments in which naval ships operate. Therefore, while this thesis integrates recent literature to advance the understanding and development of EPLA, it is also mindful of these limitations and emphasises the need for further research and testing to ensure the reliability and viability of stochastic EPLA in naval applications. The lack of maturity, inadequate testing under ship operational conditions, and unproven long-term performance are significant hurdles that must be overcome.

"Platenberg, D 2024, 'Characterizing Naval Ship Systems Power and Energy Metrics through Modeling and Analysis', Massachusetts Institute of Technology."

This thesis, like (Platenberg 2024), emphasises the importance of accurate load characterisation for naval ship systems. Platenberg employs detailed modelling and analysis techniques to characterise power and energy metrics using deterministic methods. This thesis, in contrast, utilises stochastic methods to capture the variability and uncertainty inherent in the radar's operating load. This difference in approach highlights the complementary nature of deterministic and stochastic methods to understand naval electrical systems comprehensively.

"Ren, Y, Kong, AW-K & Wang, Y 2022, 'Real-Time Shipboard Power Management Based on Monte-Carlo Tree Search', IEEE Transactions on Power Systems, vol. 38, no. 4, pp. 3669-82."

This paper shares a fundamental similarity with this thesis by utilising Monte Carlo methods, specifically Monte-Carlo Tree Search, for shipboard power management. However, (Ren, Kong & Wang 2022) focus on microgrid power management with renewable energy sources, while this thesis examines the EPLA of a surveillance radar system within a more extensive integrated power system. This difference in scope reflects the diverse applications of stochastic methods in maritime electrical systems. Nevertheless, their work reinforces the value of Monte Carlo techniques in handling uncertainties and optimising power management, which are relevant considerations for future extensions of this thesis.

“Chen, C-J, Su, C-L & Teng, J-H 2020, 'Electrical load analysis for shipboard power systems using load survey data', IEEE Transactions on Industry Applications, vol. 56, no. 2, pp. 1180-9.”

(Chen, Su & Teng 2020) demonstrate the value of data-driven approaches in understanding load behaviour in shipboard power systems. While they focus on deterministic analysis using load survey data, this thesis draws inspiration from their data-driven approach by utilising available deterministic data and expert knowledge to inform the stochastic simulation. This connection highlights the importance of incorporating real-world data, whenever possible, to enhance the accuracy and relevance of EPLA models.

"Aien, M, Fotuhi-Firuzabad, M & Aminifar, F 2012, 'Probabilistic load flow in correlated uncertain environment using unscented transformation', IEEE Transactions on Power Systems, vol. 27, no. 4, pp. 2233-41."

Like this thesis, this study acknowledges the importance of considering correlated uncertainties in power system analysis, particularly for naval applications with interconnected loads. (Aien, Fotuhi-Firuzabad & Aminifar 2012) utilise the unscented transformation method to handle these correlations in probabilistic load flow calculations. While this thesis employs Monte Carlo simulation, both approaches aim to capture the interdependencies between loads, such as the interaction between the radar system and other shipboard systems. This similarity highlights the growing recognition of the need to move beyond traditional deterministic methods that assume independent loads.

The recent literature provides valuable insights into the latest advancements and applications of stochastic methods in EPLA. It demonstrates the growing recognition of these methods in addressing the challenges of modern naval power systems, including the need to account for uncertainties, optimise energy management, and ensure system reliability. Drawing from these recent advancements, this thesis contributes to the growing knowledge of stochastic EPLA for naval warships. It provides a more accurate and comprehensive understanding of the operating load pattern of surveillance radar system and enhances the design and operation of ship electrical power systems.

a. These studies collectively emphasise the limitations of deterministic methods and the importance of incorporating uncertainty and variability in power system analysis, further supporting the motivation for this thesis.
b. The application of Monte Carlo simulation and other advanced techniques in these works provides valuable insights and inspiration for the methodology employed in this thesis.
c. The works by (Aien, Fotuhi-Firuzabad & Aminifar 2012) and (Ren, Kong & Wang 2022) offer robust theoretical frameworks and novel approaches, such as unscented transformation and Monte-Carlo Tree Search, which can be critical for developing advanced EPLA. These methodologies can enhance understanding of stochastic methods in managing power systems under uncertainty. This thesis also emphasises the significance of stochastic methods, aligning closely with these theoretical perspectives.
d. (Platenberg 2024) directly addresses naval ship systems, providing targeted analysis and metrics immediately relevant to the thesis. This work helps bridge the gap between general theoretical approaches and specific naval applications. This research similarly focuses on the applicability of EPLA systems within naval environments, making Platenberg's findings particularly relevant.
e. (Chen, Su & Teng 2020) provide empirical data and practical strategies for shipboard power systems, which can help validate models and ensure that theoretical insights are grounded in real-world applications. Similarly, this thesis

strives to incorporate empirical evidence (future work) to substantiate theoretical models, thus validating their practical applicability.

f. The focus on detailed modelling and analysis in these studies reinforces the need for accurate load characterisation, which is a central goal of this research.
g. These works suggest potential avenues for extending this research, such as incorporating dynamic load management, optimising energy storage, and integrating renewable energy sources.

While recent literature offers valuable insights, it's crucial to acknowledge that the naval environment presents unique challenges that require robust and mature technologies. Naval warships operate in harsh and unpredictable conditions, demanding high reliability, resilience, and safety. Therefore, while recent advancements in stochastic EPLA are informative, their direct applicability to naval warships might be limited until they have been rigorously tested and validated in real-world naval contexts. This thesis recognises the importance of building upon established foundational works, such as those by (Doerry 2012), while incorporating similar works of (Boveri, Gualeni & Silvestro 2016), (Boveri, Silvestro & Gualeni 2016), (Orji et al. 2014), (Sievenpiper 2013) and (Wolfe & Fanberg 2013) in stochastic methods to enhance the accuracy and comprehensiveness of EPLA for naval radar system.

Despite the contributions of recent work, these works also present limitations that must be acknowledged:

a. <u>Lack of Maturity</u> – as noted in the original context, these studies might not have undergone the extensive testing and refinement required for deployment in critical naval operations. The practical reliability of the proposed methods remains uncertain without prolonged and rigorous testing. This is a common concern in this thesis, emphasising the need for further testing and refinement.

b. Inadequate Testing Under Operational Conditions – experimental studies by (Aien, Fotuhi-Firuzabad & Aminifar 2012) and (Ren, Kong & Wang 2022) may have been conducted under controlled environments that do not accurately replicate the extreme and unpredictable conditions faced in naval operations. This makes it difficult to ascertain their robustness and reliability in real-world scenarios. This thesis also highlights the importance of testing under actual operating conditions to ensure robustness and reliability.

c. Unproven Long-Term Performance – the focus on short-term experimental data, especially in the works by (Aien, Fotuhi-Firuzabad & Aminifar 2012) and (Chen, Su & Teng 2020), does not provide sufficient evidence of long-term performance and durability, which are critical for naval applications. This aligns with this thesis's emphasis on long-term performance data to validate EPLA (future work).

d. Technological Readiness Level (TRL) – the innovations discussed are often at a low TRL, indicating they are still in the early stages of research. Naval applications require technologies that have been thoroughly vetted and are operationally ready, which these recent studies may not yet meet. Similarly, this thesis stresses the importance of high TRL for deploying stochastic EPLA in naval applications.

Incorporating the recent literature by (Aien, Fotuhi-Firuzabad & Aminifar 2012), (Ren, Kong & Wang 2022), (Platenberg 2024) and (Chen, Su & Teng 2020) into the thesis provides valuable theoretical and empirical insights into EPLA. However, it is crucial to recognise their limitations regarding maturity, testing under operating conditions, long-term performance, and technological readiness. Further research and rigorous testing are necessary to ensure the reliability and viability of these technologies for naval applications.

By explicitly connecting these recent works to this thesis and highlighting the similarities and differences in approaches, this work demonstrates how this research builds upon existing knowledge. In conclusion, while recent literature on EPLA using stochastic methods provides valuable theoretical insights, empirical evidence, and simulation results, its applicability to naval warship contexts is limited by several factors.

3.5 COMPARISON OF THIS WORK WITH (BOVERI 2018B)

Comparing this thesis with the works of Alessandro Boveri (Boveri 2018b) reveals interesting parallels and distinctions, allowing one to draw valuable conclusions about the contributions and implications of this thesis. By comparing this thesis with Boveri's works, the following similarities are drawn:

a. The similarities reinforce the validity and relevance of the direction adopted in this thesis, demonstrating that stochastic EPLA is a growing area of interest in naval (electrical) engineering.
b. This thesis contributes unique insights by focusing on a specific radar system and employing a detailed stochastic model, adding to the knowledge of EPLA for naval warships.
c. This thesis demonstrates the feasibility of conducting stochastic EPLA even with limited access to real-world data, offering a valuable approach for researchers facing similar constraints.
d. The complementary nature of this work and Boveri's work suggests potential for future collaboration and cross-validation of findings.

e. This thesis and Boveri's works emphasise the importance of stochastic methods in EPLA for naval warships. Both works recognise the limitations of deterministic approaches and advocate for incorporating uncertainty and variability into the analysis.
f. Both works utilise Monte Carlo simulation as a key tool for stochastic EPLA. This demonstrates a shared understanding of the method's effectiveness in modelling complex systems with uncertainties.
g. Both works aim to improve the accuracy of EPLA and enhance the efficiency and resilience of shipboard power systems.

The following are considered key differences between both works:

a. While Boveri's works cover a broader range of topics related to shipboard power systems, including design, management, and optimisation, this thesis focuses on the EPLA of a surveillance radar system. This narrower focus allows for a more in-depth analysis of the radar's operating load and impact on the ship's electrical system.
b. Boveri's works often utilise data from various sources, including shipboard measurements and operational data. Due to the earlier constraints, this thesis relies on publicly available information, manufacturer specifications, and expert knowledge. This difference highlights the challenges of accessing real-world data for naval warships and the need for alternative approaches when such data is limited.
c. While Boveri's works have significantly contributed to stochastic EPLA, this thesis introduces novel elements by focusing on a specific radar system and employing a

detailed Monte Carlo simulation model to analyse its operating load under various operational states and environmental conditions.

In comparison with the works of (Boveri 2018a), (BoveriD'Agostino, et al. 2018), (Boveri et al. 2017), (Boveri, Gualeni & Silvestro 2016), (Boveri, Silvestro & Gualeni 2016) and (BoveriSilvestro, et al. 2018) with this thesis, several key conclusions can be drawn. Boveri's research has significantly contributed to stochastic electric power load analysis with a strong emphasis on probabilistic methods. These methods provide valuable insights and demonstrate that Monte Carlo simulation offers a superior approach to addressing the variability and unpredictability inherent in naval power systems. This thesis highlights the robustness of Monte Carlo Simulation in accounting for a wide range of stochastic variables, offering a more realistic and comprehensive analysis.

Boveri, A. laid the necessary groundwork for the probabilistic analysis of power systems, and this thesis advances this field by demonstrating the significant advantages of Monte Carlo simulation. The enhanced modelling of uncertainties, improved risk assessment capabilities, and potential for integration with advanced technologies like MATLAB simulation define the critical role of MCS in managing modern naval power systems.

3.6 EPLA OF MODERN NAVAL SHIP

Modern naval ships are characterised by increasing electrification and complexity of electrical systems, posing challenges for EPLA (Sievenpiper 2013). Almost every function of a naval ship relies on electricity to accomplish the ship's mission. The primary objective of conducting an EPLA is to determine the ship demand power for specified operational conditions so that the rating of ships' generator sets can be determined (Doerry 2012). The process of conducting EPLA involves two main steps: identifying, compiling, estimating, and categorising all electrical loads on a ship and using an algorithm to combine these loads to determine the design requirements for electrical system components and equipment (Doerry 2012). The EPLA is critical in supporting various ship design activities, including generator selection, energy storage selection, power conversion selection, feeder cable sizing, and fuel calculations (Doerry 2012).

Different load amalgamation methods ensure equipment ratings are neither excessively high nor too low, balancing cost, efficiency, and maintenance considerations. An overview of tasks carried out during EPLA and its inter-relationship with naval ship power system design is presented in Appendix G. The wide ranging and diverse use of electric power on a modern naval ship requires the electrical systems to consist of several pieces of equipment for generating, distributing, converting, and consuming electric power. Due to the complexity of the ship's electrical system, an accurate forecast of the ship demand power must be made during the design phase. An incorrect forecast can lead to overestimating the entire electrical system, resulting in generators operating below their maximum efficiency, increased installation and maintenance costs, and an increased environmental footprint (Doerry 2012). The implications of undersize include the overloading of generators, resulting in increased maintenance costs and repairs, frequent blackouts, rising expenses, and the ship's environmental footprint (Doerry 2012).

3.7 DETERMINISTIC EPLA

Ship design involves numerous uncertain factors, including the power consumption specific to each load, which depends on the ship's mission, operating conditions, environmental conditions, load scheduling, and operating conditions (Doerry 2012). Ship designers widely utilise the deterministic approach to EPLA because of its simplicity and ease of implementation (Boveri et al. 2017). Deterministic factors are commonly known as load factor or utilisation factor method, based on past engineering experience (Boveri et al. 2017; BoveriD'Agostino, et al. 2018). Due to its reliance on outdated ship data, this approach fails to adequately consider the impact of modern electric power systems and loads on naval ships. Due to several factors, the traditional ship demand power prediction approach is no longer suitable for modern ships (Sievenpiper 2013). In the past, ships had a limited number of electrical power users. However, modern ships now have many electric devices, such as propulsion motors, pumps, compressors, lighting systems, HVAC systems, combat systems, and life-saving systems. These changes necessitate a new approach to accurately predicting and managing electrical loads on ships.

3.8 STOCHASTIC EPLA

The need for more sophisticated approaches to EPLA has led to the exploration of stochastic methods. These methods incorporate randomness and variability to provide a more realistic assessment of ship demand power. Many authors, for example (Sievenpiper 2013), (Boveri, Silvestro & Gualeni 2016) and (Wolfe & Fanberg 2013), present a probabilistic approach to EPLA, highlighting the importance of considering uncertainty in load estimations. Stochastic techniques rely on the establishment of Probability Density Functions (PDFs) and Cumulative Distribution Functions (CDFs) for each random variable that influences the operating load (Wolfe & Fanberg 2013). An essential and fundamental aspect of the stochastic approach to EPLA is the precise definition of the probability distribution of the loads. Appendix A further explains the stochastic method applied in this thesis.

3.9 MONTE CARLO SIMULATION

This section examines foundational literature on Monte Carlo simulation, providing a theoretical basis for applying these methods in this thesis. The stochastic nature of electric power loads in modern naval warships poses significant analytical challenges. This complexity arises from power demands' random and variable nature, driven by diverse and unpredictable ship operational scenarios. Monte Carlo simulation has emerged as a powerful tool to address these challenges, offering a robust framework for probabilistic analysis and decision-making. The following works provide the mathematical guiding principles behind MCS.

Kennedy, T. 2016, 'Monte Carlo Methods-a special topics course'.

This course provides a focused exploration of Monte Carlo methods, delving into the mathematical and computational aspects of the technique. It covers topics such as random number generation, variance reduction, Markov Chain Monte Carlo (MCMC), and applications in various fields. This work is valuable for gaining a deeper understanding of the mathematical foundations of Monte Carlo simulation and its potential applications in stochastic EPLA.

Kulkarni, VG 2016, Modeling and analysis of stochastic systems, Third edn, Chapman and Hall/CRC.

This book offers a comprehensive treatment of stochastic modelling and analysis, covering a wide range of topics relevant to this thesis. (Kulkarni 2016) provides a detailed introduction to stochastic processes, including Markov chains, queuing models, and renewal processes. The author discusses various analytical and computational techniques for analysing stochastic systems, including Monte Carlo simulation. This work is particularly relevant for understanding the theoretical underpinnings of stochastic EPLA and the application of Monte Carlo simulation to model the variability and uncertainty in the radar's operating load.

Reuven Y. Rubinstein, DPK 2016, Simulation and the Monte Carlo Method, John Wiley & Sons, Inc., Online.

This book is a seminal work on Monte Carlo simulation, providing a comprehensive overview of the method, its applications, and its theoretical foundations. (Reuven Y. Rubinstein 2016) cover various aspects of Monte Carlo simulation, including random number generation, variance reduction techniques, and applications in different fields. This work is essential for understanding the core principles of Monte Carlo simulation and its application in stochastic EPLA. It provides guidance on implementing the simulation, analysing the results, and ensuring the accuracy and reliability of the estimations.

Monte Carlo simulation and stochastic methods rely on several core mathematical principles to model and analyse complex systems with uncertainties. These principles provide the foundation for understanding the behaviour of random variables, generating random samples, and estimating statistical properties. Mathematically, Monte Carlo simulation involves *probability theory*. Probability theory is the branch of mathematics that deals with analysing random phenomena. It provides the framework for quantifying uncertainty and predicting the likelihood of different outcomes (Kulkarni 2016). Key concepts in probability theory relevant to Monte Carlo simulation include:

a. Random variables, whose values are subject to chance or randomness.
b. Probability distribution functions that describe the likelihood of different values for a random variable. In this thesis, common distributions in Monte Carlo simulation include the normal, uniform, and beta distributions.
c. Expected values are the average value of a random variable over many trials.

d. Variance measures the spread or dispersion of a random variable's values around its expected value.

The mathematical principles are fundamental to the application of stochastic methods in EPLA. They enable modelling uncertainties in ship demand power, generating random load profiles, and estimating statistical properties such as peak loads and exceedance probabilities (Sciberras et al. 2016). By understanding these core principles, this thesis ensures a rigorous and accurate approach to analysing the power demand of a naval surveillance radar system using Monte Carlo simulation.

The core principle behind Monte Carlo simulation is the Law of Large Numbers (Kulkarni 2016). This law states that as the number of random samples increases, the average of the samples converges to the expected value of the underlying distribution (Kulkarni 2016). By generating many random samples and simulating the system's behaviour for each sample, the Monte Carlo method approximates the system's actual behaviour, accounting for uncertainties (Boveri, Gualeni & Silvestro 2016).

In stochastic EPLA, Monte Carlo simulation models the variability and uncertainty in the radar’s operating load (Boveri, Gualeni & Silvestro 2016). The simulation generates a distribution of possible load values by incorporating random variations in radar operational states, environmental conditions, and utilisation factors. This distribution provides valuable insights into the likelihood of exceeding critical load thresholds, enabling informed risk assessment and mitigation strategies (Van Schaik 2017).

The effectiveness of MCS in stochastic electric power load analysis is well-documented in the literature. Numerous case studies and empirical research have validated its application in naval power systems, highlighting its strengths in uncertainty quantification, risk assessment, and decision support (Doerry & Amy 2011).

4 METHODOLOGY

4.1 INTRODUCTION

The method implemented in this research attempts to solve the problem by following a two-step structured process. This investigation utilised both deterministic and probabilistic methodologies to facilitate a comparative assessment of conventional and stochastic EPLA. This approach appeared necessary as a baseline must be established to compare and assess both methods. The comparative analysis critically evaluates each approach's performance, relative merits and limitations, highlighting the potential advantages of incorporating probabilistic considerations into naval warship EPLA.

The specific methodology used in this thesis draws inspiration from the work of (Boveri, Gualeni & Silvestro 2016), which similarly explored the application of deterministic data in stochastic methods in EPLA. This was essential given the significant challenge of excessing raw data for the reference ship. While their research provides a valuable foundation, this thesis extends their work by applying it to a naval warship with considerably more complex load types and load profiles. This comparative analysis, coupled with the insights gained from existing research, aims to comprehensively understand the stochastic method in optimising naval warship power system design.

Acknowledging the extensive and diverse array of electrical loads on a naval warship, a comprehensive EPLA that incorporates all loads would be both time-consuming and would exceed the scope of this thesis. Therefore, a targeted approach has been adopted in this work, which explicitly focuses on the 366.670 kW surveillance radar system on the reference ship, which will significantly impact the ship's demand power. Appendix H identifies the selected load on the reference ship's single-line diagram. The strategic selection of the system for conducting the EPLA ensures a robust analysis while maintaining the practical limitations of this work. Significant insights into the ship's demand power can be gained from the selected load. The subsequent sections will elaborate on the selected load and the rationale behind selecting it for this EPLA.

4.2 INCORPORATING SHIP ENVIRONMENTAL CONDITIONS

Three (3) environmental conditions are defined, representing the typical operating condition of the reference ship. These are:

a. "Tropical" – is characterised by high temperatures, humidity, and potentially heavy precipitation.
b. "Temperate" – represents moderate climates with less extreme temperatures and weather conditions.
c. "Sub-Arctic" – is characterised by low temperatures, icy conditions, and potential atmospheric disturbances.

Each environmental condition is assigned a probability of occurrence based on the expected operating condition of the reference ship. These probabilities are derived from historical data, mission profiles, and expert knowledge. In this thesis, the following probabilities are scaled in proportion to the radar's operating load thresholds, as shown in the provided code snippet. The operating load thresholds for the radar are:

- 322.67 kW: Tropical (highest power consumption)
- 108.168 kW: Temperate (moderate power consumption)
- 30.800 kW: Sub-Arctic (lowest power consumption)

The provided code snippet determines the probabilities based on predefined operating load thresholds for the radar in each ship's environmental condition. The code snippet defines thresholds representing the average operating load for each environmental condition. These thresholds are then normalized to create *environmentalConditionProbabilities*, ensuring they sum up to “1” and represent the relative likelihood of each environmental condition.

```
% --- 8.1 Define power operatingLoadThresholds for environmental conditions
operatingLoadThresholds = [322.67, 108.168, 30.800];
% --- 8.2 Calculate probabilities proportional to operatingLoadThresholds
environmentalConditionProbabilities = operatingLoadThresholds / 
sum(operatingLoadThresholds);
```

When the code is run, the calculated *environmentalConditionProbabilities* are approximate: [0.6990, 0.2343, 0.0667]. This means there's roughly a 69.9% chance of the ship operating in “Tropical” conditions, 23.4% chance of “Temperate” and 6.7% chance of “Sub-Arctic”.

