Health-Aware Energy Management of Ship Hybrid Power Plants

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Declaration of Authenticity and Author's Rights

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination, which has led to the award of a degree.

Signed: Charalampos Tsoumpris

Date: 27 March 2024

Dedication

To my beloved family, whose love and support helped me towards this achievement.

Abstract

Recent advances in smart and digital technologies have driven the maritime industry towards the adoption of autonomous vessels. Designed to operate with limited human intervention, autonomous ship systems have to make decisions and exhibit capabilities for intelligent real-time monitoring of both their performance and health state.

This study aims to develop health-aware energy management strategies for hybrid ship power plants. Based on the literature review, research gaps were identified. A novel methodology is proposed that integrates advanced methods for the energy management, prognostics and health management, health-aware control, and decision-making. The equivalent consumption minimisation strategy (ECMS) was employed in conjunction with a Dynamic Bayesian Network (DBN), whereas the utopia point method was customised for decision-making considering two contradictory objectives. The failure rates are updated based on a Weibull proportional hazard model (WPHM) or a Wiener process model (WPM). This study output includes two novel tools, namely a health-aware energy management tool and a health monitoring tool for hybrid power plants. These tools were verified using power plant models for two reference hybrid power plants and several case studies.

The first reference power plant pertains to a pilot boat, investigating its typical operations, whereas the case study emphasises on proposing a decision-making method that finds a compromise between the contradictory objectives of minimising fuel consumption and prolonging the system's lifetime expectancy. The results demonstrate that by operating the ship power plant for 300 hours reduces the failure rate by nearly fourfold, with a marginal increase in fuel consumption (approximately 1.5%) compared to conventional ECMS operation.

The second reference power plant pertains to a short-sea shipping cargo vessel, whereas the investigated case studies focus on the health monitoring of the power plant. This tool was used in various scenarios with different initial conditions where the criticality of components and subsystem health was investigated. Based on the data from literature and historical databases, it was inferred that the engine is the most critical subsystem, while autonomous operation cannot be yet achieved with existing setups.

This study's novelty stems from the introduction of a framework that combines several methods in high-level control, reliability engineering and decision-making with conflicting objectives. This thesis contributes towards the development of supervisory control approaches for the operation of autonomous power plants. Additionally, the developed health monitoring tool can enhance decision support systems and maintenance planning by offering valuable insights to the pertinent shipping industry stakeholders.

Keywords: Autonomous operations, Hybrid power plant, Energy management strategy, System health monitoring, Dynamic Bayesian network, Health-aware control

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Research Output

Journal Papers

Tsoumpris, C., Theotokatos, G. (2023). A decision-making approach for the health-aware energy management of ship hybrid power plants. Reliab. Eng. Syst. Saf. 235, 109263. https://doi.org/10.1016/j.ress.2023.109263

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Karvounis P, Dantas JLD, Tsoumpris C, Theotokatos G. (2022) Ship power plants decarbonisation using hybrid systems and ammonia fuel – a techno-economic-environmental analysis. Journal of Marine Science and Engineering. 10(11):1675. https://doi.org/10.3390/jmse10111675

Conference Papers

Tsoumpris, C., Theotokatos, G. (2023) In: Towards the Development of a Dynamic Reliability Tool for Autonomous Ships: A Bayesian Network Approach. 33rd European Safety and Reliability Conference. https://doi.org/1010.3850/978-981-18-8071-1_P604-cd

Tsoumpris, C., Theotokatos, G. (2022) In: A health-aware energy management strategy for autonomous ships power plants operation. Transportation Research Procedia.

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Abbreviations

Abbreviation list	
AAWA	Advanced Autonomous Waterborne Applications
ACO	ant colony optimisation
AEMC	Autonomous Engine and Monitoring Control system
AES	all-electric ship
AI	artificial intelligence
AIS	Automatic Identification System
ANN	artificial neural network
ANS	autonomic nervous system
AR	augmented reality
BN	Bayesian network
BS	British Standards
BSFC	brake-specific fuel consumption
CBM	condition-based maintenance
CM	corrective maintenance
CP	convex programming
DAG	directed acyclic graph
DBN	dynamic Bayesian network
DFTA	Dynamic Fault Tree Analysis
DP	dynamic programming
DRL	deep reinforcement learning
ECMS	equivalent consumption minimisation strategy
EKF	extended Kalman filter
EMS	energy management system
EMSA	European Maritime Safety Agency
ESC	extremum seeking control
ETA	Event Tree Analysis
FDL	fault detection and localisation
FI	fault isolation
FLC	fuzzy logic control
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Modes, Effects, and Criticality Analysis
FTA	Fault Tree Analysis
GA	genetic algorithm
GHG	greenhouse gas
GP	Gamma process

GPR	Gaussian process regression
GT	game theory
HAEM	health-aware energy management
HAZID	Hazard Identification
HAZOP	Hazard and Operability Study
HEV	hybrid electric vehicle
HJB	Hamilton-Jacobi-Bellman
HMM	hidden Markov model
ICE	internal combustion engine
ICT	Information and Communication Technology
IGP	Inverse Gaussian process
KET	key enabling technology
KF	Kalman filter
LB-EMS	learning-based energy management strategy
LP	linear programming
MASS	Maritime Autonomous Surface Ships
MILP	mixed-integer linear programming
MM	Markov model
MOCP	multi-objective optimal control problem
MO-MINLP	mixed-integer non-linear programming
MPC	model predictive control
NLP	non-linear programming
OB-EMS	optimisation-based energy management strategy
PdM	predictive maintenance
PF	particle filter
PHA	Preliminary Hazard Analysis
PHM	prognostics and health management
PM	predetermined maintenance
PMP	Pontryagin's minimum principle
PMS	power management system
PN	Petri Net
PNT	Position, Navigation, and Timing
PRS	polynomial response surface
PSO	particle swarm optimisation
PTI	power take in
PTO	power take out
PvM	preventive maintenance
QP	quadratic programming
RBD	reliability block diagram

RB-EMS	rule-based energy management strategy
RCC	remote control centre
RCM	reliability-centred maintenance
RL	reinforcement learning
RLS	regularised least squares
RTF	run-to-failure
RUL	remaining useful life
RVM	relevance vector machine
SDP	stochastic dynamic programming
SKPF	shifting kernel particle filter
SQP	sequential quadratic programming
STPA	System-Theoretic Process Analysis
SVAN	Safer Vessel with Autonomous Navigation
SVM	support vector machine
SWIFT	Structured What-If
UKF	unscented Kalman filter
VR	virtual reality
WPHM	Weibull proportional hazard model
WPM	Wiener process model

Nomenclature

Nomenclature list	
Roman Symbols	
B	Brownian motion [–]
HI	health index [–]
I	current [A]
I^B	Birnbaum importance measure [–]
I^{CR}	Criticality importance measure [-]
k_p	propeller constant [–]
L	component load fraction [–]
$\dot{m}$	flow mass rate [kg/s]
N	rotational speed [rev/m]
P	power [W]
Q	engine torque [N·m]
Q_{LHV}	lower heating value of fuel at ISO conditions [kJ/kg]
Q_{max}	battery capacity [Ah]
R	reliability [–]
R_0	series Resistance [Ω]
S	equivalence factor [–]
SM	sensor measurement [–]
SOC	state of charge [–]
V_{oc}	open circuit voltage [V]
Greek Symbols	
β	Weibull distribution shape factor [–]
γ	jump coefficient [–]
η	efficiency [–]
λ	failure rate [h–1]
µ	drift coefficient [–]
σ	diffusion coefficient [–]
Subscripts	
bat	battery
elec	electrical
em	electric machine
eng	engine
eqv	equivalent
f	fuel
max	maximum

MCR	maximum continuous rating
mean	mean
min	minimum
prop	propeller
req	requested
ress	rechargeable energy storage system

Introduction

1.1. Chapter Outline

This chapter introduces the background and motivation for this thesis. The benefits of autonomous ships are presented along with a discussion of innovative technologies that can be used for the operation of autonomous ship power plants. Additionally, the research question, the aim, the objectives, and the research focus of this thesis are discussed. Finally, the structure of the thesis is presented.

1.2. Background and Motivation

1.2.1. Towards Autonomous Shipping

The fourth industrial revolution has significantly impacted various industrial sectors, including the maritime industry. With advancements in automation, the Internet of Things, smart sensors, virtual/augmented reality, and artificial intelligence (AI), the maritime industry is embracing autonomous operations (Heffner et al., 2019) (Thombre et al., 2022). In this respect, the concept of autonomous ships has gained substantial interest, with the potential to revolutionise transportation and shape the future of the maritime industry (Ghaderi, 2019).

Unmanned and autonomous shipping has been a subject of exploration for several decades, with early proponents like Schönknecht envisioning captains operating ships from onshore offices (Bertram, 2016). However, it is only in recent years that autonomous shipping has been considered in real applications (Rokseth et al., 2019). Recent technological breakthroughs have made autonomous shipping a feasible reality, attracting significant research and industrial efforts towards the development of autonomous ship technologies (Bratić et al., 2019). As autonomy increases, the ship's subsystems become highly automated, requiring minimal crew intervention (Veitch and Andreas Alsos, 2022). Among these subsystems, the power plant holds critical importance as it generates and distributes power to various on-board systems. Operating under a wide range of conditions, the power plant must exhibit resilience to adapt to changing environmental conditions, unexpected events, and failures (Papanikolaou, 2018).

To enable autonomous operation, additional requirements are necessary compared to conventional vessels, including the implementation of advanced monitoring systems equipped with autonomous decision-making functionalities. These technologies must work together to ensure the reliable and safe operation of the ship without human intervention.

1.2.2. Benefits of Autonomous Ships

Autonomous shipping has the potential to bring numerous benefits to the maritime industry, including lower operational costs, increased safety, reduced environmental impact, and enhanced sustainability (Munim and Haralambides, 2022), (Komianos, 2018).

One of the primary advantages of autonomous shipping is its potential to reduce operational costs. The design of autonomous vessels will undergo significant changes, with remote operations being transferred to highly skilled crew members at remote control centres (RCC) (Ramos et al., 2018). These operators would control an increasing number of autonomous functions and operations on-board. The bridge's location on the vessel may need to be rethought, with advanced navigation systems enhanced with virtual reality (VR) and augmented reality (AR) content, potentially replacing traditional bridge layouts (Heffner et al., 2019). The elimination of crew accommodations and related spaces could potentially lead to cost savings and increased cargo capacity (Kirchner, 2019). Additionally, the reduced weight of the ship's structure without crew spaces can also contribute to fuel savings and reduced emissions (Chae et al., 2020).

Another significant benefit of autonomous shipping is its potential to enhance safety. According to the European Maritime Safety Agency (EMSA), over two-thirds of accidents in the maritime industry are attributed to human error (EMSA, 2019). With reduced reliance on human intervention, autonomous ships could reduce the possibility of human-based errors and contribute to lower risks of foundering and collision accidents (Hogg and Ghosh, 2016). Additionally, autonomous ships can be designed with advanced navigation and monitoring systems, further enhancing safety (Ventikos et al., 2020). According to the results of the AAWA initiative, autonomous ships are expected to be at least as safe as existing vessels (Poikonen et al., 2016).

Autonomous shipping also offers significant environmental benefits. Shipping is a major contributor to greenhouse gas (GHG) emissions, and road transport accounts for the majority of transport sector emissions in Europe (Munim, 2019). By shifting more cargo from road transport to sea transport, autonomous shipping can help reduce emissions and improve sustainability. The development of alternative fuel solutions and zero-emissions technologies for ship power plants can also contribute to reducing their environmental footprint (Chae et al., 2020).

Finally, autonomous shipping can also bring sustainability enhancement benefits and life cycle cost reduction. The use of autonomous ships can contribute to the development of highly automated transport chains, reducing operational costs and enhancing sustainability (Bratić et al., 2019). Autonomous ships, with their automated tasks related to cargo handling and transport, can fit into highly automated transport chains, and create new nautical routes. Additionally, the design of autonomous ships can incorporate advanced monitoring and maintenance strategies, leading to longer vessel lifetimes and reduced life cycle costs (Jimenez et al., 2020).

However, one of the most significant challenges that must be addressed in the context of autonomous ships is human-machine interaction (Kooij et al., 2018). The absence of crew on-board poses several potential issues in the event of unexpected events or emergencies (Kooij et al., 2018). Furthermore, while automated navigation and collision avoidance systems enhance safety by reducing the reliance on human operators, they may also introduce new challenges. For instance, there is the possibility of increased risks such as fires, explosions, or flooding, as human oversight for extensive monitoring may be lacking (Wróbel et al., 2018). Additionally, concerns have been raised regarding the vulnerability of autonomous ships to piracy in the absence of human presence on-board (Ghaderi, 2019).

1.2.3. Advanced Technologies for Autonomous Ship Power Plants

The transition to autonomy introduces innovative concepts in ship design, particularly in the functionalities of the power plant. An inherent characteristic of an autonomous ship is the absence of a permanent crew on-board. This disruptive change will alter the power plant design and operation to ensure safe and reliable autonomous operation. To enable autonomous operation, the functions traditionally carried out by human operators must be replaced with automated tasks performed by intelligent systems (Utne et al., 2019).

In conventional vessels, the purpose of the power plant is to generate distribute and consume power for propulsion and various loads (Papanikolaou, 2018). Power plants are equipped with the power management system (PMS) which defines the power flow on-board, ensuring sufficient power availability, preventing blackouts, and restoring power smoothly if any disruptions occur (Bø et al., 2015). In the case of hybrid power plants, where multiple components are included, an energy management system (EMS) is required to distribute the energy flow and optimise fuel consumption and emissions (Geertsma et al., 2017). However, the unique challenges posed by autonomous ship power plants, require more sophisticated management strategies, especially in applications with multiple components.

According to the findings of the MUNIN project, the power plant, propulsion system, and its auxiliaries are deemed the most critical systems on-board, responsible for the successful completion of extended autonomous missions (Abaei et al., 2021). These systems operate in complex scenarios and environments, facing uncertainties and requiring high levels of availability and fault tolerance (Utne et al., 2017). With limited crew availability, on-board maintenance, calibration, upgrades, and manual work must be strategically scheduled to avoid disruptions during the vessel's voyage (Ghaderi, 2019). Hence, the overall maintenance plan for autonomous ships needs to be restructured (Kooij et al., 2018). In this context, the autonomous power plant plays a vital role in enabling autonomous operation which paves the way to a new design philosophy that prioritises the availability of the considered systems (Edge et al., 2020).

MUNIN (2016) proposes the development of an Autonomous Engine and Monitoring Control system (AEMC) that integrates advanced methods to predict failures and monitor the engine room using key performance indicators (KPI) while controlling the propulsion systems and engaging redundant components when needed. According to AUTOSHIP (2020) design standards, the realisation of autonomous ships in the real world depends on the development of two main key enabling technologies (KETs): the Autonomous navigation system or Artificial Captain, and the Autonomous machinery system or Artificial Chief Engineer.

To ensure the reliable operation of autonomous power plants, the integration of advanced monitoring and diagnostic capabilities is crucial. By leveraging sensor information and diagnostics, the power plant can continuously assess the performance, health condition, and reliability of its subsystems. This enables the early detection of potential faults, abnormalities, or degradation, empowering informed decision-making for maintenance, reconfiguration, or operational adjustments (Utne et al., 2017), (Liu et al., 2016).

The fault management framework is another essential aspect of autonomous power plant operation. Detecting, localising, and isolating faults within the power plant is crucial to maintain overall robustness and resilience. Techniques such as fault detection and localisation (FDL) identify the existence and location of faults, while fault isolation (FI) aims to isolate the fault and prevent its propagation (Babaei et al., 2018). Additionally, autonomous power plants should be capable of independently reconfiguring their operation in response to faults or abnormalities, ensuring safe and continued operation (Utne et al., 2017).

Smart sensors play a crucial role in the monitoring of vital system functions on-board autonomous ships. Future ships will be equipped with an extensive array of sensors, as estimated by DNV ranging from 15,000 to 20,000 different sensors, constantly monitoring various aspects of the ship's operations (Bertram, 2016). These sensors collect and analyse data in real-time to provide valuable insights into the ship's performance, environmental conditions, and safety parameters. Additionally, smart sensors enable the display of critical information, messages, and warnings, ensuring timely and informed decision-making by the autonomous systems and human operators involved (DNV, 2020). The integration of an abundance of smart sensors on-board autonomous ships will help the establishment of advanced monitoring capabilities.

Condition-Based Maintenance (CBM) has been widely utilised in conventional ships to monitor the health of systems and alert on-board crew members when performance degradation is detected (Lazakis et al., 2018). However, to further mitigate the probability of failures and proactively schedule necessary maintenance actions, the adoption of prognostic algorithms within a predictive maintenance framework is recommended for autonomous ships (Poikonen et al., 2016). Unlike CBM, which relies on performance degradation thresholds, predictive maintenance leverages historical data, trend analysis, and statistical models to predict the future state of equipment, enabling the detection and prevention of potential faults at an early stage (Jimenez et al., 2020).

It is evident that the transition to autonomous operations, requires upgrading the capabilities of conventional ship power plants by assessing and monitoring the health of the included systems. By leveraging advanced technologies, such as smart sensors, and prognostic algorithms, these strategies enable real-time monitoring, predictive maintenance, fault management, and system reconfiguration. These strategies can be firstly adopted in conventional power plants, and while technological maturity is increasing, a gradual transition to autonomous operations can be achieved. The integration of these capabilities enhances the overall performance and resilience of power plants, contributing to the advancement of autonomous shipping in the maritime industry. These functionalities can be further improved by the use of AI tools to facilitate intelligent decision-making while considering the health state of the power plant.

1.3. Research Question

The aforementioned discussion dictates the apparent need to address the development of advanced management strategies for operating ship power plants while maintaining awareness of their health state with the goal of transitioning towards autonomous operations. In order to optimise energy efficiency, reduce emissions, and effectively monitor the health state of power plants, it will be beneficial to develop robust tools and methodologies that enable informed decision-making.

Therefore, this thesis aims to answer the following question:

"How can health-aware energy management strategies be developed for hybrid ship power plants, considering advanced monitoring capabilities and decision-making methods?"

1.4. Aim and Objectives

This research aims *to develop health-aware energy management strategies for hybrid ship power plants, integrating advanced monitoring capabilities and decision-making methods.*

In this way, the methodology will dynamically monitor the power plant's health state to prolong its lifetime expectance while managing the performance considering energy efficiency.

The objectives identified to achieve the set aim are given below:

1st Objective: Perform a comprehensive literature review to identify research gaps, critically review employed methods, and assess the requirements for power plants' autonomous operation.

This objective includes the review of (a) research and industrial projects, (b) autonomous ship power plant requirements, (c) hybrid power plant solutions, (d) energy management strategies, (e) prognostics and health management, (f) system-level dependability analysis and (g) health-aware control.

2nd Objective: Develop a methodology that integrates energy management with health monitoring to enable health-aware energy management of hybrid ship power plants.

This objective concerns the integration of various methods to build a methodology that combines the output of energy management, which prioritises energy efficiency by minimising fuel consumption, with the output of health monitoring which prioritises system reliability. By this integration, the methodology can make informed decisions that consider both energy efficiency and the health state of the power plant.

3rd Objective: Refine and adapt models to simulate and analyse the performance of hybrid ship power plants.

This objective includes the identification of key components inside ship power plants to represent the overall performance. Mathematical and computational models widely used in the field of energy management are refined and adapted to represent the behaviour and interactions of the power plant components, including internal combustion engines, electric machines, and batteries.

4th Objective: Employ and evaluate energy management strategies for hybrid ship power plants, considering energy efficiency.

In this objective energy management strategies are employed including equivalent consumption minimisation strategy and dynamic programming. These methods will allow for the optimisation of fuel consumption and performance of the power plant, considering various operational conditions and system constraints.

5th Objective: Implement health monitoring of the ship power plant based on reliability.

This objective focuses on the application of reliability methods for health monitoring of the power plant. Dynamic Bayesian networks are used to estimate the system health state considering the included component interactions while two different methods are described to update component reliability based on the failure rate.

6th Objective: Define reference ship power plants that serve as benchmarks for evaluating health-aware energy management strategies.

In this objective, the reference hybrid power plants are selected based on the findings from the literature review. Details of the power plants are provided, including technical specifications, operating profiles and health monitoring characteristics.

7th Objective: Verify the effectiveness of the developed health-aware energy management via case studies.

This objective aims to verify the effectiveness of the developed health-aware energy management for hybrid ship power plants through case studies. The two reference power plants are used in different case studies. The first case study focuses mainly on health-aware energy management of the power plant while the second on health monitoring considering component interactions.

1.5. Research Focus

The research focus and boundaries of this study are defined as follows:

Design specification: In this study, the investigated reference systems are selected based on the conducted literature review. As a result, the power plant architecture and its technical specifications are provided as input.

Operating Profiles: The operating profiles of the investigated reference systems are also considered as input in this thesis. Data were collected from the actual operation of the power plants to test the developed methodology in realistic scenarios.

Operational Scenarios: The proposed methodology will be tested in different operational scenarios, including both healthy and degraded conditions. This will ensure the verification of the power plant's performance in demanding operational scenarios, aligning with the power system verification stage proposed by (Papanikolaou, 2018).

Interconnections with other autonomous systems: While there are implicit and explicit interconnections between various ship systems for autonomous operation, this study focuses primarily on the power plant. Interactions with other systems were not investigated.

Excluded Systems: Navigation, deck operations, ship administration, coastal and port operations, on-site operations, and ship management operations are outside the scope of this study.

Human Intervention: This study emphasises the development of a self-management method independent of human intervention. The role of the RCC in the power plant operation is not explicitly examined and is left out of scope.

Communication Infrastructure: Although the autonomous ship power plant includes advanced Information and Communication Technology (ICT) components, the detailed communication infrastructure is not addressed in this study. It is assumed that the communication links are treated as an independent part of the development process for the proposed methodology.

1.6. Thesis Structure

This thesis is structured into seven chapters, where an overview of the contents of each chapter is provided as follows.

Chapter 1: An introduction to the background and motivation for this thesis is performed. Additionally, the research question, the aim, the objectives, and the research focus of this thesis are discussed.

Chapter 2: The literature review is conducted in this chapter whereas the key findings along with the research gaps identified are presented and discussed.

Chapter 3: An outline of the proposed research methodology is presented. The methods and tools that are used are justified to ensure their relevance and effectiveness in solving the identified problem.

Chapter 4: A description of the methods and tools that are used in the proposed methodology are presented in detail.

Chapter 5: An overview of the reference power plants with their technical and reliability specifications is presented along with a description of the performed case studies.

Chapter 6: The results and discussion for each respective case study are presented for the applicable reference power plants.

Chapter 7: A reflective discussion is conducted along with the novelty and the research contribution. The accomplishment of the aim and objectives is discussed. Finally, the limitations are highlighted whereas recommendations for future work are suggested.

1.7. Chapter Summary

The maritime industry is undergoing a transition to increased automation and digitalisation. Autonomous ships can bring various benefits by transforming the design and operation of conventional power plants using innovative technologies. This thesis focuses on the development of health-aware energy management strategies that can be applied to hybrid ship power plants. In this chapter, the aim and objectives, as well as the research focus of this work, were discussed and an outline of this thesis was presented. In the following chapter, a literature review of the research area is presented, and the research gaps are identified and discussed.

2. Literature Review

2.1. Chapter Outline

A comprehensive literature review is presented in this chapter, to present the theoretical background to justify the novelty and the rationale of the developed methodology. For this purpose, various requirements for autonomous power plants are critically discussed and presented. Based on the requirements, hybrid power plants are discussed as a solution to satisfy these requirements. In this respect the state of art is presented for the operation of hybrid power plants including energy management strategies, prognostics and health management methods, and system-level dependability are reviewed. Health-aware control is discussed along with relevant studies to introduce the novelty of this study concerning health-ware energy management. Lastly, the key findings from the literature review along with the research gaps identified are presented and discussed.

2.2. Research and Industrial Projects

Several research and industrial projects have been undertaken in the field of autonomous shipping. These projects concern various vessel types and focus on different aspects of autonomous operation, including navigation, propulsion, monitoring, and decision-making methods.

One notable industrial project in the domain of cargo vessels is YARA Birkeland, developed by Kongsberg Maritime (Ramos et al., 2020). It is an autonomous container ship designed for operation in Norwegian coastal waters. The vessel has a fully electric propulsion and uses batteries as energy storage device (Akbar et al., 2021). Initially manned, the ship is gradually implementing autonomous functions intending to achieve full autonomy.

The ReVolt project, initiated by DNV, aims to revolutionise cargo vessel design by developing an unmanned vessel concept (Tvete, 2019). This innovative project explores the use of batteries for power and azipods for propulsion. The fully autonomous vessel was designed to operate without human involvement, focusing on shortsea shipping within Norwegian waters.

In the field of autonomous ferries, several projects have been undertaken to develop autonomous navigation systems and optimise operations. The Gloppefjord and Eidesfjord projects involve double-ended car ferries with automated crossing systems delivered by Kongsberg (Torben, 2018). These ferries utilise azipull thrusters and lithium-ion batteries, enabling partial autonomy in docking, manoeuvring and optimising loads and weather conditions through the autocrossing system.

The SVAN (Safer Vessel with Autonomous Navigation) project, supported by Rolls-Royce and Finferries, focuses on retrofitting the existing ferry Falco to become the first fully autonomous ferry in the archipelago south of Turku, Finland (Felski and Zwolak, 2020). Falco utilises advanced sensors, sensor fusion, and artificial intelligence to navigate and avoid obstacles. While the ferry operates autonomously, there is an RCC in Turku where a captain monitors the operations and can intervene if necessary.

Svitzer Hermod is the first commercial remote-control tugboat. Equipped with cameras, sensors, and advanced software, this tugboat demonstrated its remote navigation capabilities in the port of Copenhagen in 2017 (Kirchner, 2019). The captain controls the ship remotely from an RCC using real-time data and video feeds.

Several research initiatives have also significantly contributed to the development of autonomous shipping. The Advanced Autonomous Waterborne Applications (AAWA) initiative focused on producing specifications and preliminary designs for advanced ship solutions (Poikonen et al., 2016). The AAWA project emphasises the hybrid combination of remote control and autonomous operation, highlighting the potential reduction of human-based errors and the safety of autonomous vessels.

Furthermore, another initiative concerns AUTOSHIP which focuses on the development of autonomous ship systems capable of operating without human intervention (AUTOSHIP, 2020). To achieve this goal, the project focuses on the development of two KETs. These KETs include the development of an Autonomous Navigation System, often referred to as the "Artificial Captain," and an Autonomous Machinery System, also known as the "Artificial Chief Engineer." These technologies aim to replicate the decision-making capabilities and operational functionalities traditionally carried out by human operators, paving the way for autonomous operation.

The MUNIN project has contributed to the concept of autonomous cargo ships by developing a high-level software architecture for autonomous vessel control (MUNIN, 2016). This project has investigated the feasibility of autonomous shipping and proposed solutions for advanced monitoring capabilities, decision-making algorithms, and functional software architectures.

The Autosea project, initiated in 2015, focused on developing and verifying algorithms for target tracking and collision avoidance in autonomous ships (Brekke et al., 2019). The outcome of this project was the development of collision avoidance and tracking systems that were verified in real-world scenarios. These methods were based on Model Predictive Control (MPC) that considered factors like collision risk, cost, COLREGs compliance, path deviation, and grounding risk.

The ROMAS project, initiated by DNV GL in collaboration with Høglund, and the Norwegian Maritime Authority, focused on transitioning the management of engine control rooms from ships to RCCs (Låg, 2019). A key aspect of ROMAS was the implementation of remote operations technologies, allowing chief engineers to control the propulsion and auxiliary machinery systems of a fleet of vessels from shore. A pilot test was conducted with the ferry "M/F Fannefjord", focusing on machinery monitoring and control, alarm improvements, and establishing reliable and redundant communication solutions.

2.3. Requirements for Autonomous Ship Power Plants

The autonomous shipping projects presented in the previous section have highlighted the developments focusing on KETs, advanced monitoring capabilities, and the role of human involvement in remote and autonomous operations. However, it is crucial to review the requirements of the power plants to transition into autonomy. As the backbone of the vessel's operation, the power plant plays a critical role in ensuring safe and reliable operation, even in the case where a limited crew is on-board.

In the context of systems engineering, a system is defined as an integrated set of elements, subsystems, or assemblies working together to achieve a defined objective (INCOSE, 2007). This includes products (hardware, software, firmware), processes, people, information, techniques, facilities, services, and other support elements. Therefore, it is essential to establish clear and comprehensive requirements for autonomous power plants early in the development process. These requirements form the foundation for designing the system's architecture, integration, and verification processes (INCOSE, 2007).

Autonomous power plants have distinct requirements compared to conventional vessels. Traditional requirements engineering focuses on defining system characteristics, functions, performance, and constraints. However, in the context of transitioning power plants to autonomy, the system must demonstrate resilience and adaptability to changing circumstances, including unexpected events. This high degree of uncertainty must be considered during the requirements engineering process. Vassev and Hinchey (2014) emphasise the need for further development in requirements engineering for autonomous systems, as existing approaches have limitations.

Classification societies and regulatory organisations are actively working to formulate requirements for autonomous power plants. These requirements can be broadly classified as functional and non-functional. Functional requirements pertain to the system's desired functionality, while non-functional requirements encompass qualities and constraints under which the system must operate (Vassev and Hinchey, 2014). However, the integration of various technologies to fulfil these functionalities remains an open research topic.

2.3.1. Autonomic Systems

As the autonomous power plant should undertake independent control decisions without the direct intervention of an operator, the concept of self-managing or autonomic systems becomes relevant. Autonomic systems draw inspiration from the autonomic nervous system (ANS) found in the human body, which regulates various physiological functions to maintain homeostasis (Sherwood, 2019). Analogously, autonomic systems aim to perform low-level management tasks and handle the internal functional relations of subsystems without direct human intervention (Truszkowski et al., 2010).

Hinchey and Sterritt (2006) define autonomic systems with four objectives and four attributes. The objectives include self-configuration, self-healing, self-optimisation, and self-protection. Self-configuration enables automatic readjustment of the system to varying circumstances. Self-healing allows the system to effectively recover from faults and predict and prevent health problems. Self-optimisation involves measuring performance, attempting improvements, and reacting to user policy changes. Self-protection ensures the system can defend itself against external threats.

To achieve these self-managing objectives, the autonomic system must be self-aware, self-situated, self-monitoring, and self-adjusting (Hinchey and Sterritt, 2006). Translating these objectives and attributes to the functional requirements of an autonomous power plant, it becomes essential to design the power plant with capabilities such as automatic reconfiguration, fault identification and recovery, system health monitoring, performance monitoring and optimisation, and robust security mechanisms. By incorporating autonomic systems into the design and operation of autonomous power plants, a higher level of self-management, adaptability, and resilience can be achieved.

2.3.2. Review of Requirements

Highlighting the relevance of autonomic systems, it is essential to identify and understand the specific requirements of power plants associated with their transition towards autonomy. To achieve this, a comprehensive review of relevant literature has been conducted. This review has enabled the identification and synthesis of key requirements that are crucial for the successful implementation of autonomous ship power plants. An overview of the reviewed requirements is presented, providing insights into the areas of increased situational awareness, maintenance work, fault identification and isolation, resilience and self-reconfiguration, availability and reliability, intelligent decision-making, system health monitoring, and cybersecurity.

Increased Situational Awareness: Autonomous power plants require advanced sensors and data collection systems to achieve a higher level of situational awareness (Levander, 2017). These sensors enable the systematic collection of data, providing real-time information on power plant performance which is essential for further analysis from other systems (Thombre et al., 2022)

Maintenance and Pre-Departure Work: With the absence of on-board crew, maintenance and manual work should be performed before the ship departs (DNV, 2018). This requirement entails developing comprehensive maintenance plans that include regular preventive actions (Bureau Veritas, 2017). To minimise disruptions during the voyage, maintenance tasks should be scheduled in advance, ensuring that they are conducted before departure (DNV, 2018).

Fault Identification and Isolation: Autonomous power plants must possess enhanced diagnostic functions and alerting systems to identify and isolate faults (DNV, 2018). Through continuous monitoring and diagnostics, potential failures can be detected early, enabling predictive maintenance and minimising system downtime. Fault isolation capabilities ensure that failures in one subsystem do not impact the functionality of other systems, except in cases of direct dependency (Bureau Veritas, 2017).

Resilience and Self-Reconfiguration: The autonomous power plant should possess fault tolerance to operate even in the presence of faults or unexpected events (Liu et al., 2016). The system must have resilience and self-reconfiguration capabilities to adapt and continue functioning (Song et al., 2016), (Ådnanes, 2019). In the event of faults or deviations, the power plant should be able to reconfigure itself to a safe mode in the case of emergencies or return to normal operation (MUNIN, 2016), (Utne et al., 2017). The power plant should be able to adjust the control actions, even when communication with supervisory systems is hindered (Menis et al., 2012). Additionally, failures that can be anticipated should not affect the vessel's normal operation (DNV, 2018).

Availability and Reliability: Availability is a critical requirement and it needs to be prioritised for autonomous operation (Edge et al., 2020). In AUTOSHIP (2020) design standards there is a requirement to design machinery with high availability. To ensure high availability, components and systems should present high reliability (Grotli et al., 2016). In particular, components that cannot be easily multiplied, such as propulsion units or critical power sources, should be highly reliable (Ådnanes, 2019). For other components, reliability can be enhanced by considering redundancies (Kooij et al., 2018).

System Health Monitoring: Autonomous power plants should incorporate prognostic capabilities to estimate the remaining useful life and degradation of components (Utne et al., 2017). By analysing historical data and trends, the power plant can anticipate potential failures and proactively plan maintenance and replacements. (Vartdal et al., 2018)

Intelligent Decision-Making: Autonomous power plants require advanced decision-making capabilities to handle faults, significant degradation, emergencies, and enable risk control (Utne et al., 2019), (Rødseth and Tjora, 2014). The system should be able to autonomously decide on reconfiguration actions to maintain operation and ensure safety (Parhizkar, 2022). It should also possess risk assessment and risk control functions to avert potential hazards (Rokseth and Utne, 2020). The adoption of risk-based control capabilities should be included in the system architecture to indicate the risk level of the operation while in parallel informing the operators in real-time using a decision support system (DSS) (Utne et al., 2017).

Cybersecurity: Autonomous systems are susceptible to cyber-attacks, making cybersecurity measures imperative for the protection of ship systems (Kardakova et al., 2020). Some of the key requirements for cyber security in autonomous ships include the need for secure communication systems, protection against malware and other cyber threats, and the implementation of secure software and hardware systems (Bolbot et al., 2020b). The use of encryption and authentication technologies, as well as the establishment of public key infrastructures, can help the prevention of cyber intrusions (Bolbot et al., 2022).

In the following sections, potential power plant solutions, energy management strategies, and monitoring strategies are reviewed that align with the requirements of autonomous ship power plants.

2.4. Hybrid Power Plants for Autonomous Ships

The selection of suitable power plants for autonomous operation is crucial to meet the requirements presented earlier. In recent years, significant research and development efforts have focused on exploring alternative power plant solutions, including energy storage systems, renewable energy systems, fuel cells, dual-fuel engines and hybrid configurations (Trivyza et al., 2022). This section examines the pros and cons of these options considering various factors including redundancy, maintainability, system complexity, environmental impact and energy efficiency and concludes that hybrid power plants offer a promising solution for autonomous ships.

Redundancy has been identified as an effective way to plays to enhance reliability by having multiple components (Ouzineb et al., 2010). Electrical propulsion systems have a clear advantage in this regard, as they allow for the integration of multiple components within the power plant, enabling redundancy to be easily achieved (Bureau Veritas, 2017). The incorporation of redundant components ensures that the power plant can continue operating even in the event of component failures (Abaei et al., 2021). The MUNIN project enforces the concept of redundancy through the incorporation of two main propulsive units in the power plant (Rødseth et al., 2013). Furthermore, hybrid power plants offer additional redundancy by combining different power sources and energy storage systems, further enhancing reliability and ensuring continuous operation (Nuchturee et al., 2020), (Geertsma, 2019). This redundancy factor is a significant advantage of hybrid power plants over conventional power plants that unitise mainly internal combustion engines (ICE) in mechanical propulsion architectures. However, increased redundancy incurs additional expenses to the total cost of building the ship (Kooij et al., 2018).

The simplicity and efficiency of electrical propulsion make it an attractive solution for autonomous ships, as they have been recognised for their lower maintenance costs and robustness (Heffner et al., 2019). Transitioning from marine engines to fuel cells and batteries can also significantly decrease maintenance requirements (Kretschmann et al., 2017). The adoption of fuel cells and batteries has the potential to reduce the workload of on-board engineers (Kobyliński, 2018). On the other hand, marine engines pose challenges and limitations when it comes to meeting the specific requirements of autonomous ships. The increased number of mechanical parts in marine engines has a higher likelihood of potential failures and maintenance issues, usually classifying the engine as the most critical ship subsystem (Knutsen et al., 2014). Moreover, the continuous need for manual intervention and maintenance during the ship's operation further complicates the autonomous functionality (Bratić et al., 2019).

Complexity in power plant design can lead to hidden errors, increased maintenance requirements, and challenges in operation and maintenance procedures (Hogg and Ghosh, 2016). The simplicity and efficiency of electrical propulsion systems make them an attractive option for autonomous ships, as they have lower maintenance costs, reduced system complexity, and improved robustness (Heffner et al., 2019). Electrical propulsion has been adopted in autonomous projects such as ReVolt and Yara Birkeland where it eliminates the need for rotating machinery parts while enhancing system modularity (Tvete, 2019). Hybrid power plants offer a balance between mechanical and electrical propulsion, allowing for the advantages of both technologies to be realised.

The reduction of GHG and the mitigation of environmental impact have been within the purview of the maritime industry. With existing power plants equipped with marine engines that utilise conventional fuels it is challenging to achieve the future targets of emissions reduction imposed by IMO (Xing et al., 2021). Stricter environmental regulations and the industry's commitment to sustainability have necessitated the exploration of alternative fuels and cleaner technologies (Trivyza et al., 2019). Alternative fuels like ammonia, hydrogen, and methanol have the potential to reduce or even eliminate harmful emissions (Deniz and Zincir, 2016), (Trivyza et al., 2022). However, integrating these alternative fuels alone may not be sufficient to achieve the desired environmental goals. Hybrid power plants offer a viable solution by combining mechanical and electrical components. Hybrid power plants enable the reduction of emissions and fuel consumption by optimising the operation of ICEs and supplementing them with energy sources, such as batteries, flywheels, supercapacitors or fuel cells (Nuchturee et al., 2020).

Energy efficiency is a crucial consideration for autonomous ships, as it directly impacts operational costs. Hybrid power plants offer significant advantages in terms of energy efficiency leading to fuel and emissions reductions of up to 10-30 % (Geertsma et al., 2017). By combining mechanical and electrical components, they can leverage the benefits of both technologies under different operating conditions. Hybrid configurations, such as series, parallel, or series-parallel architectures, allow for optimal power generation and distribution, resulting in fuel savings and emission reductions (Inal et al., 2022). The application of batteries in a hybrid architecture is not limited to small vessels but can also yield energy efficiency benefits for larger ships (Tvete, 2019). However, the choice between batteries and fuel cell systems depends on the mission duration, with batteries being sufficient for short-duration, high-power requirements, while fuel cell systems are more suitable for longer missions (Reddy et al., 2019). In situations where ICEs are typically inefficient, such as during berthing and manoeuvring, hybrid power plants provide enhanced fuel efficiency and operational flexibility (Nguyen et al., 2021), (Jeong et al., 2018). Furthermore, advanced energy management strategies further improve energy efficiency, reduce fuel consumption, and minimise emissions (Jaurola et al., 2019).

2.4.1. Applicability of Ship Types

Following the discussion of the autonomous ship power plants, it becomes essential to identify potential early adopters who can install the proposed solutions. To make an informed decision, a comprehensive comparison can be made based on various factors such as the type of cargo, regulatory framework, connectivity issues, operational area, and economic profitability.

When considering the nature of the cargo, unmanned vessels are expected to transport stable and non-hazardous cargoes that require minimal maintenance or monitoring during the voyage (MUNIN, 2016). Bulk carriers, general cargo vessels, and container vessels align well with these criteria as they are simpler in terms of cargo characteristics compared to tankers or passenger vessels (Wróbel et al., 2018). Passenger ships, for instance, involve continuous supervision due to the increased number of humans on-board, whose behaviour can be unpredictable (Kobyliński, 2018). Similarly, tankers carrying unstable, flammable, and explosive cargoes such as gas, chemicals, or oil may not be considered suitable for autonomous (Hogg and Ghosh, 2016).

The operational region also plays a significant role in determining the feasibility of autonomous ships. Short-sea shipping within national or regional waters is more amenable to the introduction of novel technologies and operational concepts compared to deep-sea shipping which has to comply with mandatory international maritime regulations (DNV GL, 2018). National waters, particularly for small ferries, provide an opportunity for early adoption as they are subject to different regulatory frameworks than international voyages (Kobyliński, 2018). Additionally, in terms of communication, ships relying on Position, Navigation, and Timing (PNT) systems for geo-location benefit from operating in coastal and littoral waters, where communication advantages exist compared to vessels in high seas that may face limitations in satellite system capabilities under adverse weather conditions (Poikonen et al., 2016).

Commercial viability is a major concern for stakeholders. Short-sea shipping benefits from relatively lower manpower costs as they are a larger proportion of the overall costs and these costs are often subsidised in autonomous operations (Ghaderi, 2019). Additionally, the cost of satellite communication poses a challenge for ships operating on high seas (Rødseth and Tjora, 2014).

Considering the aforementioned discussion, short-sea shipping with bulk carriers, general cargo vessels, and container vessels emerges as the most suitable candidates. These types of vessels align with the requirements of stable and non-hazardous cargoes, simplified operational frameworks, advantages in communication infrastructure, and favourable cost considerations, making them ideal for the early adoption of autonomous ships.

2.5. Energy Management Strategies

As discussed in previous subchapters, hybrid power plants have emerged as a promising solution for autonomous ships. However, to dictate the operating points of the included power sources advanced energy management strategies are necessary. In this section, various energy management strategies that can be applied to hybrid power plants are reviewed, aiming to maximise energy efficiency, minimise emissions, and ensure optimal power distribution.

The EMS plays a crucial role in optimising the performance of hybrid power plants. It serves as a high-level supervisory control system that dictates the operation of the hybrid power plant by monitoring and controlling the energy flow between different power sources fulfilling several constraints (Onori et al., 2016). Key objectives of an effective EMS concern minimising fuel consumption, reducing power losses in components, prolonging the useful life of components, and minimising emissions (Reddy et al., 2019). The selection and development of a suitable EMS is critical as it directly influences the extent to which the objectives and requirements of the hybrid power plant are met.

The development of EMS for hybrid applications has gathered significant research interest over the past years, especially in the domain of hybrid electric vehicles (HEV). This has led to the development of various energy management strategies aiming to optimise the performance of hybrid systems. While various classifications have been proposed in the literature, energy management strategies can be broadly classified into three main categories: rule-based, optimisation-based, and learning-based approaches (Tran et al., 2020), (Reddy et al., 2019).

2.5.1. Rule-based Strategies (RB-EMS)

One widely used approach for energy management of hybrid systems is the rule-based energy management strategy (RB-EMS), which employs predefined rules and thresholds to determine the distribution of power among multiple power sources within the hybrid system (Xu et al., 2019). The formulation of rules dictates the operating points based on certain conditions. These rules are typically formulated using engineering expertise, efficiency characteristics of powertrain components, and specific system requirements (Reddy et al., 2019). By defining these rules, the strategy can make informed decisions regarding power distribution and mode-switching. RB-EMS can be further classified into deterministic and fuzzy logic-based strategies.

Deterministic rule-based strategies

The main objective of deterministic RB-EMS is to ensure that the primary energy sources, such as the ICE, operate in their optimal working conditions or high-efficiency regions (Reddy et al., 2019). These strategies utilise predefined rules and thresholds to achieve operation in optimal working conditions to enhance energy efficiency and minimise energy losses. The optimal working conditions refer to the optimal operating point, optimal operation line, or optimal efficiency region (Tran et al., 2020). These strategies consider factors such as power requirements, battery state of charge (SOC), and speed setpoints. Several applications can be found in the maritime industry regarding hybrid applications (Beatrice et al., 2022), (Huotari et al., 2020), (Zhou et al., 2021), (Balestra and Schjølberg, 2021).

There are different types of deterministic rule-based strategies employed in RB-EMS. The engine optimal efficiency region strategy operates the ICE at its optimal working point while charging or discharging the battery based on the engine's state. (Chua et al., 2018) developed a set of rules to operate diesel generators at optimal working points while making decisions about battery charging or discharging based on the power demand.

The frequency-based scheme splits the power demand into high- and low-frequency regions, incorporating load levelling to improve fuel economy and reduce emissions. Based on the power demand and the fuel cell power limits, Han et al. (2014) created rules based on power demand and fuel cell power limits to dictate the operating mode for a hybrid battery and fuel cell power plant.

The state machine strategy, also known as the multi-mode strategy, divides the operation into different modes such as electric mode, hybrid mode, and mechanical mode. For example, Bassam et al. (2017) developed an RB-EMS strategy for a hybrid battery and fuel cell power plant in a passenger ship, selecting the operating mode based on battery SOC and power demand. Bui et al. (2018) defined a set of operation rules to determine the operating mode and operating points of components in a DC hybrid power plant. Hein et al. (2020a) proposed a rule-based energy management strategy that considers rules and regulations for power plant operation while ensuring redundancy and reliability by selecting appropriate operating modes.

Deterministic rule-based strategies offer simplicity, ease of implementation, and the ability to operate in real-time, making them practical and valuable tools for energy management in hybrid power plants. However, their main limitation is their lack of flexibility and scalability under different operating conditions. Since the rules and thresholds are predetermined, these strategies may not provide the most optimal solution for all operating scenarios or operating modes (Antonopoulos et al., 2021). They may require fine-tuning or optimisation techniques to adapt to different conditions.

Fuzzy logic rule-based strategies

Fuzzy Logic rule-based strategies have been successfully applied in hybrid power plants in the maritime industry (Yuan et al., 2018), (Guo et al., 2016), (Khan and Faruque, 2017). Fuzzy Logic control (FLC) was developed as a solution to the limitations of deterministic rule-based strategies in energy management systems. Fuzzy logic employs techniques such as input quantization, fuzziness, fuzzy reasoning, inverse fuzziness, and output quantization to handle numerical data (Zhao, 2022). The performance of a fuzzy logic strategy relies on the membership functions and fuzzy rules used during the fuzzy reasoning stage (Yuan et al., 2018).

The concept of approximate reasoning allows designers to integrate their knowledge and experience through a collection of rules, facilitating more efficient decision-making processes. Fuzzy logic controllers extend the capabilities of traditional rule-based controllers and provide advantages in terms of robustness against uncertainties and measurement noise, as well as the ability to be tuned and adapted, offering greater control flexibility as system complexity increases (Tran et al., 2020). Optimisation algorithms can be employed to optimise the membership functions and fuzzy rules to achieve specific control objectives, such as minimising fuel consumption, reducing emissions, and maintaining SOC (Xu et al., 2019). Fuzzy logic control can be further classified into Adaptive fuzzy logic and Predictive fuzzy control.

Adaptive fuzzy logic control integrates adaptive algorithms into the fuzzy rule-based strategy to simultaneously optimise conflicting objectives, such as fuel consumption and emission reduction. These adaptive control systems can adapt to unknown operating conditions and dynamics. Zhao (2022) developed a fuzzy logic approach based on dynamic programming (DP) associated with wavelet analysis and PI control to achieve robustness and online control in a hybrid power plant on a tourist ship. Adaptive neural fuzzy interference systems, neural network-based adaptive estimators, and machine learning algorithms are utilised to improve control performance and adaptability (Tran et al., 2020).

Predictive fuzzy control considers the current state of the system, evaluated based on available historical data and the load estimation in the near future (Tran et al., 2020). This predictive capability allows real-time control tasks while different operating scenarios are captured to enable the achievement of near-optimal solutions without relying on optimisation algorithms (Xu et al., 2019). However, predicting the future behaviour of the power plant based on known past states and deriving extensive rule sets for each possible operating condition present challenges.

In summary, fuzzy logic RB-EMS offer a robust and adaptable approach to energy management. By utilising degrees of truth and extensive rule sets, these controllers can optimise conflicting objectives and handle uncertainties and measurement noise effectively (Zhao, 2022). While deterministic strategies may lack flexibility, fuzzy logic controllers overcome this limitation by providing greater control freedom and adaptability. Nevertheless, these methods cannot guarantee optimal performance (Inal et al., 2022).

2.5.2. Optimisation-based Strategies (OB-EMS)

Optimisation-based energy management strategies (OB-EMS) aim to find the optimal control sequence that minimises a cost function while satisfying various constraints (Onori et al., 2016). These constraints include global state constraints like maintaining battery SOC and local state constraints such as power limits, speed limits, and torque limits. The cost function can represent different objectives, such as fuel consumption, emissions, or the energy efficiency of the electric generation path while they are usually implemented in the form of iterative numerical optimisation (Guzzella and Sciarretta, 2013). In general, they have received greater attention than RB-EMS. Optimisation-based strategies can be broadly categorised into offline and online strategies (Reddy et al., 2019).

Offline OB-EMS strategies

Offline OB-EMS are non-causal and global optimisation methods that require prior knowledge from typical operating profiles. They aim to calculate the optimal control sequence by minimising a cost function over a fixed and known operating profile, resulting in a globally optimal solution (Guzzella and Sciarretta, 2013). Although offline OB-EMS cannot be directly implemented in real-time due to a priori knowledge of the operating profile and computational complexity, they serve as valuable design tools. They serve as benchmarking tools to compare against other causal strategies and can be used to develop modified online strategies (Zhang et al., 2020b).

In terms of problem-solving methods, offline OB strategies can be classified into four types: direct, indirect, gradient, and derivative-free (Tran et al., 2020). Direct methods approximate the optimal control problem as a static optimisation by discretisation. Indirect methods, on the other hand, are based on optimal control theory and calculus of variations. Gradient methods utilise derivative information of the objective function under certain mathematical conditions such as continuity, and differentiability to solve the optimisation problem. In contrast, derivative-free methods employ stochastic search techniques iteratively over the entire design space to find the global optimum, avoiding reliance on derivatives.

Direct methods

Dynamic programming (DP) is a widely used method for solving the energy management problem directly. It was introduced by Bellman in the 1950s and is a numerical algorithm that subdivides the nonlinear dynamic optimisation problem into discrete time subproblems (Guzzella and Sciarretta, 2013). DP relies on the principle of optimality and provides sufficient conditions for optimality by solving the nonlinear Hamilton-Jacobi-Bellman (HJB) equation. To apply DP, the state variables, control variables, and continuous time need to be discretised, and the boundary conditions of their feasible regions must be considered. By solving these subproblems consecutively using either a backward recursive method or a forward dynamic programming technique, an optimal control sequence can be obtained (Rao, 2019).

DP has found applications in various types of marine hybrid power plants. Michalopoulos et al. (2016) presented a novel optimal power management algorithm based on DP that is applied to several configurations of marine hybrid power plants. Kanellos et al. (2014) used dynamic programming to minimise the total operation cost of all-electric ships (AES) while meeting technical and environmental constraints. However, DP is commonly used in marine applications to determine the global optimal solution and serve as a benchmarking tool for comparing the results with other methods (Kalikatzarakis et al., 2018), (Wu et al., 2020), (Xiang and Yang, 2022), (Planakis et al., 2021).

However, DP has several limitations, including heavy computational cost due to state and control variable discretisation, the "curse of dimensionality" inherent in the method, and dependence on the operating profile which must be known a priori (Rao, 2019). These drawbacks make DP infeasible for real-time implementation. Despite its limitations, DP remains useful as an optimal benchmark for other strategies and as a method to extract control rules for RB-EMSs (Kalikatzarakis et al., 2018).

Stochastic dynamic programming (SDP) is proposed as a solution to address the limitations of DDP in energy management problems. While DP provides an optimal control law for a specific operating profile, it may not guarantee optimality under different operating conditions. SDP addresses this by considering the power demand as a Markov chain with transition probabilities, allowing for optimisation over a set of random operating profiles (Tran et al., 2020). By treating the power demand as a stochastic process, SDP reflects the probability distribution and variation of future power demand under different operating conditions. It utilises existing standard operating profiles or historical data to establish a statistical model of power demand and employs DP to solve the energy management problem (Xu et al., 2019).

SDP, although mainly applied in HEV, has demonstrated potential as a viable method for obtaining a quasi-optimal policy that can be implemented in real-time, relying solely on historical data without prior knowledge of the operating profile (Zhang et al., 2020b). However, there are still challenges that need to be addressed. These include the requirement for a specific Markov chain model to accurately predict the future power demand, which limits the flexibility of SDP as it cannot guarantee robustness or accuracy in cases where the actual operating profile is different from historical data (Xu et al., 2019). Additionally, the computation process involved in solving SDP can be computationally heavy accompanied by the curse of dimensionality in DP problems (Guzzella and Sciarretta, 2013).

Indirect methods

Pontryagin's minimum principle (PMP) is an analytical optimisation method based on the calculus of variations. It was developed by Lev Pontryagin to solve optimal control problems and provide the necessary conditions for optimality (Guzzella and Sciarretta, 2013). By transforming the global optimisation problem into an instantaneous Hamiltonian optimisation problem, the PMP seeks to minimise the Hamiltonian equation, which represents the derivative of the stage cost function with respect to time and incorporates factors such as fuel consumption and battery state of charge (SOC). The Hamiltonian is characterised by a co-state, serving as a weighting factor for electrical usage (Onori et al., 2016). The optimal value of the initial co-state can be determined iteratively when complete knowledge of the operating profile is available.

Despite its usefulness, there are various limitations and challenges while it is rarely used for marine applications (Inal et al., 2022). The computational burden can be substantial due to the complexity of the Hamiltonian function and the need to explore the entire control variable domain. Furthermore, the influence of the co-state variable on the optimal solution of the PMP-based strategy and its determination in specific operating conditions present additional complexities as with different operating profiles, the co-state may have different values (Xu et al., 2019).

Efforts have been made to address these challenges. One approach involves using feedback controllers to correct the co-state based on the error between actual battery SOC and reference states (Tran et al., 2020). Approximate-PMP (A-PMP) techniques have also been proposed to reduce computation time by recognising regular patterns observed in the results using convex approximations and piecewise linear strategies (Onori et al., 2016). Zhang et al. (2020a) improved the computational efficiency by 50 % using A-PMP compared with PMP in an HEV, while achieving reductions in fuel consumption with good drivability behaviour.

Gradient methods

Gradient-based methods use gradient (derivative) information of the objective function to find their local optima. These methods operate under the assumption that the objective function satisfies certain mathematical conditions such as continuity, differentiability, or the Lipschitz condition (Rao, 2019). For the energy management problems, the power plant models and the objective functions should be efficiently simplified into analytical equations, which leads to near-optimal solutions. Gradient-based methods in EMS are typically classified into several types, including linear programming (LP), quadratic programming (QP), sequential quadratic programming (SQP), and convex programming (CP) (Tran et al., 2020).

Regarding marine applications, Baldi et al. (2016) implemented a mixed integer non-linear programming approach to optimise the distribution of load in a hybrid power plant. Jaurola et al. (2020) presented a two-layered optimisation methodology for the optimal power management of a fishing boat that combines a discrete search space for power system operating modes and a gradient-based optimisation algorithm to find local optima. Fang et al. (2019) proposed a two-step multi-objective optimisation method for managing hybrid power plants in all-electric ship microgrids. In the first step, a multi-objective mixed-integer non-linear programming (MO-MINLP) problem was formulated while the second step involved formulating a non-linear programming (NLP) problem.

Derivative-free methods

Derivative-free methods have emerged as an alternative technique to address problems without relying on explicit derivative information. Unlike gradient algorithms, derivative-free methods are capable of converging to global solutions (Rao, 2019). In the literature, various metaheuristic algorithms such as genetic algorithms (GA) and particle swarm optimisation (PSO) have been extensively explored for the energy management of hybrid applications.

Yang et al. (2020) established a multi-objective optimisation problem using the PSO algorithm for a solar-diesel hybrid generator ship power plant. Taheri et al. (2021) proposed a trip-ahead strategy for optimal energy dispatch in ship power plants focusing on reducing emissions and fuel consumption. The proposed approach was compared with other optimisation algorithms including GA and PSO. He et al. (2021) proposed a two-phase energy efficiency optimisation method for deciding the optimal ship speed and power allocation of an inland parallel hybrid bulk carrier. The global optimal results are obtained by using a GA. Tang et al. (2018)

developed a power-flow dispatching model using PSO for a hybrid power plant with photovoltaic and battery modules to reduce electricity costs. Ancona et al. (2018) introduced a load allocation framework based on GAs to maximise energy efficiency and minimise fuel consumption and thermal energy dissipation in cruise ships. Letafat et al. (2020) used an improved Sine Cosine Algorithm (ISCA) to optimise energy management and component sizing of a ferry boat to reduce operation costs.

Online OB-EMS strategies

Online OB-EMS are causal and local optimisation methods that aim to optimise power flow in real-time without requiring prior knowledge of the operating profile Yuan et al. (2020). These strategies focus on the instantaneous optimisation of the power flow based on the system's current operating conditions. The most widely used strategies are the Equivalent Consumption Minimisation Strategy and Model Predictive Control which enable the real-time optimisation of power distribution.

Equivalent Consumption Minimisation Strategy

The Equivalent Consumption Minimisation Strategy (ECMS) is a widely applied energy management strategy in hybrid applications with batteries that expresses electrical energy as an equivalent fuel quantity (Damian et al., 2022). The core idea of ECMS is to optimise energy distribution by converting electrical energy consumption into fuel consumption through the use of an equivalent factor by assigning a cost to electrical energy usage (Onori et al., 2016). In terms of the equivalent factor and co-state, ECMS and PMP share similarities. ECMS can be seen as an implementation of the optimal solution derived from PMP, achieving results that are close to the global optimal solution (Kalikatzarakis et al., 2018). While ECMS offers a simplified and computationally efficient solution, PMP provides a theoretical framework for optimal control.

Regarding the maritime industry Grimmelius et al. (2011) demonstrated the potential to use ECMS for real-time control of hybrid power plants. Dedes et al. (2016) investigated the potential of hybrid power plants using ECMS to increase fuel efficiency for ocean-going vessels incorporating various operating profiles. Yuan et al. (2016) compared ECMS with an RB-EMS on a hybrid tugboat and achieved substantial fuel savings of up to 24.4%. Kim and Kim (2021) proposed an improved ECMS using an artificial neural network (ANN) that can vary the optimal operation area according to the designer's target. Xiang and Yang (2021) proposed a two-layer energy management strategy using an improved ant colony optimisation (ACO) ECMS method for a parallel hybrid fishing boat. The inner layer uses the ECMS to optimise the operational mode and the operating point while the outer layer uses an improved ACO to optimise the equivalent factor to control battery SOC. The ACO-ECMS reduced fuel consumption by 12.1% compared to traditional ECMS and rule-based RB-ECMS.

ECMS closely approximates the global optimal solution, making it a promising option for real-world applications. Additionally, ECMS requires less computational effort compared to other optimisation-based methods such as DP (Xu et al., 2019). Notably, ECMS does not explicitly rely on detailed information about future operating conditions, reducing its dependency on future power demand (Onori et al., 2016). This characteristic makes ECMS particularly advantageous for unknown operating profiles. In fact, when compared to various control strategies, ECMS has consistently shown superior performance in terms of fuel consumption (Inal et al., 2022).

The performance of ECMS heavily relies on the accurate estimation of the equivalent factor which is estimated based on a predetermined operating profile while it gets influenced by various factors such as operating conditions and battery SOC (Xu et al., 2019). To address this, researchers have focused on accurately estimating the equivalent factor through offline and online estimation techniques using Adaptive-ECMS (A-ECMS) (Tran et al., 2020). Offline estimation aims to determine a constant optimal equivalent factor for the entire operating profile, while online estimation updates the equivalent factor in real-time.

Kalikatzarakis et al. (2018) applied ECMS and A-ECMS on a hybrid tugboat and achieved significant fuel savings and associated CO_2 emission reductions of 5% to 10% with unknown power demand. Vu et al. (2014) and Vu et al. (2015) used a predictor as an A-ECMS to estimate the equivalence factor based on operator load estimation. Gao et al. (2022) proposed an A-ECMS to update the equivalence factor using neural networks to reduce fuel consumption while also reducing the battery degradation on a hybrid power supply ship.

Model Predictive control

Model Predictive Control (MPC) has emerged as a prominent approach for the real-time energy management of hybrid power plants. It operates on a receding-horizon control strategy, allowing for online implementation without requiring prior knowledge of the entire operating profile (Haseltalab et al., 2022). MPC involves predicting the future behaviour of the system and calculating optimal inputs over a prediction horizon. The control inputs are implemented based on the first element of the derived optimal inputs, and the process is repeated by moving the prediction horizon forward (Rossiter, 2018).

By optimising a short-term finite horizon, MPC significantly reduces the computational burden compared to global optimisation methods like DP, allowing real-time implementation (Xu et al., 2019). It transforms global optimisation problems into local optimisation for the entire operating profile. Through local optimisation, receding horizon technique, and feedback correction, MPC efficiently minimises performance indexes such as fuel consumption and emissions over a specific horizon enabling real-time adaptation to changing operating conditions (Yuan et al., 2022).