The ship's environmental condition is randomly sampled based on the defined probabilities within the Monte Carlo simulation loop (in the provided code snippet). The code snippet below uses the *randsample* function to randomly select an environmental condition from the *environmentalConditions* array, with the selected probability determined by *environmentalConditionProbabilities*:

```
% --- 9.3 Sample Environmental Condition ---
    environmentalCondition = randsample(shipEnvironmentalConditions, 1, true, 
environmentalConditionProbabilities);
```

Similar to the radar operational states, numerical indices are assigned to each environmental condition for further analysis. The *switch-case* statement in the code snippet below assigns an index (1, 2, or 3) to the *environmentalConditionIndices* array based on the randomly sampled *environmentalCondition*:

```
% --- 9.6 Adjust load based on environmental condition ---
    switch environmentalCondition{1}
        case 'Tropical'
            shipEnvironmentalConditionIndices(i) = 1;
%             actualOperatingLoad = actualOperatingLoad * (1 +
(operatingLoadThresholds(1) - operatingLoadThresholds(2)) /
operatingLoadThresholds(1));
             actualOperatingLoad = actualOperatingLoad * 1;
        case 'Temperate'
            shipEnvironmentalConditionIndices(i) = 2;
%             actualOperatingLoad = actualOperatingLoad * (1 +
(operatingLoadThresholds(2) - operatingLoadThresholds(1)) /
operatingLoadThresholds(1));
            actualOperatingLoad = actualOperatingLoad * 1;
        case 'Sub-Arctic'
            shipEnvironmentalConditionIndices(i) = 3;
%             actualOperatingLoad = actualOperatingLoad * (1 +
(operatingLoadThresholds(3) - operatingLoadThresholds(1)) /
operatingLoadThresholds(1));
            actualOperatingLoad = actualOperatingLoad * 1;
```

While the current code applies a multiplier of 1.0 for all environmental conditions, treating them equally in terms of operating load analysis, this code can incorporate different multipliers if needed. This would involve modifying the code within the *switch-case* statement to apply different scaling factors to the *actualOperatingLoad* based on the *environmentalCondition*. This thesis assumes that sufficient variability already exists in simulation due to the effect of other random variables.

Incorporating environmental conditions into the simulation provides a more realistic assessment of the radar's power demand. This approach captures the variability in power consumption due to environmental factors, contributing to a more accurate and robust EPLA for the reference ship.

4.3 INCORPORATING RADAR OPERATIONAL STATES

The simulation includes different radar operational states to model the surveillance radar system's operating load. These states influence the radar's operating parameters and, consequently, its operating load. This section details how these operational states are incorporated into the simulation. Three distinct operational states are defined, reflecting typical naval surveillance radar operations and their influence on operating load:

a. “Available” – this state represents periods when the radar is at minimal activity. The radar might be in standby mode or performing basic surveillance with reduced power output.
b. “Ready” – this state signifies the ship is in a heightened state of alert. The radar actively searches for targets and might operate at a higher power level than in the "Available" state.
c. “Radiate” – in this state, the ship is actively engaged in operations, such as tracking targets, guiding weapons, or providing navigational support. The radar operates at its full capacity with maximum power output.

The radar's operational state is randomly sampled from the defined states within the Monte Carlo simulation loop. This code snippet provided uses the *randi* function to generate a random integer between 1 and the number of operational states (3 in this case). This random integer is then used to select an operational state from the *radarOperationalStates* array, which contains the strings “Available”, “Ready”, and “Radiate”:

```
% % --- Select Random Radar Operational State --- % %
    radarOperationalState =
radarOperationalStates{randi(length(radarOperationalStates))};
```

Numerical indices are assigned to each operational state to facilitate further analysis and visualisation. This *switch-case* statement assigns an index (1, 2, or 3) to the *operationalStateIndices* array based on the randomly selected *radarOperationalState*. These indices later filter and analyse data based on specific operational states.

```
% --- 9.8 Adjust load based on radar operational state ---
    switch radarOperationalState
        case 'Available'
            radarOperationalStateIndices(i) = 1;
            actualOperatingLoad = actualOperatingLoad * 1.0;
        case 'Ready'
            radarOperationalStateIndices(i) = 2;
            actualOperatingLoad = actualOperatingLoad * 1.0;
        case 'Radiate'
            radarOperationalStateIndices(i) = 3;
            actualOperatingLoad = actualOperatingLoad * 1.0;
```

While the provided code currently applies a multiplier of 1.0 for all radar operational states, effectively treating them equally in terms of operating load analysis, the code can incorporate different multipliers if needed. This would involve modifying the code within the *switch-case* statement to apply different scaling factors to the *actualOperatingLoad* based on the *radarOperationalState*.

By incorporating radar operational states into the simulation, the analysis provides a more realistic and comprehensive assessment of the radar's power demand. This approach captures the dynamic nature of naval operations and the varying operating load profile of the radar under different conditions, contributing to a more accurate and robust EPLA for the naval warship.

4.4 DETERMINISTIC METHODOLOGY

Traditional electric power load analysis (EPLA) often relies on deterministic methods, utilising fixed values and assumptions to estimate ship demand. One common deterministic approach is the utilisation factor method. While simple to implement, this method fails to capture the inherent variability in operating load and can lead to inaccurate estimations, particularly for complex systems with dynamic load profiles. The deterministic EPLA represents a well-established technique widely used to evaluate ship demand power for each operational state. In this thesis, the deterministic EPLA has been conducted to serve as a foundational analysis, thus providing a benchmark for subsequent investigations.

The deterministic method relies on pre-established static factors such as load, utilisation, and demand factors to estimate the operating load value of selected loads for each operational state (Boveri, Silvestro & Gualeni 2016). This research derives a deterministic estimate of the total electric power demand for the selected loads by integrating these factors. This approach, while providing a valuable initial assessment, inherently assumes static load behaviour and does not explicitly account for the probabilistic nature of load variability. Nevertheless, it serves as a crucial point of reference for subsequent analyses, enabling a comparative evaluation of the advantages of stochastic methods in capturing the dynamic and uncertain characteristics of electrical loads on a naval warship.

The utilisation factor denotes the average power consumption of a load for a defined period, typically two hours. The calculation divides the average power usage by the load's rated power. The utilisation factor is specified for each operating condition and environmental conditions. The utilisation factor is mathematically defined as:

$$\mathrm{UF}_{ij} = \frac{\text{Average demand in two hours}}{\text{Rated power}}$$

$$= \frac{P_{ave_{ij}}}{P_{rated_i}}$$

Where:

UF_{ij} = Utilisation factor of the i^{th} load in the j^{th} operational state.

P_{rated_i} = Connected load (kW) of the i^{th} consumer.

The demand factor is applied to the connected load of a bus feeder to ascertain the rating of the associated bus feeder (Doerry 2012). The demand factor is based on the ship's historical data and operational profile. The demand factor can be calculated mathematically using the formula:

$$DF_{ij} = \frac{\text{Maximum Demand of the Feeder}}{\text{Connected Load of the Feeder}}$$

The diversity factor is the ratio of the sum of the individual maximum demands of various subsystems to the maximum demand of the whole system (IEEE 1993). The diversity factor is always 1 or greater. A warship has various electrical loads, ranging from propulsion and weapon systems to navigation, communication, and hotel loads (lighting, HVAC, and galley equipment). These loads have different operating characteristics and don't all reach their peak demand simultaneously. The diversity factor recognises that the peak demand of the entire ship is generally less than the sum of the individual peak demands of all its loads. This is because different systems have different operating schedules and duty cycles. For example, the peak demand for the galley might occur during meal times, while the peak demand for weapon systems might occur during combat scenarios. The diversity factor can be calculated mathematically using the formula:

$$Kd_{ij} = \frac{\text{Sum of maximum Demand of subsystems}}{\text{Maximum demand of the whole system}}$$

Load factors are derived from comprehensive past operational data, reference ship data, and expert intelligence and judgement (Wolfe & Fanberg 2013). These factors quantify the ratio of operating load to connected load over designated periods (Doerry 2012). Analytically, the load factor is defined as:

$$LF_{ij} = \frac{\text{Average Load}}{\text{Connected Load}}$$

$$= \frac{1}{T_j \bullet P_{max_{ij}}} \int_0^T p_{ij}(\tau)\, d\tau$$

$$= UF_{ij} \times DF$$

Where:

LF_{ij} = Load factor of the i^{th} load in the j^{th} operational state.

T_j = Reference time for the j^{th} operational state.

$P_{max_{ij}}$ = Connected load of the i^{th} equipment in the j^{th} operational state.

$p_{ij}(\tau)$ = Instantaneous value of power absorbed in the j^{th} operational state.

4.5 STOCHASTIC METHODOLOGY

A stochastic EPLA was conducted to address the limitations associated with the deterministic approach. Many authors, for example (Doerry 2012; Orji et al. 2014; Wolfe & Roa 2016; BoveriD’Agostino, et al. 2018), support that the stochastic EPLA marks a significant advancement in estimating ship demand power whilst breaking from the conventional deterministic method. The stochastic method incorporates the variability and randomness of cyclic loads, inherent uncertainties, and probabilistic characteristics of the vast array of electrical loads on naval warships. Unlike deterministic methods, which rely on fixed load factors and often lead to conservative oversizing or under-sizing of the ship's electrical system, stochastic EPLA embraces the inherent variability of real-world operation, resulting in more accurate and optimised power system designs. Appendix A provides detailed guidance on stochastic EPLA.

The stochastic EPLA represents each load as a probability density function (Mousavi & Abyaneh 2010). The PDF defines the spectrum of potential load values and their corresponding probabilities, accurately reflecting the inherent variability of the load. Mathematically, the concept can be explained::

$$\Pr\left(x_1 < X < x_2\right) = \int_{x_1}^{x_2} f_x\left(x\right) dx$$

Where:

X_{ij} = The i^{th} operating load of the specific consumer in the j^{th} operational state.

$\Pr$ = Probability of the operating load of the specific consumer in the j^{th} operational state.

x_1 = Lower limit (value) of the operating load of the specific consumer in the j^{th} operational state.

x_2 = Upper limit (value) of the operating load of the specific consumer in the j^{th} operational state.

f_x = The probability density function of X_{ij}

The cumulative distribution function (CDF) is denoted by:

$$F_X(x) = \int_{-\infty}^{x} f_X(y)\,dy$$

The cumulative distribution function (CDF) gives the probability that a random variable, referred to as X, will assume a value that is less than or equal to a specified value, x. While this function is integral to statistical analysis, determining electrical equipment sizing requires a different focus (Doerry 2012). In the context of EPLA, it is often essential to ascertain the value of x that aligns with a specific probability of exceedance (Doerry 2012).

When sizing electrical equipment, the fundamental aim is to ensure it can supply the expected load with high confidence. Traditional deterministic approaches often add a safety margin to the estimated load (Doerry 2012). However, stochastic load analysis offers a more detailed approach by directly incorporating uncertainty through probability distributions (Doerry 2012). Instead of simply adding a fixed margin, the focus shifts to finding the operating load value corresponding to a specific probability of exceedance (Doerry 2012). This probability of exceedance (α) represents the chance that the actual load will be greater than the chosen value. The key to such an activity is to find the operating load (value of x) for which the probability of X less than or equal to x is a fixed probability represented by the term $(1-\alpha)$. The inverse cumulative distribution function (CDF) or the quantile function is implemented to achieve this (Doerry 2012). The concept is further explained by (Doerry 2012):

1. The desired confidence level is represented by $(1-\alpha)$. For example, 99% confidence is required that the equipment won't be overloaded $\alpha = 0.01$.
2. To find the corresponding load value (x), the inverse CDF is used to find the value of (x) for which the probability of the load being less than or equal to (x) is $(1-\alpha)$, i.e., $\Pr(X \le x) = 1-\alpha$.

The electrical equipment is sized based on the load value (x), which ensures that the equipment can supply the expected load with the desired confidence level.
The aim is to find the load value with a specific probability of being exceeded. This allows the equipment's capacity to be tailored to the system's specific needs, considering the inherent variability and uncertainty in the load. This approach offers several advantages over traditional methods (Orji et al. 2014):

1. Offers improved accuracy by directly incorporating uncertainty, avoiding oversizing or undersizing the equipment.
2. Facilitates risk management by explicitly controlling the risk of overload by choosing an appropriate probability of exceedance (α).
3. Cost optimisation by balancing the equipment's cost with the desired reliability level.

4.6 LOAD CHARACTERISATION

A fundamental aspect of stochastic EPLA involves characterising the diverse electrical loads on naval warships (Doerry 2012). This characterisation necessitates a probabilistic representation that captures each load's inherent uncertainties and variability (Boveri 2018b). To facilitate this process, (Kloubert 2020) and (Doerry 2012) suggest that loads can be broadly classified into three distinct categories, each requiring a specific stochastic modelling approach:

a. Constant Loads are always “on” and operate continuously for extended durations. Such loads can be represented by a single random variable that captures the inherent uncertainty of estimating their operational demand (Doerry 2012). This model acknowledges that while the load remains constant, variations in the exact power consumption level may still exist.
b. Cycling Loads – do not adhere to continuous operation but instead cycle on and off intermittently, functioning independently of the status of other loads. Loads that cycle “on” and “off” independently of other loads require a more complex stochastic model (Doerry 2012). Two random variables are utilised to model these behaviours accurately. The first variable quantifies the proportion of time the load is “on”, while the second variable represents the amount of electrical power consumed during the “on” periods. This dual-variable approach comprehensively analyses operational periods and variability of power consumption.
c. Configuration-Dependent Loads – display performance characteristics contingent upon specific configurations (Doerry 2012). In these instances, the configuration number should be treated as a discrete random variable, assigning probabilities to each unique configuration scenario (Boveri 2018b) and (Doerry 2012). For each configuration, it is necessary to develop a tailored load model that accurately reflects its distinct characteristics. This analysis can be conducted at different levels, including the overall system level and individual loads (Doerry 2012). Moreover, this concept encompasses various equipment models performing similar functions, irrespective of whether they are produced by the same manufacturer or

different entities, emphasising the significance of configuration in influencing load behaviour. For instance, a radar system with multiple operating modes and distinct power demands exemplifies a configuration-dependent load.

Acknowledging that cycling loads (b) and configuration-dependent loads (c) inherently incorporate conditional probabilities is crucial. This signifies that the probability of a specific load value is contingent upon a particular condition being met (Doerry 2012). For instance, in the case of a cycling load, the probability distribution for power consumption is relevant only when the load is actively drawing power (Doerry 2012).

This structured approach to load characterisation, emphasising distinct load categories and incorporating conditional probabilities, enables a comprehensive and refined representation of the uncertainties inherent in shipboard electrical loads. This, in turn, forms the foundation for a robust stochastic load analysis, leading to more accurate and reliable power system design.

4.7 PDF SELECTION AND CDF

This section details the rationale behind the selection of probability distribution functions (PDFs) used to model the random variables in the Monte Carlo simulation. The choice of PDFs is crucial for accurately representing the uncertainty and variability inherent in the radar's power demand (Doerry 2012) and (Boveri 2018b). Appendix A provides more information on the selection of PDFs for stochastic EPLA.

a. Radar Operating Load – the radar's operating load is modelled using a “Triangular Distribution”. The radar's operating load is bounded by nature, i.e., it has a clear minimum (0 kW when inactive) and maximum (366.67 kW, its rated power). The triangular distribution is naturally bounded, ensuring the simulated values remain within these physical limits. The triangular distribution allows for specifying a mode, representing the most likely operating load. This is useful for incorporating expert knowledge or historical data about the typical operating load of the radar. In this thesis, mode is an assumed value due to restricted access to data. The triangular distribution is relatively simple to implement and requires only three parameters (minimum, maximum, and mode), making it suitable when detailed data on the exact load distribution is limited.

b. Utilisation Factor – represents the proportion of time the radar is actively transmitting and is modelled using a "Beta Distribution". The utilisation factor is bounded by nature, i.e., a proportion between 0 and 1. The beta distribution is naturally bounded between 0 and 1, making it suitable for modelling proportions and probabilities. The beta distribution can take on a variety of shapes (symmetric, skewed left, skewed right) depending on the values of its shape parameters (alpha and beta). This flexibility allows for modelling different operational tempos and radar usage patterns. The beta distribution parameters intuitively interpret the number of "successful" and "unsuccessful" trials in a hypothetical experiment. Appendix B provides further guidance on beta distribution.

c. Environmental Conditions and Radar Operational States – the environmental conditions ("Tropical", "Temperate", and "Sub-arctic") and radar operational states ("Available", "Ready", and "Radiate") are modelled using a "Discrete Distribution". This is appropriate because these variables represent distinct categories or states, not continuous values. The discrete distribution allows for assigning probabilities to each category based on their likelihood of occurrence. The discrete distribution can accommodate any number of categories and their associated probabilities, providing flexibility in modelling different operational scenarios and environmental conditions.

The specific context of naval warships further justifies the choice of these PDFs:

a. Detailed data on the exact distributions of radar operating load and utilisation factors might be limited due to security and confidentiality concerns. The chosen distributions (triangular and beta) are suitable for situations with limited data, as they require relatively few parameters and can be informed by expert knowledge or reasonable assumptions.
b. Naval warships operate in diverse and dynamic environments, requiring flexibility in modelling the radar's operating load. The beta distribution's flexibility in shape allows for capturing different utilisation patterns under various conditions.
c. Accurate EPLA is crucial for naval warships to ensure reliable power supply to critical systems and avoid overloading. The chosen PDFs contribute to a more realistic and robust analysis with their bounded nature and ability to incorporate expert knowledge.

Selecting appropriate PDFs is crucial in developing a valid and reliable stochastic EPLA model. The nature of the random variables justifies the chosen distributions in this simulation, the specific context of naval warships, and the need for accurate and robust power demand analysis. Using these PDFs contributes to a more realistic representation of the uncertainties and variabilities inherent in the operation of a naval surveillance radar system.

4.8 MONTE CARLO SIMULATION IMPLEMENTATION

This section describes implementing the Monte Carlo method in the MATLAB code "mcSim4Var_V4.m" for the stochastic analysis of the naval surveillance radar's operating load profile. Appendix D provides the complete MATLAB code. The code simulates the variability in operating load by considering uncertainties in radar operating load, utilisation factor, environmental conditions, and radar operational states. Understanding these variables' nature and potential impact on the radar's operating load profile is essential for developing an accurate and robust simulation model. Identifying these random variables is based on carefully considering the factors that influence the operating load of a naval surveillance radar system. The Monte Carlo simulation captures the uncertainty and variability in the radar's operation by modelling these variables using appropriate probability distributions. The input (random) variables to the Monte Carlo simulation are:

a. <u>Radar Operating Load</u> – is a continuous random variable representing the operating of the radar system in kilowatts (kW). Various factors influence the radar's operational state, utilisation factor, and environmental conditions. The radar's operating load is inherently variable due to the dynamic nature of its operation. It can fluctuate depending on the number of targets being tracked, the complexity of the search patterns, and the environmental conditions affecting signal propagation and receiver sensitivity. Modelling this variability is essential for accurately assessing the operating load and its impact on the ship's demand power (Doerry 2007). In the provided code snippet, the *actualOperatingLoad* of the radar is calculated by multiplying the randomly generated radar operating load from the triangular distribution (*randRadarOperatingLoad*) and the randomly generated utilisation factor from the beta distribution the (*utilisationFactor*). The multiplication reflects the principle that the actual operating load depends on the radar's potential maximum operating load and the extent to which it is used. For example, if the radar has a high operating load but a low utilisation factor, the actual operating load will be lower. The line = > *actualOperatingLoad = min(actualOperatingLoad, radarOperatingLoadMax);* ensures that the *actualOperatingLoad* does not exceed the *radarOperatingLoadMax* (the maximum radar connected load defined in the simulation parameters = 366.67 kW). The min function compares the calculated *actualOperatingLoad* with *radarOperatingLoadMax* and returns the smaller two values. This effectively caps the load at the defined maximum, preventing unrealistic scenarios where the load exceeds the radar's connected load.

```
% --- 9.5 Apply Influencing Factors to Operating Load ---
actualOperatingLoad = randRadarOperatingLoad * utilisationFactor;
actualOperatingLoad = min(actualOperatingLoad, radarOperatingLoadMax); %
Cap the load
```

b. Utilisation Factor – the utilisation factor is a continuous random variable representing the proportion of time the radar is actively in any of the defined radar operational states. It ranges from 0 to 1, where 0 indicates no power consumption, and 1 indicates maximum power consumption. The utilisation factor captures the variability in the radar's operational state. It can fluctuate depending on the mission requirements, potential threats, and the overall operational strategy. Incorporating this variability is crucial for realistically assessing the radar's operating load and its contribution to the ship demand power. The two lines of code in the provided code snippet in (a) model the combined effect of the radar's operating load and its utilisation while ensuring that the calculated load remains within realistic bounds.