Regarding the maritime industry, Antonopoulos et al. (2021) proposed an MPC framework for the energy management of hybrid power plants to minimise fuel consumption and emissions while ensuring that the battery operates within its safe operating limits while considering different operating modes, such as charge-sustaining or charge-depleting battery modes. Planakis et al. (2021) and Planakis et al. (2022) developed nonlinear MPC strategies for a hybrid plant that optimises the torque of the diesel engine and the electric machine to minimise fuel consumption and NOx emissions. Yuan et al. (2022) combined DP and MPC to optimise power generation dispatching of a ship power plant, achieving a 2.5% reduction in fuel consumption compared to an RB-EMS. Y. Zhang et al. (2022) developed a two-level MPC for a hybrid power plant that includes both a battery and an ultra-capacitor. The high-level MPC in the first optimisation stage focuses on fuel consumption minimisation based on a larger timescale, while the low-level MPC in the second optimisation stage handles high-frequency power fluctuations in a smaller timescale.

One of the strengths of MPC is its ability to explicitly handle constraints on state variables, inputs, and outputs. This enables more precise control and optimisation, as constraints can be formulated as quadratic or nonlinear programming problems based on the system's predicted dynamic behaviour (Zhang et al., 2020b). Park et al. (2015) combined integrated perturbation analysis and SQP to optimise the power flow in shipboard power systems to solve a constrained MPC optimisation problem in real-time. Haseltalab and Negenborn (2019) developed an MPC approach that utilises Input-Output Feedback Linearisation (IOFL) and a constraint linearisation technique to decrease the computational burden while improving fuel efficiency and ensuring optimal engine loading. Haseltalab et al. (2022) used a state space model of the overall power plant with an MPC controller to optimise power generation and distribution in real-time, while ensuring stability and reliability during different ship operations.

Furthermore, accurate predictive information is crucial for the performance of MPC-based energy management strategies. Although accurately predicting the entire operating profile is challenging, partial prediction considering a small portion of the upcoming trip can still be beneficial (Zhang et al., 2020b). To achieve accurate predictions, factors such as future power demand, weather conditions, and environmental conditions need to be effectively considered. Huotari et al. (2020) developed an MPC strategy for a hybrid power supply cruise ship vessel which uses a 2-stage predictive model to predict future power demand and a Mixed-Integer Linear Programming (MILP) optimisation model to optimise the operating point of each power source. Hou et al. (2018a) introduced an adaptive model predictive control approach that incorporates propulsion-load torque estimation and prediction to address the multi-frequency load fluctuations experienced by electric ships. Hou et al. (2018b) enhanced the MPC-based approach involving the formulation of a multi-objective optimisation problem that aims to achieve power-fluctuation compensation and energy saving under various operating constraints.

Other methods

Multi-agent systems can be used for energy management by coordinating the actions of multiple agents to optimise load distribution. Each agent in the system can represent a different component or subsystem of the energy system, such as a generator, battery, or load Tang et al. (2015). The agents communicate with each other to exchange information about their current state and make decisions about how to allocate resources and adjust their behaviour to achieve a common goal (Xiao et al., 2019). This can include tasks such as load balancing, demand response, and optimising energy efficiency. Feng et al. (2012) proposed a multi-agent system for the real-time load management of all-electric ship power systems in the DC zone level to optimally determine the switch status of loads in DC zones while satisfying various constraints. Tang et al. (2015) developed a multi-agent system method for the energy management of hybrid power plants to reduce emissions, minimise fuel consumption, and improve energy efficiency.

Game theory (GT) methods have gained attention in solving energy management problems (Tran et al., 2020). As a branch of operational research, game theory provides a framework to analyse strategic interactions among multiple players, considering their rational interests and the resulting outcomes. In the context of energy management, game theory allows for the exploration of various strategies that can be used to maximise different objectives.

However, the application of game theory methods in energy management problems comes with certain challenges. One major concern is the computation burden associated with GT, which can be comparable to that of DP (Zhang et al., 2020b). This poses difficulties for online implementation, as the real-time nature of energy management requires efficient and timely execution. Another limitation of GT lies in its dependency on certain component models as this restricts its flexibility to different power plant configurations (Zhang et al., 2020b) while the majority of the applications concern HEVs.

Extremum seeking control (ESC) has emerged as a promising online optimisation algorithm for energy management problems. It is specifically designed to find the extremum (maximum or minimum) value of a static nonlinear system in real-time without requiring derivative information (Tran et al., 2020). By dynamically adjusting the system's operating points, ESC aims to optimise a performance function, leading to improved energy efficiency and overall system performance. It was first proposed by Dinc¸men et al. (2010) to search for the optimum torque distribution between an ICE and an electric machine to maximise powertrain efficiency. Nevertheless, to the best of the author's knowledge, there are no applications in the maritime industry.

2.5.3. Learning-based Strategies (LB-EMS)

Learning-based energy management strategies (LB-EMS) aim to update control parameters online by interacting with the environment and adapting to different operating conditions. They generally require a large amount of historical and past operating profile data to obtain the optimal solution without requiring precise modelling (Zhang et al., 2020b). One of the main advantages is that they can adapt to different operating profiles, which can vary significantly and are difficult to predict in different operating conditions (Tran et al., 2020). However, the main drawback in marine applications is the lack of recorded data that can accommodate stochastic operating profiles with high variations (Wu et al., 2020).

Machine learning approaches are usually grouped based on their learning type, which can be sub-categorised into supervised learning, unsupervised learning and reinforcement learning (Chowdhary, 2020). Most applications in the maritime industry concern mainly reinforcement learning (RL). RL involves a learning agent interacting with an environment. The agent receives observations of the environment's state, selects actions, and receives rewards based on the outcomes (Chowdhary, 2020). By learning from these interactions, the agent develops a control policy to maximise cumulative rewards over time. RL is a model-free approach that offers adaptability but requires sufficient training data (Zhang et al., 2020b).

Wu et al. (2020) applied a Double Q RL-based energy management on a passenger ferry, using a hybrid fuel cell and battery for power generation. The strategy was tested using stochastic operating profiles and achieved near-optimal performance 96.9% compared to DP. Hasanvand et al. (2020) formulated a deep reinforcement learning (DRL) in hybrid electric ferry that considers a real-time information from the operating profile to optimise system investment costs and system reliability. Wu et al. (2021) applied a DRL energy management strategy on a hybrid coastal ferry achieving near-optimal cost performance in highly stochastic environments. Shang et al. (2022) introduced a DRL approach that perform real-time optimisation of the operating points on generator sets and the energy storage systems without requiring precise modelling of the system uncertainty.

2.5.4. Comparison of Energy Management Strategies

The previous sections provided an extensive overview of the energy management strategies focusing on marine applications. This section aims to provide a comparative analysis of these strategies by providing a side-by-side qualitative comparison. Table 1 ranks the strategies in terms of optimality, real-time implementation, computational burden, adaptability in different operating conditions and the number of marine applications.

Table 1: Comparison of Energy Management strategies.

Strategy	Optimality	Real-time Implemenation	Computational Effort	Adaptability	Marine Applications
Deterministic RB-EMS	Sub-optimal	Yes	Low	Limited	High
Fuzzy Logic RB-EMS	Sub-optimal	Yes	Medium	Medium	Limited
DP	Optimal	No	High	Limited	Limited
PMP	Optimal	No	High	Limited	No
Gradient OB-EMS	Optimal	No	Medium to High	Limited	Limited
Derivative-free OB-EMS	Optimal	No	Medium to High	Limited	Limited
ECMS	Sub-optimal	Yes	Low	Medium	High
MPC	Sub-optimal	Yes	Medium to High	High	High
LB-EMS	Optimal (with training)	Yes	Medium to High	High	Limited

RB-EMS, such as deterministic RB-EMS and fuzzy logic RB-EMS, offer simplicity, ease of implementation, and real-time performance. They make use of predefined rules and thresholds to determine the power distribution and operating modes within the power plant. These methods are practical and valuable tools for benchmarking with other methods, but their main limitation is the lack of flexibility and optimality in all operating scenarios.

OB-EMS, including offline and online methods, aim to find the optimal control sequence that minimises an objective function while satisfying various constraints. Offline OB-EMS methods provide global optimal solutions but require prior knowledge of the operating profile. They serve as valuable design tools but are not suitable for real-time implementation. Online OB-EMS methods, such as ECMS and MPC, enable real-time optimisation without requiring prior knowledge of the entire operating profile. ECMS offers simplicity and computational efficiency, closely approximating the global optimal solution. MPC provides optimisation in a receding horizon with explicit handling of constraints.

LB-EMS, particularly RL, offer adaptability and the ability to learn optimal control policies through interactions with the environment. RL methods can adapt to different operating profiles but require sufficient training data. They have shown promising results in marine applications, achieving near-optimal performance in highly stochastic environments.

When comparing these methods, deterministic RB-EMS methods are considered sub-optimal as they lack the flexibility to handle all operating scenarios. OB-EMS, particularly MPC and ECMS, provide optimal or near-optimal solutions while considering constraints and real-time performance. Learning-based strategies, such as RL, offer adaptability but may require a large amount of training data.

2.6. Overview of Maintenance Strategies

The previous section provided insights into energy management strategies in the maritime industry, which primarily focused on optimising performance metrics such as fuel consumption and emissions. However, it is important to acknowledge the inherent assumption that the system will remain intact throughout its lifetime operation. In practice, systems experience degradation over time and through usage, which can significantly impact their ability to perform their intended functions appropriately (Zagorowska et al., 2020).

In the case of autonomous operation, it becomes crucial to assess the health condition of the system and accurately predict its future behaviour. Advanced health monitoring methods can assess the health and performance of individual components within the power plant. These monitoring techniques consider various factors such as the operating conditions, component reliability, and prevailing environmental conditions, thereby providing valuable insights into the current health state of the system (Ellefsen et al., 2019), (Abaei et al., 2021).

Practices for health monitoring methods can be extracted from maintenance strategies applied in the maritime industry. According to the British Standards (BS) maintenance is defined as "the combination of all technical and administrative actions, including supervision actions, intended to retain an item in, or restore it to, a state in which it can perform a required action" (BSI, 2010). The primary goal of maintenance is to understand the underlying failure mechanisms and ensure that the system or component functions in their intended use (Gouriveau et al., 2016).

In the maritime industry, various maintenance strategies are employed, making it beneficial to examine the most practised approaches. According to the BS maintenance is divided into two main categories: corrective maintenance (CM) and preventive maintenance (PvM). Preventive maintenance is further divided into condition-based maintenance (CBM) and predetermined maintenance (PM). However, it is crucial to include predictive maintenance (PdM) and reliability-centred maintenance (RCM), as they are widely used in the field and various methods have been proposed for system health monitoring.

Corrective maintenance (CM), also known as reactive, run-to-failure (RTF), or breakdown maintenance is one of the oldest maintenance strategies (Jimenez et al., 2020). According to the BS, CM is defined as “maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function” (BSI, 2010). The fundamental concept behind this strategy is reactive, meaning that corrective actions are performed after the occurrence of a failure (Verma et al., 2015). However, in the case of autonomous systems, where no humans are present on-board to perform in situ actions, the reactive nature of corrective maintenance renders this approach unsuitable.

The second historical maintenance strategy is known as preventive maintenance (PvM). According to the BS, preventive maintenance is defined as "maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item" (BSI, 2010). In this strategy, maintenance is based on the premise that every component or system will eventually fail after a certain period of use. Therefore, the goal of PvM is to perform maintenance tasks proactively to prevent failure or further degradation. PvM can be further divided into preventive maintenance and condition-based maintenance.

According to the BS, predetermined maintenance (PM) is defined as “preventive maintenance carried out in accordance with established intervals of time or number of units of use but without previous condition investigation” (BSI, 2010). In this strategy, maintenance tasks are scheduled based on predetermined intervals derived from historical data on similar equipment (Jimenez et al., 2020). The actual performance or condition of the components is not taken into account, which means that maintenance actions can be performed even when the components are functioning properly.

Although the specification of the maintenance intervals is based on historical patterns, this strategy is often criticised for over-maintaining equipment, leading to higher maintenance costs. One of the limitations of PM is that it does not consider real-time feedback from the actual operating performance of systems or components. As a result, maintenance tasks may be performed unnecessarily or at times when the components are faulty. Given the requirement for advanced health monitoring in autonomous systems, this strategy is considered unsuitable.

The increasing adoption of sensors has facilitated the emergence of a maintenance strategy based on real-time data analysis known as condition-based maintenance (CBM). According to the BS, CBM is defined as "preventive maintenance which includes a combination of condition monitoring and/or inspection and/or testing, analysis, and the ensuing maintenance actions" (Jimenez et al., 2020). The primary goal of CBM is to gather data from sensors to detect deviations from normal values, which can help identify faulty components.

While CBM takes into account the actual usage and performance of the equipment, it is important to note that the exact time of fault or failure remains uncertain (Gouriveau et al., 2016). Therefore, the development of predictive methods becomes crucial to forecast the point at which a component will no longer be able to function properly. This need paved the way for the development of predictive maintenance (PdM), which aims to provide estimates of remaining useful life (RUL) supported by confidence intervals.

The rationale behind PdM is to analyse the historical usage pattern while in parallel analysing real-time data to predict when the component will fail. According to the BS, PdM is defined as "condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item" (BSI, 2010). This emphasises that PdM relies on CBM as its foundation for making future predictions.

According to (Mobley, 2002), PdM is more than just a maintenance strategy. It is a philosophy or attitude that leverages the actual operating condition of plant equipment to optimise overall plant operation. A comprehensive PdM management program utilises cost-effective tools such as vibration monitoring, thermography, and tribology to gather real-time data on the operating condition of critical plant systems. Based on this actual data, maintenance activities are scheduled on an as-needed basis, resulting in more efficient and effective maintenance practices.

Although PdM is the most promising for the successful implementation of autonomous operations, its application is currently limited by the lack of empirical data necessary for conducting comprehensive case studies (Kang et al., 2023). However, there is a maintenance strategy that combines elements of corrective, preventive, and predictive maintenance, known as reliability-centred maintenance (RCM).

According to Bloom (2005), RCM can be defined as a set of tasks generated through a systematic evaluation process to develop or optimise a maintenance program. RCM incorporates decision logic to assess the safety and operational consequences of failures and identifies the underlying mechanisms responsible for those failures. The key focus of RCM is on component reliability, classifying components based on their criticality to system operation. This classification allows for the adoption of different maintenance strategies based on the importance of the components, ensuring a targeted and efficient maintenance strategy (Cheliotis, 2020).

2.7. Prognostics and Health Management (PHM)

Prognostics and health management (PHM) is a vital enabling technology for the successful implementation of advanced health monitoring techniques derived from predictive maintenance practices. By incorporating various disciplines such as sensing technologies, failure physics, machine learning, modern statistics, and reliability engineering, PHM enables real-time health assessment and future state prediction of ship systems under their actual operating conditions (Kim et al., 2016). With the increasing adoption of sensors in autonomous ships, PHM gathers data that facilitates the development of health indicators and prognostic models.

The integration of PHM in autonomous ships brings several benefits. Firstly, it enhances system safety by allowing the anticipation of incipient faults before they escalate into catastrophic failures. PHM plays a crucial role in identifying faults and failures, impeding their propagation, and estimating the health state of components. PHM possesses also the ability to continuously or periodically measure degradation levels (e.g., crack size, corrosion depth, wear amount) (Kim et al., 2016). By monitoring system health in real-time, operators can take appropriate actions under different usage conditions, thus increasing the service lifetime while maintaining the intended system reliability (Escobet et al., 2012).

Especially for autonomous ships, this allows for scheduling maintenance procedures at the next appropriate port of call or dispatching maintenance personnel while the system is still in operation (Ellefsen et al., 2019). This proactive approach significantly enhances operational performance, reduces unexpected system failures, and thus enhances resilience.

Based on the physical knowledge of the degradation mechanism, PHM methods can be classified into physics-based, data-driven, and hybrid methods (Olesen and Shaker, 2020), (Guo et al., 2020).

2.7.1. Physics-based Methods

Physics-based methods combine fundamental physical principles and knowledge of material properties, system dynamics, and degradation mechanisms to capture the degradation behaviour of components or systems over time. By quantifying the characteristics of the degradation process under various loads and operation conditions, they allow for the estimation of the RUL of components (Guo et al., 2020).

These methods incorporate the physical understanding of the system by using mathematical models. This allows for easier interpretation of the model parameters and provides insights into the underlying degradation mechanisms. In this way, model errors caused by unexplained features or unmodeled phenomena can be significantly reduced (Guo et al., 2020). Another advantage of physics-based methods is their ability to accurately describe degradation behaviour and make long-term predictions, requiring a relatively smaller amount of data compared to other methods (P. Zhang et al., 2022).

Physics-based methods usually utilise the physics of failure, including phenomena like crack growth, fatigue, and wearing, to predict component RULs. Nevertheless, the most widely used methods concern stochastic filters, which use a state-space model to represent the unobserved condition and observed process-related variables. Among the commonly used stochastic filters are the Kalman filter (KF), extended Kalman filter (EKF), unscented Kalman filter (UKF), histogram filter, and particle filter (PF) (Guo et al., 2020).

Concerning the components which are commonly used in energy systems, (Kim et al., 2021b) introduced a Shifting Kernel Particle Filter (SKPF), which combines the PF Particle Filter with a shifting kernel technique to accurately predict the RUL of lithium-ion batteries. Mishra et al. (2018) employed a Bayesian hierarchical model-based approach to predict the end of discharge (EoD) of lithium-ion batteries. Yu et al. (2014) utilised a PF approach for joint state and unknown parameters estimation for faulty parameters to predict the RUL of electric machines. Lei et al. (2016) used a PF method to predict the RUL of machinery using vibration signals from accelerated degradation tests of rolling bearings. Kim (2021) developed an algorithm which predicts the RUL by obtaining the winding temperature to prevent stator winding turn faults of electric motors in EGR blower systems.

One of the main challenges is the complexity of understanding the physics of damage, especially for complex mechanical systems. This complexity can limit the application of physics-based methods, as it may be difficult to develop accurate physical models that capture all the intricacies of the degradation process (Lei et al., 2018). Model calibration and parameter estimation are also challenging steps in physics-based methods to ensure accurate results (Kim et al., 2016). Furthermore, the mathematical models used in physics-based prognostics often involve complex differential or partial differential equations, which results in high computational costs (P. Zhang et al., 2022).

Additionally, the scarcity of physical degradation models and the time-consuming process of developing them limits the scalability of transferring them to different physical systems. Usually, physics-based methods are system or component-specific and they are mainly used for predicting the RUL of simpler equipment like fans, and bearings (P. Zhang et al., 2022).

2.7.2. Data-driven Methods

Data-driven methods utilise historical operational data to establish models to predict the future state and RUL of a component. These models are built using machine learning, soft computing, and statistical techniques, and they do not require an explicit analytical model of the system's behaviour or failure mechanisms (Olesen and Shaker, 2020). By analysing patterns in the available data, data-driven models can capture the degradation progress and make predictions without relying on a physical degradation law (Kim et al., 2016). The main hypothesis is that observed data are the most reliable and strongest source of information to understand degradation mechanisms (Gouriveau et al., 2016).

Data-driven methods can achieve high accuracy, especially when provided with a large volume of high-quality data (Olesen and Shaker, 2020). The use of machine learning algorithms allows for complex patterns to be discovered in the data without requiring physical understanding, leading to accurate predictions of system degradation and RUL (Guo et al., 2020). Data-driven models also offer flexibility and rapid development, as they do not require detailed knowledge of the underlying physics or an intricate understanding of the degradation process (P. Zhang et al., 2022). This makes them suitable for complex systems where the physical behaviour is difficult to model.

The data-driven methods are divided in general into statistical and AI approaches. Statistical data-driven methods utilise trend extrapolation techniques using observed data without relying on specific physics or principles to capture the degradation process (Lei et al., 2018). These models use regression or probabilistic methods to capture the degradation trend of equipment and make predictions about the RUL through extrapolation. The most common methods include Gamma processes (GP), Inverse Gaussian processes (IGP), Wiener processes (WP), hidden Markov models (HMM) and proportional hazards models (Lei et al., 2018), (P. Zhang et al., 2022), (Guo et al., 2020).

Concerning the statistical data-driven methods in the maritime industry, Abaei et al., 2021) and Abaei et al. (2022) utilised probabilistic models using the Bayesian inference to calculate reliability metrics for unattended power plants considering unexpected and disruptive events. Bolbot et al. (2021) proposed a monitoring methodology for cruise ship power plants, using sensor measurements to predict the dynamic blackout probability. Prakash and Kaushik (2020) developed a wiener-based degradation modelling approach, on systems with either one or two-phase degradation patterns which updates model parameters using the Bayesian inference to accurately predict the RUL.

AI data-driven methods employ AI techniques to learn degradation patterns from available observations. Observed data are fed into trained algorithms that determine the current health state of a component and then make future predictions about future degradation Knutsen et al. (2014). These approaches are particularly well-suited for addressing prognostic challenges in complex mechanical systems where the interrelation of degradation processes is difficult to capture using traditional models (Lei et al., 2018). The most widely used methods are ANNs, fuzzy logic, Gaussian process regression (GPR), and relevance/support vector machines (RVM/SVM) (Lei et al., 2018), (P. Zhang et al., 2022). Especially ANNs and deep learning methods have witnessed increased popularity (Ellefsen et al., 2019).

Regarding AI data-driven methods for energy systems, Mitici et al. (2023) explored the use of Convolutional ANNs to produce probabilistic RUL estimates for turbofan engines. (Coraddu et al., 2016) benchmarked the potential use of regularised least squares (RLS) and SVM to model the degradation of gas turbines inside marine power plants. Sampaio et al. (2019) trained an ANN to predict the failure time of a motor based on vibration measurements. Aizpurua et al. (2023) introduced an approach that combines data-driven and physics-based degradation models to estimate motor torque and winding temperature for electric motors in marine power plants. He et al. (2011) estimated the state of health and predicted the RUL of lithium-ion batteries by using Dempster–Shafer theory and advanced statistical techniques such as the Bayesian Monte Carlo approach. Richardson et al. (2017) proposed an approach based on GPR to predict the future capacity and the RUL of lithium-ion batteries. Bahootoroody et al. (2022) proposed a machine learning approach in a hierarchical Bayesian inference framework (HBI) to calculate the remaining useful life (RUL) of an autonomous ship's main engine with different degrees of autonomy using actual measurements. Niculita et al. (2017) proposed a PHM development process to identify and optimise sensor locations. This method was applied to the fuel oil feeding system of a diesel engine using a functional model-based approach in MADe™.

Especially for marine engines, M. Cheliotis, Lazakis, and Cheliotis (2022) applied a machine learning fault detection technique combined with Bayesian Networks (BN) to examine the probability of faults in marine engine subsystems. Tsitsilonis et al. (2023) developed a framework for the health assessment of marine engines using first principles models combined with machine learning tools. Velasco-gallego and Lazakis (2022) developed a methodology for fault classification in marine engines using time series imaging and image classification approaches. Kang et al. (2023) proposed a hierarchical-level fault detection and diagnosis method for ship engine systems using data clustering, dimension reduction, and regression analysis. Karatuğ and Arslanoğlu (2022) trained an ANN to develop a performance model for a marine engine which was used to diagnose faults. Stoumpos and Theotokatos (2022) developed an innovative engine diagnostics system (EDS) which included an intelligent engine monitoring system and an advanced faults/failure detection system, where the sensor measurements uncertainty was identified via a novel data-driven model based on ANNs.

However, data-driven methods present certain limitations. Interpretability is a major concern, as data-driven models often act as "black boxes" making it challenging to understand the underlying logic behind their predictions (Olesen and Shaker, 2020). Since limited physical knowledge of the degradation process is involved, the developed mathematical model potentially does not necessarily express any physical meaning (Kim et al., 2016).

Data-driven methods rely solely on observed data patterns, as a result, biases present in the data may propagate into the model (Kim et al., 2016). Additionally, the accuracy and reliability of data-driven models heavily depend on the quality and quantity of the available data (P. Zhang et al., 2022). The presence of noise along with faulty or unreliable data can lead to a deterioration in the accuracy of the resulting model (Olesen and Shaker, 2020). Obtaining sufficient and representative data can be a time-consuming and costly process.

Moreover, data-driven models are highly data-specific and may not be easily transferable or reusable across different applications or contexts (Guo et al., 2020). The lack of physical understanding in these models can also lead to the risk of undetected phenomena or limited insight into the underlying degradation mechanisms (Guo et al., 2020).

2.7.3. Hybrid Methods

Hybrid methods integrate data-driven and physics-based methods to improve prediction performance. By combining the advantages of both methods, hybrid methods offer a promising solution to address the limitations of individual methods (Guo et al., 2020).

One advantage of hybrid methods is the use of data-driven methods which allow for the analysis and prediction of complex systems with multiple failure modes. Additionally, the integration of physics-based methods enhances the interpretability of the prognostic results, providing valuable insights into the underlying degradation mechanisms (Guo et al., 2020).

For instance, Aizpurua et al. (2018) proposed a hybrid approach to estimate the RUL of circuit breakers which integrates deterministic and stochastic models using piecewise deterministic Markov processes. Aizpurua et al. (2019) this paper combined soft computing with probabilistic reasoning techniques to evaluate power transformer health under uncertainty.

2.7.4. Comparison of PHM methods

The previous sections provided an overview of the methods that are used in PHM. This section aims to provide a comparative analysis of these methods by providing a side-by-side qualitative comparison. Table 2 ranks the methods in terms of interpretability, data requirement, flexibility, knowledge requirements.

Table 2: Comparison of PHM methods.

Method	Interpretability	Data Requirements	Flexibility	Knowledge Requirements
Physics-based	High (physical principles)	Less data	Low	High
Data-driven	Low (black-box models)	Large amount of data	High	Moderate
Hybrid	Moderate to High	Varies	High	High

Physics-based methods incorporate the physical understanding of the degradation mechanisms to develop mathematical models. In this way, the developed models can provide a high degree of interpretability since predictions are based on well-established physical laws and principles. However, to develop this kind of models, a substantial knowledge on the physics of degradation is required, which usually makes them more challenging to develop, as limited components have been extensively researched, limiting their transferability. Additionally, opposed to data-driven methods, they usually don't require large amounts of data, however their computational costs can be significant, especially when the models use complex differential equations.

Data-driven methods, on the other hand, rely on patterns in historical data to make predictions. They require large amount of data to develop models, without relying on physical understanding of the degradation processes. Statistical and AI approaches can capture complex relationships in large datasets but usually are considered "black boxes," as their predictions can be difficult to interpret. They can be highly accurate and flexible, adapting to various data patterns, by using several methods.

Hybrid methods aim to combine the strengths of both physics-based and data-driven methods. They can exploit the strengths of physics-based methods to increase interpretability with the adaptability of data-driven methods. They blend the knowledge and data requirements of both methods becoming more flexible, offering a balanced approach to degradation predictions.

2.7.5. PHM Limitations

From the previous discussion, PHM can be the enabling technology to assess the health of various components within the autonomous power plant. Especially PHM can be suitable for components present in the power plant which have a considerable lifespan (Guo et al., 2020). A huge potential exists in the development of detection, diagnostics, and prognostics techniques in the whole lifecycle of the ship. Nevertheless, there are several challenges and limitations.

In the shipping sector, there are usually several data-related challenges which significantly affect the effectiveness of PHM methods. The recorded data are usually high-dimensional, they have substantial measurement errors, and they are usually unlabelled with insufficient quality (Kang et al., 2023). PHM methods are usually tested in experimental conditions where experimental data sets are typically more fine-tuned and carefully controlled, whereas measured data tends to be noisier along with errors (Olesen and Shaker, 2020). Furthermore, the quality of PHM methods heavily relies on collecting significant amounts of data and running simulation models, which can be computationally expensive to run on-board a ship (Knutsen et al., 2014). Additionally, in many cases, the models rely on direct measurement of damage data which usually is not feasible on-board, and instead, system responses that are influenced by damage are measured (Kim et al., 2016).

The operating conditions in which a system is operating can affect the prediction results. Variations in load conditions or operating profiles can introduce inaccuracies when relying solely on historical data for health assessment (Knutsen et al., 2014). It is important to consider that different units or components may exhibit distinct degradation trajectories even under similar operation environments. For instance, lithium-ion batteries subjected to the same profile and environment can display varying capacity degradation processes (Guo et al., 2020).

Uncertainty is a significant challenge in PHM methods, and it can be classified into different categories. One category is epistemic uncertainty, which arises from limitations in knowledge and understanding (Kim et al., 2016). It includes factors such as model errors, inappropriate methods, unexplained features, and simplifying assumptions that may not fully capture the complexity of the system's behaviour (Guo et al., 2020).

On the other hand, aleatory uncertainty is inherent randomness or variability in the system. It includes factors related to operational conditions, environmental variations, and inherent variability in processes (Kim et al., 2016). Aleatory uncertainty represents the natural variability that exists in the system, independent of our knowledge or understanding. Input uncertainties arise from inherent variability in processes, including initial state estimation, material properties, geometric characteristics, and manufacturing variability (Guo et al., 2020). Measurement uncertainties are also present, resulting from factors like sensor noise and filter errors, which can impact the accuracy of measurement data (Guo et al., 2020).

These uncertainties can affect the accuracy of early RUL predictions, but as the system approaches its end-of-life, RUL predictions tend to become more accurate (J I Aizpurua et al., 2017). It is important to consider these uncertainties and their sources when developing prognostic models and interpreting the results, as they contribute to the overall uncertainty bounds of long-term RUL predictions.

While most PHM methods presented earlier primarily aim to accurately compute the degradation and RUL of individual components, it is more important to understand the overall performance degradation of the system. System-level health assessment plays a crucial role by shifting the focus from individual component-level predictions to the degradation and performance of subsystems and systems (Khorasgani et al., 2016). This is especially important for autonomous operation which focuses on a holistic view of the entire system or ship.

However, system-level health assessment poses several challenges due to the complex interactions between degrading components. The behaviour of the system is not solely determined by the RUL distributions of individual components but is also influenced by the system configuration and the interactions among the components (Khorasgani et al., 2016). RUL estimates at the component level can be propagated to the system level to obtain RUL estimates for the overall system (Laag et al., 2015). It is important to note that the system-level RUL distributions may differ significantly from the RUL distributions of the individual components. Accurate system-level RUL prediction requires a systematic approach that combines degradation models for individual components and considers the interrelation and correlation between them (Kim et al., 2021a). The correlation between components presents a particular challenge for system-level prognostics.