This calculated *actualOperatingLoad* is further adjusted based on the radar's environmental conditions and operational state in subsequent code sections.

c. Environmental Condition – is a discrete random variable representing the environmental conditions in which the radar operates. This simulation considers three categories: “Tropical”, “Temperate”, and “Sub-Arctic”. Environmental conditions can significantly affect the radar's performance and operating load profile. Temperature, humidity, precipitation, and atmospheric disturbances can influence signal propagation, receiver sensitivity, and cooling requirements. Modelling the variability in environmental conditions is essential for capturing the potential range of operating load scenarios. In the provided code snippet *shipEnvironmentalConditions* is the cell array containing the possible environmental conditions: {“Tropical”, “Temperate”, “Sub-Arctic”}. The “1” specifies that only one element from the *shipEnvironmentalConditions* array is sampled. “*true*” indicates that a different environmental condition must be sampled in every iteration of the loop because the same condition can be selected multiple times in different iterations. The *environmentalConditionProbabilities* is a vector containing the probabilities associated with each environmental condition. The code calculates these probabilities based on predefined operating load thresholds. The environmentalConditionProbabilities are [0.6 0.3 0.1], i.e., “Tropical” has a 60% chance of being selected. “Temperate” has a 30% chance of being selected, and “Sub-Arctic” has a 10% chance. The random selection of environmental conditions adds another layer of variability to the Monte Carlo simulation, allowing for a more realistic assessment of the radar's operating load under different conditions.

```
% --- 9.3 Sample Environmental Condition ---
```

```
environmentalCondition = randsample(shipEnvironmentalConditions, 1, true, environmentalConditionProbabilities);

% --- 9.6 Adjust load based on environmental condition ---
switch environmentalCondition{1}
  case 'Tropical'
        shipEnvironmentalConditionIndices(i) = 1;
        %              actualOperatingLoad = actualOperatingLoad * (1 + (operatingLoadThresholds(1) - operatingLoadThresholds(2)) / operatingLoadThresholds(1));
        actualOperatingLoad = actualOperatingLoad * 1;
  case 'Temperate'
        shipEnvironmentalConditionIndices(i) = 2;
        %              actualOperatingLoad = actualOperatingLoad * (1 + (operatingLoadThresholds(2) - operatingLoadThresholds(1)) / operatingLoadThresholds(1));
        actualOperatingLoad = actualOperatingLoad * 1;
  case 'Sub-Arctic'
        shipEnvironmentalConditionIndices(i) = 3;
        %              actualOperatingLoad = actualOperatingLoad * (1 + (operatingLoadThresholds(3) - operatingLoadThresholds(1)) operatingLoadThresholds(1));
        actualOperatingLoad = actualOperatingLoad * 1;
end
```

In the provided code snippet *shipEnvironmentalConditionIndices(i) = 1*; (and similar lines), assign an index value (1 for “Tropical”, 2 for “Temperate”, 3 for “Sub-Arctic”) to the *shipEnvironmentalConditionIndices* array. This is intended for additional visualisation of utilisation factor distribution (PDF and CDF) for each environmental condition and radar operational state (see Appendix F). The actual *OperatingLoad = actualOperatingLoad * 1* is where the load adjustment occurs. However, multiplying by 1 does not affect the *actualOperatingLoad*, making the environmental condition irrelevant in the current calculation. Note the removal of further adjustment to the load resulting from operating load thresholds (will be used in future work). The specific adjustment factors for different environmental conditions require further data collection and analysis. For this thesis, it is assumed that environmental adjustments exist in the code since the objectives of the thesis have been achieved.

d. Radar Operational State – is a discrete random variable representing the operational mode of the radar system. Three states are considered: Available, Ready, and Radiate. The radar's operational state can significantly influence its power consumption. Different modes like search, tracking, and guidance have distinct power requirements. Incorporating the radar's operational state into the simulation allows for capturing the variability in power demand associated with different operational modes and functions. The provided code snippet *radarOperationalStates* is the cell array defined earlier in the code, containing the possible radar operational states: {“Available”, “Ready”, and “Radiate”}. The *length(radarOperationalStates)* calculates the number of elements in the *radarOperationalStates* array, which in this case is 3. The *randi(length(radarOperationalStates))* generates a random integer between 1 and the length of the *radarOperationalStates* array (i.e., a random integer between 1 and 3).

```
    % --- 9.4 Select Radar Operational State ---
    radarOperationalState =
radarOperationalStates{randi(length(radarOperationalStates))};
```

```
% --- 9.8 Adjust load based on radar operational state ---
switch radarOperationalState
    case 'Available'
        radarOperationalStateIndices(i) = 1;
        actualOperatingLoad = actualOperatingLoad * 1.0;
    case 'Ready'
        radarOperationalStateIndices(i) = 2;
        actualOperatingLoad = actualOperatingLoad * 1.0;
    case 'Radiate'
        radarOperationalStateIndices(i) = 3;
        actualOperatingLoad = actualOperatingLoad * 1.0;
end
```

In the provided code snippet *radarOperationalStateIndices (i) = 1*; (and similar lines), assign an index value (1 for “Available”, 2 for “Ready”, and 3 for “Radiate”) to the *radarOperationalStateIndices* array. This is intended for additional visualisation of utilisation factor distribution (PDF and CDF) for each environmental condition and radar operational state (see Appendix F). The actual OperatingLoad = actualOperatingLoad * 1 is where the load adjustment occurs. However, multiplying by 1 does not affect the *actualOperatingLoad*, making the radar operational state irrelevant in the current calculation. Note the removal of further adjustment to the load resulting from operating load thresholds (will be used in future work). The specific adjustment factors for different radar operational states require further data collection and analysis. For this thesis, it is assumed that environmental adjustments exist in the code since the objectives of the thesis have been achieved.

4.9 TESTING AND EVALUATION

This section outlines the techniques and methodology employed to test and evaluate the accuracy, reliability, and validity of the Monte Carlo simulation developed for this thesis. Rigorous testing and evaluation are crucial to ensure that the simulation results accurately reflect the behaviour of the radar system and provide meaningful insights for naval warship EPLA. These testing and evaluation techniques ensure the reliability and validity of the Monte Carlo simulation and contribute to the robustness of the conclusions drawn from the analysis. The combination of convergence testing, comparison with deterministic results, and visual and numerical analysis provided a comprehensive framework for evaluating the simulation and extracting meaningful insights for naval warship EPLA.

a. Convergence Testing – Convergence testing ensures that the simulation results stabilize and converge to a reliable solution as the number of iterations increases. This involves monitoring the *currentError* variable, which represents the relative error in the estimated mean operating load.

b. Error Calculation – The *calculatedError* function calculates the relative error using the standard deviation, mean, and number of iterations, see Figure 12.

c. Convergence Criterion – The simulation loop continues until the *currentError* falls below a predefined *targetError* threshold (set to 0.01 or 1% in the code). This ensures that the simulation has run for sufficient iterations to achieve a stable and accurate estimate of the mean operating load.

d. Simulation and Analysis – The simulation is run for each combination, and the mean and standard deviation of the operating load are stored in matrices.

e. Validation against Deterministic Results – The stochastic simulation results are compared with those obtained from a deterministic EPLA (utilisation factor method). This comparison helps to:

   i. Establish a baseline for comparison, assessing the differences between the two approaches.

   ii. With their distribution of possible operating load values, the stochastic results highlight the variability the deterministic method fails to capture.

   iii. The comparison demonstrates the advantages of the stochastic approach in providing a more comprehensive and realistic assessment of the radar's operating load.

f. Visual and Numerical Analysis – The simulation results are visualised using various plots, including histograms, PDFs, CDFs, and scatter plots. These visualisations, along with accompanying numerical analysis (e.g., correlation coefficients, standard deviations), provide insights into:

   i. The overall distribution of the radar's operating load.

   ii. The likelihood of the load exceeding critical load thresholds.

iii. The impact of environmental conditions and radar operational states on the operating load.
iv. The distribution and relationship between the utilisation factor and operating load.

5 RESULTS

5.1 GENERALISED FINDINGS

The Monte Carlo simulation offers several advantages over a deterministic approach for naval warship Electric Power Load Analysis (EPLA). Based on the simulation results, the following advantages are observed:

a. More realistic representation of uncertainty and variability in radar’s operating load.
b. Provides a distribution of radar’s operating load values for risk assessment (future work).
c. Explicitly models the impact of environmental conditions on radar’s operating load.
d. Facilitates sensitivity analysis to identify critical factors affecting operating load (future work).
e. Allows for a data-driven approach to improve the accuracy of radar’s operating load.

These findings highlight the value of MCS simulation in providing a more comprehensive understanding of the radar's operating load and its impact on the ship's electrical system. The following subsections critically analyse calculated and simulated deterministic and stochastic EPLA results.

5.2 ANALYSIS OF DETERMINISTIC EPLA

This section presents the results of the deterministic EPLA for the naval ship's surveillance radar system. The deterministic approach employed the utilisation factor method, utilising fixed values for the utilisation factor, diversity factor, and load factor. These factors were predominantly determined based on historical data and expert knowledge. The utilisation factor method, a common deterministic approach, estimates the operating load of radar by multiplying its connected load by a predetermined utilisation factor. This thesis applied a fixed utilisation factor of 0.8880 to the radar's connected load of 366.67 kW, resulting in an estimated operating load of 322.670 kW for "Tropical" conditions. This calculation uses the parameters provided in Table 1.

$$\begin{aligned}
&\text{Load Factor (LF)} && = 1.000 \\
&\text{Diversity Factor (DF)} && = 1.000
\end{aligned}$$

$$\begin{aligned}
&\text{Utilization Factor (UF):} && \\
&\text{Tropical} && = 0.880 \\
&\text{Temperate} && = 0.295 \\
&\text{Sub-Arctic} && = 0.084
\end{aligned}$$

The operating load of the radar system in each environmental condition was calculated using the following formula:

$$\text{Operating Load} = \text{Connected Load x Load Factor x Diversity Factor x Utilisation Factor}$$

Given the radar's connected load of 366.67 kW, the operating load calculations are:

$$\begin{aligned}
&\text{Tropical:} && 366.67\text{ kW x }1.000\text{ x }1.000\text{ x }0.880 = 322.67\text{ kW} \\
&\text{Temperate:} && 366.67\text{ kW x }1.000\text{ x }1.000\text{ x }0.295 = 108.17\text{ kW} \\
&\text{Sub-Arctic:} && 366.67\text{ kW x }1.000\text{ x }1.000\text{ x }0.084 = 30.80\text{ kW}
\end{aligned}$$

These results indicate that the operating load of the radar system is highest in tropical environments and lowest in sub-arctic environments, reflecting the varying utilisation factors. The deterministic results provide a single-point estimate of the operating load for each environmental condition. However, they do not capture the variability and uncertainty inherent in the radar's operation. In contrast, the stochastic Monte Carlo simulation, as described in Chapter 4, generates a distribution of possible operating load values, accounting for the probabilistic nature of influencing factors.

The stochastic results reveal a more comprehensive range of possible operating load values compared to the deterministic estimates. This highlights the limitations of the deterministic approach in capturing the dynamic behaviour of the radar system. The deterministic results serve as a baseline for comparison with the stochastic analysis. While the deterministic method provides a simplified estimation of the operating load, the stochastic method offers a more realistic assessment by incorporating uncertainty and variability. This enhanced understanding is crucial for informing design decisions, optimising operational efficiency, and ensuring the resilience of naval electric power systems.

Table 1: Results of deterministic EPLA

690V 60 Hz Three-Phase Load		**Tropical**		**Temperate**		**Sub-Artic**	
System	Connected Load (kW)	UF	kW	UF	kW	UF	kW
Surveillance Radar	366.67	0.88	322.67	0.295	108.168	0.084	30.800

5.3 ANALYSIS OF STOCHASTIC EPLA

This section presents a comprehensive analysis of the simulation results, drawing insights from the visualisations generated by the MATLAB code provided in Appendix D and discussing their implications for understanding the operating load of the naval surveillance radar system. The Monte Carlo simulation was run for 20,000 iterations (convergence at 16477, error < 0.01), generating a distribution of operating load values for the radar system. Appendix E provides a statistical summary of the simulation, which is discussed in the following subsections.

5.3.1 Probability Distribution (Overall)

The histogram in Figure 1 visually appears to be well-approximated by the fitted normal distribution (the red curve). This suggests that the normal distribution is a reasonable model for the overall radar operating load, considering the combined effects of the various influencing factors in the simulation. The mean operating load of 163.61 kW indicates that, on average, the radar consumes a significant amount of power. The relatively large standard deviation of 70.006 kW suggests considerable variability in the operating load, likely due to the combined effects of the utilisation factor, ship environmental conditions, and radar operational states. At this stage, it is important to point out that no additional multipliers are used to adjust the operating load for ship environmental conditions and radar operational states after applying the necessary adjustment by the utilisation factor. The removal of further adjustments to the operating load resulting from operating load thresholds (will be used in future work). The specific adjustment factors for different environmental conditions require further data collection and analysis. For this thesis, it is assumed that environmental conditions and radar operational state adjustments exist in the simulation resulting from the combination of random variables; therefore, the objectives of the thesis have been achieved. The 99% confidence interval (CI) for the mean (162.41 kW to 165.02 kW) provides a range within which it can be 99% confident that the *true mean* operating load lies within this range. The maximum observed operating load of 346.63 kW is well within the radar's rated capacity of 366.67 kW, indicating that the system is not exceeding its connected load limits in the simulated scenarios. The 95% confidence interval for the maximum operating load (345.10 kW to 346.63 kW) suggests that the true maximum operating load is likely within this narrow range.

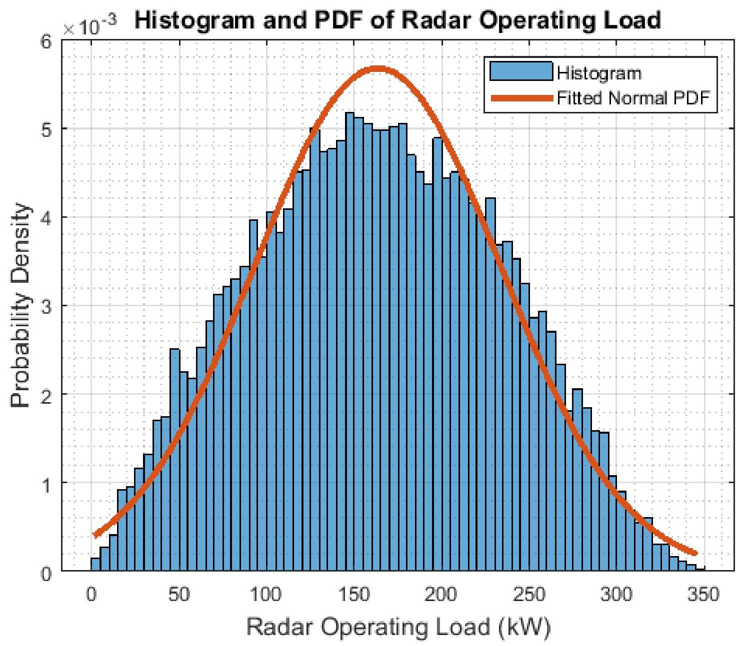


Figure 1: Radar overall operating load PDF.

The cumulative distribution function (CDF) of the simulated radar operating load Figure 2 provides a comprehensive view of the probability distribution. From the CDF, it can be inferred that the probability of the operating load exceeding 346.63 kW (95th percentile upper bound) is approximately 0.9951. From the CDF, it can be inferred that the radar will likely never reach its connected load value of 366.67 kW. This information is valuable for assessing the risk of exceeding design limits and making informed decisions regarding electrical system capacity.

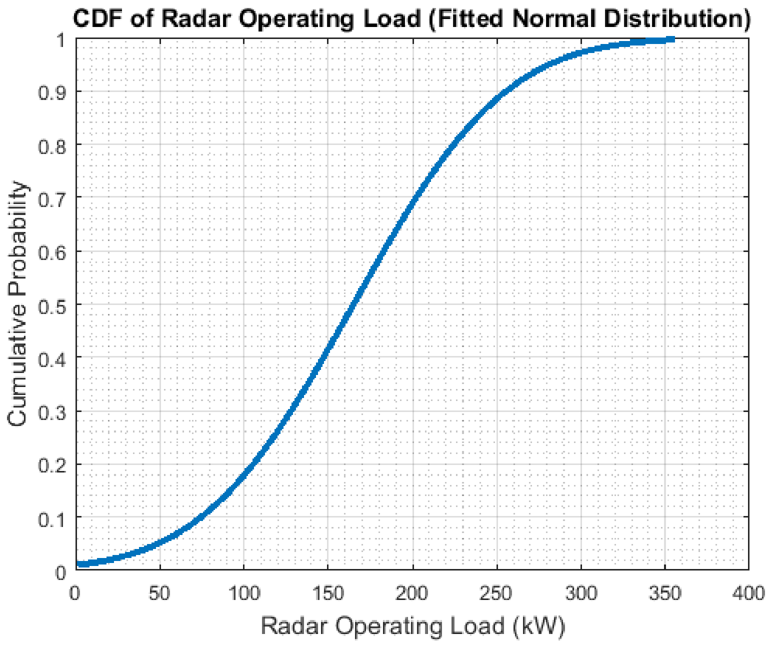


Figure 2: Radar overall operating load CDF.

5.3.2 Probability Distribution (Tropical)

Figure 3 presents the radar operating load's probability density function (PDF) for the "Tropical" environmental condition. The PDF illustrates the distribution of operating load in this environment, with the peak of the curve indicating the most likely load value (163.62 kW). The wide spread of the PDF suggests high variability in the load. Figure 4 shows the radar operating load's cumulative distribution function (CDF) specifically for the "Tropical" environmental condition. From the CDF, it can be inferred that the probability of the load exceeding 322.67 kW in this environment is approximately

0.0035011. Moreover, the 95th percentile of the operating load in tropical conditions is estimated to be 281.706 kW. This information is valuable for assessing the risk of exceeding design limits and making informed decisions regarding power system capacity in such environments.

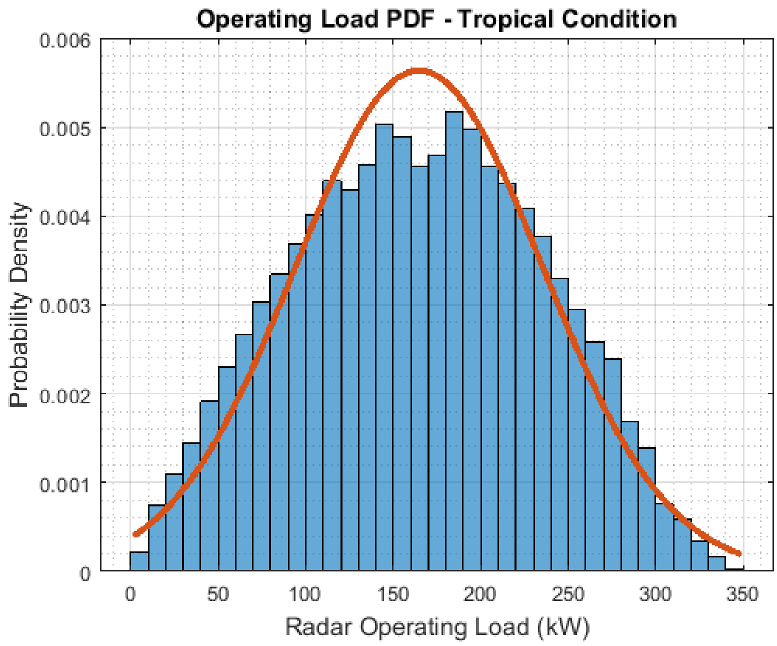


Figure 3: Radar operating load PDF in *tropical condition*.

5.3.3 Probability Distribution (Temperate)

Figure 5 presents the radar operating load's probability density function (PDF) for the "Tropical" environmental condition. The PDF illustrates the distribution of operating load in this environment, with the peak of the curve indicating the most likely load value (163.12 kW). The wide spread of the PDF suggests high variability in the load. Figure 6 shows the radar operating load's cumulative distribution function (CDF) specifically for the "Tropical" environmental condition. From the CDF, it can be inferred that the probability of the load exceeding 322.67 kW in this environment is approximately 0.0040754. Notably, the probability of load exceeding the predefined threshold (108.17 kW) for this environmental condition is significantly high (0.75755). Moreover, the 95th percentile of the operating load in temperate conditions is estimated to be 281.462 kW, almost the same as that for "Tropical" conditions. This information is valuable for assessing the risk of exceeding design limits and making informed decisions regarding power system capacity in such environments.

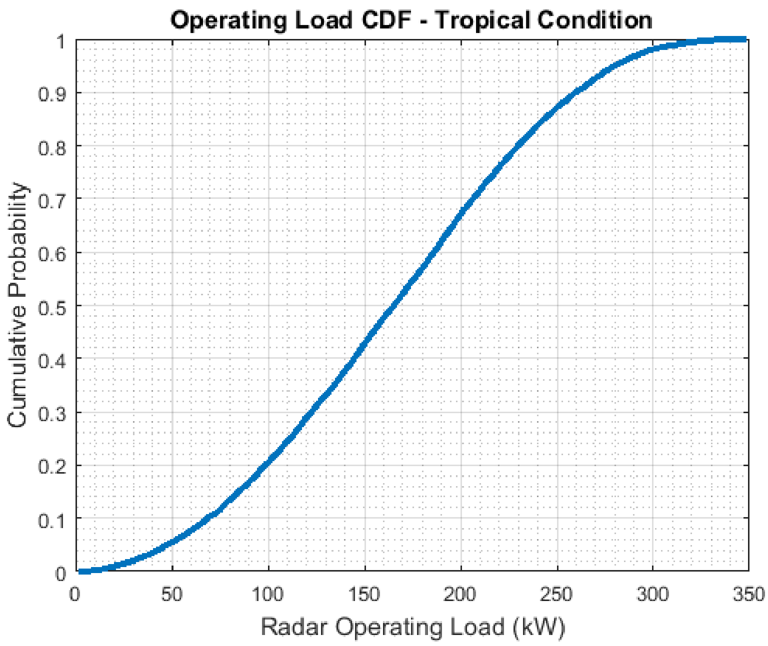


Figure 4: Radar operating load CDF in *tropical condition*

5.3.4 Probability Distribution (Sub-Arctic)

Figure 7 presents the probability density function (PDF) of the total radar operating load for the "Sub-Arctic" environmental condition. The PDF illustrates the distribution of power demand in this environment, with the peak of the curve indicating the most likely load value. The wide spread of the PDF suggests high variability in the load. Figure 8 illustrates the cumulative distribution function (CDF) of the total radar operating load specifically for the "Sub-Arctic" environmental condition. From the CDF, it can be inferred that the probability of the load exceeding 30.8 kW in this environment is approximately 0.98401 kW. Furthermore, the 95th percentile of the operating load in "Sub-Arctic" conditions is estimated to be 278.118 kW. This information is valuable for assessing the risk of exceeding design limits and making informed decisions regarding power system capacity in such environments.

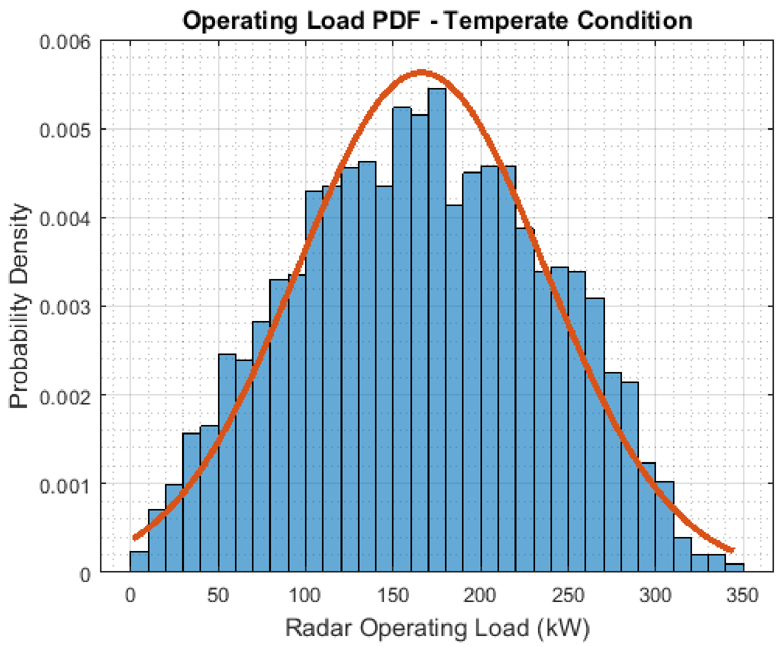


Figure 5: Radar operating load PDF in *temperate condition*.

5.3.5 Probability of Exceedance

Exceedance Probabilities enabled the estimation of exceedance probabilities (see Appendix E), providing crucial information for risk assessment and system design. For example, the overall probability of the radar load exceeding 322.67 kW was found to be 0.0038235 and in “Tropical” condition, it was found to be 0.0035011, in “Temperate” condition, it was found to be 0.0040754, in “Sub-Arctic” condition was found to be 0.0062167. This information allows for informed decisions regarding power generation capacity and mitigation strategies

to prevent overloading. The probability of exceeding operating load thresholds based on defined operating load for each environmental condition:

- Probability of exceeding 322.67 kW: 0.0038235
- Probability of exceeding 108.17 kW: 0.7590
- Probability of exceeding 30.80 kW: 0.97997

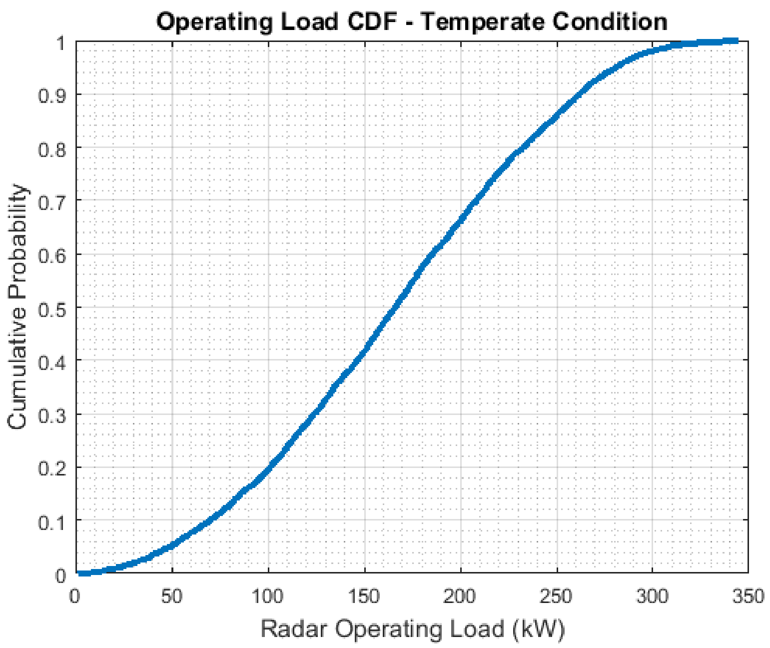


Figure 6: Radar operating load CDF in *temperate condition*.

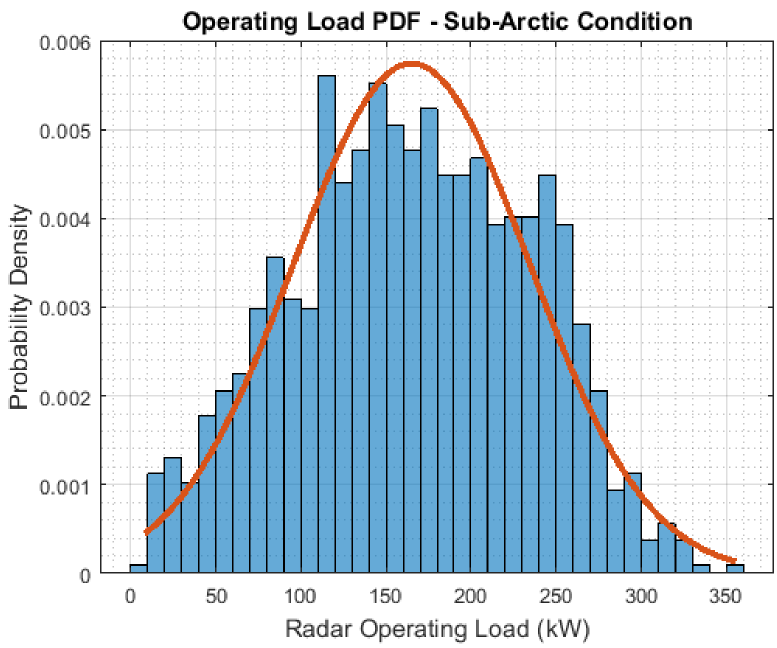


Figure 7: Radar operating load PDF in *sub-arctic condition*.

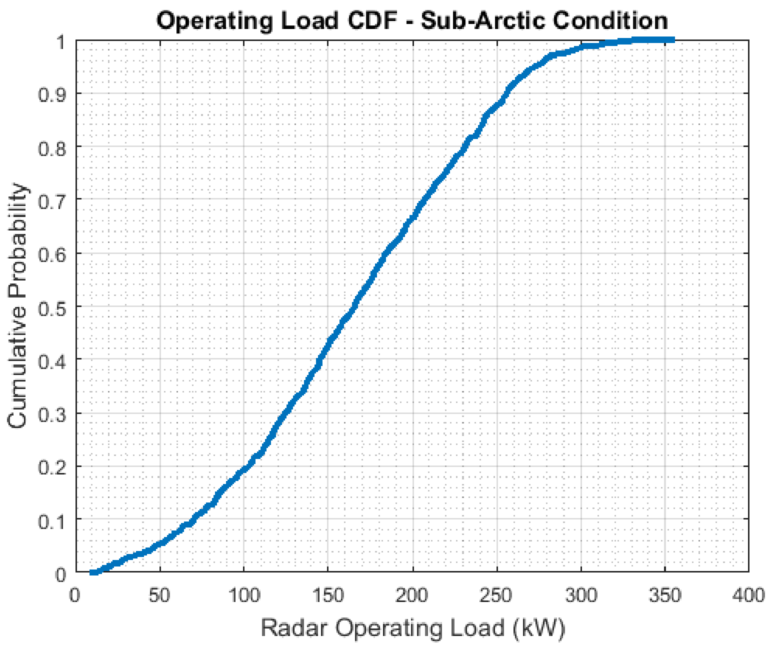


Figure 8: Radar operating load CDF in *sub-arctic condition*.

5.3.6 Operating Load and Utilisation Factor

The reader is directed to Appendix C for background on the statistical technique (correlation coefficient) mentioned in this subsection. Figure 9, Figure 10 and Figure 11 visualise the relationship between the maximum operating load and utilisation factor for each environmental condition ("Tropical", "Temperate", and "Sub-Artic"). The calculated correlation coefficient confirms a consistent positive linear relationship between the utilisation factor and the radar's operating load within each environmental condition. A higher utilisation factor generally leads to a higher operating load.

Tropical Correlation Coefficient	= 0.514096
Temperate Correlation Coefficient	= 0.517328
Sub-Arctic Correlation Coefficient	= 0.474569

The coefficient range indicates a moderate positive correlation in all environments. While the correlation was positive in all environments, it was slightly stronger in the "Temperate" conditions compared to the "Tropical" and "Sub-Arctic" conditions. While the differences are not drastic, they might suggest that environmental factors subtly influence the relationship between utilisation factor and operating load. Potential explanations for this include:

a. Different environments might have varying cooling requirements for the radar system. In hotter climates (Tropical), the cooling system might need to work harder, potentially leading to a slightly stronger link between utilisation factor and operating load.
b. Atmospheric conditions (e.g. humidity, air density, etc.) could affect the radar's performance and power consumption in subtle ways, contributing to the variations in correlation.

c. Ship operational procedures or radar settings might be adjusted slightly in different environments, which could influence the relationship between utilisation factor and operating load.

The consistent positive correlation across all environments highlights the importance of considering utilisation patterns when predicting and managing the radar's operating load, regardless of the environmental conditions. This information can be used to optimise power allocation strategies and ensure the electrical system can handle the radar's load under various conditions.

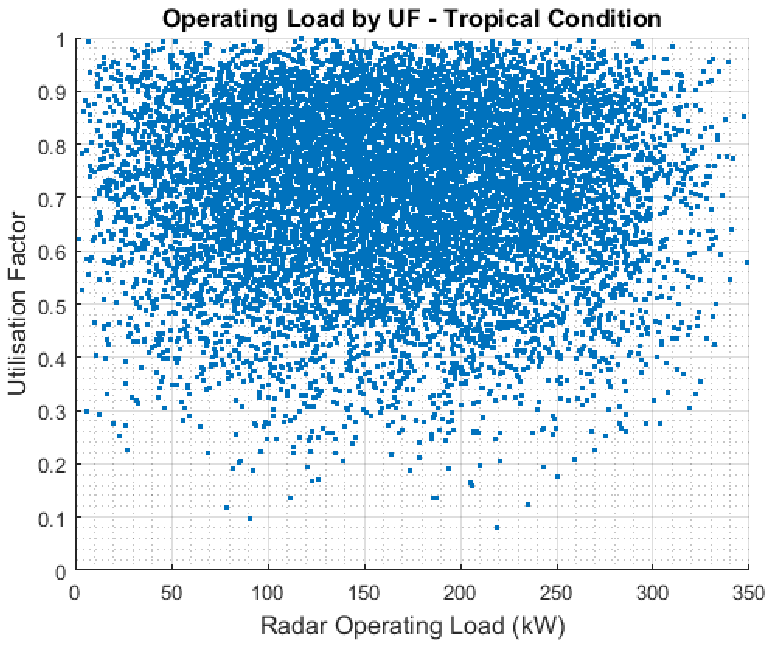


Figure 9: Radar operating load by utilisation factor in *tropical condition*.

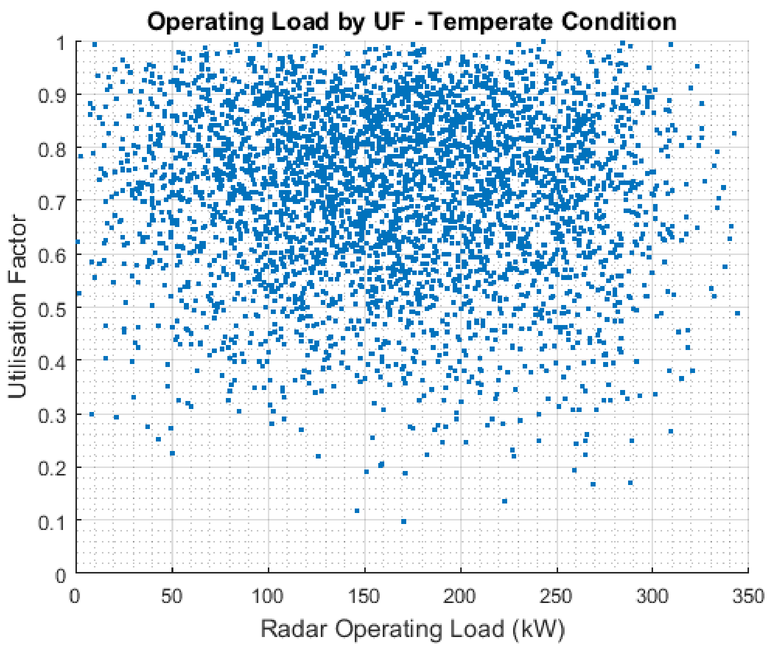


Figure 10: Radar operating load by utilisation factor in *temperate condition*.

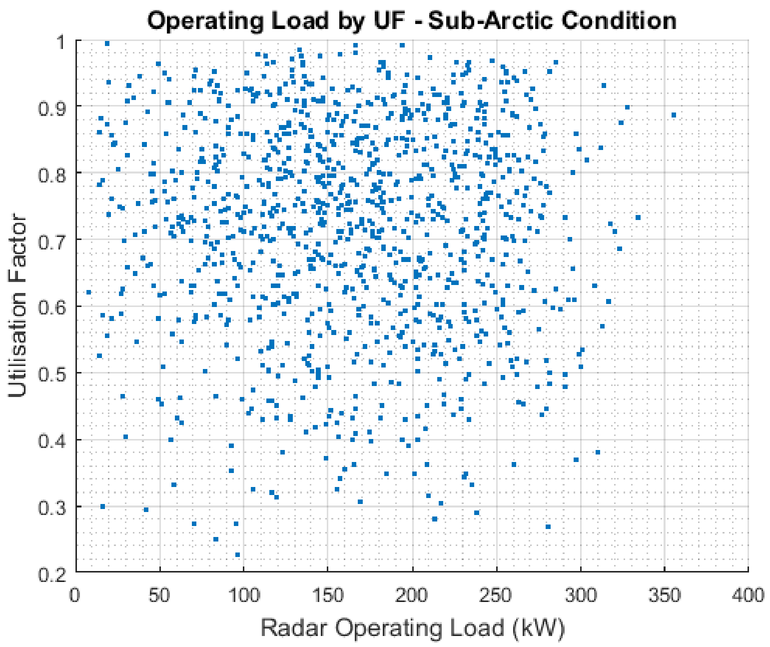


Figure 11: Radar operating load by utilisation factor in *sub-arctic condition*.

Figure 12 illustrates the convergence of the Monte Carlo simulation by plotting the error in the estimated mean operating load against the iteration number. The error exhibits a decreasing trend, indicating convergence towards a stable solution. The simulation achieved the target error of 1% within 16477 iterations (see Appendix E), demonstrating the efficiency and reliability of the estimation process.

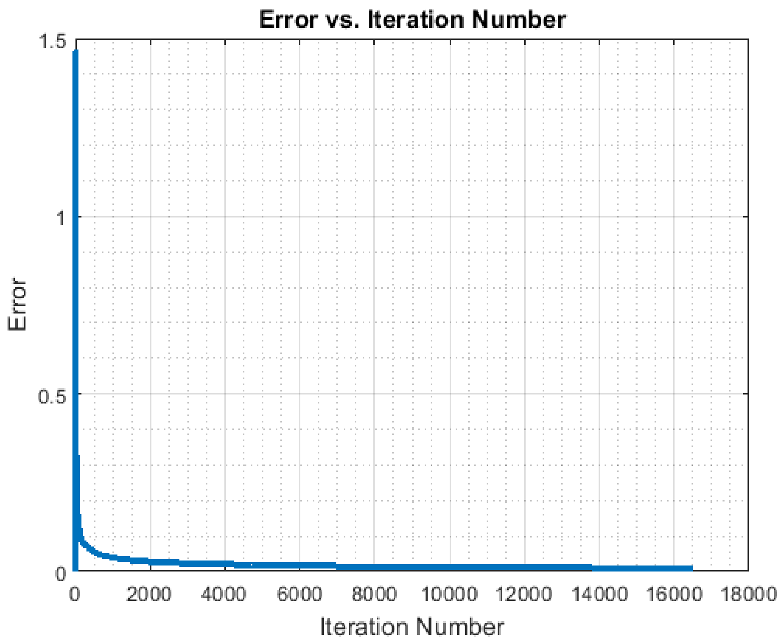


Figure 12: Monte Carlo simulation error tracking by the iteration number.

:

5.4 COMPARATIVE ASSESSMENT

The stochastic results provide a stark contrast to the deterministic estimates presented in the previous section. While the deterministic method yielded single operating load values for each environmental condition (322.67 kW for Tropical, 108.17 kW for Temperate, and 30.80 kW for Sub-Arctic), the stochastic simulation revealed a much more comprehensive range of possibilities and captured the variability inherent in the radar's operation. This comparison highlights the limitations of the deterministic approach in accurately representing the dynamic behaviour of the radar system. By incorporating uncertainty and variability, the stochastic method offers a more comprehensive and realistic assessment of the operating load, enabling more robust system design and operation.

The stochastic EPLA results demonstrate the value of incorporating uncertainty and variability into EPLA for naval warships. The Monte Carlo simulation provides valuable insights that are not available from deterministic methods, such as exceedance probabilities and detailed operating load distributions for different environmental conditions. In the context of naval warship EPLA, these findings can inform the design and operation of naval warships' electrical power systems. For example, the variability in power demand emphasises the need for robust power generation and distribution systems that can handle load fluctuations and peak loads. The exceedance probabilities can guide decisions on the sizing of generators and energy storage systems to mitigate the risk of overloading.

5.5 POSITIVE FINDINGS

Overall, the Monte Carlo simulation provides a robust and comprehensive analysis of the power demand of the naval surveillance radar system. The positive findings highlight the accuracy, reliability, and insights gained from this simulation, which can be valuable for system design, risk assessment, and operational planning. Based on the simulation and the visualisations it produced, positive findings from this work include:

a. The simulation demonstrated convergence, meaning the error in the estimated mean operating load decreases with increasing iterations and reaches below the predefined target error threshold. This indicates that the simulation provides an accurate and reliable estimate of the radar's operating load.

b. The simulation incorporated various factors influencing the radar's operating load, including operational states, environmental conditions, and utilisation factors. This comprehensive approach provides a more realistic and clear understanding of the radar's operating load in different scenarios.

c. The simulation provided detailed summary statistics (mean, standard deviation, variance) of the radar operating load, allowing for a quantitative assessment of the power demand and its variability.

d. The simulation calculated the probabilities of exceeding specific load thresholds, which is crucial for risk assessment and system design. This information helps determine the likelihood of the radar's operating load exceeding critical levels, allowing for proactive mitigation measures.

e. The cumulative distribution functions (CDFs) generated for each environmental condition provide a comprehensive view of the probability distribution of the radar operating load. This enables a deeper understanding of the load's behaviour and potential impact on the ship's power system.

f. The simulation generated various plots, including histograms, PDFs, CDFs, and scatter plots, to visualise the distribution and relationships between different variables. These visualisations provide valuable insights into the radar's operating load and influencing factors.

g. The simulation explicitly modelled the impact of different environmental conditions (“Tropical”, “Temperate”, and “Sub-Arctic”) on the radar's operating load. This allows a better understanding of how the radar's performance and power demand vary in different operational environments.

5.6 UNEXPECTED FINDINGS

It's important to remember that these "unexpected" findings are relative to the initial expectations and assumptions. Further investigation and analysis, combined with domain expertise or real-world data, might reveal that these findings are reasonable or explain the observed behaviour. By critically examining these unexpected findings, a deeper understanding of the radar system's behaviour, refinement of the simulation model and potential areas for optimisation or further research can be identified. While the Monte Carlo simulation generally aligns with expectations for a radar system's power consumption, a few findings might be unexpected or warrant further investigation.

5.6.1 High Environmental Multipliers:

The multipliers initially selected for adjusting operating load for different environmental conditions (1.2 for Tropical, 0.8 for Temperate, 0.3 for Sub-Arctic) seemed quite large. It's unexpected that the radar's operating load would be almost twice as high in tropical conditions as in temperate ones. You might want to investigate whether these multipliers are realistic or need adjustment based on more accurate data or domain expertise. As such, all environmental condition multipliers were set to "1" in the final version of the code provided in Appendix D.

5.6.2 Low Utilisation in Sub-Arctic Condition

The scatter plot (Figure 11) shows a tendency for lower utilisation factors in the "Sub-Arctic" environment, even when the total operating load is relatively high. This is somewhat unexpected, as you might expect higher utilisation when the radar operates at a higher power level. It could be due to the specific operational scenarios or constraints in "Sub-Arctic" conditions, which might be worth exploring further.

5.6.3 Variability in Tropical Conditions:

The scatter plot for the "Tropical" environment (Figure 9) shows high variability in the relationship between the total operating load and the utilization factor. This suggests that other factors beyond the utilization factor might significantly influence the radar's power consumption in tropical environments. These factors could include humidity, temperature, or precipitation, affecting the radar's performance and power requirements.

5.7 FUTURE IMPROVEMENTS

This work, particularly the Monte Carlo simulation, provides a solid foundation for analysing the surveillance radar's operating load. However, in the context of a naval warship's electrical power load analysis, several improvements can enhance the simulation accuracy and usefulness of the stochastic method. By incorporating these improvements, a more sophisticated and realistic simulation of the naval warship's electrical power load analysis can be achieved, enabling better design, operation, and management of the ship's power system.

5.7.1 Whole of Ship Integration

Analysing the radar's impact within the context of the entire ship's electrical system is crucial for understanding load interactions and potential bottlenecks. Integrating the radar model into a comprehensive EPLA tool, as demonstrated in (Sievenpiper 2013), would enable a more realistic assessment of power system performance and inform design choices for future warships. This would allow analysis of the impact of the radar's operating load on the overall power generation and distribution network, including interactions with other loads, thereby providing the foundation for conducting the EPLA of the entire ship using the stochastic method.

5.7.2 Dynamic Load Modelling

While this thesis establishes a foundational stochastic EPLA model for the surveillance radar system, it primarily considers steady-state operating conditions. However, as highlighted by (Orji et al. 2014), naval radar systems exhibit significant dynamic load behaviour due to factors like varying operational modes, target tracking activities, and environmental changes. Future research will focus on implementing dynamic load modelling to capture this dynamic behaviour and enhance the model's accuracy. This involves representing the radar's power consumption as a time-varying function, as demonstrated by (Xie et al. 2022), which responds to these dynamic factors.

The need for dynamic load modelling in naval applications, particularly for systems with rapidly changing power demands like surveillance radars, has been emphasised in recent research (Xie et al. 2022). Incorporating dynamic load profiles, as demonstrated in (Su et al.

2018) for a similar system, would enable a more accurate assessment of the radar's impact on power system stability and transient response. Additionally, implementing dynamic load modelling for the radar, capturing how its power demand changes rapidly in response to different operational modes, target tracking, and environmental conditions, would provide a more realistic assessment of the radar's impact on the power system stability and transient response.

5.7.3 Model Validation

To ensure the accuracy and reliability of the developed stochastic EPLA model, thorough validation is crucial. Model validation involves assessing how well the model represents the real-world system intended to simulate. This involves comparing the model's predictions with actual observations or data from an operational radar system. The primary validation approach involves comparing the simulated power consumption data with measured data collected from operational naval radar systems. This will involve obtaining data from actual ship operations and comparing it with the model's predictions under similar conditions.

5.7.4 Sensitivity Analysis

Sensitivity analysis will assess how changes in input parameters affect the model's outputs. This will help identify parameters significantly impacting the model's accuracy and highlight areas where further data collection or refinement may be needed. Implementing a detailed sensitivity analysis to assess how modifications in the input parameters affect the resultant outcomes will aid in identifying the key variables that are most influential in driving changes in operating load. Therefore, conducting a comprehensive sensitivity analysis is crucial in further refining the EPLA model. This analysis will involve systematically varying input parameters, such as (radar operational states and environmental conditions) to assess their impact on the operating load and overall system performance. This will help identify the most influential parameters, guide efforts to improve data accuracy and reduce uncertainty in the analysis (Prempraneerach et al. 2008).

5.7.5 Review by Subject-Matter Experts

Subject-matter experts in naval radar systems and electrical power engineering will review the model and its validation results. Their feedback will provide valuable insights into the model's strengths and limitations and identify potential areas for improvement.

Successful validation of the stochastic EPLA model will provide confidence in its ability to accurately predict the radar's operating load and assess its impact on the ship's electrical system. This will enable more informed decision-making regarding power system design, operation, and management, ultimately contributing to naval warships' enhanced performance and resilience.