2.8. System-level Dependability Analysis

One effective approach to assess the system-level health is through the application of methods derived from dependability analysis. The concept of system dependability encompasses a wide range of scientific areas, including safety, reliability, availability, maintainability, confidentiality, and integrity (Aizpurua et al., 2017). These methods offer a comprehensive framework for understanding and evaluating component interactions within the system, thereby enabling the quantification of various metrics including reliability and risk.

Dependability analysis methods encompass both qualitative and quantitative techniques, each contributing unique insights into system behaviour and potential vulnerabilities. The most widely used qualitative methods include Hazard Identification (HAZID), Hazard and Operability Study (HAZOP), Preliminary Hazard Analysis (PHA), Structured What-If (SWIFT), System-Theoretic Process Analysis (STPA), Failure Modes and Effects Analysis (FMEA), and Failure Modes, Effects, and Criticality Analysis (FMECA) (Bolbot et al., 2019). However, these qualitative methods are highly effective in uncovering possible failure modes, dependencies, and hazards descriptively, while they are primarily employed during the system's design phase (Cheliotis et al., 2021).

On the other hand, quantitative methods allow for a more in-depth evaluation of system-level failure modes by offering numerical calculations of the investigated metrics (Cheliotis et al., 2021). The most widely used methods in literature include Fault Tree Analysis (FTA), Reliability Block Diagrams (RBD), Event Tree Analysis (ETA), Markov Models (MM), and Bayesian Networks (BN) (Bolbot et al., 2019), (Chemweno et al., 2018). These quantitative methods allow quantifying the likelihood and consequences of component and system failures, providing an overview of system-level health to allow more informed decisions to reduce risk and improve safety.

2.8.1. Fault Tree Analysis (FTA)

FTA is a widely recognized hazard and safety analysis method that serves as a valuable tool for assessing the causes of undesired events within a system (Bolbot, 2020). FTA's origins can be traced back to its conceptualisation by the US Air Force in 1962 (Cheliotis, 2020).

This method employs a top-down approach, starting with the identification of an undesired event and then deductively tracing its causes (Lazakis et al., 2018). The core principle of FTA is to represent the occurrence of a failure using a logical tree. It utilises logic gates and events to construct a model of an engineering system by interconnecting various pathways that can lead to an undesirable failure. Logic gates simulate the functional dependencies within the examined system, typically representing sub-systems and sub-assemblies (Cheliotis et al., 2021). Conversely, events are used to model individual components and are positioned at the lower level of the system's model architecture.

Concerning the application of FTA in marine power systems, Ta et al. (2017) evaluated the reliability of marine propulsion systems, highlighting the method's effectiveness in identifying and quantifying potential failure modes and their impact on system reliability. (Kirolivanos and Jeong (2022) performed a comparative analysis of marine dual-fuel engines using Dynamic Fault Tree Analysis (DFTA), revealing enhanced reliability in dual-fuel engines over conventional diesel engines, under the premise of using predictive maintenance strategies. Lazakis et al. (2018) integrated FTA with ANNs in predicting ship machinery system conditions. Milioulis et al. (2022) introduced an innovative approach to safety analysis of high-pressure fuel gas supply systems in LNG-fueled vessels, employing model-based safety techniques powered from MADe software like FMECA and FTA, to identify and mitigate risks. Trivyza et al. (2021) combined preliminary HAZID and model-based techniques including FTA and FMECA to evaluate the safety and reliability of an ammonia-powered fuel-cell system.

Nevertheless, while FTA is a practical method it exhibits several challenges. FTA excels in capturing dependencies between functions and component failures but may require refinements to address common cause failures, where multiple components fail simultaneously due to shared causes (Bolbot et al., 2020b). This challenge becomes particularly pertinent in complex systems with intricate dependencies, as it can lead to the combinatorial explosion problem (Chemweno et al., 2018). Additionally, classic FTA do not possess the capability to capture software and cybersecurity-related failures, limiting its effectiveness in assessing these critical aspects of autonomous systems operation (Bolbot, 2020).

Furthermore, FTA is static in nature, as it is an open-loop method incapable of adapting to changing operating conditions or incorporating new observations (Abaei et al., 2021). This static attribute can constrain its applicability, particularly when assessing systems with possessing temporal behaviour properties. To overcome these limitations, DFTA methods have been proposed, offering the potential to overcome these challenges by accommodating dynamic gates (Li et al., 2017).

2.8.2. Event Tree Analysis (ETA)

ETA is a method used to identify possible event sequences leading to specific accident scenarios. It starts with an initiating event, such as a system failure, and explores various outcomes by branching out into different sequences (Wang et al., 2021). Each branch represents a possible event and includes its probability. This analysis is effective in modelling successive events and analysing hazard propagation (Cheliotis et al., 2021).

Bolbot et al. (2020a) integrated ETA with STPA and FTA to introduce a methodology for safety analysis applied to a ship exhaust gas scrubber system. ETA was employed for identifying event sequences and multi-point failures within the system, to unveil potential hazards and their propagation in the system. Aziz et al. (2019) presented a bow-tie model, which integrates ETA with FTA, to evaluate potential failure scenarios for various events like fire/explosion and propulsion system failure. ETA was employed as part of a formal safety assessment procedure by Wang et al. (2021) for the risk assessment of a battery-powered ferry.

However, ETA presents several limitations. It considers only one failure mode per event, which may not be sufficient for identifying complex failure modes (Bolbot, 2020). Additionally, the incorporation of common cause failures in ETA can present specific challenges that require careful consideration (Bolbot, 2020). These limitations highlight that ETA it may not fully capture the dependencies of certain types of system failures.

2.8.3. Reliability Block Diagram (RBD)

RBDs are graphical tools used for modelling the reliability of systems. In an RBD, each system component is represented by a block, which can be in either an operating or failed state (Vasconcelos et al., 2019). These blocks are connected based on the logical relationship of their reliability, reflecting the system's structure. By integrating various components into sub-models or blocks, RBDs facilitate the analysis of how individual component failures impact different system configurations (Verma et al., 2015).

Dionysiou and Bolbot (2021) used RBDs to estimate system reliability and availability metrics using the MADe software in a lubricating oil system inside a marine engine. Laskowski (2015) used RBDs and FTA to represent the reliability structure of marine main engines, offering a comprehensive approach to identify and evaluate critical failure modes and their implications on overall system performance.

While the RBDs are effective for visualising and evaluating system reliability, they present several limitations. RBDs do not inherently account for different failure modes, external events such as human error, or the priority of events (Verma et al., 2015). Additionally, RBDs may not effectively represent the interdependencies between components, especially in complex systems where failures can have cascading effects (Rausand et al., 2021).

2.8.4. Markov Model (MM)

Markov models play a crucial role in system reliability analysis by enabling the representation and evaluation of various system states and their transitions. The fundamental assumption of a Markov process is its memory-less nature, meaning that the future behaviour of a system in any given state depends solely on its present state, irrespective of its history (Chiachío et al., 2020). These transitions are generally caused by either the failure or repair of one or more subsystem components. Markov models use a state transition diagram, where each node represents a distinct state of the system, and the arcs represent the transitions between these states

(Verma et al., 2015). They allow to model different system states such as working, degraded and failure states (Hassan et al., 2016).

Jurjević et al. (2012) used Markov models to build a ship propulsion system reliability model to detect weak spots in the system and prevent upcoming failures. Markopoulos and Platis (2018) developed Markov models for a gas and a diesel engine to predict the system availability. In their case study on the availability analysis of a LNG processing plant, Hassan et al. (2016) utilised a Markov Model to effectively model the random behaviour of the plant's equipment.

Markov models, while valuable in system reliability analysis, exhibit significant limitations, particularly when applied to large-scale multi-state systems. As the size of the system increases, they can suffer from what is known as the "dimension curse" (Ding et al., 2010). Solving models with a large number of states can be computationally intensive and can increase the computation burden.

2.8.5. Bayesian Network (BN)

BNs are a form of probabilistic Directed Acyclic Graphical (DAG) models originating from computer science, developed by Judea Pearl in 1985 (Cheliotis et al., 2021). They depict functional and causal dependencies between random variables, representing a joint probability distribution of these variables. The qualitative aspect of BNs is defined by a DAG, where each variable is represented as a node, and directed links between nodes establish causal relationships and dependencies (Bobbio et al., 2001).

BNs are powerful in modelling complex systems, making them suitable for applications like power systems with multiple components. They integrate information from various sources for robust reliability calculations (Jiang et al., 2019). Unlike simpler models, BNs can handle complex relationships that are not easily represented by traditional fault tree gates (Lee and Pan, 2018). They have the ability to use probability distributions for node values unlike binary values with other methods (Bobbio et al., 2001). Additionally, Dynamic Bayesian Networks (DBNs) can account for time variations by representing variables across different time slices (Weber et al., 2006).

Cai et al. (2012) used BNs to evaluate the reliability of subsea Blowout Preventer (BOP) control systems. This approach provided a detailed assessment of the reliability of these critical systems in subsea operations. Rebello et al. (2018) combined DBNs and HMMs to model the relationship between component degradation and system functionality by relating the degradation state of components to the system's functional state. Gao et al. (2021) used DBNs for the reliability analysis of an USV by mapping Dynamic Fault Trees into DBNs to account for the system's logical structure, redundant configuration, and dynamic behaviour. Guo et al. (2022) proposed an integrated model that uses DBNs and XGBoost for evaluating the operational reliability of complex systems. Han et al. (2024) a DBN model was developed to evaluate the availability of machinery systems in both conventional ships and Maritime Autonomous Surface Ships (MASS).

One of the main challenges in using BNs lies in constructing the network, particularly in defining states for each node and constructing Conditional Probability Tables (CPTs) (Johansen and Utne, 2022). The computational complexity increases with the size of the network and the number of parent nodes, leading to NP-hardness in large Bayesian networks (Neapolitan, 2003). This complexity might limit the practicality of BNs in certain applications, requiring increased computational resources.

2.9. Health-aware Control

From the preceding discussion and while considering the specified requirements, it is crucial to combine monitoring methods and energy management strategies to ensure the reliable operation of autonomous ship power plants while being aware of the health state. This integration gives rise to a novel concept known as health-aware control, also referred in literature to as fault-tolerant control or prognostics decision-making (Escobet et al., 2012), (Brown and Vachtsevanos, 2014), (Balaban et al., 2019).

The underlying principles of health-aware control involve the integration of system health monitoring with control processes. By incorporating information from the monitoring module regarding the system's health, the control system can make informed decisions in selecting subsequent actions for the system (Escobet et al., 2012). This approach not only considers performance optimisation but also takes into account the health status of system components, thus prolonging their lifespan (Yue et al., 2019). Moreover, this integrated architecture enhances safety and reliability by detecting and accommodating impending failures, minimising the occurrence of unexpected and costly mission failures (Brown and Vachtsevanos, 2014). In cases of faults or failures within the machinery system, the health-aware control system enables emergency actions to be taken without relying on the failed component (Johansen and Utne, 2022). This approach ensures the continued operation and performance of the system while effectively handling failures.

Applications of health-aware control can be found in several industrial sectors. Salazar et al. (2017) applied the concept of health-aware control to a drinking water network considering the trade-off between control performance and system reliability. Pour et al. (2019) included the health-aware aspect of the control of water networks using system reliability in the objective function. Verheyleweghen et al. (2018) proposed a hierarchical health-aware control approach for operating a compressor subject to degradation, with the goal of maximising gas throughput while ensuring continuous operation until a planned maintenance stop. Sanchez et al. (2018) explored the use of health-aware MPC and fatigue prognosis to minimise fatigue load and degradation of wind turbine components. Langeron et al. (2017) modelled the deterioration of control systems focusing on the actuator, which allowed the health assessment of the actuator to prolong its residual use. Yue et al. (2019) proposed a novel strategy based on prognostics-enable decision-making to mitigate power source degradation and save economic costs in fuel cell HEVs. Skima et al. (2019) introduced a strategy for post-prognostics decision-making in distributed MEMS-based systems, with the goal of maintaining the performance of a conveying surface designed for fragile micro-objects. Balaban et al. (2019) proposed an approach to unify prognostics and health management with automated decision-making for complex systems in the presence of uncertainties.

Regarding the maritime industry, Tang et al. (2020) used a static optimisation method for the energy management of a hybrid ship power plant employing models to predict the battery RUL, aiming to minimise emissions and fuel consumption whilst extending the battery's lifetime. Hein et al. (2020b) applied a multi-objective optimisation method for the energy management of a hybrid ferry considering battery degradation. Chen et al. (2022) presented a fault-tolerant control method based on the sliding mode technique that can stabilise a USV in the presence of partial actuator degradation and wave-induced disturbance. Mitropoulou et al. (2020) proposed an energy management strategy for a hybrid navy vessel considering multiple objectives including fuel consumption, lifecycle costs, noise, and infrared signature.

A similar concept closely related to health-aware control is the integration of risk models into control systems. The incorporation of online risk control functionality is crucial for ensuring the safe and efficient operation of autonomous systems (Utne et al., 2017). Effective risk models should be able to assess risk scenarios proactively and reactively, considering environmental conditions, operational limitations, and potential hazards (Parhizkar, 2022). Supervisory risk control, as a dynamic functionality, should be integrated into the control system of autonomous systems to enable continuous assessment and control of risks during operation. There is a growing demand for online risk assessment tools that can offer decision support by providing risk-related information for autonomous systems (Parhizkar, 2022).

Fan et al. (2021) presented a four-step framework for assessing the operational risks associated with autonomous ships with varying degrees of autonomy. Yang and Utne (2022) examined how various risk methods can be used to develop an online risk model for autonomous ships. Lee et al. (2023) used FTA as a risk tool to support risk-informed decision-making for an autonomous collision avoidance system. Johansen and Utne (2022) integrated STPA and Bayesian networks to enable supervisory risk control for autonomous ships.

2.10. Key Findings and Research Gaps

The expected outcome of the literature review is the identification of the key findings and research gaps related to the operation of autonomous ship power plants. Thereafter, this will lead to the appropriate research and development direction that should be adopted to cover this study's aim and objectives.

The following key findings were identified from the preceding literature review:

(1) Autonomous ships have not yet been widely commercialised as a result new hazards, safety-related issues, and risk control options that arise from their operation have not been yet explored. This highlights the need for further research into emerging technologies to address these uncertainties (known or unknown) to facilitate the adoption of autonomous ships in commercial applications.

(2) There is a lack of comprehensive design methodologies for autonomous ships. While there have been advancements in autonomous ship technology, the development of systematic and standardised design approaches that include the requirements and challenges of autonomous vessels is still limited. Only frameworks are proposed like AURA and SEATONOMY that can be used in the preliminary stages to facilitate the design process (AUTOSHIP, 2020), (Grotli et al., 2016).

(3) As pointed out in Section 2.3, there is a lack of clear and standardised guidelines regarding the requirements that should be considered during the design and operation phases. The absence of well-defined requirements makes it challenging to assess compliance with regulatory standards and industry best practices.

(4) Current studies in the field of power plant energy management primarily focus on optimising performance metrics such as fuel consumption and emissions reduction with the assumption that the system will remain intact throughout its lifetime operation.

(5) Although there are several techniques that can model component degradation there are limited energy management studies that consider system degradation and component failures in the control process.

(6) In the field of PHM, there are several existing challenges including uncertainties in both epistemic and aleatory sources in the prediction of RUL, limited availability of empirical data, and the need for a systematic approach to verify and validate degradation models. This lack of robust methodologies hinders the accurate assessment of the system's health state.

(7) The behaviour of the system is influenced by the system configuration and the interactions among its constituent components. While there are several well-developed methods that focus on individual component degradation, there is a lack of attention given to the holistic evaluation of the system's health state.

(8) A significant challenge exists in the integration of health metrics, such as reliability and risk, into energy management strategies for autonomous systems. Although there are several risk models and reliability methods, there are few studies that have integrated them into control systems.

(9) Finally, there is a lack of comprehensive approaches that address multi-criteria objectives for optimal control. Existing literature predominantly focuses on single optimisation criteria, overlooking the complex trade-offs and interdependencies among multiple contradictory objectives. To tackle this gap, there is a need to explore and develop multi-objective optimisation and decision-making processes that can effectively balance various criteria, such as reliability, fuel consumption, and emissions, in power plant energy management.

Considering the aforementioned discussion, this thesis aims to address the following research gaps:

Gap 1: A significant research gap in the field of energy management strategies for power plants is the limited consideration of component and system health. To address this gap, there is a need for enhanced energy management strategies that explicitly incorporate health metrics.

Gap 2: A research gap in the field of decision-making approaches for power plant operation is the limited exploration of trade-offs between fuel consumption and system health consideration. Existing studies often focus on optimising a single objective, such as fuel consumption, without adequately addressing the trade-offs between conflicting objectives.

Gap 3: An important research gap in the field of system health assessment is the limited development of monitoring approaches that dynamically assess the health of complex systems, considering the interactions between components. Current monitoring techniques often focus on individual component health without fully considering the interactions between the components that influence system behaviour.

2.11. Chapter Summary

The research background through an extensive literature review was presented in this chapter. The thematic areas investigated concern (a) research and industrial projects, (b) autonomous ship power plant requirements, (c) hybrid power plant solutions, (d) energy management strategies, (e) prognostics and health management, (f) system-level dependability analysis and (g) health-aware control.

From the requirements discussion it was inferred that for the successful implementation of autonomous ships, the key enabling technology lies in the concept of an autonomic power plant. In the context of energy management strategies, it was observed that the majority of studies primarily focus on optimising performance metrics such as energy efficiency and emissions. Moreover, there is a noticeable gap in research where limited focus is given to the assessment of system health, considering the complex interactions among the considered components. Finally, the concept of health-aware control was investigated, highlighting its potential application in the health-aware energy management of power plants. The research methodology adopted in this thesis to cover the identified gaps is presented in the following chapter.

3. Research Methodology

3.1. Chapter Outline

In this chapter, a comprehensive outline of the proposed research methodology is presented to address the identified gaps and achieve the objectives defined earlier. The selection of methods and tools are justified by explaining the rationale behind their choice and their specific sequence, to ensure their relevance and effectiveness in solving the identified problem.

3.2. Overview

To effectively address the aim of this research, a comprehensive research methodology is employed. Based on the requirements of autonomous ship power plants, concerning increased situational awareness, increased reliability and availability, system health monitoring and intelligent decision-making, this methodology includes the formulation of an energy management problem that aims to optimise energy efficiency and prolong the health condition of hybrid power plants. This methodology can be an initial step towards the operation of autonomous ship power plants, emphasising on hybrid architectures, which can be suitable candidates according to discussion in Section 2.4.

To systematically tackle this problem, a framework is developed by integrating multiple methods and tools.

The framework presented in Figure 3.1 serves as a visual representation of the combined methods used in this research. The following key components are incorporated:

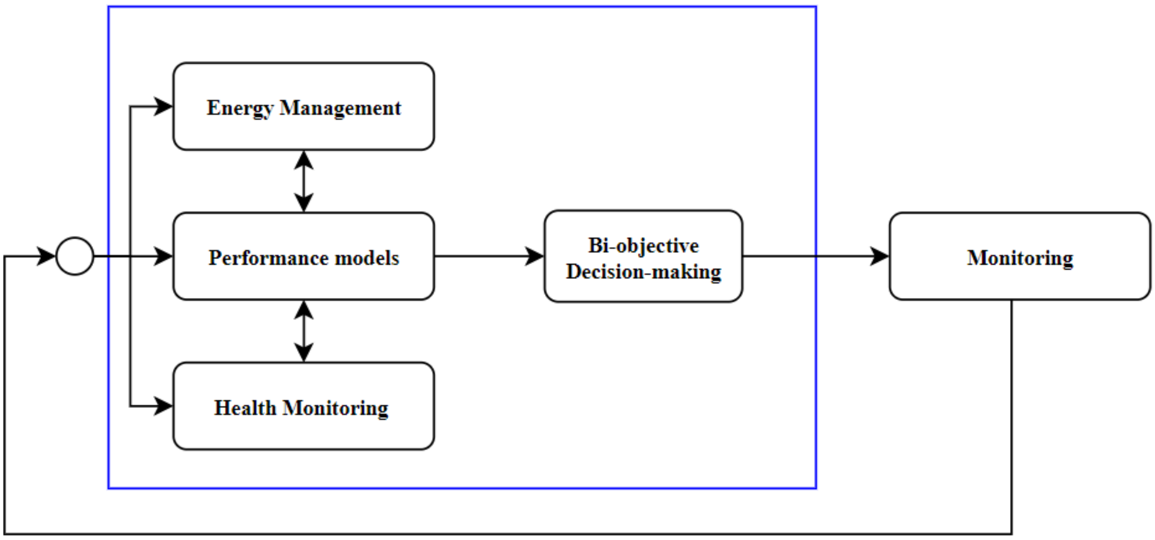

Figure 3.1: Proposed high-level control process framework.

(1) Performance Models: Performance models are utilised to simulate the behaviour and performance of components inside hybrid power plants.

(2) Energy Management Strategy: An energy management strategy is used to optimise the energy efficiency of the investigated hybrid power plants.

(3) Health Monitoring using Reliability: Reliability-based health monitoring techniques are employed to assess the health state of the power plants.

(4) Bi-objective decision-making: A decision-making method is employed that considers two conflicting objectives to find a balance between energy efficiency and system health.

(5) Monitoring: All the necessary outputs from the power plants' operation are recorded and kept monitored and fed into the power plant model to update the state of the included components.

3.3. Methodological Steps

3.3.1. Performance Models

To effectively develop and test energy management strategies for hybrid power plants, the integration of a reliable simulation model is important. The power plant model plays a crucial role in optimising the overall fuel consumption, as a result, the considered models must accurately capture the intricate physics to represent the actual system behaviour.

A key consideration during the development of the simulation model is its computational efficiency. To facilitate fast simulations during the control scheme's development and testing, the model should be non-computationally intensive, ensuring rapid evaluation of various operating points at each time step. To strike a balance between accuracy and efficiency, different modelling approaches have been proposed. While high-fidelity models offer detailed insights into the power plant's behaviour, they often come with increased complexity and computational costs (Bohme and Frank, 2017). On the other hand, quasi-static modelling approaches have demonstrated sufficient capability in calculating fuel consumption and evaluating the performance parameters of power plant components (Guzzella and Sciarretta, 2013).

The components of the investigated power plants include electric machines, ICEs and batteries which are modelled using efficiency maps, fuel consumption maps, and first principles models. This approach enables sufficient representation of energy flows within the power plant, leading to precise estimations of fuel consumption and battery SOC, considering various control inputs.

3.3.2. Energy Management Strategy

The selection of an appropriate energy management strategy that can be for controlling hybrid power plants is crucial. As highlighted in the literature review, various strategies have been proposed for hybrid power plants.

For the proposed methodology, the energy management strategy must satisfy specific criteria. It should be adaptable to real-world scenarios where the operating profile is not always known in advance, while it can exhibit high variability due to operating in unknown environmental and operational conditions. Moreover, it should be able to be easily integrated with other methods which prioritise criteria such as system degradation, while being able to achieve results close to optimality. Lastly, the computational cost must remain reasonably low to facilitate real-time execution in the overall control process.

Regarding these considerations, the ECMS emerges as a suitable strategy for the proposed methodology. ECMS aims to transform the global optimisation problem of minimising fuel consumption over the operating profile into an instantaneous optimisation of equivalent fuel consumption. This is achieved by assigning a cost to the use of the battery in discharge mode, representing the expected amount of fuel consumption required to recharge the battery, while simultaneously assigning a negative cost to charging the battery, equivalent to the expected fuel savings when the battery provides power.

ECMS can be seen as an implementation of the optimal solution, achieving results that are close to the global optimal solution. Furthermore, ECMS requires less computational effort compared to other OB-EMS, especially when being compared with MPC which is computationally heavy. Furthermore, ECMS does not explicitly rely on detailed information about future operating conditions, reducing its dependency on predicting future power demand. This characteristic renders ECMS particularly advantageous for handling unknown operating profiles. Finally, when compared to various energy management strategies, ECMS consistently demonstrates near-optimal results in terms of fuel consumption.

3.3.3. Health Monitoring using Reliability

To incorporate the health condition of the power plant into the control process, the development of system health monitoring tools becomes crucial. Since power plants consist of multiple components, it is vital to create tools that can effectively capture the health of individual components while considering their interactions to provide a comprehensive estimation of the system's health state.

Various factors can influence component degradation and, consequently, impact the overall system health performance. However, the proposed health monitoring approach takes a more generalised perspective, focusing on monitoring the system's health through component interactions, where individual component degradation does not deteriorate the overall system performance. In this respect, reliability is used which is defined as the probability of an item functioning without reaching a failure threshold within a specified time frame (Zagorowska et al., 2020). By using reliability as a key metric, it provides an alternative way by considering both individual component health and the impact of their interactions on the system.

An approach is needed to model the interactions among the components' health and their influence on the overall system. To achieve this, dynamic Bayesian networks (DBN) prove to be a valuable choice, offering several benefits for this purpose.

One of the significant advantages of Bayesian networks (BN) lies in their ability to capture the intricate dependencies between components within a network, making them suitable for analysing complex systems like power plants (Jiang et al., 2019). By arranging the network appropriately, it becomes possible to explore and evaluate the functional interdependencies among different systems, subsystems, and components.

Moreover, extending BNs to be dynamic, enables the updating of estimates over time with the available monitoring data (Prakash and Kaushik, 2020). This dynamic feature provides valuable insights into the time variations of system health, making it a powerful tool for online health assessment. The continuous updates from the monitoring data can serve as valuable inputs for later decision-making processes, further enhancing the overall effectiveness of the health-aware control strategy.

By using DBNs, system reliability is estimated by leveraging the information from individual component reliability. However, to update calculations of component reliability to consider the effect of the operating profile, it is essential to take into account the operating time and the specific operating point or load for every component. In this way, dynamic updates of component reliability can be achieved by incorporating the information inside the DBN, which, in turn, contributes to the online estimation of the overall system reliability.

In this study, two distinct methods are investigated to update component reliability. The first method involves the utilisation of a Weibull proportional hazard model (WPHM), which enables the continuous updating of the failure rate for each component or system (Jardine et al., 1989). By considering observed operating time and relevant covariate information, such as load variation specific to each component, the WPHM provides a dynamic estimation of the failure rate.

The second method involves the application of a Wiener process model, to consider the influence of random effects in reliability. Additionally, this model takes into the influence of transitions in operating point by exploiting sensor measurements. The component failure rate gets updated based on the health index associated with the estimation from Wiener process model (WPM).

Both methods aim to update the failure rate in order to calculate component reliability. The reliability information is then fed into the DBN, where it is used to estimate the reliability of subsystems and the entire system. This process undergoes continuous updates at every time step during the execution of the control process, ensuring that the estimations of reliability are kept up-to-date based on real-time operating and monitoring data.

3.3.4. Bi-objective Decision-making

To achieve energy management of the power plant, considering both system health and optimal fuel consumption in the control process, a combination of the methods presented in the previous sections is necessary. Specifically, the ECMS calculates the instantaneous equivalent fuel flow mass rate, while the DBN estimates system reliability based on the actual operating conditions up to the following time step, considering various operating points.

However, it is important to note that the optimal fuel consumption and optimal system reliability may not always align at the same operating point. Thus, a trade-off strategy becomes essential to determine the operating point that finds a balance between these two conflicting objectives.

In this study, the reference or utopia point method is used (Gambier, 2022), (Peitz and Dellnitz, 2018). The Pareto front, representing all feasible operating points satisfying the specified constraints, is plotted for the two selected objectives. The final operating point is then selected based on its proximity to an infeasible target or utopia point. This utopia point represents an ideal state with the minimum fuel consumption and maximum system reliability, serving as a reference for making the final decision.

By using the utopia point method, the proposed methodology aims to find an optimal operating point that optimises both fuel consumption and system reliability, to enable reliable energy management of the power plant while considering its health conditions.

3.3.5. Definition of Reference Systems

In Chapter 2, the comprehensive review of the literature and the identification of research gaps provided valuable insights for this research study. To address the identified gaps and contribute to the existing knowledge, it is crucial to establish reference power plants that can serve as a basis for the proposed methodology.

As discussed in Section 2.4, hybrid power plants present several advantages, including improved redundancy, enhanced maintainability, reduced environmental impact, and increased energy efficiency. Additionally, it is essential to select an appropriate ship type. According to the discussion in Section 2.4.1, short-sea shipping vessels are regarded as suitable candidates due to their alignment with stability and non-hazardous cargo requirements, simplified operational frameworks, reliable communication infrastructure, and favourable cost considerations. Hence, they are well-suited for the early adoption of autonomous ships.

In this study, two reference power plants have been chosen to represent different scenarios. The first is a hybrid power plant installed in a pilot boat, where the focus lies on implementing the proposed health-aware energy management strategy. This strategy emphasises a decision-making method which works as a trade-off between minimising fuel consumption and prolonging the system's lifetime expectancy. On the other hand, the second reference power plant represents a hybrid power plant installed in a short-sea shipping cargo vessel. In this case, the emphasis is placed on developing a health monitoring tool that decomposes the power plant into various components and subsystems which enables a detailed examination of components interaction. This tool can serve as a decision support tool that can inform ship operators about the criticality of components and subsystem health condition.

The technical specifications of the investigated power plants are provided in Chapter 5, along with the decomposition of the power plants into their respective components and subsystems to understand their interconnections. Furthermore, real ship performance data have been collected to represent the actual operating profiles of these reference power plants.

3.3.6. Verification via Case Studies

To validate the effectiveness of the proposed methodology, the reference hybrid power plants presented earlier were used as case studies. The verification of the proposed methodology using case studies serves several purposes. Firstly, it allows to thoroughly test the proposed methodology under operating profiles from real ship applications, ensuring that it performs as intended. Additionally, case studies help to identify any potential limitations or challenges that may arise when applying the methodology using tools in practical scenarios. By uncovering these limitations, valuable insights are gained to improve the methodology for future applications.

As mentioned earlier, two different methods were utilised to update the failure rate, with each method applied to a different power plant. In the case of the pilot boat, the WPHM was employed, which involved decomposing the power plant into subsystems. Through this approach, the health-aware energy management strategy was thoroughly tested and evaluated. On the other hand, for the short-sea shipping cargo vessel, the subsystems were further decomposed into components, and the WPM was used to update the failure rate. In this way, real-world applications can be resembled where operating data from on-board sensors can be used to monitor the health state of individual components.

Nevertheless, the health-aware energy management strategy was not applied in the case of the short-sea shipping cargo vessel. The focus of this case study remained on assessing the health of subsystems based on the components' health condition. This allowed to gain comprehensive insights into the system's health condition and understand how the components' operating conditions impact the overall subsystem health.

3.4. Control Process Framework

The schematic representation of the control process framework for the health-aware energy management of hybrid power plants, based on the proposed methodology outlined in the preceding sections, is presented in Figure 3.2. This comprehensive plan incorporates all the essential methods and tools, along with their interactions which will be described extensively in the next sections.