6 DISCUSSION

6.1 GENERAL

This thesis investigated a stochastic approach to Electric Power Load Analysis (EPLA) specifically for the surveillance radar system of a naval warship, using Monte Carlo simulation techniques. This approach facilitates a more accurate evaluation of the operating load compared to conventional deterministic (utilisation factor) methodology. Monte Carlo simulation effectively addresses the inherent uncertainties and variabilities associated with a naval ship's operational and environmental conditions, thereby providing a more robust analysis of power requirements. The insights presented in this work are sufficiently general to be applied to many stochastic processes in the industry.

6.2 DATA LIMITATIONS

Obtaining sufficient data for the Monte Carlo Simulation proved difficult due to restricted access to naval ships and associated data. Data limitation is considered an unforeseen circumstance in this thesis, as earlier assumptions about data availability are needed to address the hierarchical approval process of ship designers, ship commanding officers, and other stakeholders. Despite my professional experience in the naval space, data on naval ship power systems is frequently restricted due to intergovernmental confidentiality agreements, national security concerns, and the protection of sensitive military resources. Such limits typically challenge scholars seeking comprehensive insights into naval operations and capabilities. Therefore, this research predominantly utilised a range of different sources. The analysis was based on publicly accessible information, including official publications, declassified papers, and scholarly writings.

Despite these limitations, the simulation was designed to include various combat conditions and mission profiles that naval warships may face in real-world situations. Different environmental conditions and radar operational states were incorporated into the simulation, substantially impacting the radar operating load. Additionally, various utilisation factors were included to illustrate the influence of different simulation parameters on the operating loads of radar systems during extended missions. The analysis endeavoured to comprehensively understand the radar's operating load by systematically approaching this array of variables.

6.3 SIMULATION DEVELOPMENT

The development of this simulation involved a *significant investment* of time and effort in coding, debugging, and validation. The complexities of modelling the radar's behaviour under various conditions, coupled with the intricacies of the Monte Carlo method, demanded meticulous attention to detail and a thorough understanding of both the radar system and the statistical techniques involved. This has proved a more challenging problem than initially anticipated due to my inexperience with Monte Carlo simulations, despite having MATLAB coding experience through many courses in my BENH program, with ENG3104 providing the fundamentals of MATLAB coding.

6.4 COMPARISON WITH DETERMINISTIC METHODS

In contrast to the stochastic method employed in this thesis, traditional EPLA often relies on deterministic methods, such as the load factor and utilisation factor methods. This method applies a fixed load factor to the nameplate power rating (*connected load*) of equipment to estimate its operating load. While more straightforward to implement, the deterministic method fails to capture the inherent variability in ship power demand and can lead to inaccurate estimations, particularly for complex systems like naval surveillance radar.

6.5 KEY FINDINGS AND IMPLICATIONS

The findings of this simulation highlight the importance of considering uncertainty and variability in EPLA for naval warships. The stochastic approach provides a more detailed understanding of the radar's operating load, enabling better design, operation, and management of the ship's electric power system. Estimating exceedance probabilities and visualising the load distribution under various conditions allows for informed risk assessment and mitigation strategies (future work).

6.6 FUTURE RESEARCH AND REFINEMENTS

Despite the challenges faced in accessing real-world data, this simulation offers valuable insights into the operating load pattern of naval surveillance radar systems. Future research could focus on refining the simulation by incorporating more detailed operational scenarios, dynamic load modelling, and advanced statistical techniques. Access to real-world data and sea trial results would further enhance the accuracy and validation of the simulation.

6.7 CONTRIBUTIONS AND CONCLUSION

This research contributes to naval electrical engineering by demonstrating the value of stochastic methods in EPLA. The findings can inform design decisions, operational strategies, and power management for naval warships, ultimately enhancing their operational effectiveness and resilience.

7 CONCLUSIONS

This thesis investigated applying stochastic methods, specifically Monte Carlo simulation, to Electric Power Load Analysis (EPLA) for a naval warship's surveillance radar system. Driven by the limitations of traditional deterministic approaches in capturing the dynamic and uncertain nature of modern warship electrical loads, this research sought to provide a more realistic and comprehensive assessment of the radar's operating load.

The background section established the context of EPLA in naval ship design, highlighting the increasing complexity of electrical loads and the challenges posed by their variability and dependence on operational and environmental factors. The literature review examined existing research on deterministic and stochastic EPLA, Monte Carlo simulation, and modern naval ship design, revealing a growing recognition of the need for more sophisticated approaches to EPLA.

The methodology section detailed the mixed-method approach, incorporating deterministic and stochastic methodologies. The implementation of the Monte Carlo simulation in MATLAB was described, including the modelling of various influencing factors and the use of probability distributions to represent uncertainty. The tools and techniques used for analysis and visualisation were also outlined, along with the investigation setup and testing procedures.

The simulation results demonstrated the capability of the stochastic approach to capture the variability and uncertainty in the radar's operating load. Generating load distributions, exceedance probabilities, and CDFs provided valuable risk assessment and system design insights (future work). The visualisations generated by the simulation aided in understanding the complex relationships between the radar's power demand and various influencing factors.

The discussion section highlighted the key findings of the simulation, emphasising the advantages of the stochastic approach over deterministic methods. The challenges in accessing real-world data were acknowledged, and potential avenues for future research and refinements were identified.

In conclusion, this thesis contributes to naval electrical engineering by demonstrating the value of stochastic methods in EPLA. The developed Monte Carlo simulation provides a more realistic and comprehensive assessment of the operating load of a naval surveillance radar system, enabling better design, operation, and management of the ship's electric power system. The findings can inform decision-making in various warship design and operation aspects, ultimately enhancing their effectiveness and resilience.

This research underscores the importance of embracing advanced analytical techniques to address the challenges of modern naval warships' increasing complexity and electrification. By incorporating uncertainty and variability into EPLA, the naval engineering community can ensure the reliable and efficient operation of critical shipboard systems, contributing to the overall success of naval missions.

REFERENCES

Aien, M, Fotuhi-Firuzabad, M & Aminifar, F 2012, 'Probabilistic load flow in correlated uncertain environment using unscented transformation', *IEEE Transactions on Power Systems*, vol. 27, no. 4, pp. 2233-41.

Boveri, A 2018a, 'Approaches to shipboard power generation systems design and management. Probabilistic approach to load prediction and system optimal design, sizing and management'.

Boveri, A 2018b, 'Approaches to Shipboard Power Generation Systems Design and Management', Thesis for the degree of Philosophiae Doctor thesis, University of Genoa, Genoa, Italy.

Boveri, A, Gualeni, P & Silvestro, F 2016, 'Stochastic electrical plan load Analysis for increasing flexibility in electrical ship system'.

Boveri, A, Silvestro, F & Gualeni, P 2016, 'Ship electrical load analysis and power generation optimisation to reduce operational costs', *2016 international conference on electrical systems for aircraft, railway, ship propulsion and road vehicles & international transportation electrification conference (ESARS-ITEC)*, IEEE, pp. 1-6.

Boveri, A, Gualeni, P, Neroni, D & Silvestro, F 2017, 'Stochastic approach for power generation optimal design and scheduling on ships', *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, IEEE, pp. 1-6.

Boveri, A, Silvestro, F, Molinas, M & Skjong, E 2018, 'Optimal sizing of energy storage systems for shipboard applications', *IEEE Transactions on Energy Conversion*, vol. 34, no. 2, pp. 801-11.

Boveri, A, D'Agostino, F, Gualeni, P, Neroni, D & Silvestro, F 2018, 'A stochastic approach to shipboard electric loads power modeling and simulation', *2018 IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC)*, IEEE, pp. 1-6.

Chen, C-J, Su, C-L & Teng, J-H 2020, 'Electrical load analysis for shipboard power systems using load survey data', *IEEE Transactions on Industry Applications*, vol. 56, no. 2, pp. 1180-9.

Doerry, N 2012, *Electric Power Load Analysis (EPLA) for Surface Ships,* DoN, Naval Sea Systems Command, Washington Navy Yard, DC 20376-5124, viewed 10 February 2024, <.

Doerry, NH 2007, 'Sizing power generation and fuel capacity of the all-electric warship', *2007 IEEE Electric Ship Technologies Symposium*, IEEE, pp. 1-6.

Doerry, NH & Amy, JV 2011, 'Implementing quality of service in shipboard power system design', *2011 IEEE Electric Ship Technologies Symposium*, IEEE, pp. 1-8.

IEEE 1993, *IEEE Recommended Practice for Electric Power Distribution for Industrial Plants*, IEEE Std 141-1993, Institute of Electrical and Electronics Engineers, New York, viewed 3 November 2024, <https://ieeexplore-ieee-org.ezproxy.usq.edu.au/stamp/stamp.jsp?tp=&arnumber=398556>.

Kloubert, M-L 2020, 'Probabilistic Load Flow Approach Considering Dependencies of Wind Speed, Solar Irradiance, Electrical Load and Energy Exchange with a Joint Probability Distribution Model', *Energies*, vol. 13, no. 7, p. 1727.

Kulkarni, VG 2016, *Modeling and analysis of stochastic systems*, Third edn, Chapman and Hall/CRC.

Moore, DS, Notz, W & Fligner, MA 2013, *The Basic Practice of Statistics*, W.H. Freeman and Company.

Mousavi, SM & Abyaneh, HA 2010, 'Effect of load models on probabilistic characterization of aggregated load patterns', *IEEE Transactions on Power Systems*, vol. 26, no. 2, pp. 811-9.

Orji, U, Sievenpiper, B, Gerhard, K, Leeb, SB, Doerry, N, Kirtley, JL & McCoy, T 2014, 'Load modeling for power system requirement and capability assessment', *IEEE Transactions on Power Systems*, vol. 30, no. 3, pp. 1415-23.

Platenberg, D 2024, 'Characterizing Naval Ship Systems Power and Energy Metrics through Modeling and Analysis', Massachusetts Institute of Technology.

Prempraneerach, P, Hover, FS, Triantafyllou, MS, Mccoy, TJ, Chryssostomidis, C & Karniadakis, GE 2008, 'Sensitivity analysis of the shipboard integrated power system', *Naval Engineers Journal*, vol. 120, no. 1, pp. 109-21.

Ren, Y, Kong, AW-K & Wang, Y 2022, 'Real-Time Shipboard Power Management Based on Monte-Carlo Tree Search', *IEEE Transactions on Power Systems*, vol. 38, no. 4, pp. 3669-82.

Reuven Y. Rubinstein, DPK 2016, *Simulation and the Monte Carlo Method*, John Wiley & Sons, Inc., Online.

Sciberras, EA, Zahawi, B, Atkinson, DJ, Breijs, A & van Vugt, JH 2016, 'Managing shipboard energy: A stochastic approach special issue on marine systems electrification', *IEEE Transactions on Transportation Electrification*, vol. 2, no. 4, pp. 538-46.

Sievenpiper, BJ 2013, 'Electrical ship demand modeling for future

generation warships', Massachusetts Institute of Technology, Cambridge, Massachussetts.

Su, C-L, Chen, C-J, Teng, J-H & Liao, C-H 2018, 'Estimation of demand factor and generator demand in shipboard microgrids from load measurement data', *2018 5th International Conference on Electric Power and Energy Conversion Systems (EPECS)*, IEEE, pp. 1-6.

The MathWorks, I 2024, *Beta Distribution*, The MathWorks, Inc., https://au.mathworks.com/help/stats/prob.betadistribution.html>.

Van Schaik, M 2017, 'A study on the stochastic modelling of load balances and the auxiliary power demand of superyachts in an early design phase'.

Wolfe, J & Roa, MJ 2016, 'Advanced methods for tabulation of electrical loads during special modes of marine vessel operation', *IEEE Transactions on Industry Applications*, vol. 53, no. 1, pp. 667-74.

Wolfe, JM & Fanberg, MM 2013, 'Statistical analysis for shipboard electrical power plant design', *SNAME Maritime Convention*, SNAME, p. D011S05R08.

Xie, P, Tan, S, Bazmohammadi, N, Guerrero, JM & Vasquez, JC 2022, 'A real-time power management strategy for hybrid electrical ships under highly fluctuated propulsion loads', *IEEE Systems Journal*, vol. 17, no. 1, pp. 395-406.

APPENDIX

Appendix A Guidance On Stochastic EPLA

Doerry, N 2012, Electric Power Load Analysis (EPLA) for Surface Ships, DoN, Naval Sea Systems Command, Washington Navy Yard, DC 20376-5124, viewed 10 February 2024, pp. 19-25.

5.6.1 Stochastic load analysis guidance.

5.6.1.1 Introduction.

While traditional load factor and zonal load factors account for uncertainty with margins, stochastic load analysis incorporates the uncertainty normally accommodated with margin in a PDF for each load. The definite integral of the PDF over an interval from x_1 to x_2 is the probability that the value for x will be between x_1 and x_2. The value for each load; therefore, is modeled as a function of one or more random variables, each characterized by a PDF.

A PDF accounts for many sources of uncertainty including:

a. Especially during early stages of design, the specific hardware to implement a load may not be selected. Many times, the particular piece of hardware is not chosen until detail design. The stochastic model of the load must account for the range of different equipment that could be chosen in detail design.

b. Especially for early stage design or new equipment, the load values provided by manufacturer's data sheets may not be completely reliable or reflective of the manner in which the equipment is integrated and employed onboard the ship.

c. The electrical power required by a variety of loads is determined by the mechanical power demand provided by the load to other systems. For example, the power consumed by a pump is determined by the flow requirements of the fluid system it serves. The uncertainty in the flow requirements is reflected as an uncertainty in the electrical load.

d. A load may cycle among several power levels. For example, a water heater may have zero, one, or two heating elements energized depending on the need to regulate the water temperature.

For a random variable X, the PDF of X is represented by $f_X(x)$. The probability that X is between x_1 and x_2 is given by:

$$\boldsymbol{Pr}(x_1 < X < x_2) = \int_{x_1}^{x_2} f_X(x)dx \qquad [5]$$

The cumulative distribution function (CDF) represented by $F_X(x)$ is the probability that the value of X is less than or equal to x.

$$F_X(x) = \int_{-\infty}^{x} f_X(y)dy \qquad [6]$$

For sizing electrical equipment, we are typically interested in the inverse of this problem: the load (value of x) for which the probability of X less than or equal to x is some fixed probability represented by the term (1 - α), where α represents the probability that the actual load is greater than x. In other words, we are seeking the value of x for which:

$$F_X(x) = \int_{-\infty}^{x} f_X(y)dy = (1 - \alpha) \qquad [7]$$

The value for (1 - α) to use for calculating ship demand power or equipment demand power depends on the consequence of not having sufficient capacity. If the generators/equipment have a significant overload capability for a reasonable duration of time, and there are a significant amount of cyclic loads, then an appropriate value for (1 - α) would be on the order of 0.95 (there is a 5 percent chance that the equipment would be undersized). On the other hand, equipment such as power electronics which typically have only a small overload capability, an appropriate value for (1 - α) would be on the order of 0.99 (there is a 1 percent chance that the equipment would be undersized). The actual numbers to use for (1 - α) should be based on balancing the cost of adding additional power capacity against the risk of having undersized power system equipment.

For fuel consumption calculations, an average value is desired. While the median value corresponds to (1 - α) = 0.50, fuel consumption calculations typically should use the mean value ($\bar{x}$) which is calculated using equation 8.

$$\bar{x} = \int_{-\infty}^{\infty} x f_X(x)dx \qquad [8]$$

5.6.1.2 Load characterization.

Many loads can be characterized by three types of stochastic models:

a. Loads that are always "on" can be represented by a single random variable that corresponds to the uncertainty in estimating that load.

b. Loads that cycle on and off independently of other loads can be represented by a function of two random variables. The first random variable describes the fraction of time that the load is on and the second corresponds to the amount of electrical power the load consumes when on.

c. For loads that are dependent on configuration, make the configuration "number" a discrete random variable that provides the probability for each unique configuration. For each unique configuration, develop a model of the load as appropriate. A configuration can either be at the system level, or specifically for the individual load. A configuration can also refer to different models of equipment fulfilling the same function produced by the same or different manufacturers.

For example, at the system level, if 2 of 6 fire pumps are required to be on, then there are 15 different combinations or configurations that can meet this requirement. In this case, each of the 15 configurations would likely have the same probability. For each configuration a given fire pump would be either off, or have its own stochastic model for the load when on.

Another example, at the load level, could correspond to a radar with multiple modes of operation. Each mode of operation would correspond to a "configuration" and the associated load would be modeled as in case (a) or (b).

Note that cases (b) and (c) incorporate conditional probabilities where the probability only applies if a given condition happens (i.e., the load estimate only applies if the load is on).

Note that margins are not explicitly included in this method. The intended purpose of a margin, to account for uncertainty of the estimate, is accomplished through the PDFs for each load. On the other hand, service life allowances should be applied to the results of the stochastic analysis for determining the rating of the power system equipment. Service life allowances account for the growth of loads during the operational life of the ship following delivery and due to maintenance and modernization efforts.

While the three types of stochastic models will cover many if not all the loads typically encountered in an electric load analysis, special cases will undoubtedly occur which will require a different type of model. The stochastic modeler must be capable of recognizing this situation and developing an appropriate model. The level of detail of the model is bounded by the complexity needed and resources available to the user.

In modeling an electric load, PDFs of three standard types are typically employed: uniform, triangular, and discrete. In the uniform distribution (figure 6), a variable is uniformly likely to occur between a minimum and maximum value. In early stages of design, this is likely the most appropriate model to use when very little is known about the loads. Once a "most likely" value of a load is known (the mode), a triangular distribution (figure 7) can reflect the additional information available from more mature design information. A discrete distribution (figure 8) allows one to model different modes or configurations of a load or a load's system. The discrete distribution is composed of one or more impulse functions whose magnitude is equal to the probability of x having the value equal to the impulse functions location. While the normal distribution (figure 9) is commonly used in stochastic modeling, it should be used with caution in power system modeling. The normal distribution has unbounded lower and upper limits. Most loads cannot physically have a negative load, nor if they are working correctly, will they have a load larger than some maximum value. If a normal distribution is used, some provision in the modeling should be employed to address these anomalies.

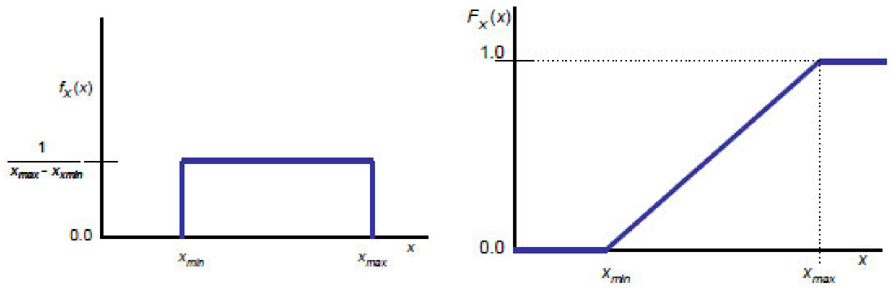


Figure 6. Uniform distribution PDF and CDF.

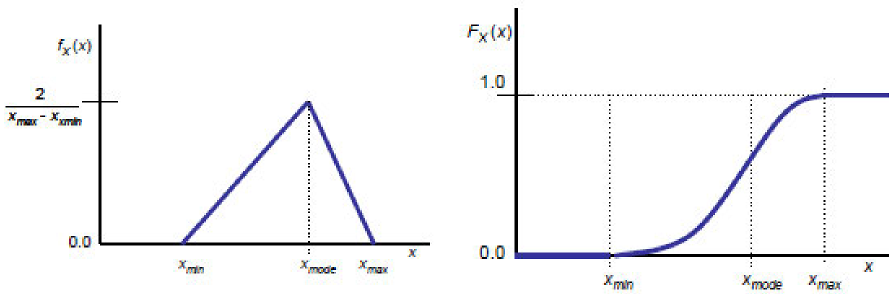


Figure 7. Triangular distribution PDF and CDF.

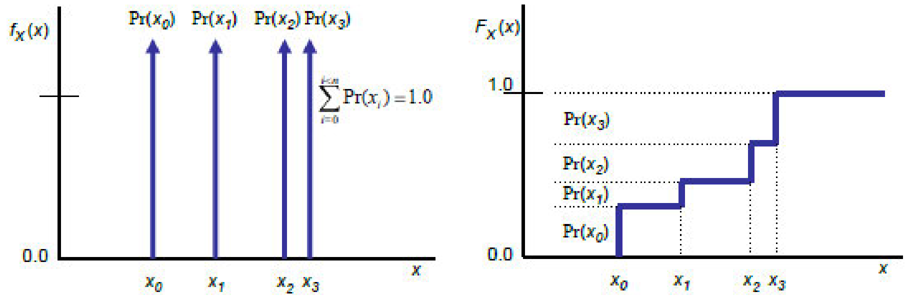


Figure 8. Discrete distribution PDF and CDF.

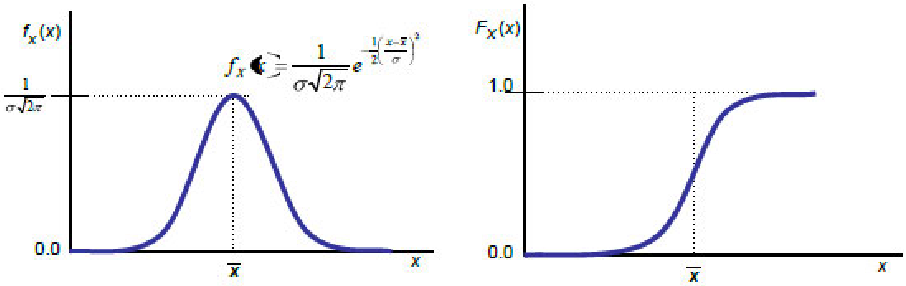


Figure 9. Normal distribution PDF and CDF.

5.6.1.3 Monte Carlo Simulation.

Determining the PDF for the total load served by a power system component is accomplished by summing the values, also expressed as a PDF, of the individual loads served. While there are a number of techniques for developing the PDF for the total load served, the method most often used is a variant of the Monte Carlo Simulation Method.

In a Monte Carlo Simulation, the process depicted in figure 10 is used:

a. A model of the system is developed using real numbers as inputs and producing real numbers as output.

b. PDFs are developed for each of the inputs.

c. The model of the system is executed multiple times. For each iteration:

(1) A value for each input is randomly chosen according to its PDF.

(2) The models output is recorded.

d. After an initial number of iterations are completed (typically on the order of 500 (should be large enough to develop a reasonable error estimate)), the mean and variance of the set of model outputs is calculated. From these values, an estimate of the error is made. If the error estimate is small enough (typically 2 percent of the mean value), then the output PDF is calculated and the process terminates. If the error estimate is too high, then an estimate for the number of iterations required is made and the additional iterations executed.

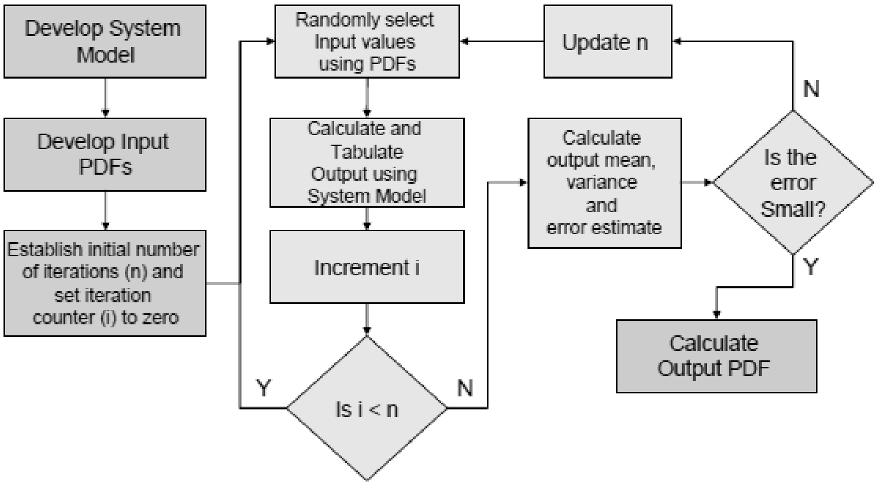


Figure 10. Monte Carlo Simulation Algorithm.

5.6.1.4 Random variable generation.

There are a number of ways to create a random sample for a given PDF to generate an input value to drive the system model. Some computer software systems can directly create random numbers for specific types of PDFs such as a normal distribution. Virtually all systems can create a random number in the interval [0:1] using a uniform distribution. This uniform distribution, through the use of the Inverse Transform Technique (figure 11), can be used to produce random variables of an arbitrary PDF. The steps of the Inverse Transform Technique are:

a. Develop the CDF $F_X(x)$ from the PDF $f_X(x)$ using equation 6.

b. Create a sample u from a uniform distribution over the interval [0:1].

c. Solve the equation $F_X(x) = u$ for x. x is now a random sample from the PDF $f_X(x)$.

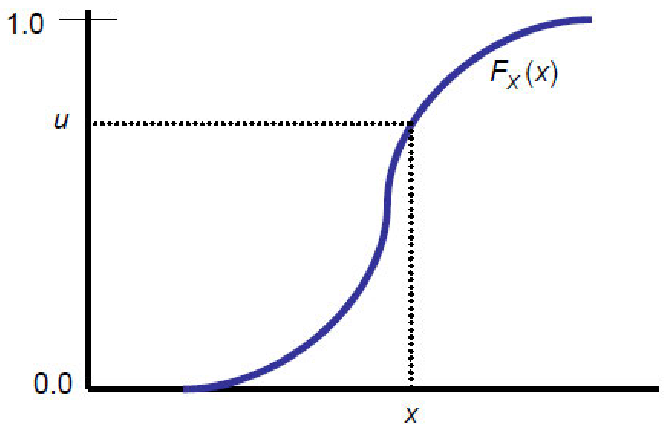


Figure 11. Inverse transform technique.

5.6.1.5 Estimating output PDF properties.

Estimating the mean ($\bar{x}$), standard deviation (σ_x), and variance (σ_x^2) of the output PDF from the set of outputs x_i for n iterations is straight forward:

$$\bar{x} = \frac{1}{n}\sum_{i=0}^{n-1} x_i \qquad [9]$$

$$\sigma_x^2 = \frac{1}{n-1}\sum_{i=0}^{n-1} \left(x_i - \bar{x}\right)^2 \qquad [10]$$

Note that in equation 10, the term (n-1) is used instead of the n of the formal definition of a standard deviation. (n-1) reflects the common usage of Bessel's correction to account for the limited sample size of the output PDF. For large n, it doesn't practically matter whether one uses n or (n-1).

For electrical load analysis, characterizing the error (E) as a fraction of the mean value is a reasonable approach. A conservative estimate for E for a sufficiently large n is given by:

$$E = \frac{3\sigma_x}{\bar{x}\sqrt{n}} \qquad [11]$$

Typically, one would like this value of E to be less than or equal to 0.02. Once a sufficient number of iterations (500 is a good starting point) have been established to estimate σ_x and $\bar{x}$, then the number of iterations (n) required to achieve a given value of E can be calculated from:

$$n = \left[\frac{3\sigma_x}{\bar{x}E}\right]^2 = \frac{9}{E^2}\left(\frac{\sigma_x}{\bar{x}}\right)^2 \qquad [12]$$

5.6.2 Stochastic load analysis reports.

For each ambient condition, an EPLA detailed report shall at a minimum contain the following fields for each load on the ship:

1. Line number (or other unique identifier for load)
2. SWBS (3-digit)
3. Nomenclature of the equipment
4. Identification plate rating of the equipment (include units)
5. Connected load (kW)
6. For each operating condition, a description of the stochastic model used and a reference for model details
7. For each operating condition, the mean value and standard deviation of the operating load
8. Notes for documenting special considerations such as interdependencies with other loads
9. Vital/Non-vital status or mission prioritization information

For each ambient condition, an EPLA zonal summary report shall at a minimum contain the following fields:

1. Zonal power conversion equipment name
2. Zonal power conversion equipment output group name

3. Connected load (kW)
4. PDF, mean value, and standard deviation of the equipment demand power (kW) for each ship operating condition

For each ambient condition, an EPLA ship summary report shall at a minimum provide the PDF, mean value, and standard deviation of the ship demand power (kW) and contain the following fields for each 1-digit SWBS group of loads:

1. SWBS (1-digit) and SWBS group name (plus one row for the total ship)
2. Connected load (kW)
3. PDF, mean value, and standard deviation of the operating load for each ship operating condition

Appendix B Understanding Beta Distribution

The beta distribution is a continuous probability distribution defined on the interval [0, 1] (The MathWorks 2024). It's often used to model random variables representing proportions or probabilities, such as the utilisation factor in this thesis. The following parameters are used in beta distribution:

a. Shape Parameters – the shape of the beta distribution is controlled by the two parameters, *alpha* and *beta*. Influence of alpha and beta:
    - If alpha > 1 and beta > 1, the distribution is unimodal (i.e., it has one peak).
    - If alpha > beta, the peak is skewed towards the right (higher utilisation factors are more likely).
    - If alpha < beta, the peak is skewed towards the left (lower utilisation factors are more likely).
    - If alpha = beta, the distribution is symmetric.
    - If alpha < 1 or beta < 1, the distribution can take on various shapes, including U-shaped or J-shaped.
b. Impact on Simulation Results:
    - The alpha and beta values affect the beta distribution's mean, influencing the average utilisation factor in the simulation. A higher mean utilisation factor generally leads to a higher mean operating load for the radar system.
    - The shape parameters also control the variance of the distribution. Higher alpha and beta values generally lead to a narrower distribution with less variability. This means the utilisation factor values will be more concentrated around the mean.

- As mentioned earlier, the relative values of alpha and beta determine the skewness of the distribution. This affects the simulation's likelihood of observing higher or lower utilisation factors.
- Since the utilisation factor directly influences the radar's operating load, alpha and beta values indirectly affect the overall operating load distribution, exceedance probabilities, and other results of the stochastic EPLA.

In this thesis, the beta distribution is unimodal and skewed towards the left. This means that lower utilisation factors are more likely to be sampled in your simulation, leading to lower average power demand for the radar system than in a higher alpha and lower beta scenario. A sensitivity analysis is recommended to understand the impact of alpha and beta more precisely. This involves varying alpha and beta values and observing how the simulation results change. This can help assess the robustness of the simulation and identify the range of plausible operating load scenarios.

Appendix C Correlation Coefficient

The correlation coefficient measures the strength and direction of the linear relationship between two variables (Moore, Notz & Fligner 2013). This thesis shows how strongly the utilisation factor (*utilisationFactors*) is related to the radar's operating load (*powerDemand*) for each combination of environmental conditions and operational state.

Correlation coefficients range from -1 to +1 (Moore, Notz & Fligner 2013):

- +1 indicates a perfect positive linear relationship (as one variable increases, the other increases proportionally).
- -1 indicates a perfect negative linear relationship (as one variable increases, the other decreases proportionally).
- 0 indicates no linear relationship between the variables.

The correlation coefficients provided in this thesis (see Appendix E) are positive and range from approximately 0.47978 to 0.52939 (overall condition). This indicates a moderate positive linear relationship between the utilisation factor and operating load. In other words, the operating load increases as the utilisation factor increases.

The moderate positive correlation confirms that the utilisation factor significantly influences the radar's operating load, which supports the decision to include it as a random variable in the stochastic model. The fact that the correlations are not extremely high (closer to +1) suggests that other factors besides the utilisation factor also contribute to the variability in operating load. This highlights the importance of considering the simulation's environmental conditions and radar operational states.

Comparing the correlation coefficients for each combination of environmental condition and radar operation state, the slightly higher correlation coefficients for the "Temperate - Ready" scenario (0.53169) indicate that the utilisation factor is more dominant in determining power demand in that specific condition than others. Similar inference can be made for the "Temperate - Radiate" scenario (0.53909) and "Tropical - Ready" scenario (0.52149)

Additional statistical analysis, such as regression analysis, can be performed to quantify the relationship between the utilisation factor and operating load more precisely. This could involve developing a regression model (future work) to predict operating load based on the utilisation factor and other relevant variables.