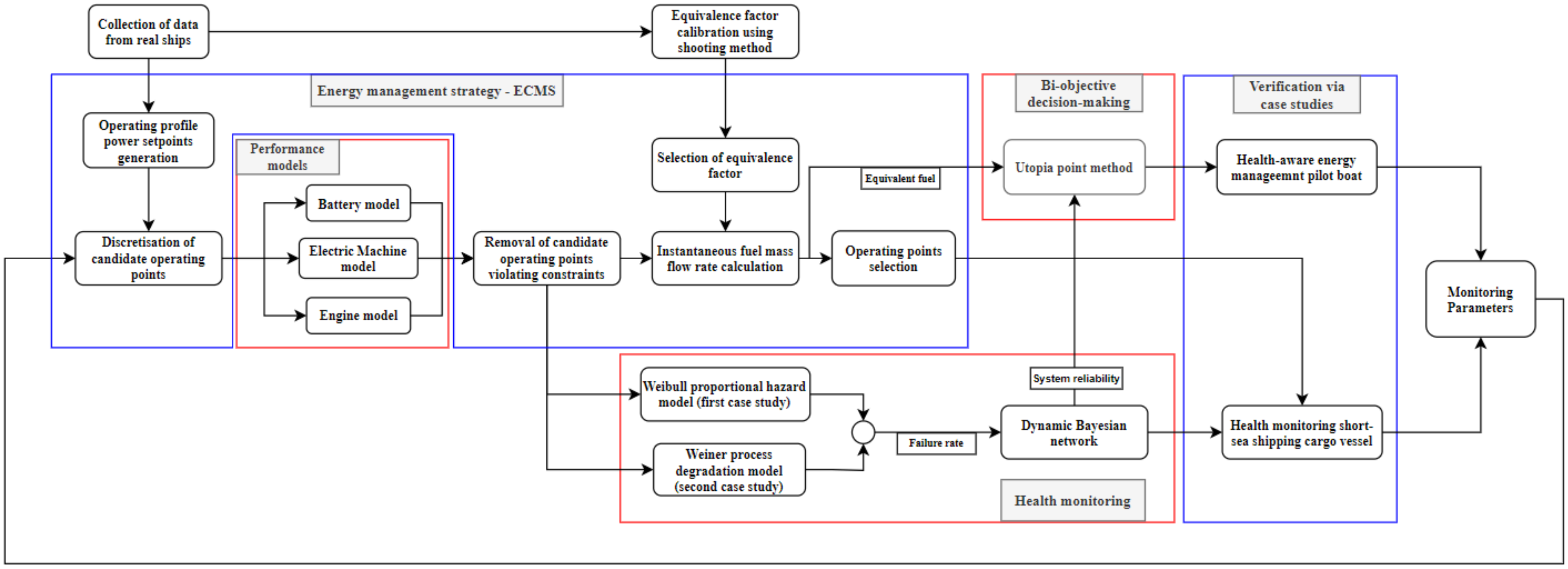

Figure 3.2: Control process framework for the health-aware energy management of hybrid power plants.

3.5. Chapter Summary

This chapter outlined the proposed methodology and provided justifications for the methods and tools employed. The methodology was designed to incorporate various techniques, enabling the energy management of hybrid power plants integrating system health in the control process. For energy management, the ECMS was selected, allowing the calculation of instantaneous equivalent fuel flow mass rate. To include the health aspect in the control process, component reliability was calculated, and a DBN is used to estimate subsystem and system reliability. Moreover, a decision-making method is employed to find a trade-off between optimal fuel consumption and system reliability. The subsequent chapters will present a detailed explanation of the presented methods and demonstrate the application of the proposed methodology to build tools in specific case studies.

4. Methods & Tools Description

4.1. Chapter Outline

In this chapter, the methods and tools that are used in the proposed methodology are presented. More specifically, the performance models used in the power plant are described. In addition, two energy management strategies are presented along with the approach of health monitoring using reliability. Finally, a bi-objective decision-making method is presented to find a balance between two conflicting objectives.

4.2. Performance Models

To develop an energy management strategy for the hybrid power plants in the considered case studies, it is crucial to employ appropriate models that accurately represent the behaviour of the components involved. In this study, the power plants consist of ICEs, electric machines, and batteries, which are modelled by different modelling approaches.

When selecting these models, computational efficiency is crucial. The models should be capable of finding a balance between accuracy and computational cost. By utilising quasi-static models, such as interpolation functions for lookup tables and first principles models with simplified calculations, rapid evaluation of various operating points can be achieved while still simulating the power plant's performance with sufficient accuracy.

For the ICEs, fuel consumption maps are used from data derived from engine manufacturers. These maps provide valuable insights into the engine's fuel efficiency at different operating points, helping to estimate the fuel mass flow rate based on the engine speed and torque. This allows for the evaluation of different operating points with the goal of minimising fuel consumption.

In the case of electric machines, efficiency maps are used to characterise the motor's behaviour at various operating points. These maps are able to capture the motor's efficiency in both motoring and generating modes, to determine the optimal power distribution between the motor and engine. By incorporating motor efficiency models, the power flow within the hybrid system can be optimised to achieve higher overall energy efficiency.

Batteries are another critical component in the hybrid power plants, contributing to energy storage and power delivery. To model battery behaviour accurately, first principles models are used, which consider battery capacity and charge/discharge limits. These models enable to control the battery's charging and discharging processes effectively, ensuring optimal energy utilisation.

4.2.1. Internal Combustion Engine model

In this study, the internal combustion engine model used is based on the brake-specific fuel consumption (BSFC) map, which is used to estimate the engine's fuel mass flow rate at various operating points. The BSFC map is derived from engine manufacturer data and serves as a valuable tool in understanding the engine's fuel efficiency characteristics.

The BSFC map is represented as a two-dimensional table, where one axis represents the engine rotational speed, and the other axis represents the engine torque. Each cell of the table contains a value corresponding to the fuel mass flow rate at a specific combination of engine speed and torque. As a result, the engine fuel mass flow rate as a function of engine speed and torque is given by (Guzzella and Sciarretta, 2013):

$$\dot{m}_f = f_{eng}\left(Q_{eng}, N_{eng}\right) \tag{1}$$

where $\dot{m}_f$ is fuel flow mass rate, Q_{eng} is the engine torque and N_{eng} is the engine rotational speed.

By using this map model, the amount of fuel required can be determined by the engine to produce a certain power output at a given speed and torque. Additionally, this map-based model enables the calculation of the engine's fuel consumption in real-time during the control process, allowing for dynamic optimisation of the power plant by identifying the operating points where the engine operates at its highest efficiency. While the power demand changes, the engine can be operated at different points on the BSFC map to achieve the desired power output while minimising fuel consumption.

4.2.2. Electric Machine Model

The electric machines in a hybrid power plant can be effectively modelled using a similar approach to the engine model, by using efficiency maps. In this modelling approach, the map provides the efficiency of the electric machine as a function of speed and torque or speed and electrical power, depending on the specific implementation (Ehsani et al., 2017). The efficiency map model allows for the estimation of the performance behaviour of the electric machine at different operating points understanding the machine's response to various control inputs.

During operation, when a positive value of mechanical power is applied to the electric machine, it functions as a motor in power take in (PTI) mode, converting electrical power to mechanical power to drive various loads. Conversely, when a negative value of mechanical power is applied, the machine operates as a generator in power take out (PTO) mode, converting mechanical power into electrical power that can be delivered to the power grid. The provided mechanical power P_{em} is then expressed as (Onori et al., 2016):

$$P_{em} = \eta_{em}(N_{em}, P_{elec}) N_{em} Q_{em}, \quad P_{elec} \geq 0 \ (Motoring\ Mode) \tag{2}$$

$$P_{em} = \frac{1}{\eta_{em}(N_{em}, P_{elec})} N_{em} Q_{em}, \quad P_{elec} < 0 \ (Generating\ Mode) \tag{3}$$

where η_{em} denotes the electric machine efficiency, Q_{em} denotes the electric machine torque, P_{elec} denotes the machine's electrical power, and N_{em} denotes the electric machine rotational speed.

4.2.3. Battery Model

The battery model used in this study employs a quasi-static approach based on the first-order equivalent circuit. In this circuit, the battery is represented by an ideal open-circuit voltage source connected in series with an internal resistance as presented in Figure 4.1. The battery power is thus calculated as:

$$P_{bat} = V_L I = V_{oc} I - R_0 I^2 \tag{4}$$

where P_{bat} is the battery power, V_{oc} is the open circuit voltage, R_0 is the series resistance.

The current I is then calculated as a function of power using the following formula:

$$I = \frac{V_{oc}}{2R_0} - \sqrt{\left(\frac{V_{oc}}{2R_0}\right)^2 - \frac{P_{bat}}{R_0}} \tag{5}$$

where P_{bat} is the battery power, V_{oc} is the open circuit voltage, R_0 is the series resistance.

This simplified model neglects voltage dynamic which allows to capture the essential characteristics of the battery's performance without the need for complex and computationally intensive simulations. This quasi-static approach is particularly useful for energy management strategies, as it enables fast and reliable calculations of the battery's SOC and power limits to integrate it with other performance models of the power plant.

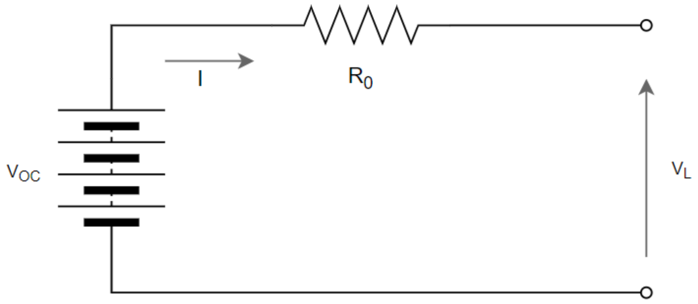

Figure 4.1: First-order equivalent circuit battery model.

The SOC represents the remaining energy storage capacity of the battery and is essential for determining the battery's performance and range. By using this battery model, the SOC based on the electrical load and operating conditions can be estimated. The calculation of the SOC's time variation in the next time step using the battery model is given by:

$$SOC_{k+1} = SOC_k - \frac{V_{oc} - \sqrt{{V_{oc}}^2 - 4P_{bat}R_0}}{2Q_{max}R_0} \tag{6}$$

where k denotes the current time step, $k+1$ is the following time step, and Q_{max} is the battery capacity.

However, it is important to acknowledge some limitations associated with this model, particularly concerning battery aging and temperature effects. Battery aging is a significant concern in operation, primarily due to the aggressive loading cycles they undergo during operation. These cycles, including frequent charge and discharge events, can lead to the degradation of the battery over time. The aging process results in a reduction of the battery's capacity and an increase in internal resistance, ultimately affecting the overall performance and range (Onori et al., 2016).

Furthermore, the model assumes that the battery temperature has a negligible influence on its performance. Temperature variations can significantly affect battery behaviour, influencing its efficiency, capacity, and rate of aging (Serrao et al., 2013). The lack of temperature consideration in the model may limit its accuracy in predicting battery performance under diverse operating conditions and environments.

4.2.4. Propeller Load Model

The propeller load model used in this study uses the propeller law to estimate the demanded power by the propeller. The propeller law describes the relationship between the propeller torque and the propeller rotational speed at different operating points according to this formula:

$$Q_{prop} = k_p N_{prop}^2 \tag{7}$$

where Q_{prop} is the propeller torque, N_{prop} is the propeller rotational speed, k_p is the propeller coefficient.

To calculate the propeller torque at a given operating point, the model is calibrated using the MCR point of the engine considering that the propeller can be directly coupled to the engine (Theotokatos, 2010). From the MCR point, the propeller coefficient is derived using the above formula:

$$k_p = \frac{Q_{MCR}}{N_{MCR}^2} \tag{8}$$

where Q_{MCR} is the engine torque at MCR point, N_{MCR} is the engine rotational speed at MCR point.

4.3. Energy management strategies

In this study, two energy management strategies are used, each serving a different purpose. The ECMS is selected as the primary energy management strategy to be incorporated into the proposed methodology for health-aware control. However, ECMS needs to be verified against another strategy capable of offering global optimal solutions. Therefore, DP is chosen as a verification method, as it offers the ability to find global optimal solutions in optimal control problems.

4.3.1. Equivalent Consumption Minimisation Strategy (ECMS)

The Equivalent Consumption Minimization Strategy (ECMS) was first introduced by Paganelli in 1999 as a method to tackle the energy management problem in HEVs (Onori et al., 2016). The primary objective of ECMS is to convert the global optimisation problem of minimising fuel consumption over the entire operating profile into an instantaneous optimisation problem of equivalent fuel consumption at each moment.

ECMS achieves this transformation by considering the battery as an energy buffer stored in a virtual reversible fuel tank so that all the energy ultimately comes from fuel. It is assumed that the difference between the initial and final SOC of the battery is relatively small and negligible compared to the total energy used. The instantaneous equivalent fuel mass flow rate $\dot{m}_{f,eqv}$ is the sum of the engine fuel mass flow rate and the equivalent or virtual fuel mass flow rate corresponding to the rechargeable energy storage system (battery) $\dot{m}_{ress}$:

$$\dot{m}_{f,eqv} = \dot{m}_f + \dot{m}_{ress} \tag{9}$$

During a battery discharge phase, when the battery power is positive, the energy stored in the battery will need to be replenished in the future, resulting in additional fuel consumption. The amount of fuel required for replenishment depends on the operating conditions of the engine at the time of battery recharge which is dictated by the operating profile.

On the other hand, when the battery power is negative, indicating a charging phase, the stored electrical energy is used to reduce the engine load required to meet the power demand, leading to instantaneous fuel savings. Again, the use of electrical energy as a substitute for fuel energy is dependent on the operating profile.

To convert the global optimisation problem to the instantaneous optimisation problem, ECMS uses an equivalence factor tuned for a typical operating profile. This involves assigning a cost to the use of the battery in discharge mode, representing the expected amount of fuel consumption required for battery recharge. Simultaneously, a negative cost is assigned to charging the battery, which is equivalent to the expected fuel savings when the battery provides power. Usually, the equivalence factor varies for the charging and discharging phases respectively (Onori et al., 2016). Nevertheless, a single value suffices to capture the efficiency in the electrical path (Kalikatzarakis et al., 2018). Consequently, the equivalent or virtual fuel flow mass rate is calculated by:

$$\dot{m}_{ress} = s\frac{P_{bat}}{Q_{LHV}} \tag{10}$$

where s is the equivalence factor and Q_{LHV} is the fuel's lower heating value at ISO conditions.

To ensure that the battery's SOC remains within the admissible limits during the control process a penalty function is integrated with ECMS as described in (Onori et al., 2016). The penalty function is designed to penalise deviations of SOC from a target value SOC_t.

When the actual SOC is higher than the target SOC (SOC > SOCt), the penalty function takes a value less than 1. In this case, the penalty function reduces the cost attributed to battery energy, which promotes an increased likelihood of discharging the battery. On the other hand, when the actual SOC is lower than the target SOC ($SOC < SOC_t$), the penalty function takes a value greater than 1. In this scenario, the penalty function increases the cost of battery energy, making discharging less likely.

$$p(SOC) = 1 - \left(\frac{SOC - SOC_t}{(SOC_{max} - SOC_{min})/2}\right)^3 \tag{11}$$

where SOC_{max} *and* SOC_{min} are the maximum and minimum admissible limits of the battery SOC.

Based on the penalty function, the instantaneous equivalent fuel mass flow rate takes the following final form:

$$\dot{m}_{f,eqv} = \dot{m}_f + s\frac{P_{bat}}{Q_{LHV}}p(SOC) \tag{12}$$

Based on this discussion, the procedure to determine the setpoints for the power plant components follows these steps:

1) Control points discretisation: The system's state as well the requested power P_{req} and current battery SOC is considered to discretise the operating points into a range of candidate control points. The control points are bounded in the respected domains so that $u \in U_k$

2) Control points removal: The performance models, including engine and motor maps, are utilised to calculate the outputs for each candidate control point. The control points that violate instantaneous constraints, such as power, torque, or battery limits, are removed from consideration.

3) Equivalent fuel consumption calculation: For the remaining valid control points, the equivalent fuel consumption $\dot{m}_{f,eqv}$ is calculated. This involves considering the fuel consumption of the engine and the virtual fuel energy of the battery as well as the penalty applied based on the battery SOC deviation from its target value.

4) Control point selection: The control point that minimises the equivalent fuel consumption is selected according to this equation:

$$u^* = \underset{u \in U_k}{\operatorname{argmin}} \, \dot{m}_{f,eqv}(u, SOC, P_{req}) \tag{13}$$

In this study the MATLAB environment is used to deploy the proposed methodology. The described ECMS algorithm is implemented via a MATLAB function which integrates the performance models described earlier.

Equivalence factor estimation

The performance of ECMS relies on the value of the equivalence factor. In this study, the equivalence factor is considered constant and is tuned based on the employed operating profile. The selection of the equivalence is based on the shooting method as described in (Onori et al., 2016).

The method starts with an initial guess of the equivalence factor given a known operating profile. The ECMS is then deployed to solve the control problem throughout the duration of the specified operating profile. At the end of the simulation, the calculated SOC is compared to the desired target final SOC where the goal to terminate the process is to minimise the difference between these two values. Depending on the difference between the calculated SOC and the desirable SOC, the value of the equivalence factor is adjusted for the next iteration. If the difference is still significant, the algorithm continues to iterate, and the process repeats. Once the desired target is achieved (i.e., the difference is close to zero within the tolerance), the algorithm terminates, and the optimal value of the equivalence factor is obtained.

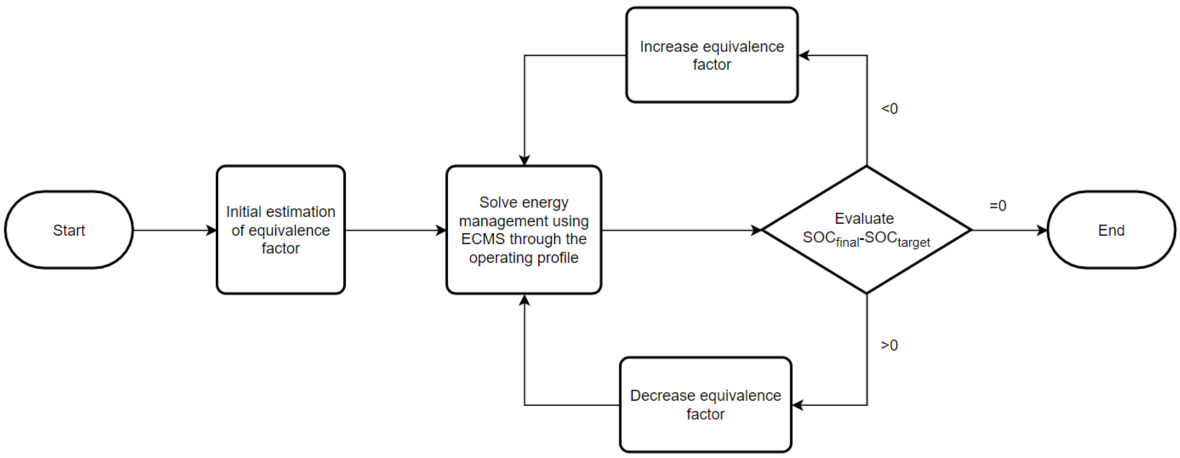

Figure 4.2: Equivalence factor tuning based on shooting method.

4.3.2. Verification using Dynamic Programming (DP)

DP is a powerful numerical method used for solving complex multistage decision-making problems (Onori et al., 2016). Its capability to provide optimal solutions makes it a valuable tool for various applications, including hybrid power plants. However, DP is non-causal, meaning it requires complete knowledge of the entire optimisation horizon beforehand (Kalikatzarakis et al., 2018). As a result, it can be used to verify the results of ECMS assuming that the operating profile is known a priori.

The DP algorithm is based on Bellman's principle of optimality, which states that an optimal policy must result in an optimal trajectory from any given point (Onori et al., 2016). This principle guides the algorithm in a backward way, where it starts from the final time step and recursively computes the optimal cost-to-go from each state to the end of the optimisation horizon. The cost-to-go represents the minimum cost that can be achieved from a specific state by applying the corresponding control action.

To utilise DP in the context of hybrid power plants, the continuous model of the system must be discretised in the following form:

$$x_{k+1} = f_k(x_k, u_k) \tag{14}$$

Both the state x and the control u are bounded and discretized to take values in their respective domains: $u \in U_k$ and $x \in \Omega_k$. In this study the state variable that is discretised is the SOC as the battery state changes through the operation of the power plant.

The instantaneous cost or arc cost function L_k is defined:

$$J(x_0, u) = L_N(x_N) + \sum_{k=1}^{N-1} L_k(x_k, u_k) \tag{15}$$

where the optimal solution is then obtained by finding the optimal policy u*:

$$J^*(x_0) = \min_u J(x_0, u) \tag{16}$$

The objective is to find an optimal control policy that minimises the cost-to-go function Y at each node in the discretised state-time space till the final time step.

$$Y(x_i, i) = L_N(x_N) + \sum_{k=1}^{N-1} L_k(x_k, u_k) \tag{17}$$

Based on the principle of optimality the cost-to-go calculation involves a backward computation. The final cost is calculated first at the final time step, and then following a backwards process, the cost-to-go at each previous time step is determined recursively.

$$u_k = \mu^*(x_\kappa, k) = \underset{u \in U_k}{\operatorname{argmin}}\left(L_k(x_k, u) + Y_{k+1}(f_k(x_k, u_k), u_k)\right) \tag{18}$$

for $k = N-1, N-2, \dots, 1$.

By the previous process the optimal control signal map is obtained, which provides the optimal control action for each discrete point in the state-space grid. This map is then used during a forward simulation of the model to generate the optimal state trajectory from a given initial state (in this case the initial battery SOC). In cases where the actual state does not coincide with the points in the state grid, interpolation methods are employed to obtain the appropriate control point.

In this study the generic DP MATLAB function of Sundström and Guzzella (2009) is used as the tool to solve the DP problem for the reference case studies. This DP function enables the use of the boundary line, which provides more accurate results with fewer function evaluations compared to the original DP algorithm (Sundström and Guzzella, 2009).

4.4. Health Monitoring using Reliability

This section focuses on the development of health monitoring tools utilising reliability as the health indicator. Two distinct methods for estimating component reliability, based on updating the failure rate, are presented. Both methods update the failure rate by considering the operating time and the operating point. Furthermore, the reliability data is integrated into DBNs, allowing for accurate estimation of both subsystem and overall system reliability.

4.4.1. Dynamic Bayesian Network (DBN)

As highlighted earlier there is a research gap in the field of system health monitoring in capturing component interactions to accurately estimate the overall system health. This study addresses this challenge by employing DBNs as a method for system health assessment.

The DBN is an extension of the Bayesian network (BN), specifically designed to capture the temporal behaviour of interconnected variables (Adedipe et al., 2020). A BN is structured as a probabilistic directed acyclic graph (DAG), where nodes represent variables, and edges define the dependencies between these variables, all quantified using conditional probability tables (CPT). This combination of nodes and edges forms the qualitative aspect of the BN, while the conditional probabilities enable quantitative analysis. The joint probability distribution in a Bayesian network is expressed using the following equation (Amin et al., 2018):

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i | Pa(X_i)) \tag{19}$$

where $Pa(X_i)$ represents the parent set of any variable X_i, and $P(X_i|Pa(X_i))$ is the conditional probability distribution function of variable X_i given its parent set.

Unlike traditional BNs, which are static models representing relationships between variables at a specific point in time, DBNs take the analysis a step further. DBNs have the capability to represent multiple time slices, allowing for the examination of temporal dependencies and changes over time (Weber et al., 2006). In DBNs, nodes from different time slices can be connected using directed temporal edges, revealing the evolving patterns and interdependencies across time.

The transition between the previous time slice and the current time slice is expressed using conditional probabilities. These probabilities capture how the system evolves over time, given the current state and the previous state. In this way, the DBN can iteratively update and adjust its beliefs at each time step. The transition between the previous time slice and the current time slice is expressed by the following equation (Amin et al., 2018):

$$P(Z_t | Z_{t-1}) = \prod_{i=1}^{n} P\left(Z_{i,t} \middle| Pa(Z_{i,t})\right) \tag{20}$$

where Z is the family of random variables X_1,X_2, to X_N, $Z_{i,t}$ is the ith node at the time slice t, and $Pa(Z_{i,t})$ is the parent nodes of $Z_{i,t}$ from the same and previous time slices.

The final joint probability distribution for all the time slices takes the following form (Amin et al., 2018):

$$P(Z_{1:N}) = \prod_{t=1}^{N} \prod_{i=1}^{n} P\left(Z_{i,t} \middle| Pa(Z_{i,t})\right) \tag{21}$$

BNs are powerful in elucidating the intricate dependencies between random variables. In contrast to methods like FTA and RBDs which are constrained by Boolean logic rules, BNs exhibit wider flexibility. They are able to consider multiple states, in the form of probability distributions (Jiang et al., 2019). As such, BNs can be regarded as a generalisation of traditional RBDs and FTA, as RBDs and Fault trees can be easily mapped into BNs (Lee and Pan, 2018), (Bobbio et al., 2001). This attribute is particularly advantageous when dealing with complex systems like power plants, which consist of numerous interconnected components.

4.4.2. Reliability Modelling using DBN

In this study, the random variable which is used to characterise the health condition of various components concerns reliability. As a result, reliability is employed herein to represent the system health state, as reliability expresses the probability of a component performing the required function at a specific time period (Rausand et al., 2021), (Zagorowska et al., 2020).

Moreover, establishing a clear understanding of the dependencies among the components within the power plant is essential for accurate system reliability calculations. The power plant as a system undergoes a decomposition into distinct subsystems and individual components. This decomposition is driven by the identification of critical components and their various interconnections. Consequently, a structured network similar to a fault tree is formulated, depicting the relationships between the components within the system.

In this study, the nodes in the BN have two states, represented by 'working' and 'failure'. The approach described by Bobbio et al. (2001) is followed, where fault trees are mapped into BNs. Each component in the power plant is assigned to a root node in the BN, where the prior probability is introduced as an input, representing component reliability. Afterwards, in the case of subsystems and system in the power plant, noisy gates are introduced which are used to specify the interactions between the component and subsystem nodes. Noisy-OR and Noisy-AND gates are equivalent to the logical gates employed in FTs (Cai et al. 2012). They are a type of conditional probability distribution that takes into account the values of the parent nodes by specifying conditional probability tables (CPT) (Bobbio et al., 2001). They lead to a significant reduction in computational costs by linearly reducing the required parameters for the parents' number (Bobbio et al., 2001).

The tool which was used to carry out the quantitative analysis is based on the SMILE library provided by BayesFusion, LLC (BayesFusion, 2021). The SMILE (Structural Modeling, Inference, and Learning Engine) is a software library for performing Bayesian inference, written in C++. Since, the tools that are used in this study are based on MATLAB, a wrapper was used to import SMILE into MATLAB environment. This library supports the use of virtual evidence as input, where the evidence is provided in the form of a probability distribution (GeNIe, 2020). This functionality was used to update the input to component nodes.

According to the preceding discussion, the developed BN has been static in nature. To introduce a dynamic element that accounts for the temporal evolution of reliability, time slices should be considered. In this study two time slices are considered: one for the current time step and another to calculate system reliability at the end of the investigated time step, while considering the operating conditions. This approach enables to generate future predictions considering the operating time at each time step. Throughout the execution of the control process, DBN gets continuously updated while keeping a record to monitor the evolution of reliability. Finally, one important aspect concerns component nodes where their input gets updated by providing component reliability by calculating the updated failure rate. The methods that are used to perform the calculations are outlined in the subsequent sections. Figure 4.3 presents a graph illustrating the update process of the DBN at both the component and subsystem levels using two time slices.

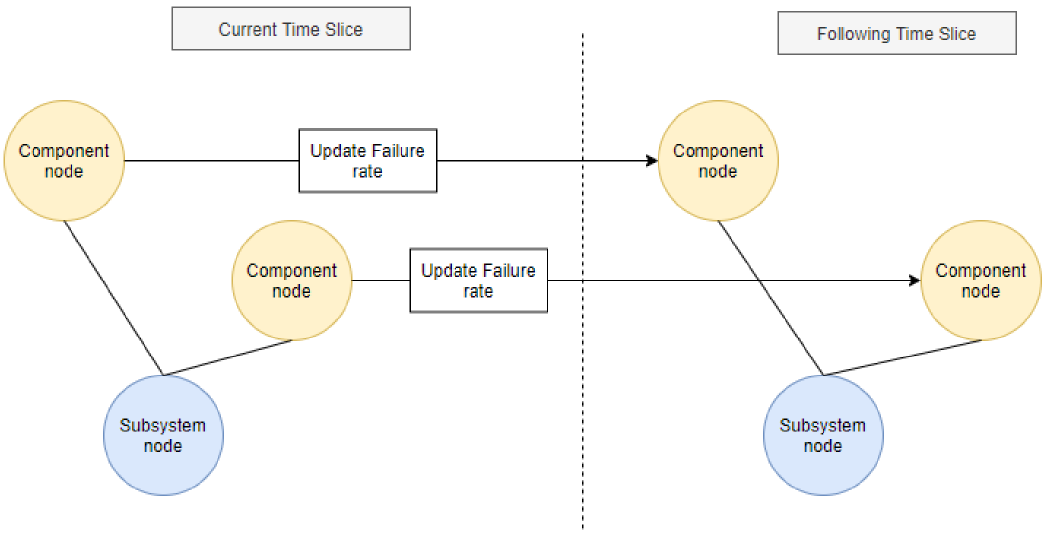

Figure 4.3: DBN structure presenting component and subsystem level.

Criticality Importance Measure

DBNs, apart from system reliability calculations, can be used to calculate importance measures. Importance measures can evaluate components based on the relative importance on the system structure (Kuo, 2012). In this respect it is possible to rank components based on their relative criticality with respect to system failure.

In literature various importance measures have been proposed including Birnbaum, Criticality, and Fussell-Vesely (Rausand et al., 2021). In this study, the criticality importance is used which can provide an indication on how each component's failure affects system reliability. According to Rausand et al. (2021) the criticality importance measure is the probability that component i fails and is critical for system failure at time t, given that the system fails at time t and it calculated as:

$$I^{CR}(i|t) = \frac{I^B(i|t)[1 - p_i(t)]}{1 - h[p(t)]} \qquad (22)$$

where $I^B(i|t)$ is the Birnbaum importance measure, $1 - p_i(t)$ is the probability that component i fails, $1 - h[p(t)]$ is the probability that system fails.

The Birnbaum importance measure is calculated as (Rausand et al., 2021):

$$I^B(i|t) = h[1_i, p(t)] - h[0_i, p(t)] \qquad (23)$$

where $h[1_i, p(t)]$ is the (conditional) probability that the system is functioning when it is known that component *i* is functioning (at time *t*), and $h[0_i, p(t)]$ is the (conditional) probability that the system is functioning when component *i* is in a failed state (at time *t*).