Appendix D MATLAB Code for MCS

```
%% mcSim4Var_V4.m
% % --- Description ---
% This MATLAB code performs a stochastic electric power load analysis
% for a naval surveillance radar system using Monte Carlo simulation.
% Stochastic analysis accounts for the inherent uncertainties and
% variability present in real-world dynamic systems. By incorporating
% probabilistic models and random sampling, this code provides a more
% realistic assessment of operating load variability compared to
% deterministic methods.
%
% Monte Carlo simulation is used to generate a large number of possible
% scenarios for the naval ship's surveillance radar power demand by
% randomly varying the following influencing factors:
%
%  1. Radar operating load [min max]
%  2. Utilisation factor [min max]
%  3. Radar operational states [Available, Ready, Radiate]
%  4. Ship environmental conditions [Tropical, Temperate, Sub-Arctic]
%
% The computation allows for a probabilistic assessment of the radar's
% maximum operating load, providing valuable insights into its statistical
% properties and potential impact on the ship's electrical system.
%
% The simulation incorporates an error function to assess the accuracy of
% the estimated mean demand. This function dynamically adjusts the number
% of simulation iterations until the error falls below a predefined
% threshold, ensuring reliable and statistically significant results.
%
% The code includes comprehensive analysis and visualisation of the
% simulation results, including summary statistics, probability
% calculations, histograms, probability density functions (PDFs),
% cumulative distribution functions (CDFs), and error analysis. These
% visualisations provide a clear and intuitive understanding of the
% radar's operating load under various influencing factors.

clc; close all; clear; format short;

% % ----------------------------------------------------------------------% %

% --- 1. Simulation Parameters

maxIterations = 20000;    % Maximum number of simulations
targetError = 0.01;       % Desired error threshold (1%)

% --- 2. Radar Parameters (in kW)

radarOperatingLoadMin = 0;           % Minimum radar operating load
radarOperatingLoadMax = 366.67;      % Maximum radar operating load
radarOperatingLoadMode = 322.670;    % Mode of the radar operating load

% --- 3. Utilisation Factor Parameters (Beta Distribution)

utilisationFactorMin = 0;   % Minimum radar utilisation factor
utilisationFactorMax = 1;   % Maximum radar utilisation factor
```

```
alpha = 5;       % Shape parameter for beta distribution (see Appendix B)
beta = 2;        % Shape parameter for beta distribution (see Appendix B)

% --- 4. Environmental and Operational Conditions (Methodology)

shipEnvironmentalConditions = {'Tropical', 'Temperate', 'Sub-Arctic'};
radarOperationalStates = {'Available', 'Ready', 'Radiate'};

% --- 5. Pre-allocate Arrays

simulatedRadarOperatingLoad = zeros(maxIterations, 1);
errorTracking = zeros(maxIterations, 1);
utilisationFactors = zeros(maxIterations, 1);
shipEnvironmentalConditionIndices = zeros(maxIterations, 1);
radarOperationalStateIndices = zeros(maxIterations, 1);

% --- 6. Initialize arrays to store power demand for each condition and state

operatingLoadTropicalAvailable = [];
operatingLoadTropicalReady = [];
operatingLoadTropicalRadiate = [];
operatingLoadTemperateAvailable = [];
operatingLoadTemperateReady = [];
operatingLoadTemperateRadiate = [];
operatingLoadSubArcticAvailable = [];
operatingLoadSubArcticReady = [];
operatingLoadSubArcticRadiate = [];

% --- 7. Error Function

calculatedError = @(stdLoad, meanOperatingLoad, numIterations) ...
    (3 * stdLoad) / (meanOperatingLoad * sqrt(numIterations));

% -----------------------------------------------------------------------%
% --- 8. Monte Carlo Simulation --- (Methodology)
% -----------------------------------------------------------------------%

currentError = 1; % Initialise error above the threshold

% --- 8.1 Define power operatingLoadThresholds for environmental conditions

operatingLoadThresholds = [322.67, 108.168, 30.800];

% --- 8.2 Calculate probabilities proportional to operatingLoadThresholds

environmentalConditionProbabilities = operatingLoadThresholds /
sum(operatingLoadThresholds);

% --- 8.3 Initialise arrays to store maxTotalLoad for each environmental
condition

maxOperatingLoadTropical    = [];
maxOperatingLoadTemperate   = [];
maxOperatingLoadSubArctic   = [];

% --- 9. Monte Carlo Simulation Loop ---

for i = 1:maxIterations
```

```
    % --- 9.1 Generate Random Operating Load (Triangular Distribution) ---
    pd = makedist('Triangular', 'a', radarOperatingLoadMin, 'b',
radarOperatingLoadMode, 'c', radarOperatingLoadMax);
    randRadarOperatingLoad = random(pd);

    % --- 9.2 Generate Utilisation Factor (Beta Distribution) ---
    utilisationFactor = utilisationFactorMin + ...
        (utilisationFactorMax - utilisationFactorMin) * betarnd(alpha, beta);
    utilisationFactors(i) = utilisationFactor;

    % --- 9.3 Sample Environmental Condition ---
    environmentalCondition = randsample(shipEnvironmentalConditions, 1, true,
environmentalConditionProbabilities);

    % --- 9.4 Select Radar Operational State ---
    radarOperationalState =
radarOperationalStates{randi(length(radarOperationalStates))};

    % --- 9.5 Apply Influencing Factors to Operating Load ---
    actualOperatingLoad = randRadarOperatingLoad * utilisationFactor;
    actualOperatingLoad = min(actualOperatingLoad, radarOperatingLoadMax); %
Cap the load

    % --- 9.6 Adjust load based on environmental condition ---
    switch environmentalCondition{1}
        case 'Tropical'
            shipEnvironmentalConditionIndices(i) = 1;
%             actualOperatingLoad = actualOperatingLoad * (1 +
(operatingLoadThresholds(1) - operatingLoadThresholds(2)) /
operatingLoadThresholds(1));
             actualOperatingLoad = actualOperatingLoad * 1;
        case 'Temperate'
            shipEnvironmentalConditionIndices(i) = 2;
%             actualOperatingLoad = actualOperatingLoad * (1 +
(operatingLoadThresholds(2) - operatingLoadThresholds(1)) /
operatingLoadThresholds(1));
            actualOperatingLoad = actualOperatingLoad * 1;
        case 'Sub-Arctic'
            shipEnvironmentalConditionIndices(i) = 3;
%             actualOperatingLoad = actualOperatingLoad * (1 +
(operatingLoadThresholds(3) - operatingLoadThresholds(1)) /
operatingLoadThresholds(1));
            actualOperatingLoad = actualOperatingLoad * 1;
    end

    % --- 9.7 Cap the load to Radar Connected Load
    actualOperatingLoad = min(actualOperatingLoad, radarOperatingLoadMax);

    % --- 9.8 Adjust load based on radar operational state ---
    switch radarOperationalState
        case 'Available'
            radarOperationalStateIndices(i) = 1;
            actualOperatingLoad = actualOperatingLoad * 1;
        case 'Ready'
            radarOperationalStateIndices(i) = 2;
            actualOperatingLoad = actualOperatingLoad * 1;
        case 'Radiate'
```

```
            radarOperationalStateIndices(i) = 3;
            actualOperatingLoad = actualOperatingLoad * 1;
    end

    % --- 9.9 Cap the load to Radar Connected Load
    actualOperatingLoad = min(actualOperatingLoad, radarOperatingLoadMax);

    % --- 9.10 Calculate Total Radar Operating Load ---
    simulatedRadarOperatingLoad(i) = actualOperatingLoad;

    % --- 9.11 Store maxTotalLoad for each condition ---
    switch environmentalCondition{1}
        case 'Tropical'
            maxOperatingLoadTropical = [maxOperatingLoadTropical,
actualOperatingLoad];
        case 'Temperate'
            maxOperatingLoadTemperate = [maxOperatingLoadTemperate,
actualOperatingLoad];
        case 'Sub-Arctic'
            maxOperatingLoadSubArctic = [maxOperatingLoadSubArctic,
actualOperatingLoad];
    end

    % --- 9.12 Cap the load to Radar Connected Load
    maxOperatingLoadTropical = min(maxOperatingLoadTropical,
radarOperatingLoadMax);

    % --- 9.13 Assign power demand based on condition and state ---
    if shipEnvironmentalConditionIndices(i) == 1 &&
radarOperationalStateIndices(i) == 1
        operatingLoadTropicalAvailable = [operatingLoadTropicalAvailable,
actualOperatingLoad];

    elseif shipEnvironmentalConditionIndices(i) == 1 &&
radarOperationalStateIndices(i) == 2
        operatingLoadTropicalReady = [operatingLoadTropicalReady,
actualOperatingLoad];

    elseif shipEnvironmentalConditionIndices(i) == 1 &&
radarOperationalStateIndices(i) == 3
        operatingLoadTropicalRadiate = [operatingLoadTropicalRadiate,
actualOperatingLoad];

    elseif shipEnvironmentalConditionIndices(i) == 2 &&
radarOperationalStateIndices(i) == 1
        operatingLoadTemperateAvailable = [operatingLoadTemperateAvailable,
actualOperatingLoad];

    elseif shipEnvironmentalConditionIndices(i) == 2 &&
radarOperationalStateIndices(i) == 2
        operatingLoadTemperateReady = [operatingLoadTemperateReady,
actualOperatingLoad];

    elseif shipEnvironmentalConditionIndices(i) == 2 &&
radarOperationalStateIndices(i) == 3
        operatingLoadTemperateRadiate = [operatingLoadTemperateRadiate,
actualOperatingLoad];
```

```
    elseif shipEnvironmentalConditionIndices(i) == 3 &&
radarOperationalStateIndices(i) == 1
        operatingLoadSubArcticAvailable = [operatingLoadSubArcticAvailable,
actualOperatingLoad];

    elseif shipEnvironmentalConditionIndices(i) == 3 &&
radarOperationalStateIndices(i) == 2
        operatingLoadSubArcticReady = [operatingLoadSubArcticReady,
actualOperatingLoad];

    elseif shipEnvironmentalConditionIndices(i) == 3 &&
radarOperationalStateIndices(i) == 3
        operatingLoadSubArcticRadiate = [operatingLoadSubArcticRadiate,
actualOperatingLoad];
    end

    % --- 9.14 Calculate Error ---
    if i > 1 % Calculate the error after the second iteration
        meanOperatingLoad = mean(simulatedRadarOperatingLoad(1:i));
        stdOperatingLoad = std(simulatedRadarOperatingLoad(1:i));
        currentError = calculatedError(stdOperatingLoad, meanOperatingLoad, i);
        errorTracking(i) = currentError;
    end

    % --- 9.15 Check if Error is Below Threshold ---
    if currentError <= targetError
        fprintf('\nSimulation converged after %d iterations. Error: %.4f\n\n',
i, currentError);
        break;
    end
end

% -----------------------------------------------------------------------%

% --- 10. Analyse and Visualise Results ---

% -----------------------------------------------------------------------%

% --- 10.1 Calculate and Display Overall Operating Load Statistics --

% --- 10.1.1 Calculate and Display Summary Statistics ---
meanOperatingLoad = mean(simulatedRadarOperatingLoad(1:i));
stdOperatingLoad = std(simulatedRadarOperatingLoad(1:i));
varianceOperatingLoad = var(simulatedRadarOperatingLoad(1:i));

% --- 10.1.2 Calculate 99% Confidence Interval for Mean Operating Load ---
standardError = stdOperatingLoad / sqrt(i);
criticalValue = norminv(0.995);  % 0.995 for 99% confidence interval
marginOfError = criticalValue * standardError;
lowerBound = meanOperatingLoad - marginOfError;
upperBound = meanOperatingLoad + marginOfError;

% --- 10.1.3 Calculate 95% Confidence Interval for Maximum Operating Load ---
maxLoadOverallCI = bootci(1000, @max, simulatedRadarOperatingLoad(1:i));

% --- 10.1.4 Create a table for Operating Load statistics ---
overallStats = table({'Minimum Operating Load (kW)'; 'Mean Operating Load
(kW)'; '99% CI Lower Bound (Mean) (kW)'; '99% CI Upper Bound (Mean) (kW)';
```

```
'Standard Deviation (kW)'; 'Variance (kW)'; 'Maximum Operating Load (kW)'; '95%
CI Lower Bound (Max) (kW)'; '95% CI Upper Bound (Max) (kW)'},
[min(simulatedRadarOperatingLoad); meanOperatingLoad; lowerBound; upperBound;
stdOperatingLoad; varianceOperatingLoad; max(simulatedRadarOperatingLoad);
maxLoadOverallCI(1); maxLoadOverallCI(2)], 'VariableNames', {'Statistics (Radar
Operating Load)', 'Value (kW)'});

% --- 10.1.5 Display Operating Load statistics in tabulated form ---
disp(overallStats);

% --- 10.2 Calculate and Display Statistics for Each Environmental Condition --
-

% --- 10.2.1 Tropical Condition ---
minTropical = min(maxOperatingLoadTropical);
maxTropical = max(maxOperatingLoadTropical);
meanTropical = mean(maxOperatingLoadTropical);
stdTropical = std(maxOperatingLoadTropical);
varTropical = var(maxOperatingLoadTropical);

% --- 10.2.2 Calculate 99% Confidence Interval for Tropical Condition ---
standardErrorTropical = stdTropical / sqrt(length(maxOperatingLoadTropical));
criticalValue = norminv(0.995);
marginOfErrorTropical = criticalValue * standardErrorTropical;
lowerBoundTropical = meanTropical - marginOfErrorTropical;
upperBoundTropical = meanTropical + marginOfErrorTropical;

% --- 10.2.3 Calculate 95% Confidence Intervals for Maximum Load in Tropical
Condition ---
maxLoadTropicalCI = bootci(1000, @max, maxOperatingLoadTropical);

% --- 10.2.4 Create a table for Tropical condition statistics ---
tropicalStats = table({'Minimum Load (kW)'; 'Maximum Load (kW)'; 'Mean Load
(kW)'; 'Standard Deviation (kW)'; 'Variance (kW)'; '99% CI Lower Bound (kW)';
'99% CI Upper Bound (kW)'; '95% CI Lower Bound (kW)'; '95% CI Upper Bound
(kW)'}, [minTropical; maxTropical; meanTropical; stdTropical; varTropical;
lowerBoundTropical; upperBoundTropical; maxLoadTropicalCI(1);
maxLoadTropicalCI(2)], 'VariableNames', {'Statistics (Tropical Operating
Load)', 'Value (kW)'});

% --- 10.2.5 Display Tropical statistics in tabulated form ---
disp(tropicalStats);

% --- 10.3.1 Temperate Condition ---
minTemperate = min(maxOperatingLoadTemperate);
maxTemperate = max(maxOperatingLoadTemperate);
meanTemperate = mean(maxOperatingLoadTemperate);
stdTemperate = std(maxOperatingLoadTemperate);
varTemperate = var(maxOperatingLoadTemperate);

% --- 10.3.2 Calculate 95% Confidence Interval for Temperate Condition ---
standardErrorTemperate = stdTemperate /
sqrt(length(maxOperatingLoadTemperate));
criticalValue = norminv(0.995);
marginOfErrorTemperate = criticalValue * standardErrorTemperate;
lowerBoundTemperate = meanTemperate - marginOfErrorTemperate;
upperBoundTemperate = meanTemperate + marginOfErrorTemperate;
```

```
% --- 10.3.3 Calculate 95% Confidence Intervals for Maximum Load in Temperate
Condition ---
maxLoadTemperateCI = bootci(1000, @max, maxOperatingLoadTemperate);

% --- 10.3.4 Create a table for Temperate condition statistics ---
temperateStats = table( ...
    {'Minimum Load (kW)'; 'Maximum Load (kW)'; 'Mean Load (kW)'; 'Standard
Deviation (kW)'; 'Variance (kW)'; '99% CI Lower Bound (Mean) (kW)'; '99% CI
Upper Bound (Mean) (kW)'; '95% CI Lower Bound (Max) (kW)'; '95% CI Upper Bound
(Max) (kW)'}, ...
    [minTemperate; maxTemperate; meanTemperate; stdTemperate; varTemperate;
lowerBoundTemperate; upperBoundTemperate; maxLoadTemperateCI(1);
maxLoadTemperateCI(2)], ...
    'VariableNames', {'Statistics (Temperate Operating Load)', 'Value (kW)'});

% --- 10.3.5 Display Temperate statistics in tabulated form ---
disp(temperateStats);

% --- 10.4.1 Sub-Arctic Condition ---
minSubArctic = min(maxOperatingLoadSubArctic);
maxSubArctic = max(maxOperatingLoadSubArctic);
meanSubArctic = mean(maxOperatingLoadSubArctic);
stdSubArctic = std(maxOperatingLoadSubArctic);
varSubArctic = var(maxOperatingLoadSubArctic);

% --- 10.4.2 Calculate 99% Confidence Interval for Sub-Arctic Condition ---
standardErrorSubArctic = stdSubArctic /
sqrt(length(maxOperatingLoadSubArctic));
criticalValue = norminv(0.995);
marginOfErrorSubArctic = criticalValue * standardErrorSubArctic;
lowerBoundSubArctic = meanSubArctic - marginOfErrorSubArctic;
upperBoundSubArctic = meanSubArctic + marginOfErrorSubArctic;

% --- 10.4.3 Calculate 95% Confidence Intervals for Maximum Load in Sub-Arctic
Condition ---
maxLoadSubArcticCI = bootci(1000, @max, maxOperatingLoadSubArctic);

% --- 10.4.4 Create a table for Sub-Arctic condition statistics ---
subArcticStats = table( ...
    {'Minimum Load (kW)'; 'Maximum Load (kW)'; 'Mean Load (kW)'; 'Standard
Deviation (kW)'; 'Variance (kW)'; '99% CI Lower Bound (Mean) (kW)'; '99% CI
Upper Bound (Mean) (kW)'; '95% CI Lower Bound (Max) (kW)'; '95% CI Upper Bound
(Max) (kW)'}, ...
    [minSubArctic; maxSubArctic; meanSubArctic; stdSubArctic; varSubArctic;
lowerBoundSubArctic; upperBoundSubArctic; maxLoadSubArcticCI(1);
maxLoadSubArcticCI(2)], ...
    'VariableNames', {'Statistics (Sub-Arctic Operating Load)', 'Value (kW)'});

% --- 10.4.5 Display Sub-Arctic statistics in the tabulated form ---
disp(subArcticStats);

% -------------------------------------------------------------------------%
% --- 11. Probability of Exceedance ---
% -------------------------------------------------------------------------%

% --- 11.1 Calculate Probabilities of Exceeding Load operatingLoadThresholds --
-
```

```
operatingLoadThresholds = [322.67, 108.168, 30.800]; % kW

% --- 11.2 Overall Probability of Exceedance (any condition) ---

% 11.2.1 Create an array to store exceedance probabilities
probExceedOverall = zeros(length(operatingLoadThresholds), 1);

for t = 1:length(operatingLoadThresholds)
    probExceedOverall(t) = sum(simulatedRadarOperatingLoad(1:i) >
operatingLoadThresholds(t)) / i;
end

% 11.2.2 Create a table for overall exceedance probabilities (any condition)
overallExceedance = table( ...
    {'Threshold 1 (kW)'; 'Threshold 2 (kW)'; 'Threshold 3 (kW)'}, ...
    operatingLoadThresholds', ...
    probExceedOverall, ...
    'VariableNames', {'Threshold', 'Value (kW)', 'Probability of Exceedance
(Overall)'});

% 11.2.3 Display overall exceedance probabilities in tabulated form
disp(overallExceedance);


% --- Probability of Exceedance for each Environmental Condition ---

% --- 11.3 Tropical Condition ---
tropicalLoads = simulatedRadarOperatingLoad(shipEnvironmentalConditionIndices
== 1);

% --- 11.3.1 Create an array to store exceedance probabilities for Tropical
condition
probExceedTropical = zeros(length(operatingLoadThresholds), 1);

for t = 1:length(operatingLoadThresholds)
    probExceedTropical(t) = sum(tropicalLoads > operatingLoadThresholds(t)) /
length(tropicalLoads);
end

% 11.3.2 Create a table for Tropical condition exceedance probabilities
tropicalExceedance = table( ...
    {'Threshold 1 (kW)'; 'Threshold 2 (kW)'; 'Threshold 3 (kW)'}, ...
    operatingLoadThresholds', ...
    probExceedTropical, ...
    'VariableNames', {'Threshold', 'Value (kW)', 'Probability of Exceedance
(Tropical)'});

% 11.3.3 Display Tropical exceedance probabilities in tabulated form
disp(tropicalExceedance);

% --- 11.4 Temperate Condition ---
temperateLoads = simulatedRadarOperatingLoad(shipEnvironmentalConditionIndices
== 2);

% 11.4.1 Create an array to store exceedance probabilities for Temperate
condition
probExceedTemperate = zeros(length(operatingLoadThresholds), 1);
```

```
for t = 1:length(operatingLoadThresholds)
    probExceedTemperate(t) = sum(temperateLoads > operatingLoadThresholds(t)) /
length(temperateLoads);
end

% 11.4.2 Create a table for Temperate condition exceedance probabilities
temperateExceedance = table( ...
    {'Threshold 1 (kW)'; 'Threshold 2 (kW)'; 'Threshold 3 (kW)'}, ...
    operatingLoadThresholds', ...
    probExceedTemperate, ...
    'VariableNames', {'Threshold', 'Value (kW)', 'Probability of Exceedance
(Temperate)'});

% 11.4.3 Display Temperate exceedance probabilities in tabulated form
disp(temperateExceedance);

% --- 11.5 Sub-Arctic Condition ---
subArcticLoads = simulatedRadarOperatingLoad(shipEnvironmentalConditionIndices
== 3);

% 11.5.1 Create an array to store exceedance probabilities for Sub-Arctic
condition
probExceedSubArctic = zeros(length(operatingLoadThresholds), 1);

for t = 1:length(operatingLoadThresholds)
    probExceedSubArctic(t) = sum(subArcticLoads > operatingLoadThresholds(t)) /
length(subArcticLoads);
end

% 11.5.2 Create a table for Sub-Arctic condition exceedance probabilities
subArcticExceedance = table( ...
    {'Threshold 1 (kW)'; 'Threshold 2 (kW)'; 'Threshold 3 (kW)'}, ...
    operatingLoadThresholds', ...
    probExceedSubArctic, ...
    'VariableNames', {'Threshold', 'Value (kW)', 'Probability of Exceedance
(Sub-Arctic)'});

% 11.5.3 Display Sub-Arctic exceedance probabilities in tabulated form
disp(subArcticExceedance);

% ------------------------------------------------------------------------%
% --- 12. PDF and CDF Overall Operating Load ---
% ------------------------------------------------------------------------%

% --- 12.1 Create Histogram and PDF of Maximum Operating Load  ---
figure(1);
histogram(simulatedRadarOperatingLoad(1:i), 'BinWidth', 5, 'Normalization',
'pdf');
hold on;

% --- 12.2 Fit Normal Distribution to Data ---
pd = fitdist(simulatedRadarOperatingLoad(1:i), 'Normal');

% --- 12.3 Generate x values for PDF and CDF plots ---
x = linspace(min(simulatedRadarOperatingLoad(1:i)),
max(simulatedRadarOperatingLoad(1:i)), 1000);

% --- 12.4 Calculate and Plot PDF for Maximum Operating Load ---
```

```
y_pdf = pdf(pd, x);
plot(x, y_pdf, 'LineWidth', 3);
xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Probability Density', 'FontSize', 12);
title('Histogram and PDF of Radar Operating Load', 'FontSize', 12);
legend('Histogram', 'Fitted Normal PDF');
grid on;
grid minor;

% --- 12.5 Calculate and Plot CDF for Maximum Operating Load ---
figure(2);
y_cdf = cdf(pd, x);
plot(x, y_cdf, 'LineWidth', 3);
xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Cumulative Probability', 'FontSize', 12);
title('CDF of Radar Operating Load (Fitted Normal Distribution)', 'FontSize',
12);
grid on;
grid minor;

% ------------------------------------------------------------------------%
% --- 13. Operating Load Visualisation of Each Environmental Condition ---
% ------------------------------------------------------------------------%

% --- 13.1 Calculate and Plot PDF for Each Environmental Condition ---

% --- 13.1.1 Tropical Condition ---
figure(3);

% --- 13.1.2 Ensure maxOperatingLoadTropical is a column vector ---
maxOperatingLoadTropical = maxOperatingLoadTropical(:);

% --- 13.1.3 Bin the data for smoother visualization (adjust bin width as
needed)
binWidth = 10;
histogram(maxOperatingLoadTropical, 'BinWidth', binWidth, 'Normalization',
'pdf');
hold on;

% --- 13.1.4 Fit and plot PDF for Tropical Condition ---
pd_tropical = fitdist(maxOperatingLoadTropical, 'Normal');
x_tropical = linspace(min(maxOperatingLoadTropical),
max(maxOperatingLoadTropical), 1000);
y_pdf_tropical = pdf(pd_tropical, x_tropical);
plot(x_tropical, y_pdf_tropical, 'LineWidth', 3);
xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Probability Density', 'FontSize', 12);
ax = gca;
ax.YRuler.Exponent = 0;
title('Operating Load PDF - Tropical Condition', 'FontSize', 12);
grid on;
grid minor;

% --- 13.1.5 Temperate Condition ---
figure(4);

% --- 13.1.6 Ensure maxOperatingLoadTemperate is a column vector ---
maxOperatingLoadTemperate = maxOperatingLoadTemperate(:);
```

```
% --- 13.2.3 Bin the data for smoother visualization
binWidth = 10;
histogram(maxOperatingLoadTemperate, 'BinWidth', binWidth, 'Normalization',
'pdf');
hold on;

% --- 13.1.7 Fit and plot PDF for Temperate Condition ---
pd_temperate = fitdist(maxOperatingLoadTemperate, 'Normal');
x_temperate = linspace(min(maxOperatingLoadTemperate),
max(maxOperatingLoadTemperate), 1000);
y_pdf_temperate = pdf(pd_temperate, x_temperate);
plot(x_temperate, y_pdf_temperate, 'LineWidth', 3);
xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Probability Density', 'FontSize', 12);
ax = gca;
ax.YRuler.Exponent = 0;
title('Operating Load PDF - Temperate Condition', 'FontSize', 12);
grid on;
grid minor;

% --- 13.1.8 Sub-Arctic Condition ---
figure(5);

% --- 13.1.9 Ensure maxOperatingLoadSubArctic is a column vector ---
maxOperatingLoadSubArctic = maxOperatingLoadSubArctic(:);

% --- 13.1.10 Bin the data for smoother visualization ---
binWidth = 10;
histogram(maxOperatingLoadSubArctic, 'BinWidth', binWidth, 'Normalization',
'pdf');
hold on;

% --- 13.1.11 Fit and plot PDF for Sub-Arctic Condition ---
pd_subarctic = fitdist(maxOperatingLoadSubArctic, 'Normal');
x_subarctic = linspace(min(maxOperatingLoadSubArctic),
max(maxOperatingLoadSubArctic), 1000);
y_pdf_subarctic = pdf(pd_subarctic, x_subarctic);
plot(x_subarctic, y_pdf_subarctic, 'LineWidth', 3);
xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Probability Density', 'FontSize', 12);
ax = gca;
ax.YRuler.Exponent = 0;
title('Operating Load PDF - Sub-Arctic Condition', 'FontSize', 12);
grid on;
grid minor;

% --- 13.2 Calculate and Plot CDF for Each Environmental Condition ---

% --- 13.2.1 Tropical Condition ---
figure(6);

% --- 13.2.2 Sort the data before plotting CDF
maxOperatingLoadTropical = sort(maxOperatingLoadTropical);

% --- 13.2.3 Increase the number of points for smoother CDF
[f,x] = ecdf(maxOperatingLoadTropical);
[x, ia, ~] = unique(x); % Keep only the unique x values and their indices
```

```
f = f(ia); % Adjust f to match the unique x values

x_smooth = linspace(min(x),max(x),1000);
f_smooth = interp1(x,f,x_smooth,'pchip');
plot(x_smooth,f_smooth, 'LineWidth', 3);

xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Cumulative Probability', 'FontSize', 12);
title('Operating Load CDF - Tropical Condition', 'FontSize', 12);
grid on;
grid minor;

% --- 13.2.2 Temperate Condition ---
figure(7);

% 13.2.3 Sort the data before plotting CDF
maxOperatingLoadTemperate = sort(maxOperatingLoadTemperate);

% 13.2.4 Increase the number of points for smoother CDF and ensure uniqueness
[f,x] = ecdf(maxOperatingLoadTemperate);
[x, ia, ~] = unique(x); % Keep only the unique x values and their indices
f = f(ia); % Adjust f to match the unique x values

x_smooth = linspace(min(x),max(x),1000);
f_smooth = interp1(x,f,x_smooth,'pchip');
plot(x_smooth,f_smooth, 'LineWidth', 3);

xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Cumulative Probability', 'FontSize', 12);
title('Operating Load CDF - Temperate Condition', 'FontSize', 12);
grid on;
grid minor;

% --- 13.3.1 Sub-Arctic Condition ---

figure(8);

% 13.3.2 Sort the data before plotting CDF

maxOperatingLoadSubArctic = sort(maxOperatingLoadSubArctic);

% --- 13.3. Increase the number of points for smoother CDF and ensure
uniqueness
[f,x] = ecdf(maxOperatingLoadSubArctic);
[x, ia, ~] = unique(x); % Keep only the unique x values and their indices
f = f(ia); % Adjust f to match the unique x values

x_smooth = linspace(min(x),max(x),1000);
f_smooth = interp1(x,f,x_smooth,'pchip');
plot(x_smooth,f_smooth, 'LineWidth', 3);

xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Cumulative Probability', 'FontSize', 12);
title('Operating Load CDF - Sub-Arctic Condition', 'FontSize', 12);
grid on;
grid minor;

% -----------------------------------------------------------------------%
```

```
% --- 14.Visualise Load vs. Utilisation Factor for Each Environmental Condition
---
% -----------------------------------------------------------------------%

% --- 14.1 Tropical Condition ---

figure(9);
scatter(maxOperatingLoadTropical,
utilisationFactors(1:length(maxOperatingLoadTropical)), '.', 'MarkerEdgeAlpha',
0.5);
xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Utilisation Factor', 'FontSize', 12);
title('Operating Load by UF - Tropical Condition', 'FontSize', 12);
grid on;
grid minor;

% --- 14.2 Temperate Condition ---

figure(10);
scatter(maxOperatingLoadTemperate,
utilisationFactors(1:length(maxOperatingLoadTemperate)), '.',
'MarkerEdgeAlpha', 0.5);
xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Utilisation Factor', 'FontSize', 12);
title('Operating Load by UF - Temperate Condition', 'FontSize', 12);
grid on;
grid minor;

% --- 14.3 Sub-Arctic Condition ---

figure(11);
scatter(maxOperatingLoadSubArctic,
utilisationFactors(1:length(maxOperatingLoadSubArctic)), '.',
'MarkerEdgeAlpha', 0.5);
xlabel('Radar Operating Load (kW)', 'FontSize', 12);
ylabel('Utilisation Factor', 'FontSize', 12);
title('Operating Load by UF - Sub-Arctic Condition', 'FontSize', 12);
grid on;
grid minor;

% -----------------------------------------------------------------------%
% --- 15. Visualise Error Over Time ---
% -----------------------------------------------------------------------%

figure(12);

% --- 15.1 Plot error only up to the last iteration

plot(errorTracking(1:i), 'LineWidth', 3);

xlabel('Iteration Number', 'FontSize', 12);
ylabel('Error', 'FontSize', 12);
title('Error vs. Iteration Number', 'FontSize', 12);
grid on;
grid minor;

% -----------------------------------------------------------------------%
```

```
% --- 16. Visualise PDF and CDF of Utilisation Factors For Each Environmental
Condition ---
% -----------------------------------------------------------------------%

% --- 16.1 Extract utilisation factors for each condition and radar state ---

utilisationFactorsTropicalAvailable = utilisationFactors(
(shipEnvironmentalConditionIndices == 1) & (radarOperationalStateIndices == 1)
);
utilisationFactorsTropicalReady = utilisationFactors(
(shipEnvironmentalConditionIndices == 1) & (radarOperationalStateIndices == 2)
);
utilisationFactorsTropicalRadiate = utilisationFactors(
(shipEnvironmentalConditionIndices == 1) & (radarOperationalStateIndices == 3)
);

utilisationFactorsTemperateAvailable = utilisationFactors(
(shipEnvironmentalConditionIndices == 2) & (radarOperationalStateIndices == 1)
);
utilisationFactorsTemperateReady = utilisationFactors(
(shipEnvironmentalConditionIndices == 2) & (radarOperationalStateIndices == 2)
);
utilisationFactorsTemperateRadiate = utilisationFactors(
(shipEnvironmentalConditionIndices == 2) & (radarOperationalStateIndices == 3)
);

utilisationFactorsSubArcticAvailable = utilisationFactors(
(shipEnvironmentalConditionIndices == 3) & (radarOperationalStateIndices == 1)
);
utilisationFactorsSubArcticReady = utilisationFactors(
(shipEnvironmentalConditionIndices == 3) & (radarOperationalStateIndices == 2)
);
utilisationFactorsSubArcticRadiate = utilisationFactors(
(shipEnvironmentalConditionIndices == 3) & (radarOperationalStateIndices == 3)
);

% --- 16.2 Calculate Correlation Coefficients ---

% Calculate correlation coefficients for the overall condition
corrTropical =
corrcoef(simulatedRadarOperatingLoad(shipEnvironmentalConditionIndices == 1),
utilisationFactors(shipEnvironmentalConditionIndices == 1));
corrTemperate =
corrcoef(simulatedRadarOperatingLoad(shipEnvironmentalConditionIndices == 2),
utilisationFactors(shipEnvironmentalConditionIndices == 2));
corrSubArctic =
corrcoef(simulatedRadarOperatingLoad(shipEnvironmentalConditionIndices == 3),
utilisationFactors(shipEnvironmentalConditionIndices == 3));

corrCoefTropicalAvailable = corrcoef(utilisationFactorsTropicalAvailable,
operatingLoadTropicalAvailable);
corrCoefTropicalReady = corrcoef(utilisationFactorsTropicalReady,
operatingLoadTropicalReady);
corrCoefTropicalRadiate = corrcoef(utilisationFactorsTropicalRadiate,
operatingLoadTropicalRadiate);

corrCoefTemperateAvailable = corrcoef(utilisationFactorsTemperateAvailable,
operatingLoadTemperateAvailable);
```

```
corrCoefTemperateReady = corrcoef(utilisationFactorsTemperateReady,
operatingLoadTemperateReady);
corrCoefTemperateRadiate = corrcoef(utilisationFactorsTemperateRadiate,
operatingLoadTemperateRadiate);

corrCoefSubArcticAvailable = corrcoef(utilisationFactorsSubArcticAvailable,
operatingLoadSubArcticAvailable);
corrCoefSubArcticReady = corrcoef(utilisationFactorsSubArcticReady,
operatingLoadSubArcticReady);
corrCoefSubArcticRadiate = corrcoef(utilisationFactorsSubArcticRadiate,
operatingLoadSubArcticRadiate);

% --- 16.3 Create a table for Correlation Coefficients ---

correlationCoefficients = table( ...
    {'Tropical - Available'; 'Tropical - Ready'; 'Tropical - Radiate'; ...
     'Temperate - Available'; 'Temperate - Ready'; 'Temperate - Radiate'; ...
     'Sub-Arctic - Available'; 'Sub-Arctic - Ready'; 'Sub-Arctic - Radiate';
...
     'Tropical (Overall)'; 'Temperate (Overall)'; 'Sub-Arctic (Overall)'}, ...
    [corrCoefTropicalAvailable(1,2); corrCoefTropicalReady(1,2);
corrCoefTropicalRadiate(1,2); ...
     corrCoefTemperateAvailable(1,2); corrCoefTemperateReady(1,2);
corrCoefTemperateRadiate(1,2); ...
     corrCoefSubArcticAvailable(1,2); corrCoefSubArcticReady(1,2);
corrCoefSubArcticRadiate(1,2); ...
     corrTropical(1, 2); corrTemperate(1, 2); corrSubArctic(1, 2)], ... % Added
overall values
    'VariableNames', {'Environment Condition and Radar Operational State',
'Correlation Coefficient'});

% --- 16.4 Display Correlation Coefficients in tabulated form ---

disp('Correlation Coefficients:');
disp(correlationCoefficients);

% --- 16.5 Create figures for PDF and CDF for each environmental condition ---

% --- 16.5.1 Tropical Condition ---

figure(13);

% --- 16.5.1.1 Tropical Condition PDF ---

subplot(2,3,1);

histogram(utilisationFactorsTropicalAvailable, 'Normalization', 'pdf');
hold on;
pd = fitdist(utilisationFactorsTropicalAvailable,'Beta');
x =
linspace(min(utilisationFactorsTropicalAvailable),max(utilisationFactorsTropica
lAvailable),100);
y = pdf(pd,x);
plot(x,y,'LineWidth',2);
title('Tropical - Available (PDF)');
xlabel('Utilisation Factor');
ylabel('Probability Density');
grid on;
```

```
grid minor;
hold off;

subplot(2,3,2);

histogram(utilisationFactorsTropicalReady, 'Normalization', 'pdf');
hold on;
pd = fitdist(utilisationFactorsTropicalReady,'Beta');
x =
linspace(min(utilisationFactorsTropicalReady),max(utilisationFactorsTropicalRea
dy),100);
y = pdf(pd,x);
plot(x,y,'LineWidth',2);
title('Tropical - Ready (PDF)');
xlabel('Utilisation Factor');
ylabel('Probability Density');
grid on;
grid minor;
hold off;

subplot(2,3,3);

histogram(utilisationFactorsTropicalRadiate, 'Normalization', 'pdf');
hold on;
pd = fitdist(utilisationFactorsTropicalRadiate,'Beta');
x =
linspace(min(utilisationFactorsTropicalRadiate),max(utilisationFactorsTropicalR
adiate),100);
y = pdf(pd,x);
plot(x,y,'LineWidth',2);
title('Tropical - Radiate (PDF)');
xlabel('Utilisation Factor');
ylabel('Probability Density');
grid on;
grid minor;
hold off;

% --- 16.5.1.2 Tropical Condition CDF ---

subplot(2,3,4);

h = cdfplot(utilisationFactorsTropicalAvailable);
set(h, 'LineWidth', 3);
title('Tropical - Available (CDF)');
xlabel('Utilisation Factor');
ylabel('Cumulative Probability');
grid on;
grid minor;

subplot(2,3,5);

h = cdfplot(utilisationFactorsTropicalReady);
set(h, 'LineWidth', 3);
title('Tropical - Ready (CDF)');
xlabel('Utilisation Factor');
ylabel('Cumulative Probability');
grid on;
grid minor;
```

```
subplot(2,3,6);

h = cdfplot(utilisationFactorsTropicalRadiate);
set(h, 'LineWidth', 3);
title('Tropical - Radiate (CDF)');
xlabel('Utilisation Factor');
ylabel('Cumulative Probability');
grid on;
grid minor;

% --- 16.5.2 Temperate Condition ---

figure(14);

% --- 16.5.2.1 Temperate Condition PDF ---

subplot(2,3,1);

histogram(utilisationFactorsTemperateAvailable, 'Normalization', 'pdf');
hold on;
pd = fitdist(utilisationFactorsTemperateAvailable,'Beta');
x =
linspace(min(utilisationFactorsTemperateAvailable),max(utilisationFactorsTemper
ateAvailable),100);
y = pdf(pd,x);
plot(x,y,'LineWidth',2);
title('Temperate - Available (PDF)');
xlabel('Utilisation Factor');
ylabel('Probability Density');
grid on;
grid minor;
hold off;

subplot(2,3,2);

histogram(utilisationFactorsTemperateReady, 'Normalization', 'pdf');
hold on;
pd = fitdist(utilisationFactorsTemperateReady,'Beta');
x =
linspace(min(utilisationFactorsTemperateReady),max(utilisationFactorsTemperateR
eady),100);
y = pdf(pd,x);
plot(x,y,'LineWidth',2);
title('Temperate - Ready (PDF)');
xlabel('Utilisation Factor');
ylabel('Probability Density');
grid on;
grid minor;
hold off;

subplot(2,3,3);

histogram(utilisationFactorsTemperateRadiate, 'Normalization', 'pdf');
hold on;
pd = fitdist(utilisationFactorsTemperateRadiate,'Beta');
```

```
x =
linspace(min(utilisationFactorsTemperateRadiate),max(utilisationFactorsTemperat
eRadiate),100);
y = pdf(pd,x);
plot(x,y,'LineWidth',2);
title('Temperate - Radiate (PDF)');
xlabel('Utilisation Factor');
ylabel('Probability Density');
grid on;
grid minor;
hold off;

% --- 16.5.2.2 Temperate Condition CDF ---

subplot(2,3,4);

h = cdfplot(utilisationFactorsTemperateAvailable);
set(h, 'LineWidth', 3);
title('Temperate - Available (CDF)');
xlabel('Utilisation Factor');
ylabel('Cumulative Probability');
grid on;
grid minor;

subplot(2,3,5);

h = cdfplot(utilisationFactorsTemperateReady);
set(h, 'LineWidth', 3);
title('Temperate - Ready (CDF)');
xlabel('Utilisation Factor');
ylabel('Cumulative Probability');
grid on;
grid minor;

subplot(2,3,6);

h = cdfplot(utilisationFactorsTemperateRadiate);
set(h, 'LineWidth', 3);
title('Temperate - Radiate (CDF)');
xlabel('Utilisation Factor');
ylabel('Cumulative Probability');
grid on;
grid minor;

% --- 16.5.3 Sub-Arctic Condition ---

figure(15);

% --- 16.5.3.1 Sub-Arctic Condition PDF ---

subplot(2,3,1);

histogram(utilisationFactorsSubArcticAvailable, 'Normalization', 'pdf');
hold on;
pd = fitdist(utilisationFactorsSubArcticAvailable,'Beta');
x =
linspace(min(utilisationFactorsSubArcticAvailable),max(utilisationFactorsSubArc
ticAvailable),100);
```

```
y = pdf(pd,x);
plot(x,y,'LineWidth',2);
title('Sub-Arctic - Available (PDF)');
xlabel('Utilisation Factor');
ylabel('Probability Density');
grid on;
grid minor;
hold off;

subplot(2,3,2);

histogram(utilisationFactorsSubArcticReady, 'Normalization', 'pdf');
hold on;
pd = fitdist(utilisationFactorsSubArcticReady,'Beta');
x =
linspace(min(utilisationFactorsSubArcticReady),max(utilisationFactorsSubArcticR
eady),100);
y = pdf(pd,x);
plot(x,y,'LineWidth',2);
title('Sub-Arctic - Ready (PDF)');
xlabel('Utilisation Factor');
ylabel('Probability Density');
grid on;
grid minor;
hold off;

subplot(2,3,3);

histogram(utilisationFactorsSubArcticRadiate, 'Normalization', 'pdf');
hold on;
pd = fitdist(utilisationFactorsSubArcticRadiate,'Beta');
x =
linspace(min(utilisationFactorsSubArcticRadiate),max(utilisationFactorsSubArcti
cRadiate),100);
y = pdf(pd,x);
plot(x,y,'LineWidth',2);
title('Sub-Arctic - Radiate (PDF)');
xlabel('Utilisation Factor');
ylabel('Probability Density');
grid on;
grid minor;
hold off;

% --- 16.5.3.2 Sub-Arctic Condition CDF ---

subplot(2,3,4);

h = cdfplot(utilisationFactorsSubArcticAvailable);
set(h, 'LineWidth', 3);
title('Sub-Arctic - Available (CDF)');
xlabel('Utilisation Factor');
ylabel('Cumulative Probability');
grid on;
grid minor;

subplot(2,3,5);

h = cdfplot(utilisationFactorsSubArcticReady);
```

```
set(h, 'LineWidth', 3);
title('Sub-Arctic - Ready (CDF)');
xlabel('Utilisation Factor');
ylabel('Cumulative Probability');
grid on;
grid minor;

subplot(2,3,6);

h = cdfplot(utilisationFactorsSubArcticRadiate);
set(h, 'LineWidth', 3);
title('Sub-Arctic - Radiate (CDF)');
xlabel('Utilisation Factor');
ylabel('Cumulative Probability');
grid on;
grid minor;


% % ---------------------END OF CODE ------------------------------- % %
```