One inherent limitation of the Birnbaum Importance Measure is that it doesn't consider the probability of component failure. As a result, if two components have similar roles in the system, their rankings according to the Birnbaum Importance Measure will be similar, even if their actual probabilities vary significantly (Dutuit and Rauzy, 2015). Criticality importance measure addresses this limitation by multiplying the Birnbaum importance measure with the probability of component's failure to that of the probability of system failure.

4.4.3. Weibull Proportional Hazard Model (WPHM)

The constituent parts of the DBN that get updated at each time step of the control process are the component nodes. As reliability is a function that depends on time, component reliability must be calculated at every time step and update the component nodes of the DBN.

Furthermore, the components inside the power plant operate at different points which influences both their performance and reliability, and consequently the remaining component lifespan (Tang et al., 2020). As a result, it is essential to capture the influence of the operating point on each component reliability, whilst considering the effect of the previous operational history.

To consider the influence of both the operating point variation and operational history, the failure rate is used to calculate reliability. In this respect, a Weibull proportional hazard model (WPHM) is used to update the failure rate. The WPHM is an extension of the classical proportional hazard model introduced by Cox (1972), where the failure rate function follows the Weibull distribution (Jardine et al., 1989). Contrary to exponential approaches where the failure rate is constant, using values of the Weibull distribution shape factor (β) greater than 1, results in increasing the failure rates with time; thus, capturing the components' reliability decrease. According to the WPHM, the failure rate $\lambda(t, l)$ is given by (Gorjian et al., 2009):

$$\lambda(t, l) = \beta {\lambda_0}^{\beta} t^{\beta-1} g(l, \theta) \tag{24}$$

where λ_0 is the baseline failure rate and the function $g(l,\theta)$ is called the covariate function that depends on the covariate l representing the component load and a component parameter θ.

In health-aware control applications, the covariate function can take many forms including exponential, linear and quadratic (Zagorowska et al., 2020), (Salazar et al., 2017). In this study, the linear form is chosen where the values for the failure rates are based on the OREDA database (SINTEF Technology and Society et al., 2015). In particular, the mean and maximum values of the failure rate (λ_{mean} and λ_{max}) are considered, whereas the failure rate is considered a linear function of the load. The component failure rate is thus expressed according to the following equation:

$$\lambda(t,l) = \beta {\lambda_{mean}}^{\beta} t^{\beta-1}\left(1+\left(\left(\frac{\lambda_{max}}{\lambda_{mean}}\right)^{\beta}-1\right)l\right) \tag{25}$$

This model is used for all the components except for the engine, where its failure rate is modelled to depend also on the engine speed. More specifically, regions of the engine operating envelope close to the torque/speed limit as well as low loads are preferred to be avoided, as they can potentially accelerate degradation. Thus, it is assumed that the engine failure rate exhibits its maximum values for loads of 20% (and less) and at the torque limit region. For the other operating regions, the engine failure rate is a linear function of the load. According to the considered WPHM, the engine failure rate is calculated by the following equations:

$$\lambda(t,l) = \beta {\lambda_{max}}^{\beta} t^{\beta-1}, \qquad 0 \le l < 0.2 \tag{26}$$

$$\lambda(t,l) = \beta {\lambda_{mean}}^{\beta} t^{\beta-1}\left(1+\left(\left(\frac{\lambda_{max}}{\lambda_{mean}}\right)^{\beta}-1\right)\frac{l-0.2}{l_{limit}-0.2}\right), 0.2 \le l < 1 \tag{27}$$

where l_{limit} the maximum load at every engine speed at the torque/speed limit curve.

Since the values of the failure rates from the OREDA database are considered constant, a transformation is necessary for their use in the Weibull distribution. The correction procedure as described by William Denson et al. (1990) is followed herein.

The power plant components' failure rates are calculated at every time step using Eqs. (25)–(27). For operational components in the current time step, these failure rates provide information to calculate the conditional probability of the component failing in the next time step. Nonetheless, it is essential to calculate the components' reliability time variation by including the influence of the previous operating points and the past operational time. In this respect, a nonhomogeneous semi-Markov chain is adopted.

In the classical Markov chain, the future states depend only on the present state without considering history (memoryless property) (Chiachío et al., 2020). By extending the Markov chain to a semi-Markov chain, a stochastic process can be modelled where transitions can occur at different times, satisfying the Markov property of each transition (Wang and Miao, 2021). The difference between a homogeneous semi-Markov chain and a nonhomogeneous semi-Markov chain is that in the former transition probabilities are independent of time, whereas in the latter they depend on the current state and the elapsed time.

In this respect, a nonhomogeneous semi-Markov chain is built for every component with a discrete random variable x_i having two mutually exclusive states (working or failure) and the transition probabilities matrix (Salazar et al., 2017) according to the following equation:

$$P\big(x_i(k+1)\big|x_i(k)\big) = \begin{bmatrix} 1-p_i(k) & p_i(k) \\ 0 & 1 \end{bmatrix} \tag{28}$$

where k denotes the current time step, and $p_i(k)$ is the probability of the i_{th} component failing in the next time step $(k+1)$ given that it was working in the current time step.

From the above definition, the probability $p_i(k)$ is calculated based on the failure rate definition of Rausand et al. (2021) according to the following equation:

$$p_i(k) = \lambda_i(k,l)\Delta t \tag{29}$$

where Δt is the interval between the following and the current time step.

Moreover, component reliability R_i is defined based on the failure rate using the following formula:

$$R_i(t) = e^{-\int_0^t \lambda_i(t,l)dt} \tag{30}$$

By discretising the above expression for the different time steps, each component reliability is calculated as:

$$R_i(k) = e^{-T_s \sum_{k=0}^{k} \lambda_i(k,l)} \tag{31}$$

where T_s is the sampling interval of the time steps.

Each component reliability is calculated for the next time step based on the dictated operating profile, and subsequently, it is fed into the component nodes for the current and the next time slices of the DBN. The DBN gets updated at every execution of the control process by providing the components reliability of the next time steps. It should be noted that the input of the component nodes is in the form of a probability distribution, as it represents reliability, which is provided to the DBN in the form of virtual evidence. By using the WPHM and the semi-Markov chain, the past operational period and the influence of the previous points can be explicitly captured in the reliability of the components.

4.4.4. Wiener Process Model (WPM)

Apart from the influence of the operating point and elapsed time, random effects can also affect the reliability of components. Among the stochastic processes that are extensively used to model random mechanisms is the Wiener process (Li et al., 2021). The Wiener process has the ability to capture the trajectories associated with random noise which components may undergo during their operational lifecycle (Si et al., 2013).

The Wiener process incorporates a term associated with Brownian motion, a concept from physics used to model random fluctuations in the movement of small particles in fluids and air (Si et al., 2013). This stochastic process has found extensive application in characterising the trajectories of random processes, particularly when fluctuations are observed (Zhang et al., 2021). In general, the formula that describes the wiener process model (WPM) takes the following form (Zhang et al., 2021):

$$D(t) = D(0) + \mu t + \sigma B(t) \tag{32}$$

where $D(0)$ denotes the initial health state, μ and σ are the parameters representing the drift and diffusion coefficients respectively. The notation $B(t)$ is used to denote standard Brownian motion, and $\sigma B(t) \sim N(0, \sigma t^2)$ is employed to describe the time-varying nature of the stochastic process.

The drift component in the preceding equation is used to model characteristics, typically determined by factors such as age, degradation state, or various covariates like stress, environmental conditions, and load (Zhang et al., 2021). On the other hand, the diffusion term is used to model the stochastic aspects, captured by the Brownian motion.

Furthermore, transitions in operating conditions may affect reliability. Assuming that sensor measurements from a component can detect these transitions in operating conditions, the

WPM can be extended to accommodate such effects, accounting for upward or downward jumps. The WPM as proposed by Bian et al. (2015) can be used which takes the following form:

$$D(t) = D(0) + \mu t + \sum_{i=1}^{N(t)} J(A_i) + \sigma B(t) \tag{33}$$

where A_i is the i_{th} transition time of the operating condition, $N(t)$ is the cumulative number of the operating condition transitions up to time t, and $J(A_i)$ is a function of the transition jump (either upward or downward) that occurs at time t.

By having the current and previous sensor measurements, the function of the transition jump can take the following form (Bian et al., 2015):

$$J(A_i) = \gamma \frac{|SM_k - SM_{k-1}|}{SM_{k-1}} \tag{34}$$

where SM_k is the current sensor measurement, SM_{k-1} is the previous sensor measurement, and γ is a jump coefficient.

Based on the WPM, a Health Index (HI) can be computed that effectively represents the current health state of a specific component. The HI is defined within the domain [0, 1] and can be determined using either Equation 32 or Equation 33, depending on whether operating conditions explicitly influence the process, as follows:

$$HI(t) = 1 - D(t) \tag{35}$$

Based on the estimation of the HI, the failure rate can be updated according to the following equation (Bolbot et al., 2021):

$$\lambda(t) = \lambda^{HI} \tag{36}$$

By using the exponential form to update the failure rate based on the HI, a consistently increasing trend in the failure rate is modelled, which is expected as the component approaches the end of its lifespan. Component reliability is then calculated following the nonhomogeneous semi-Markov chain described in the previous section which is then fed into the DBN.

4.5. Decision-making

The preceding sections have outlined methods for calculating fuel consumption and reliability across various operating points within the power plant. However, the final setpoint for the power plant must find a balance between these two objectives. Optimal fuel consumption and optimal system reliability may not always align perfectly at the same operating point. Consequently, a bi-objective decision-making method is required to find an operating point that is a trade-off between these two conflicting objectives.

The most straightforward approach to solving multi-objective optimal control problems (MOCP) is by a scalarisation technique using weighting factors (Peitz and Dellnitz, 2018). A weighting factor is assigned to every objective, as a result, the control problem employs a single objective function that must be minimised or maximised. The weighting factors are typically determined by using experts' knowledge, which is not always available in the case of hybrid systems and autonomous operations. Consequently, a more sophisticated method should be followed, where the weight for each objective dynamically changes based on the power demand and the prevailing conditions.

4.5.1. Utopia Point Method

This study employs the reference or utopia point method (Gambier, 2022), (Peitz and Dellnitz, 2018) for facilitating decision-making. To select the final setpoint operating point at each execution of the control process, the Pareto front of the two selected objectives is identified. All the solutions in the Pareto front are feasible, however, the final solution is selected based on the distance minimisation to an infeasible target or utopia point. The distance to an infeasible target point T should be minimised, so that does not belong to the Pareto front J, according to the following equation:

$$\min_{u} \bar{J}(u) = \min_{u} \|T - J(u)\| \tag{37}$$

The infeasible point is identified as the point with the lowest equivalent fuel mass flow rate and the highest system reliability, which apparently cannot be achieved. Both objectives are scalarised from zero to unity based on their extreme values to make their contribution equal (their maximum values and minimum values are set to one and zero, respectively). An example of applying this method to the Pareto front of this case study is shown in Figure 4.4. The circle at the bottom right corner represents the utopia point, while the other circle denotes the selected setpoint which is selected based on the calculated minimum distance highlighted by the dashed line. This process of building the Pareto front and minimising the distance to the utopia point is repeated in every time step.

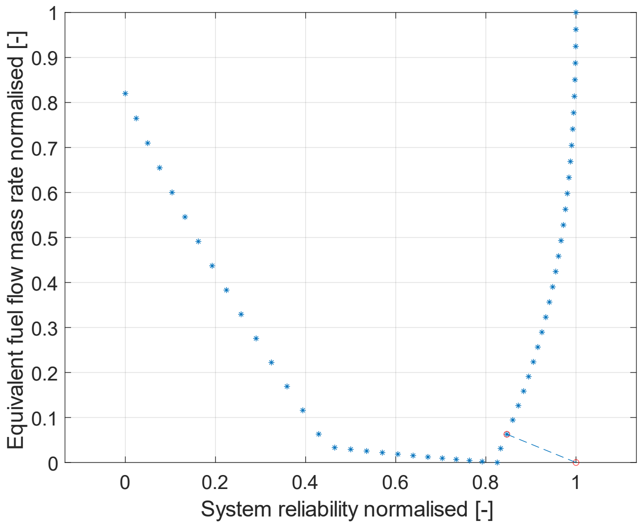

Figure 4.4: Example at a specific time step of the Pareto front with the two objectives normalised.

By employing the utopia point method, the proposed methodology seeks to identify an optimal operating point that simultaneously optimises both fuel consumption and system reliability. In this way, health-aware control is enabled where a balance is achieved between minimising fuel consumption and prolonging the health condition of the power plant using reliability as the health indicator.

4.6. Optimisation Problem Formulation

Based on the description of the methods outlined earlier, this section presents the formulation of the optimisation problem that is solved. A structured approach is followed, to clearly define the optimisation variables, set the constraints to include physical limitations of power plant components, and establish the objective functions.

Given the use of a DBN for evaluating system reliability, which can calculate reliability only at discretised points in the state space, a continuous model approach is not feasible. Consequently, a set of discrete control variables is established within the operational range of the system. These control variables include engine power ($P_{eng} = u_1$), engine rotational speed ($N_{eng} = u_2$), electric machine power ($P_{em} = u_3$) and rotational speed ($N_{em} = u_4$), and battery power ($P_{bat} = u_5$). The system's state variable is defined by the battery's SOC, denoted as x_1. Both the state and the control variables are bounded and discretised to assume values within their respective domains: $u_k \in U_k$ and $x_k \in \Omega_k$. The specific variables utilised are detailed in Table 3, along with other pertinent inputs and parameters.

Table 3: State and control variables along with inputs and constants.

Parameter	Description	Role
SOC	Battery state of charge	State
P_{eng}	Engine power reference	Control
P_{em}	Electric machine power reference	Control
P_{bat}	Battery power reference	Control
Ne_{ng}	Engine rotational speed reference	Control
N_{em}	Electric machine rotational speed reference	Control
P_{prop}	Requested propulsive power	Input
P_{elec}	Requested electrical power	Input
s	equivalence factor	Constant
Q_{max}	battery capacity	Constant
Q_{LHV}	lower heating value of fuel at ISO conditions	Constant

The optimisation problem is further characterised by a set of constraints. The primary constraint is an equality constraint ensuring the balance between the demanded and generated power:

$$P_{req} = P_{Gen} \tag{38}$$

Additional constraints are imposed to limit each component to its operational range, defined by its upper and lower limits.

$$\mathcal{O}_{lower} \leq \mathcal{O} \leq \mathcal{O}_{upper} \tag{39}$$

For each set of control variables, two key calculations are performed: one for the equivalent fuel consumption (as per Equation 12) and the other for system reliability evaluation based on the DBN output. The Pareto front for these two objectives is constructed using the Utopia point method, establishing the objective function as described in Equation 37. This leads to the following optimisation problem: identifying the set of optimal control inputs u_k that minimise the objective function J:

$$\text{Minimise:} \qquad J\big(u(\cdot\,|k)\big)$$

s.t.

$$x_{k+1} = f(x_k, u_k) \tag{40}$$

$$g_{in}(x_k, u_k) \leq 0$$

$$g_{eq}(x_k, u_k) = 0$$

In contrast to continuous optimisation problems that demand advanced solution strategies, this problem is addressed by choosing the control variables u_k that yield the minimum value of the objective function J, similar to the optimisation problems solved in DP. This framework has been implemented in the MATLAB environment, offering practical and computationally feasible solutions.

4.7. Chapter Summary

This chapter introduces the methods and tools used in the proposed methodology. Firstly, performance models are described, which capture the performance behaviour of the power plant. Additionally, two energy management strategies are presented. In specific, ECMS is used as a method for determining the equivalent fuel consumption in hybrid power plants, and DP is used for verification purposes. Furthermore, a system health monitoring approach using DBN is presented where component reliability can be either calculated using WPHM or WPM. Finally, a bi-objective decision-making method is presented to find a balance between fuel consumption and system reliability.

5. Reference Systems & Case Studies

5.1. Chapter Outline

This chapter presents an overview of the refence power plants along with their technical and reliability specifications. A description of the case studies is performed by specifying the interactions between the methods for each tool in the associated reference power plant along with details about their operation.

5.2. Reference Power Plants

5.2.1. Pilot Vessel Arrow

The first power plant configuration is based on the pilot vessel Arrow. This pilot boat is primarily operated in the coastal waters near the Falmouth port in England. Its usual operational profile lasts less than 3 hours, maintaining a consistent cruising speed ranging from 16 to 18 knots, with the capability to reach a maximum speed of 22 knots. The general ship characteristics can be found in Table 4.

Figure 5.1: Pilot Vessel Arrow. Source: https://www.vesselfinder.com/

Table 4: General ship characteristics Pilot Vessel Arrow.

Ship characteristic	Value
Length overall (m)	16.7
Breadth (m)	5.2
Draught (m)	1.5
Gross tonnage (t)	24
Capacity (people)	15

Technical Specification

The original power plant has a conventional setup where the primary mover (diesel engine) is directly connected to the propeller. However, regarding the requirements discussed in Chapter 2, which pertain to the transition towards autonomous operations, significant modifications were made to transform the power plant into a hybrid configuration.

In this case, the hybrid configuration is of the parallel type, which indicates that the two prime movers (diesel engine and the electric machine) are coupled in a gearbox providing power either individually or simultaneously to the propeller. In the power take-in (PTI) mode, the electric machine operates as a motor receiving energy from the battery and providing power to the propeller. In the power take-out (PTO) mode, the electric machine operates as a generator charging the battery. A schematic representation of the investigated power plant configuration is presented in Figure 5.2.

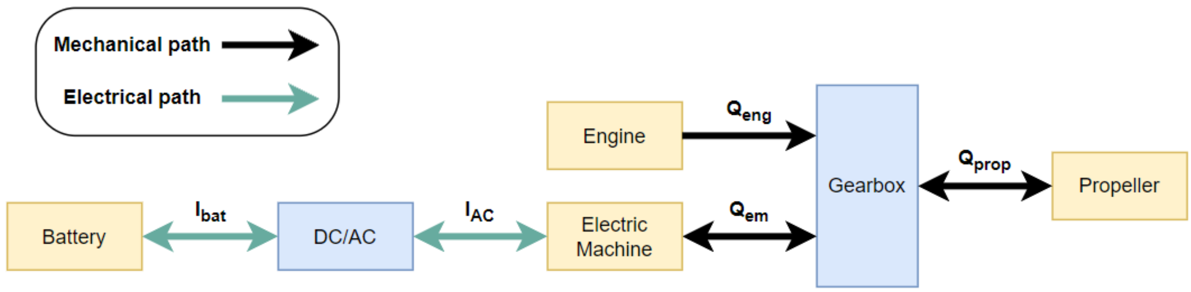

Figure 5.2: Parallel hybrid power plant configuration of pilot boat.

The engine manufacturer data were employed to develop the fuel consumption map. In particular, the considered marine engine is the Scania DI16M, which is a twin-turbo four-stroke diesel engine (SCANIA, 2016). For the other components, the models described in Section 4.2 were deployed with the power plant parameters provided in Table 5.

Table 5: Power plant parameters Pilot Vessel Arrow.

Component	Parameter	Value
Diesel Engine	Type	Scania DI16M
	Power MCR (kW)	423
	Speed MCR (RPM)	2100
Electric Machine	Nominal power (kW)	100
Battery	Type	Lithium-ion
	Module capacity (Ah)	100
	Nominal Voltage (V)	12
	Number of modules	100

Reliability Specification

Apart from the technical specification, the investigated power plant must be decomposed accordingly for reliability calculations. The DBN described in Section 4.4.1 has a qualitative and a quantitative part. The qualitative part presents the structure of the network showing the nodes' interconnections. Figure 5.3 presents the developed DBN for the investigated ship hybrid power plant, where the arcs above the root nodes represent the temporal dependences.

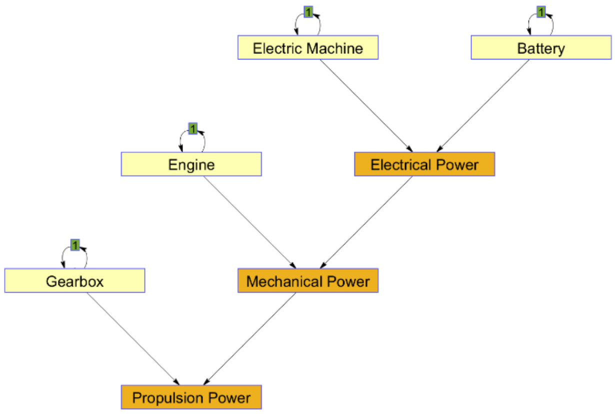

Figure 5.3: Unrolled dynamic Bayesian network structure.

In this reference power plant, the WPHM is used to update the failure rate. As a result, the components are considered subsystems, where the WPHM is used to update the failure rate. Component reliability is calculated in every time step and is used as input in the form of virtual temporal evidence to the DBN. In addition, for the intermediate nodes, noisy-OR gates were used to speed up the inference computation as described in Section 4.4.1.

Furthermore, the values for the shape parameters employed for the WPHM are based on the data reported in Tsoumpris and Theotokatos (2022). The failure rates are taken from the

OREDA database, whereas their mean and maximum values are chosen by aggregating all the failure modes of the investigated components.

Table 6: Failure rates and shape parameters for Pilot Vessel Arrow.

Component	Maximum failure rate (h^{-1})	Mean failure rate (h^{-1})	Shape parameter β (–)
Diesel Engine	$32.42\ 10^{-4}$	$17.68\ 10^{-6}$	2.4
Electric Machine	$97.56\ 10^{-6}$	$43.76\ 10^{-6}$	1.2
Battery	$136.81\ 10^{-6}$	$63.57\ 10^{-6}$	1.69
Gearbox	$3.80\ 10^{-6}$	$1.01\ 10^{-6}$	2.028

5.2.2. MV Eidsvaag Pioner

The MV Eidsvaag Pioner is selected as the second reference vessel for the application of the proposed methodology. It is a short-sea shipping cargo ship specifically designed to carry fish feed in bulk. The ship's sailing route extends between Hirtshals in Denmark and Kristiansand in Norway. The MV Eidsvaag Pioner operates on a seven-day cycle where each cycle contains two loadings at the factory at Averøy. The ship has approximately a 10-hour slot time at the factory quay. Starting from the factory in Averøy, two different transport route directions (southbound and northbound) along the Norwegian coast can be followed. The use case assumes one northbound trip and one southbound trip for each seven-day-cycle. On each trip, the MV Eidsvaag Pioner delivers feed to approximately 10 fish farms during a period of 30 hours, not accounting for delays. After that, the ship has to wait at a public quay until the start of the next seven-day cycle.

Figure 5.4: MV Eidsvaag Pioner. Source: https://www.autoship-project.eu/wp-content/uploads/2022/01/AUTOSHIP-article.pdf

The general ship characteristics of the MV Eidsvaag Pioner are presented in Table 7.

Table 7: General ship characteristics MV Eidsvaag Pioner.

Ship characteristic	Value
Length overall (m)	74.7
Length between perpendiculars (m)	72.9
Breadth (m)	13.6
Depth (m)	7.9
Maximum draught (m)	5.1
Deadweight (t)	1743

Technical specification

The reference power plant is based on the case study analysed by the AUTOSHIP project. The original power plant has electrical power generation provided by diesel generators and hybrid propulsion by coupling two prime movers (the gas engine and the electric machine) into a controllable pitch propeller. However, various amendments are undergone in the design to better satisfy the requirements discussed earlier.

The selected power plant has a similar layout to the pilot boat configuration. The diesel generators are substituted with a battery which can provide power to the electric machine as well as to the electrical demands of the vessel. The hybrid propulsion arrangement is kept identical using a natural gas main engine and an electric machine. Again, the electric machine can be used both for PTO and PTI purposes. The electrical grid of the power plant is based on AC, although various electronics are included to transform AC to DC and vice versa for specific components. Figure 5.5 presents a schematic representation of the investigated power plant.

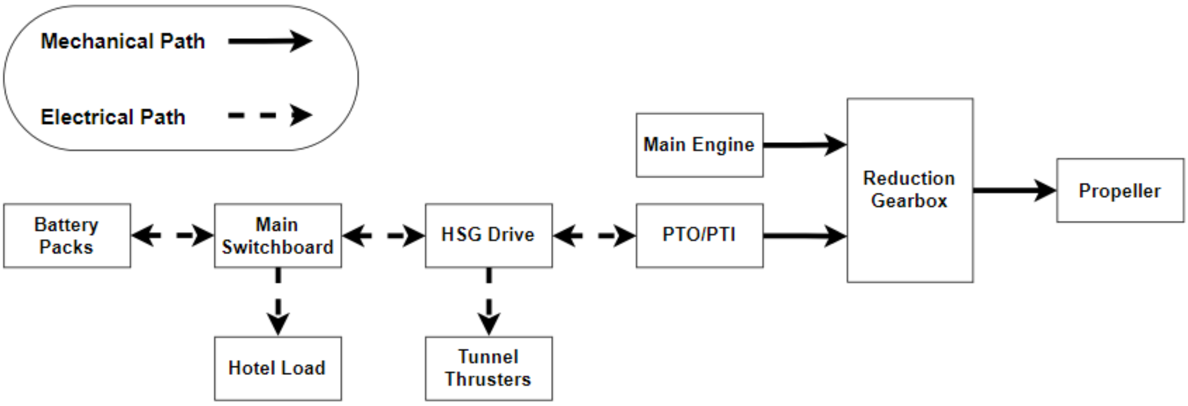

Figure 5.5: Parallel hybrid power plant configuration of short-sea shipping cargo vessel.

The fuel consumption map of the gas engine (Bergen C26:33 L9PG) was constructed based on the project guide provided by the manufacturer (Bergen Engines AS, 2018). For the other components, the models described in Section 4.2 were deployed with the power plant parameters provided in Table 8.

Table 8: Power plant parameters MV Eidsvaag Pioner.

Component	Parameter	Value
Gas Engine	Type	Bergen C26:33L9PG
	Fuel	Natural gas
	Power MCR (kW)	2430
	Speed MCR (RPM)	1000
Electric Machine	Nominal Power (kW)	1100
	Nominal Speed (RPM)	1500
	Nominal voltage (V)	440
Battery	Type	Lithium-ion
	Nominal capacity (Ah)	746.1
	Rated voltage (V)	805
Propeller	Type	CP
	Diameter (mm)	3200
	Number of Blades	4
Electrical installation	Main Switchboard voltage (V)	440

Reliability Specification

For the reliability calculations performed in this study, the power plant must be decomposed power into a structured format suitable for a DBN. By utilising technical drawings from the actual ship, a DAG was constructed. This DAG has both subsystem and component layers.

Since all the examined components cannot be shown graphically, Figure 5.6 presents higher-level subsystems. Detailed graphical representations of the subsystems are presented in Appendix A.

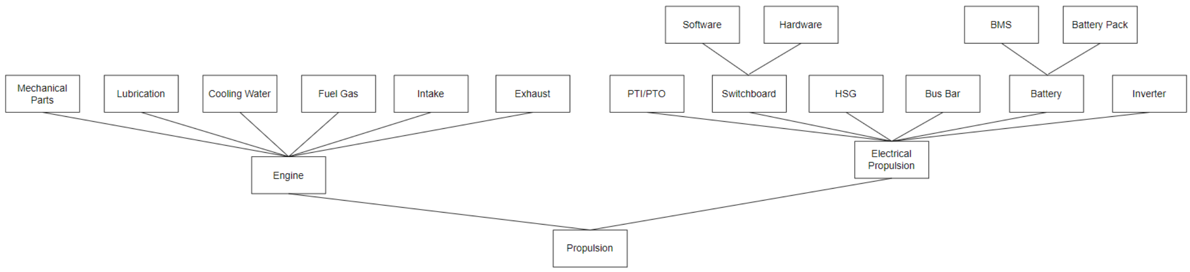

Figure 5.6: Bayesian Network with power plant subsystems.

The component failure rates which are used in this study are derived from the pertinent literature as well as reliability databases. Primarily, data from the OREDA database (OREDA, 2015) and the PDS Data Handbook (Hauge and Onshus, 2010) are used, which are widely sourced in the reliability domain. An exhaustive list of the component failure rates used in this study is presented in Appendix B.

In this reference power plant, the WPM described in Section 4.4.4 is used to update the failure rate. Specifically, most of the components within the DBN are modelled without considering sensor measurements using Equation 32, as their health condition cannot be adequately characterised by the influence of a feature that is related to the operating point. However, for selected components, there are features that can be used to represent their health condition, which has similarly been demonstrated by Bolbot et al. (2021). These selected features are presented in Table 9 and are usually recorded in the existing ship alarm and monitoring system.

Table 9: Components with selected features to represent health condition.

Component	Feature
Compressor	Boost pressure (bar)
Cylinder Liner	Mean peak in-cylinder pressure (bar)
Cylinder Head	Mean peak in-cylinder pressure (bar)
Engine Valve Outlet	Temperature at exhaust manifold (^{o}C)
Turbine	Temperature at upstream of turbine (^{o}C)

The components investigated within this study concern the main engine, where their health condition is influenced by operating factors such as engine rotational speed and load. To capture this behaviour feature maps are used. These maps illustrate how variations between the current and previous operating points can influence engine health. The specific feature maps utilised in this study are derived from the work of Tsitsilonis et al. (2023) who modelled a similar engine. To ensure relevance to the engine of this reference power plant, appropriate scaling adjustments were applied, with reference to parameters of MCR and nominal speed.

An example of a feature map for the engine compressor is presented in Figure 5.7. The feature maps are generated using a polynomial response surface (PRS) by fitting the provided data from Tsitsilonis et al. (2023). During the control process execution, the operating point of the engine, which corresponds to a specific engine speed and power, is matched to a value from the corresponding map as a sensor measurement. In the case of the engine compressor, depicted in Figure 5.7., the sensor measurement corresponds to the boost pressure. By feeding the previous and the current sensor measurements, the WPM in Equation 33 is used. Additionally, in this study since there is not enough information for the parameters in Equation 33, the failure rate for each component is used for drift, diffusion and jump parameters.

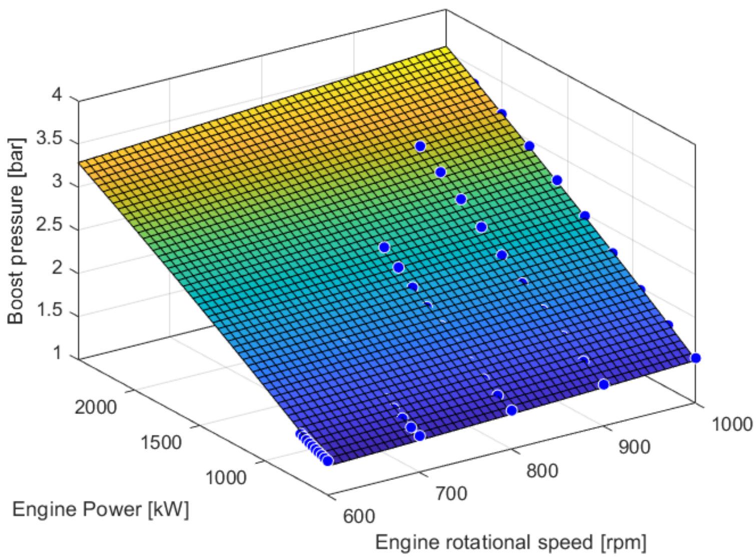

Figure 5.7: Boost pressure map.

5.3. Case Studies

The reference power plants presented previously are used in two distinct case studies, where the proposed methodology is modified accordingly to build tools for each case study purpose. These case studies are listed in Table 10 and the results of which are subsequently presented in Chapter 6. Additionally, Table 11 provides an overview of the key components by specifying their inputs and outputs described in the methods and tools of Chapter 4.

Table 10: Case studies list.

Case Study	Description	Reference Power Plant	Section
I: Health-Aware Energy Management	Energy management evaluation	Pilot boat	6.2.1
	Half-month operating profile		6.2.2
II: Health Monitoring	Energy management	Short-sea shipping cargo vessel	6.3.1
	New condition power plant - 500 hours operation		6.3.2
	Compressor in degraded region - 500 hours operation		6.3.3
	Lubrication filter in degraded region - 500 hours operation		6.3.4

Table 11: Key components Input-Output table.

Key Component	Input	Output	Equation number
Performance models			
Internal Combustion Engine	Torque, Rotational speed	Fuel flow mass rate	(1)
Electric Machine	Torque, Rotational speed	Power	(2), (3)
Battery	Voltage, Current, Capacity	Power, SOC	(4) - (6)
Energy Management			
ECMS	Power Demand, SOC, Equivalence factor	Optimal fuel operating point	(9) - (13)
DP	Power Demand, SOC	Optimal fuel operating point	(14) - (18)
Health Monitoring using Reliability			
DBN	DAG structure, Component Reliability	Subsystem reliability, Criticality Importance measures	(21)-(23)
WPHM	Failure rate, Load, Elapsed time	Component Reliability	(25) - (31)
WPM	Failure rate, Sensor measurements, Elapsed time	Component Reliability	(32) - (36), (28) - (31)
Decision-making			
Utopia point method	Equivalent fuel points, System reliability points	Final operating point	(37)

5.3.1. Case Study I: Health-Aware Energy Management of a Pilot Boat

In the first case study of the pilot boat, the aim is to achieve health-aware energy management of the power plant using the decision-making method as a trade-off strategy between two objectives.

The hybrid power plant's components are modelled using the models described in Section 4.2 where the ECMS is applied to find the optimal instantaneous equivalent fuel flow mass rate. The DBN described in Section 5.2.1 is used where the WPHM is employed to update the failure rate while component reliability is calculated based on the semi-Markovian approach, considering the elapsed time and the influence of the operating point. Finally, at every instance of the control process execution, the decision-making method is used to provide the final setpoints based on the optimal fuel consumption point identified by the energy management strategy and the optimal system reliability point proposed by the DBN. Figure 5.8 presents the modified methodology to build the tool for this case study application.

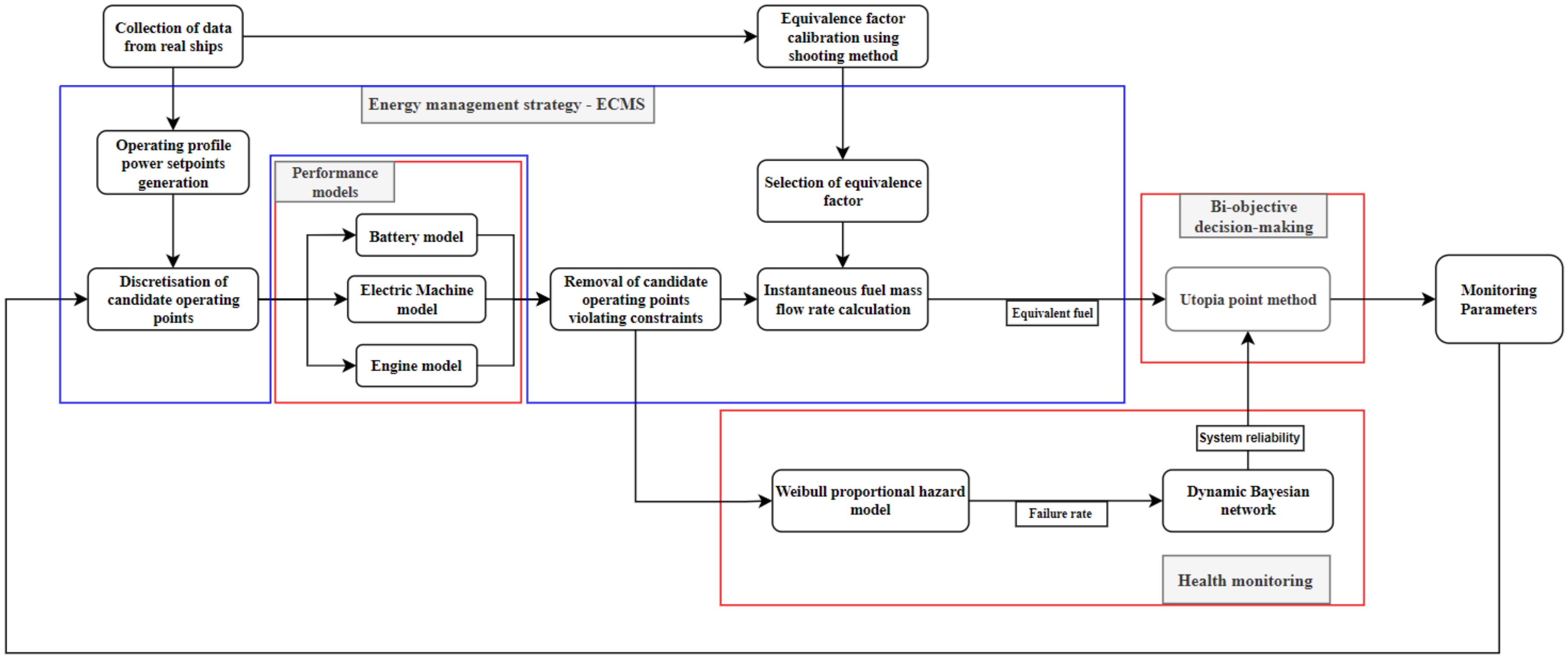

Figure 5.8: Health-aware energy management tool control process.

Both case studies need an operating profile to verify the effectiveness of proposed methodology. In the case of the pilot boat, to examine the behaviour of the tool as close as possible to real operating conditions, available engine speed data corresponding to three voyages, which were acquired from the actual pilot boat equipped with a mechanical propulsion system and marine diesel engines, were collected.

Subsequently, the demanded propulsion power that is required as input is estimated by using the propeller law, i.e., considering the cubic function of the provided engine speed. Furthermore, the recorded speed has an inherent noise due to the operating condition disturbances and the sensor's uncertainty, thus filtering was performed to provide the power setpoints. Figure 5.9 presents the power setpoints combining the three sample voyages. Based on the power demand profile for these voyages, a half-month operating profile was developed by arranging the three voyages in random order as well as by altering the power setpoints with a ± 10% random variation to represent a more realistic scenario.

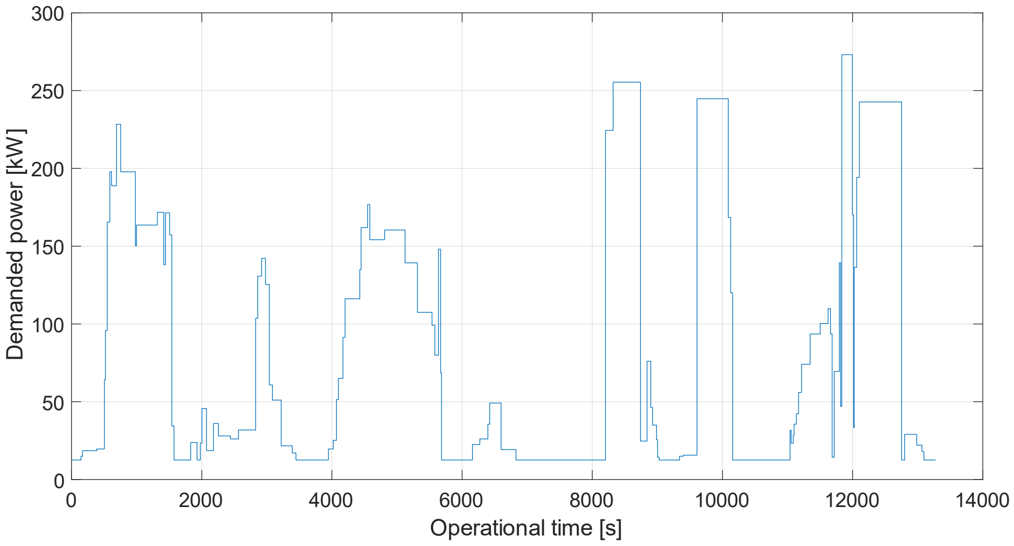

Figure 5.9: Sample operating profile of pilot boat with the three sample voyages combined.

5.3.2. Case Study II: Health Monitoring of a Short-sea Shipping Cargo Vessel

The second case study focuses on the health monitoring of the short-sea shipping cargo vessel by utilising the DBN described in Section 5.2.2. The WPM described in Section 4.4.4 is adopted to update the failure rate of components. Additionally, ECMS is executed as the energy management strategy of the hybrid power plant to calculate performance metrics using the models described in Section 4.2. Figure 5.10 presents the modified methodology to build the tool for this case study application.

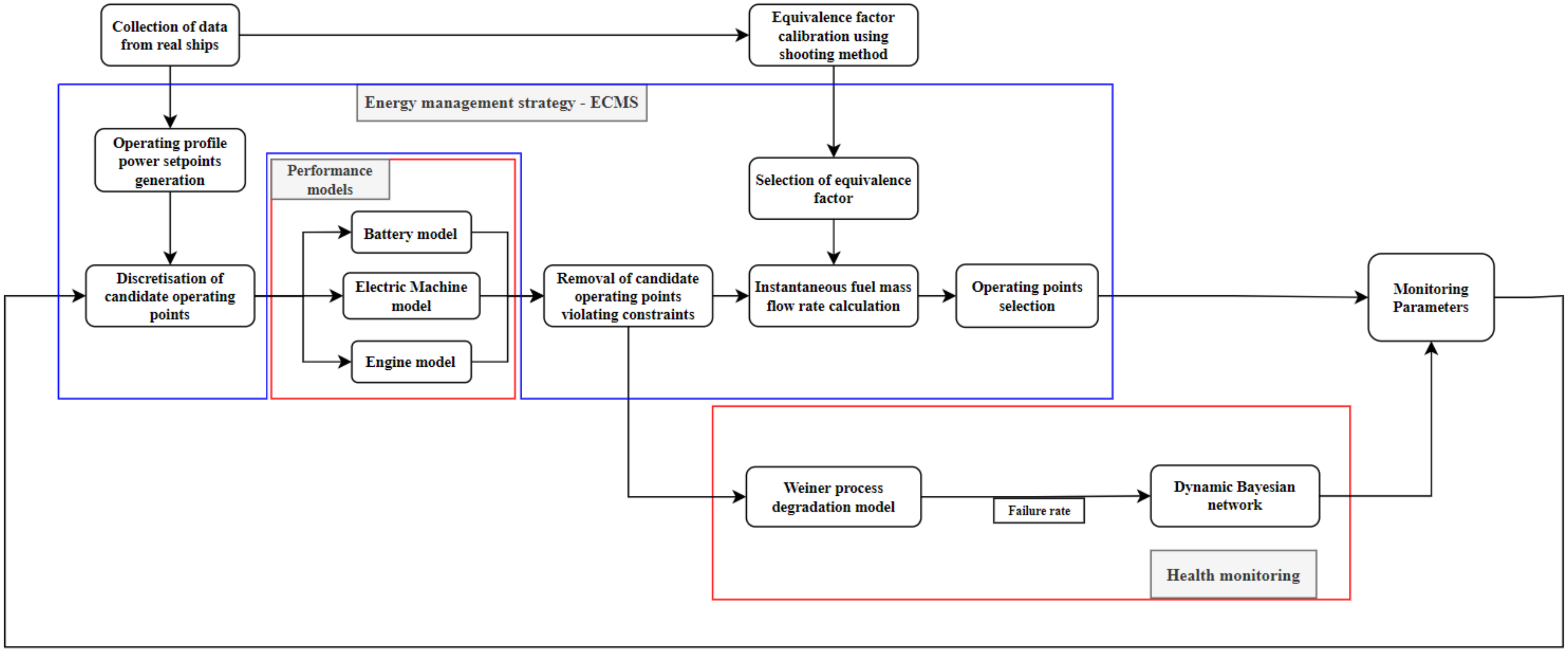

Figure 5.10: Health monitoring tool control process.

To construct the operating profile for this case study, actual ship data were obtained from measurements during sampled voyages and sea trials. These measurements provide information about demanded propulsive and electrical power versus the ship speed under both calm and rough water sea conditions. Additionally, voyage characteristics were collected from data acquired via the Automatic Identification System (AIS) (Dantas and Theotokatos, 2023).

By analysing this data, four distinct operational modes were identified: loading at the factory, sailing, berthing, and unloading at the fish farms. A sample operating profile including these operational modes is presented in Figure 5.11. In this sample operating profile, the ship departs from the port, where there is a zone with high propulsive demand, followed by an extended sailing phase. Afterwards, the ship approaches the fish farms where again there is a zone with high propulsive demand. Finally, the ship operates in Dynamic Positioning during unloading of the cargo at the fish farms, where the tunnel thrusters are engaged. This sample operating profile is repeated at various stops at the fish farms, with varying sailing and unloading duration. The operating profile that was examined in this case study lasts 27 hours and is constructed based on these operational modes according to the data collected from AIS.

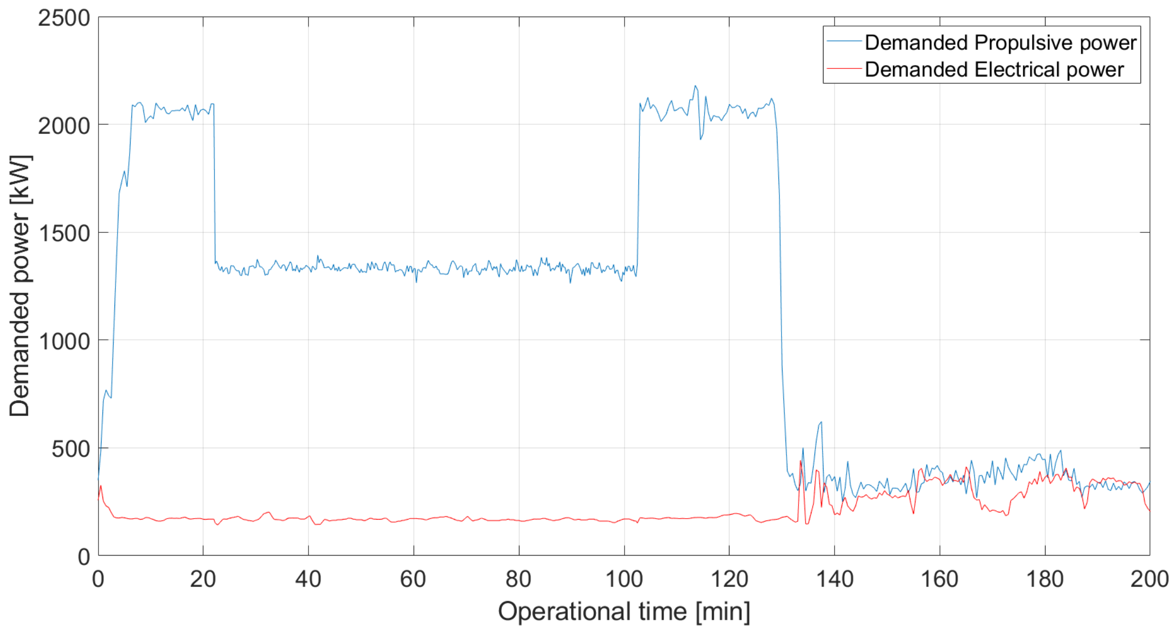

Figure 5.11: Sample operating profile of short-sea shipping cargo vessel.

Since the operating profile has different operational modes, where the duration varies from a couple of minutes to hours, the ECMS was modified. The target battery's SOC is adjusted accordingly for each operational mode. In this respect, high SOC targets are imposed during the sailing phase where the battery is expected to end this mode by having enough reserve for berthing and unloading. As a result, in the other phases, the target SOC is lower where propulsive and electrical demands can be managed by the battery.

Three different scenarios are investigated where components in the power plants have different initial conditions, while the operating profile is extended to last 500 hours in order to see the effect in reliability decrease. Initial component reliability is calculated based on exponential distribution by providing the elapsed time, while the initial health indicator is calculated based on Equation 30 by providing the elapsed time. In every scenario component and subsystem reliability is calculated, while components are ranked based on the criticality importance measure described in Section 4.4.2 .

To enable autonomous operations, the establishment of health levels with distinct thresholds denoting state changes is crucial (Edge et al., 2020). Although standardised health levels are yet to be defined for autonomous operations, this study adopts the thresholds proposed by Bahootoroody et al. (2022) and Okoh et al. (2014), which were specified based on crew experts and engineering knowledge. Specifically, the 'healthy region' is characterised by reliability values ranging from 1 to 0.8, the 'degraded region' spans from 0.8 to 0.5, and the 'failure region' includes values below 0.5. Table 12 presents the range of these regions by assigning a corresponding colour as a visual aid. This approach enables real-time monitoring of system health which can proactively inform the ship operator about upcoming failures when the monitored variables violate the specific thresholds.

Table 12: Health regions range.

Health Region	Range
Healthy	0.8 - 1
Degraded	0.5 - 0.8
Failure	0 - 0.5

The first scenario concerns the power plant’s operation where all the components are in new condition and the operating profile finishes at 500 hours of operation. The rationale behind this scenario is to test the proposed limit for autonomous operation in unmanned power plants proposed by the MUNIN project (Abaei et al., 2021).

Based on the proposed health levels, the second scenario concerns the state where a single component is in the degraded region without redundant arrangements while the third scenario concerns the state where a component is in the degraded state where there is another redundant component serving the same function. The rationale behind these two scenarios is to explore how redundancy affects subsystem's health.

5.4. Chapter Summary

In this chapter, the details of the reference systems were presented. The proposed methodology described in Chapter 3 has been modified to two different reference hybrid power plants. The case studies and the scenarios that are investigated for each reference power plant were presented. Based on the developed tools, the results that were generated are presented and discussed in the following Chapter.

6. Results & Discussion

6.1. Chapter Outline

This Chapter presents the case studies results that are generated by performing simulation runs using the developed tools. The first case study presents the health-aware energy management tool for the pilot boat whereas the second case study the health monitoring tool for the short-sea shipping cargo vessel.

6.2. Case Study I: Health-Aware Energy Management of a Pilot Boat

6.2.1. Energy Management Strategy Verification

As mentioned earlier, the use of the ECMS for energy management does not guarantee the globally optimal solution, as the problem is converted to an instantaneous minimisation problem for real-world applications, where the operating profile is not known a priori. However, it can achieve near-optimal solutions with a considerably low computational burden.

Nevertheless, to verify the results provided by ECMS a comparison is carried out with the results provided by Dynamic Programming (DP). In the energy management problem of hybrid configurations, DP is the method that approximates the globally optimal solution, since the full history of the operating profile is provided as input and the optimisation problem is solved backwards in time.

Furthermore, the results obtained by ECMS are greatly affected by the selection of the equivalence factor. In this study, the equivalence factor is considered constant and is tuned based on the employed operating profile. The selection of the equivalence is based on the shooting method described in Section 4.3.1.

Regarding the tuning of parameters in the DP problem, the state variable (SOC) is discretised considering Nx=101, whereas the control variables were discretised with Nu=201 values. To make the comparison equivalent the same discretisation was performed for the ECMS.

Figure 6.1 presents the time variations of the battery SOC and consumed fuel amount, which were derived by employing the DP and ECMS, for the sample operating profile. This duration offers a comparison of the two strategies over the realistic operating profile, which is critical for assessing the performance of both ECMS and DP. The charging-discharging of the battery using ECMS is compared with the global optimal results obtained from DP, as well the cumulative fuel consumption through the pilot boat operation. The initial SOC is set to 70% for both methods. The total fuel consumption calculated by ECMS is 3.2% more than the global optimal solution achieved by the DP, demonstrating that ECMS is an effective strategy to achieve near-optimal results with a relatively low computational cost. However, there exists a slight difference in the final SOC value, which can be expected as in DP final state is explicitly set by the user, contrary to ECMS.

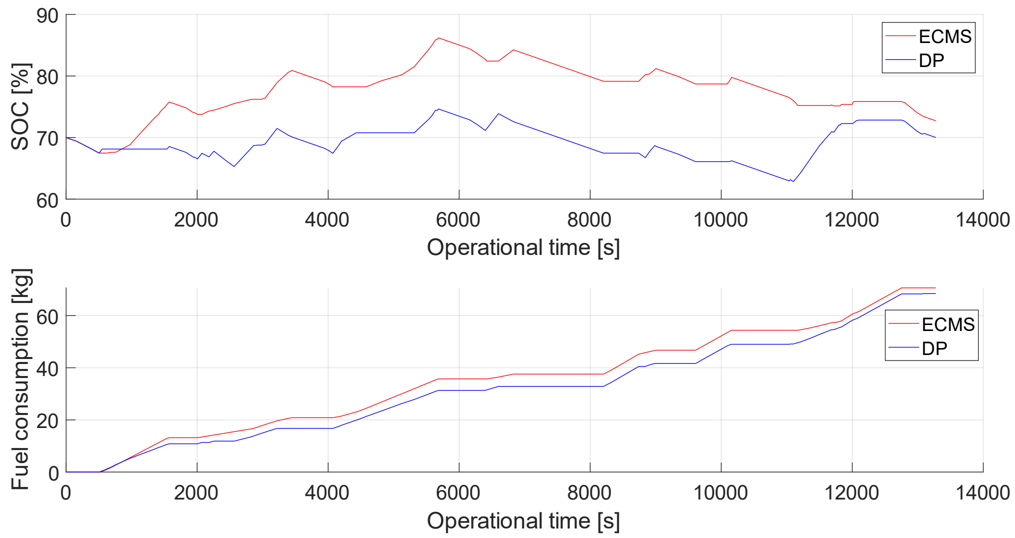

Figure 6.1: Performance comparison of ECMS with DP.

6.2.2. Half-month Operating Profile Results

In this section, the results for the half-month operating profile are presented. It should be noted that the half-month operating profile refers only to the operational time and not the calendar time. Calendar time is longer, as the ship does not operate continuously. In addition, the initial reliability of the investigated components of the power plant is set to 0.95, to represent a close-to-new condition and not perfect condition.

To reveal the advantages of the proposed tool (called health-aware energy management HAEM in this section) incorporating health-aware capabilities, a comparison is made against the ECMS considering the same operating profile. ECMS only employs the objective of reducing the total fuel consumption, consequently, it can be used as a benchmark to unveil the differences in the components and the hybrid power plant reliability as well as the total fuel consumption.

Since the power setpoints for the half-month operating profile are too many to be plotted in a single diagram, only the sample operating profile is presented in Figure 6.2 to examine how the ECMS and HAEM dictate the setpoints for the investigated hybrid power plant components. During periods of low load, the electric machine operates using energy from the battery to provide the requested power to the propeller. In this operational mode is engine exhibits high BSFC values under such conditions, making electric propulsion more energy efficient. Conversely, in high load scenarios, the engine's lower BSFC values make it the preferred source of power. In this case, not only does the engine fulfil the immediate power needs of the propeller, but it also contributes to recharging the battery, where the electric machine absorbs power from the engine. This functionality is integral to the system's efficiency, ensuring that the battery is replenished in preparation for subsequent low-load intervals. The transitions observed in Figure 6.2, characterised by electric machine operating between positive and negative power values, correspond to the dynamic switching between operational modes as dictated by the EMS strategies.

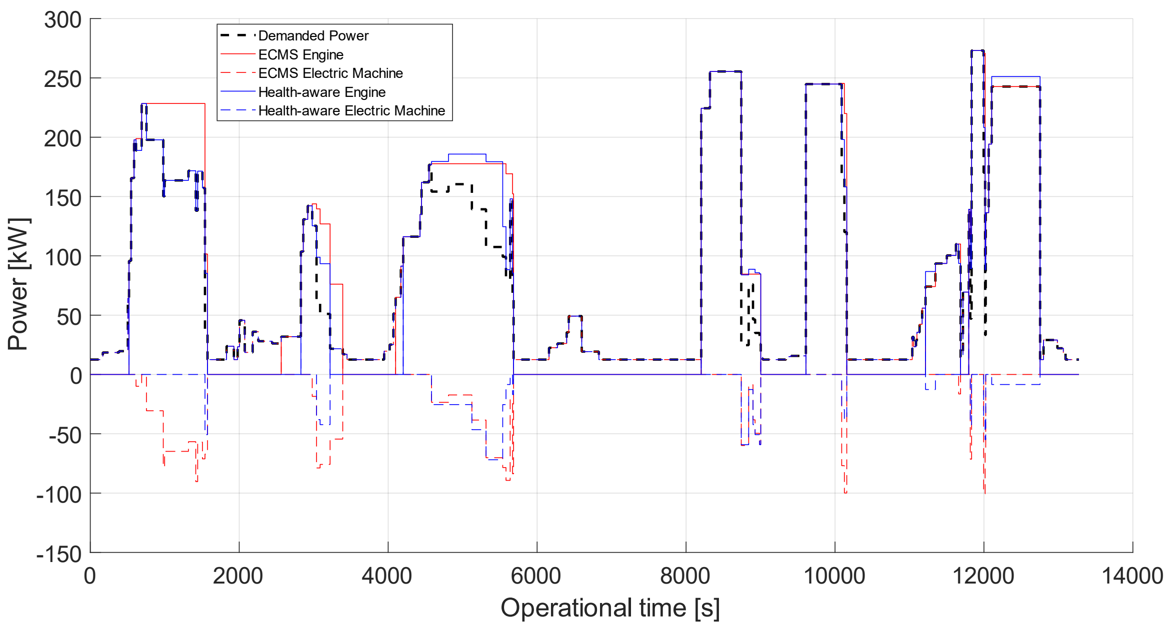

Figure 6.2: Power plant components operating setpoints results.

Figure 6.3 presents a comparison of the battery SOC values along the half-month operation for both strategies. This study assumed that the initial battery SOC is 70% whereas the battery charging takes place via power generated from the diesel engine operation (shore/port stations charging was not considered). It can be inferred from Figure 6.3 that in both strategies the battery SOC exhibits distinct cycles of discharging and charging. Nonetheless, both methods succeed in keeping the SOC around the set target value. The ECMS manages to keep the average value to the target of 70% through the implementation of the penalty function described in Section 4.3.1. However, HAEM leads to the initial SOC decrease for the first 20 h operating period. This means that the battery provided more power/energy compared to the engine during this period, which is attributed to the battery's lower failure rate compared to the engine. However, it manages to keep the SOC target value to around 55% throughout the considered time period, avoiding the risk of keeping the battery at a low SOC.

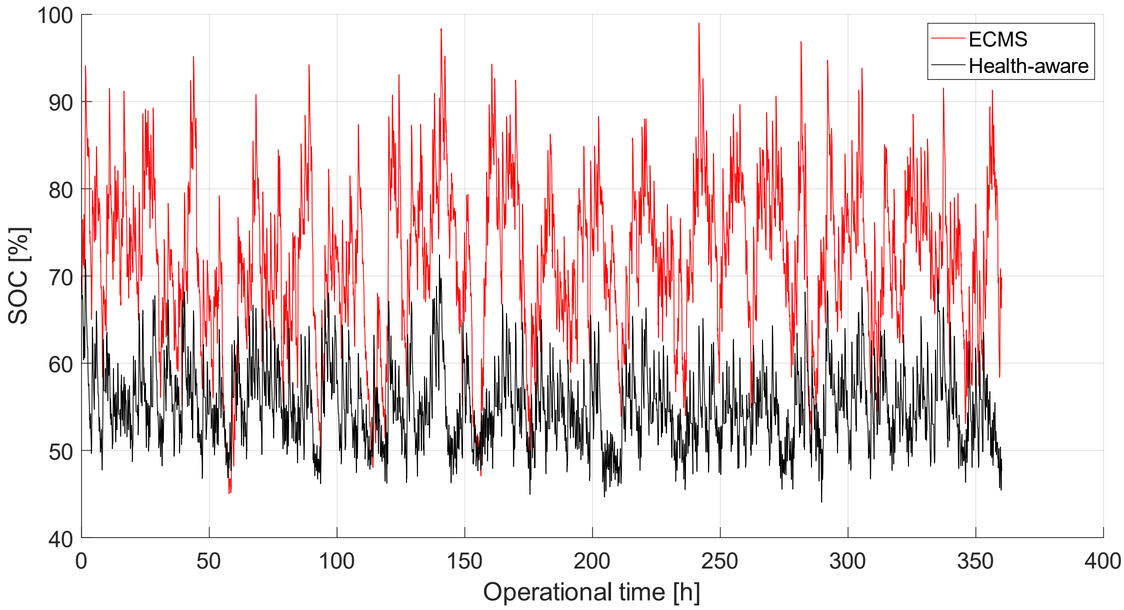

Figure 6.3: Battery State of Charge time variation results.

To quantify the fuel savings, Figure 6.4 presents the total (cumulative) fuel consumption for the considered operating period derived from the two approaches as well as the fuel consumption of the baseline power plant. It is evident that the hybrid configuration with the ECMS results in a fuel reduction of around 17% compared to the baseline configuration (conventional power plant). This behaviour is in alignment with results from pertinent studies dealing with the potential reductions in fuel and operational costs by using hybrid architectures compared to mechanical propulsion (Geertsma et al., 2017), (Nuchturee et al., 2020).