Appendix E Simulation Statistical Summary

Simulation converged after 16477 iterations. Error: 0.0100

Statistics (Radar Operating Load)	**Value (kW)**
{'Minimum Operating Load (kW)' }	0
{'Mean Operating Load (kW)' }	163.61
{'99% CI Lower Bound (Mean) (kW)'}	162.21
{'99% CI Upper Bound (Mean) (kW)'}	165.02
{'Standard Deviation (kW)' }	70.006
{'Variance (kW)' }	4900.9
{'Maximum Operating Load (kW)' }	346.63
{'95% CI Lower Bound (Max) (kW)' }	345.1
{'95% CI Upper Bound (Max) (kW)' }	346.63

Statistics (Tropical Operating Load)	**Value (kW)**
{'Minimum Load (kW)' }	0.80522
{'Maximum Load (kW)' }	346.63
{'Mean Load (kW)' }	163.62
{'Standard Deviation (kW)'}	70.002
{'Variance (kW)' }	4900.3
{'99% CI Lower Bound (kW)'}	161.93
{'99% CI Upper Bound (kW)'}	165.3
{'95% CI Lower Bound (kW)'}	345.1
{'95% CI Upper Bound (kW)'}	346.63

Statistics (Temperate Operating Load)	**Value (kW)**
{'Minimum Load (kW)' }	3.5064
{'Maximum Load (kW)' }	344.23
{'Mean Load (kW)' }	163.12
{'Standard Deviation (kW)' }	69.986
{'Variance (kW)' }	4898.1
{'99% CI Lower Bound (Mean) (kW)'}	160.24
{'99% CI Upper Bound (Mean) (kW)'}	166
{'95% CI Lower Bound (Max) (kW)' }	340.52
{'95% CI Upper Bound (Max) (kW)' }	344.23

Statistics (Sub-Arctic Operating Load)	Value (kW)
{'Minimum Load (kW)' }	6.5499
{'Maximum Load (kW)' }	340.47
{'Mean Load (kW)' }	165.31
{'Standard Deviation (kW)' }	70.153
{'Variance (kW)' }	4921.5
{'99% CI Lower Bound (Mean) (kW)'}	159.93
{'99% CI Upper Bound (Mean) (kW)'}	170.7
{'95% CI Lower Bound (Max) (kW)' }	340.4
{'95% CI Upper Bound (Max) (kW)' }	340.47

Threshold	Value (kW)	Probability of Exceedance (Overall)
{'Threshold 1 (kW)'}	322.67	0.0038235
{'Threshold 2 (kW)'}	108.17	0.759
{'Threshold 3 (kW)'}	30.8	0.97997

Threshold	Value (kW)	Probability of Exceedance (Tropical)
{'Threshold 1 (kW)'}	322.67	0.0035011
{'Threshold 2 (kW)'}	108.17	0.75755
{'Threshold 3 (kW)'}	30.8	0.98004

Threshold	Value (kW)	Probability of Exceedance (Temperate)
{'Threshold 1 (kW)'}	322.67	0.0040754
{'Threshold 2 (kW)'}	108.17	0.76261
{'Threshold 3 (kW)'}	30.8	0.9786

Threshold	Value (kW)	Probability of Exceedance (Sub-Arctic)
{'Threshold 1 (kW)'}	322.67	0.0062167
{'Threshold 2 (kW)'}	108.17	0.7611
{'Threshold 3 (kW)'}	30.8	0.98401

Correlation Coefficients:

Environment Condition and Radar Operational State	Correlation Coefficient
('Tropical - Available')	0.51468
('Tropical - Ready')	0.52149
('Tropical - Radiate')	0.50839
('Temperate - Available')	0.51901
('Temperate - Ready')	0.53169
('Temperate - Radiate')	0.53909
('Sub-Arctic - Available')	0.49441
('Sub-Arctic - Ready')	0.45774
('Sub-Arctic - Radiate')	0.48761
('Tropical (Overall)')	0.5149
('Temperate (Overall)')	0.52939
('Sub-Arctic (Overall)')	0.47978

Appendix F Utilisation Factor Distribution

Figure 13, Figure 14 and Figure 15 display the utilisation factor distributions for different environmental conditions (“Tropical”, “Temperate”, and “Sub-Arctic”) and radar operational states (“Available”, “Ready”, and “Radiate”). In all three figures, the histograms of the utilisation factor generally resemble the shape of the fitted Beta distributions. This suggests that the beta distribution is a suitable model for representing the utilisation factor of the radar system across different environments, conditions, and operational states.

These visualisations provide valuable insights into the utilisation factor of the naval surveillance radar under different environmental conditions and operational states. The analysis reveals that the utilisation factor tends to be highest in the 'Tropical' environment, particularly during the 'Radiate' state, indicating more frequent transmission in this condition. Conversely, the 'Sub-Arctic' environment shows a slightly lower utilisation factor across all operational states. These findings highlight the influence of environmental factors on the radar's operating load and show the importance of considering these factors in EPLA.

The histograms complement the scatter plots in Figure 9, Figure 10, and Figure 11 by providing a different perspective on the utilisation factor. The scatter plots show the relationship between the utilisation factor and operating load, while the histograms show the distribution of the utilisation factor itself. The histograms reinforce the stochastic nature of the operating load by showing the variability in the utilisation factor. This variability is a key input to the Monte Carlo simulation and contributes to the overall uncertainty in the radar's operating load.

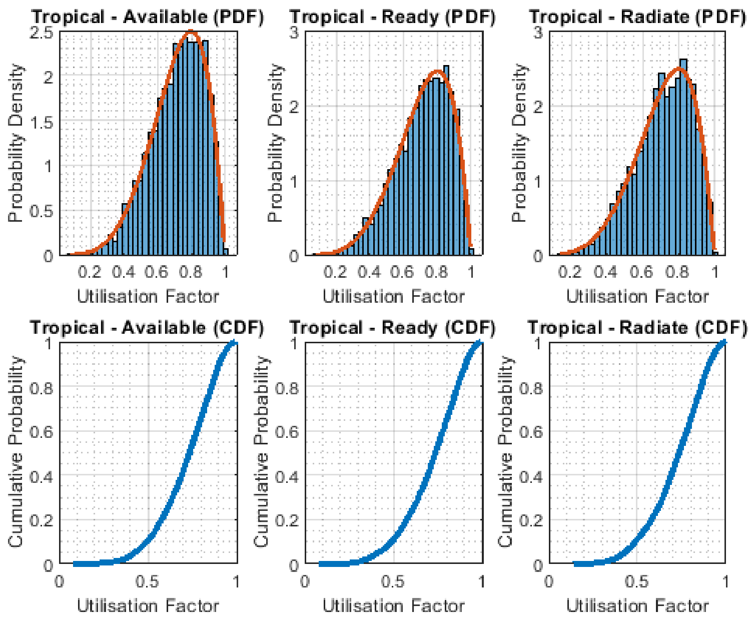


Figure 13: PDFs and CDFs for each operational state in the Tropical environment.

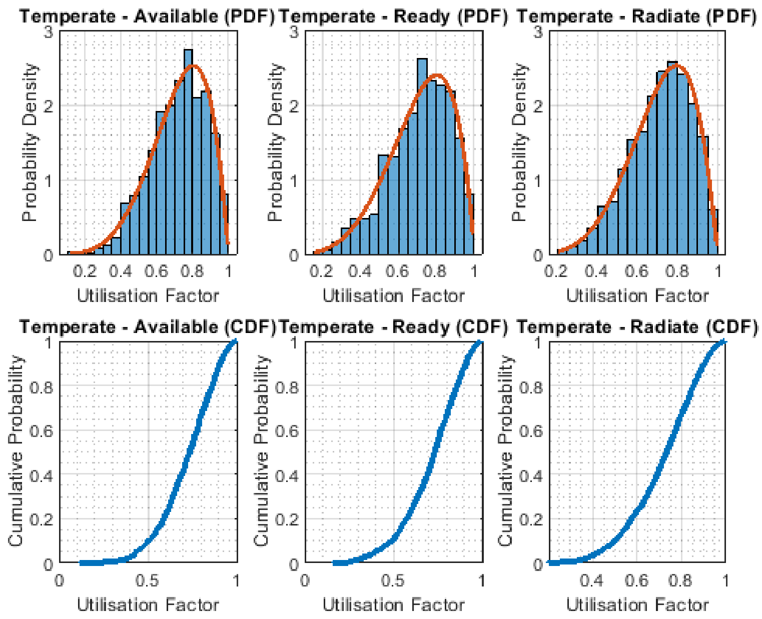


Figure 14: PDFs and CDFs for each operational state in the Temperate environment.

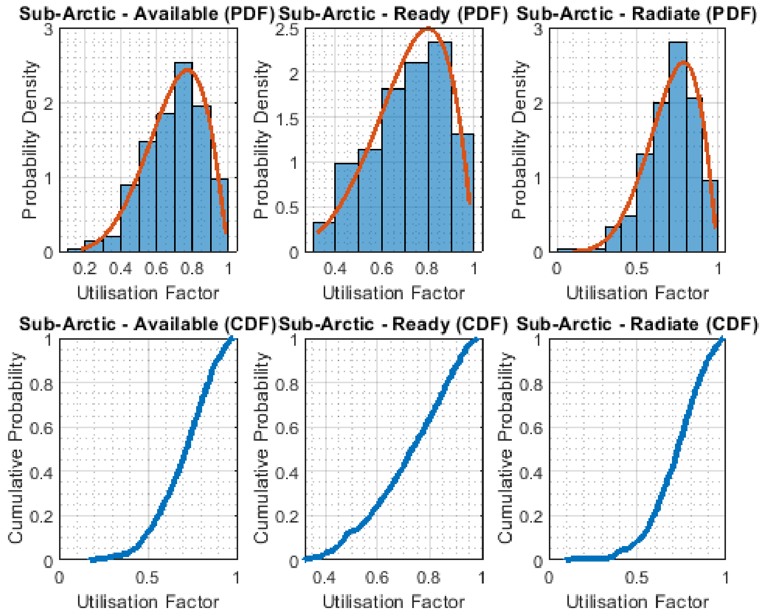
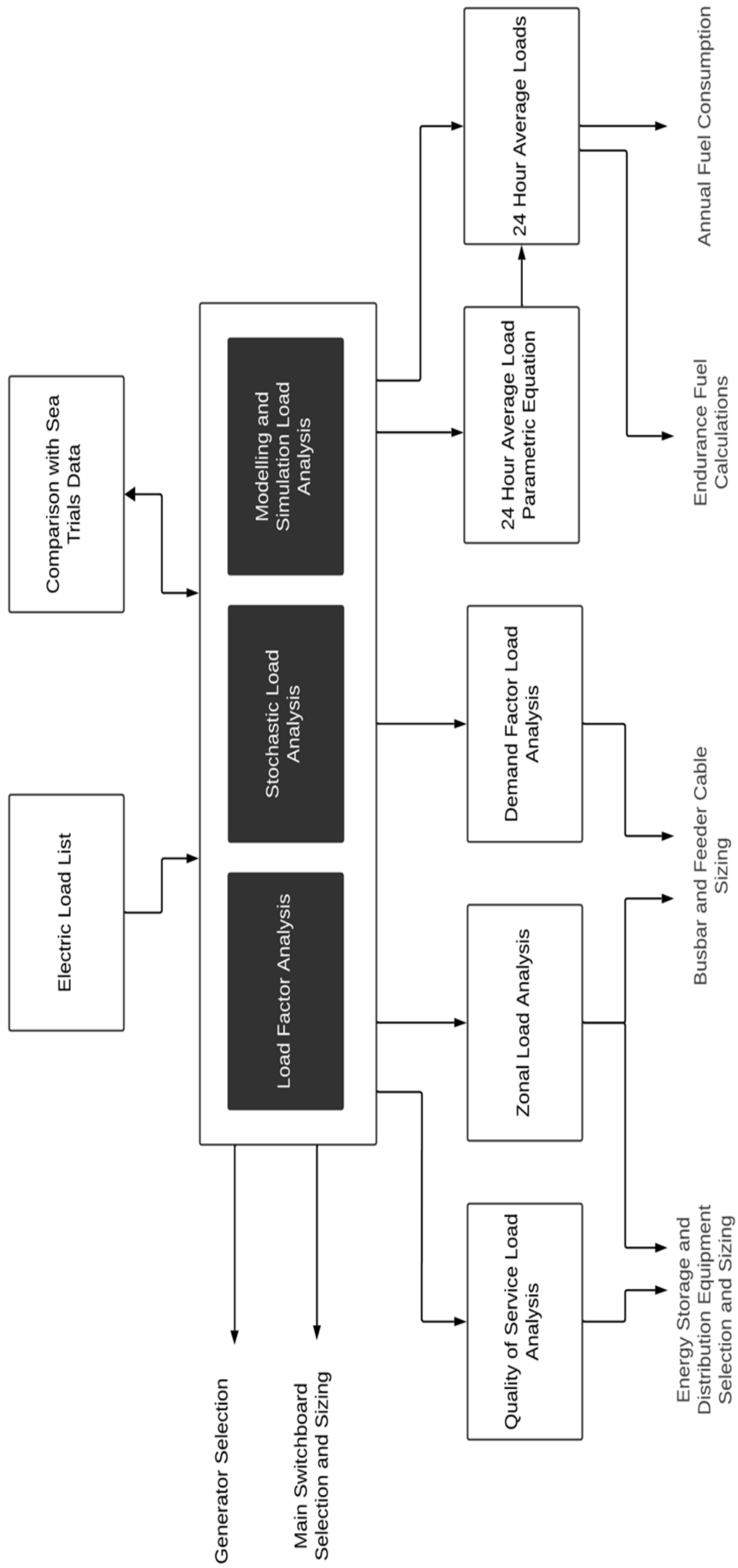


Figure 15: PDFs and CDFs for each operational state in the Sub-Arctic environment.

Appendix G EPLA Block Diagram



Appendix H Reference Ship Single Line Diagram