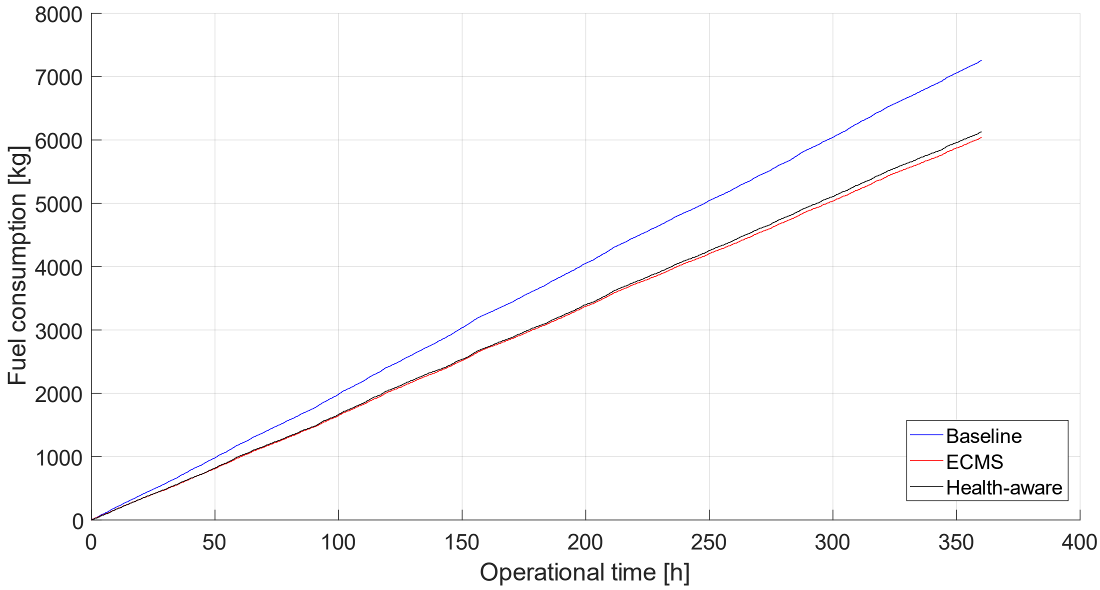

Figure 6.4: Total (cumulative) fuel consumption comparison results.

Figure 6.5 presents the comparison of the system reliability calculated in the terminal node for the ECMS and HAEM, respectively. To determine the system reliability time variation using HAEM, two time slices were considered at 150 and 300 h, respectively to account for behaviour of the half month operating profile for almost half and full duration. The system reliability increases compared to the scenario where the ECMS is employed, by 0.015 at 150 h and 0.029 at 300 h. Since these values represent probabilities and cannot be interpreted explicitly, the failure rate was estimated by differentiating system reliability at two consecutive time slices. At 150 h the system failure rate is estimated to be 2.97 10^{-6} h^{-1} and 3.28 10^{-6} h^{-1} with the ECMS and HAEM, respectively. At 300 h, the system failure rate is found 2 10^{-6} h^{-1} and 7.65 10^{-6} h^{-1} for the ECMS and HAEM, respectively, which is almost 4 times smaller compared to ECMS. Apparently, the HAEM gains are more evident as the operating period of the hybrid power plant increases, resulting in prolonging the system's lifetime expectancy as well as retaining high reliability.

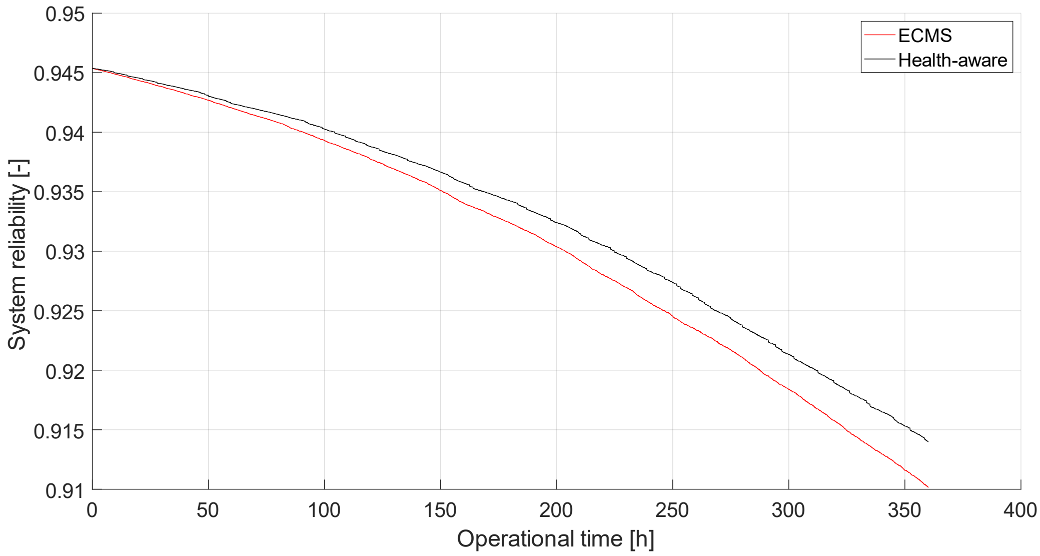

Figure 6.5: System reliability time variation.

In the context of autonomous operations, the engine inside the power plant has the highest failure rate. It is noted that the MUNIN project recommended that the engine should operate reliably without human intervention for 500 hours (Abaei et al., 2021). Figure 6.6 presents the engine reliability time variations for the two approaches and the baseline configuration. The baseline configuration exhibits a pronounced decline in reliability over the operational time. As a result, the MUNIN target cannot be achieved as the engine enters the threshold of unacceptable reliability levels well before the 500-hour mark.

The ECMS and HAEM strategies demonstrate a more gradual decline in engine reliability, mainly due to the hybrid architecture of the power plant, where the engine operating point is adjusted to meet the power demands. The ECMS, shows a reliability trend that suggests a better management of engine load and potentially reduced wear and tear over time compared to the baseline. Moreover, the HAEM, offers a slightly more conservative decline in engine reliability compared to ECMS. This could be attributed to its health-aware aspect captured by the WPHM, which affects the operating point decisions by avoiding regions of rapid reliability decline. This strategy can help in maintaining engine health over prolonged periods, thereby enhancing the prospects for autonomous operation.

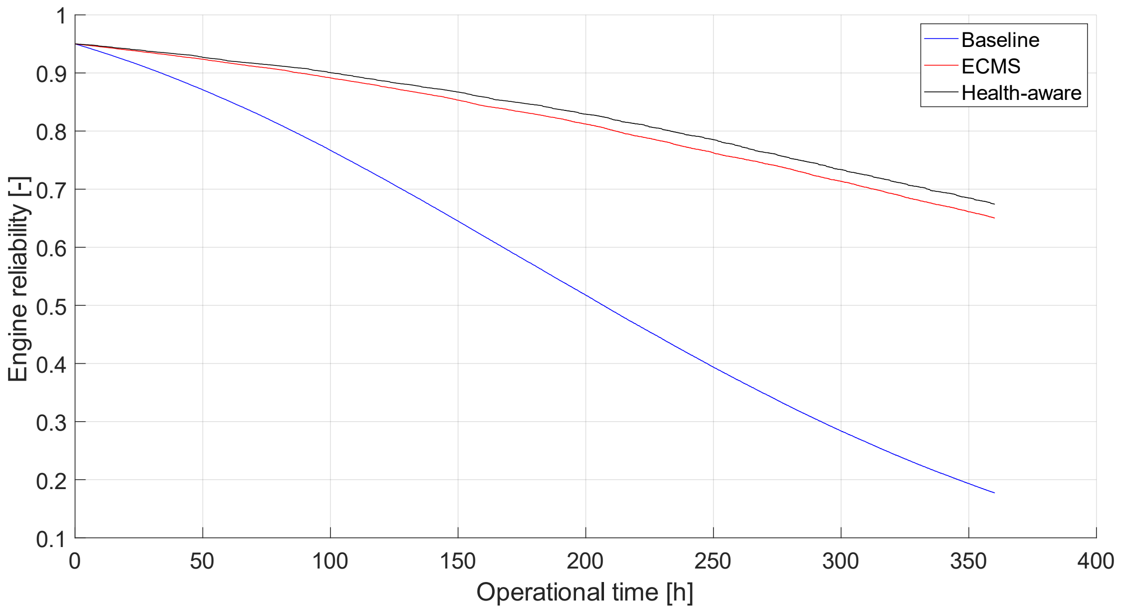

Figure 6.6: Engine reliability evolution.

Figure 6.7 presents the engine load diagram with superimposed BSFC contours, providing a visual depiction of the operational efficiency across different engine speeds and power outputs. The Figure 6.7 displays a scatter of operating points that have been achieved using operating points derived from both the ECMS and HAEM.

By using the HAEM, the operating points show a clear pattern of avoidance below the 20% load region and near the torque limit. This operation not only enhances the engine's lifetime by preventing operation in less efficient and potentially damaging regions but also promotes safer operation by avoiding zones that could reduce the reliability of engine components. In contrast, the ECMS's operating points are more dispersed across the entire engine operating region, suggesting a strategy that prioritises fuel efficiency without considering the health-aware aspect. This method, while effective for optimising fuel consumption in real-time, does not consider the long-term implications of operating at loads and speeds that could accelerate wear and decrease reliability.

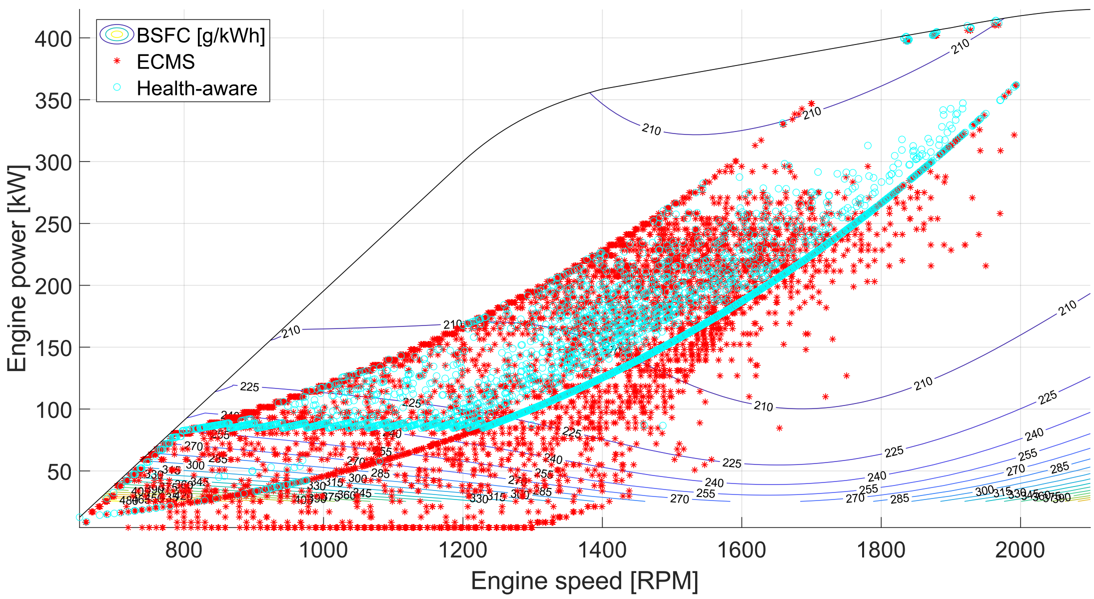

Figure 6.7: Comparison of the engine operating points.

6.3. Case Study II: Health Monitoring of a Short-sea Shipping Cargo Vessel

This section presents the results of the second case study concerning a short-sea shipping cargo vessel. The operating profile introduced in Section 5.3.2 is used for running the ECMS as the energy management strategy to obtain the performance results focusing on fuel consumption. Subsequently, the operating profile is extended to last 500 hours to investigate if the power plant can be operated without human intervention to transition into autonomy according to the suggestion from the results of the MUNIN project (Abaei et al., 2021). The obtained results are analysed to assess the health condition of the power plant at the end of the operating profile.

6.3.1. Performance Results

The setpoints for the various components within the power plant are presented in Figure 6.8. Similar to the pilot boat case study, the operating profile represents operational time rather than calendar time. Since the operating profile has different operational modes, the target SOC is adjusted accordingly for each mode, as discussed in Section 5.3.2.

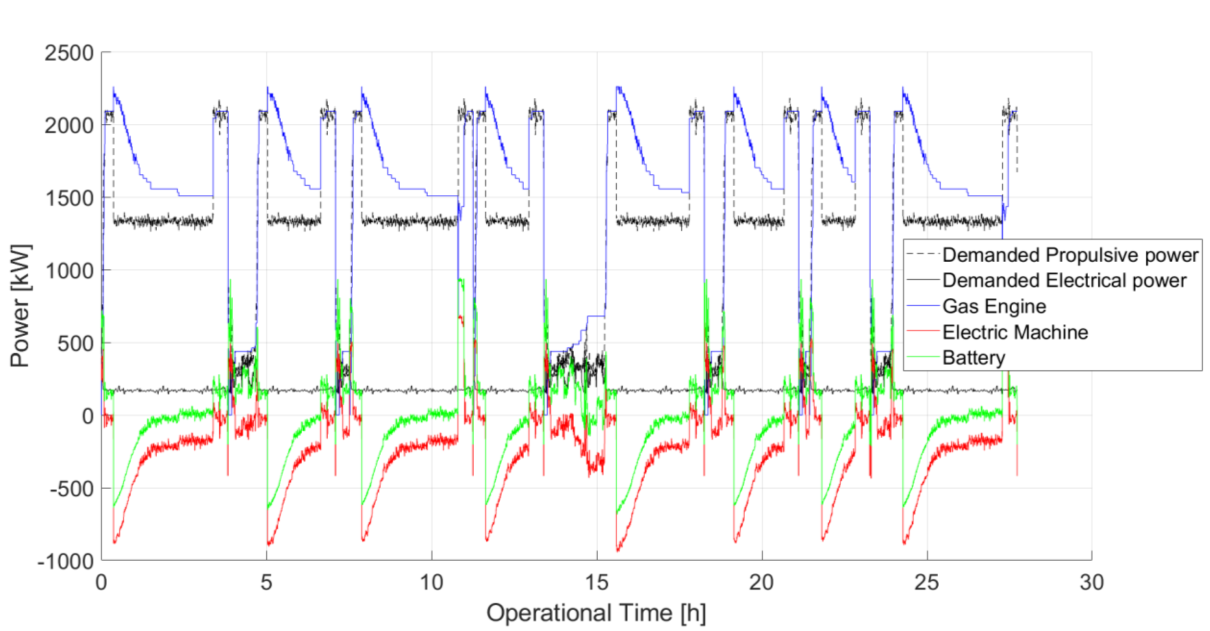

Figure 6.8: Power plant components operating setpoints results.

The graph presents the power setpoints of the gas engine, electric machine, and battery along with the demanded propulsive and electrical power. A key observation from the engine setpoints is their frequent operation at high loads, closely aligning with regions of optimal BSFC. This operational characteristic can be attributed to the use of ECMS with variable SOC target which tries to optimise fuel efficiency, particularly during peak demand periods. Conversely, during periods of low demand, where operation falls into inefficient BSFC regions, the strategy shifts the load to the electric machine, which draws power from the battery.

The load fluctuations are absorbed by the electric machine and the battery while the engine maintains a constant load, with fewer and less pronounced fluctuations. Such a pattern of operation, where the engine load does not present variability, can have substantial benefits. The engine operates in a steady state, which is typically associated with reduced wear and tear, potentially extending the engine's life expectancy and simplifying maintenance requirements.

The negative values observed in the graph, particularly for the electric machine and battery power setpoints, represent instances where the electric machine is generating power rather than consuming it, effectively acting as a generator. The battery's negative values indicate charging phases, receiving energy rather than supplying it to the electric machine. This operational characteristic allows the storage of energy during periods of excess production, which can then be used during peak demand periods, enhancing overall system efficiency.

The results presented in Figure 6.9 illustrate the battery SOC variation throughout the operating profile. As anticipated, the SOC exhibits cycles of discharging and charging, aligning with the different operational modes. Importantly, the SOC limits remain unviolated throughout the entire operating profile. Additionally, regarding the desired SOC, the obtained results clearly demonstrate the ECMS's ability to reach the target SOC for each operational mode. Finally, the initial SOC is set at 50%, and it is effectively managed to be kept close to this value at the end of the trip.

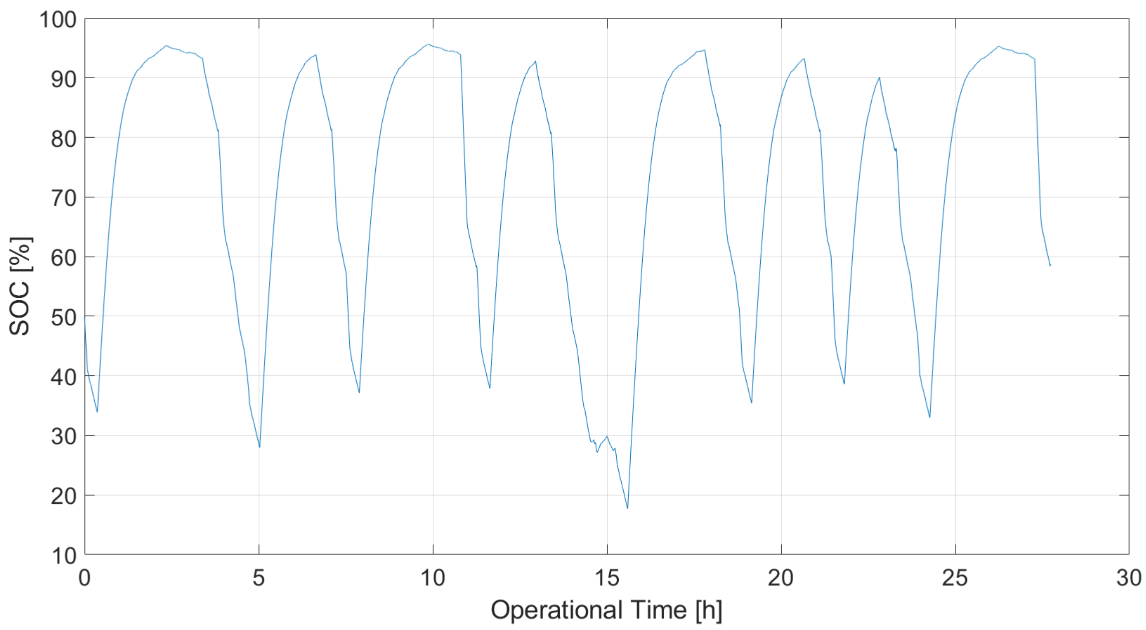

Figure 6.9: Battery State of Charge time variation results.

Since the operating profile of the original power plant was used, a comparison is performed. Figure 6.10 presents the engine operating points for both configurations (original and parallel hybrid) within the BSFC map. Given the use of a controllable pitch propeller, the engine speed is adjusted to ensure operation at optimal BSFC points for various loads. This behaviour is validated through the results as in both cases consistent operation is achieved at optimal BSFC points. However, it's important to note that this figure doesn't provide information on the frequency of selecting each engine operating point during the trip since it plots the operating points obtained through the trip. It can be observed that the parallel hybrid configuration demonstrated slightly lower total fuel consumption (2%) compared to the original configuration, which can be attributed to an increased number and duration of operating points within more efficient BSFC regions.

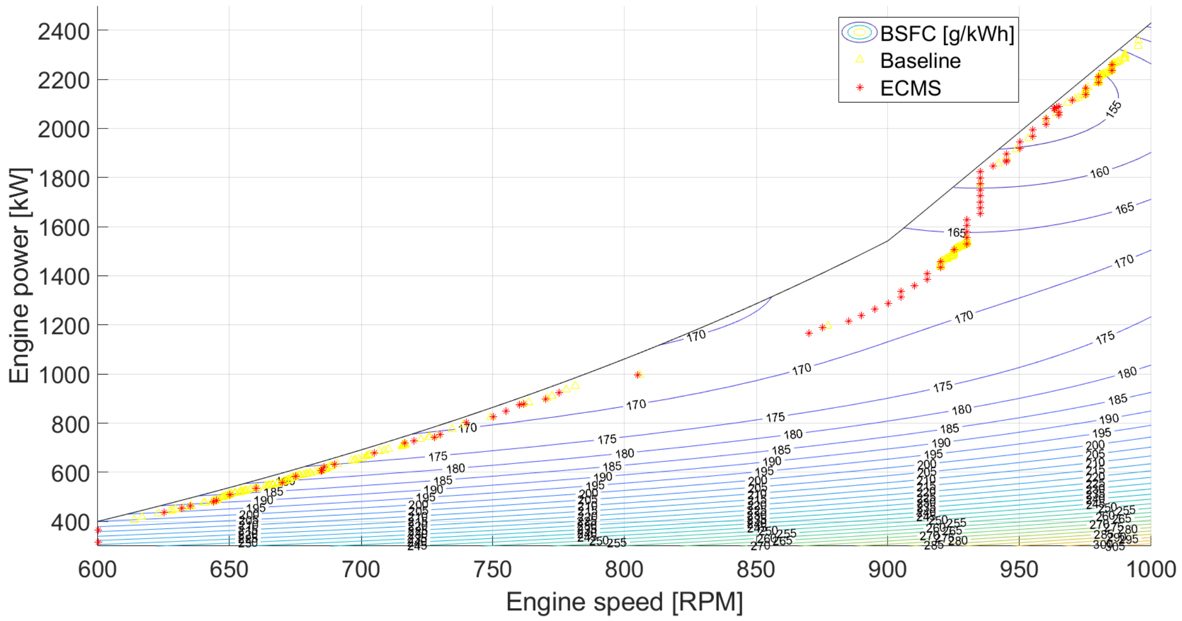

Figure 6.10: Comparison of the engine operating points.

6.3.2. New Condition Power Plant - 500 Hours Operation

After the performance results were presented, in this section the scenario concerning the new condition of the power plant is firstly discussed. The operating profile lasts approximately 500 hours while the initial time is set to zero. All the components are in a new state where the initial reliability is set to 1.

Table 13 presents the reliability and criticality concerning individual components that are highlighted with the appropriate colour based on the health levels as presented in section 5.3.2. The components are ranked based on the criticality importance measure at the start of the operating profile. Since the number of the individual components is more than one hundred, the 10 most critical components in this scenario are presented. The engine-driven and normal pumps within the low and high-temperature cooling water circuits present the highest criticality. These pumps have low reliability values, placing them within the degraded zone. This aligns with findings from a similar power plant study presented by Bolbot et al. (2021) concerning component criticality importance measure order, as most failure rate values are based on the OREDA database.

Table 13: New condition power plant components results.

Component	Criticality		Reliability		
	Initial (t=0)	Final (t=500)	Initial (t=0)	Final (t=500)	Difference [%]
Compressor	0.123	0.014	1	0.996	-0.4
Turbine	0.059	0.004	1	0.999	-0.1
Exhaust Valve	0.052	0.003	1	0.999	-0.1
Intake Valve	0.052	0.003	1	0.999	-0.1
LT Pump Engine	0	0.324	1	0.704	-29.6
HT Pump Engine	0	0.333	1	0.704	-29.6
LT Pump	0	0.324	1	0.704	-29.6
HT Pump	0	0.332	1	0.697	-30.3
Filter 1	0	0.004	1	0.965	-3.5
Filter 2	0	0.004	1	0.965	-3.5

In Figure 6.11, the criticality importance measure variation over time is presented for the above components. The components that have the same failure rate are grouped. It can be observed that criticality changes dynamically over time. As anticipated, the compressor emerges as the most critical component before 300 hours of operation, which aligns with its high failure rate and the fact that its failure can lead to a complete engine shutdown, since it is a single component. Nonetheless after 300 hours, the cooling water pumps exhibit an increase in criticality over time, while the other components demonstrate a decline in their criticality. This behaviour can be attributed to the decreasing reliability values corresponding to increasing failure rates as time progresses, captured by the WPM. It is evident that the criticality in cooling water pumps is accelerating at a notable pace in this scenario. This should serve as a warning for the ship operator, indicating the requirement for proactive measures to avoid entering the failure region. These measures might include operating the engine within specific regions to mitigate further failure propagation.

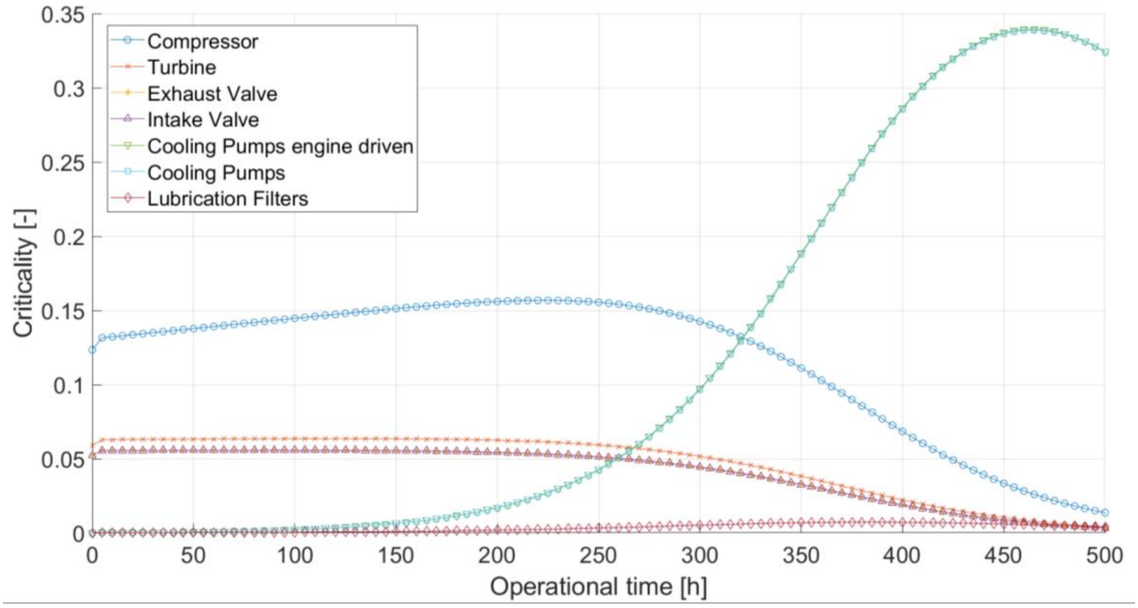

Figure 6.11: Component criticality importance measure time variation at new condition power plant.

Table 14 presents the results pertaining to the subsystems, each highlighted in the corresponding colour. All the subsystems remain within the healthy region. The cooling water subsystem, however, is very close to entering the degraded region, primarily due to the lower reliability values of the pumps. Additionally, Figure 6.12 presents the subsystem reliability time variation for the cooling water subsystem and lubrication subsystem, as the other subsystems do not present significant variations. It is noticeable that the cooling water subsystem experiences a more rapid decrease in reliability compared to the lubrication subsystem. This can be attributed to the presence of multiple components within the cooling water subsystem, notably the pumps, which are increasing in criticality. These observations should serve as warning signals to ship operators, highlighting the decrease of subsystem health and prompting them to consider preventive actions to avoid entering the failure region.

Table 14: New condition power plant subsystem results.

Subsystem	Initial (t=473)	Final (t=500)	Difference [%]
Lubrication	1	0.970	-3.0
Cooling	1	0.806	-19.4
Fuel Gas	1	0.997	-0.3
Intake	1	0.996	-0.4
Exhaust	1	0.998	-0.2
Mechanical Parts	1	0.996	-0.4
Battery	1	0.999	-0.1
Electrical Propulsion	1	0.999	-0.1

From the results in this scenario, it can be inferred that achieving the 500-hour autonomous operation limit may be challenging, as the criticality of specific components are accelerating. Nevertheless, this simulation before the trip, provides valuable insights for the ship operator, offering criticality assessments of individual components and allowing for an evaluation of subsystem health, which can help identify potential safety risks.

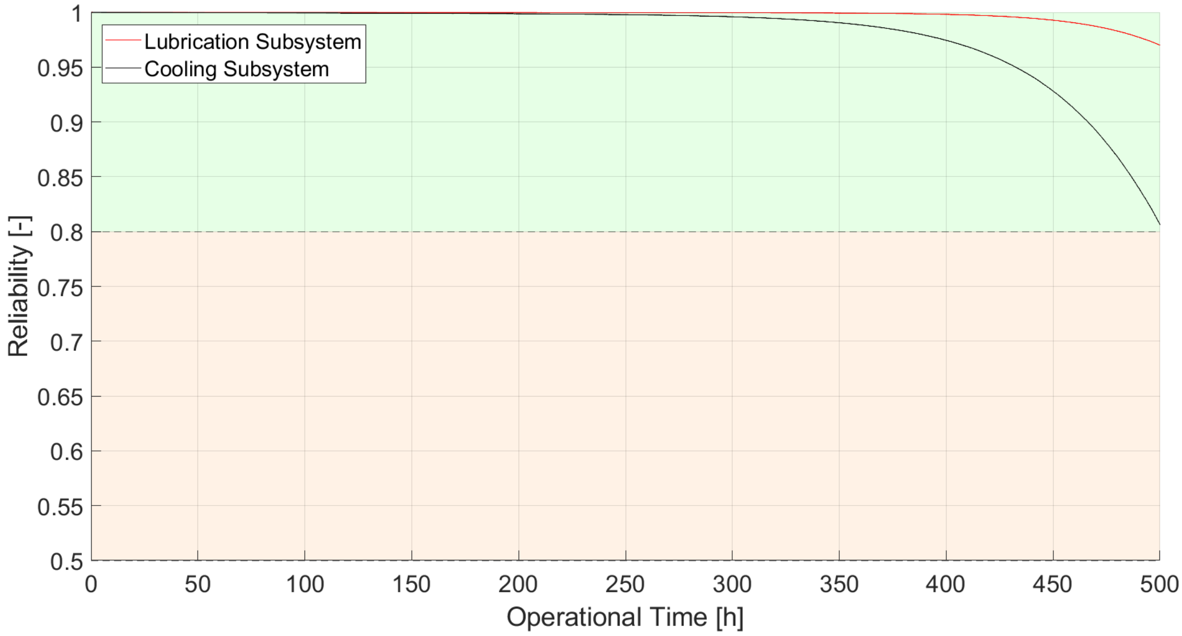

Figure 6.12: Subsystem reliability time variation at new condition power plant.

6.3.3. Compressor in Degraded Region - 500 Hours Operation

This section presents the scenario in which the compressor is in the degraded region, while all other components remain in new condition. The initial reliability of the compressor is set at 0.80, which is the transitioning value entering the degraded region. This scenario can be considered of significant importance as the failure of a single component results in the complete shutdown of the engine.

Table 15 presents the reliability and criticality of the power plant components over the 500-hour operating period. Components are ranked according to their initial criticality. In the beginning of the operating profile, the compressor is identified as the most critical component, principally due to its lower initial reliability and being a single component within the system. While the compressor starts as the most critical due to its degraded state, the reliability of other components begins to diminish over time. This decline is attributed to their inherently higher failure rates, which, increase over time using the WPM. Consequently, components that were initially less critical may ascend in criticality ranking as their condition degrades and the probability of their failure grows.

Table 15: Compressor in degraded region components results.

Component	Criticality		Reliability		
	Initial (t=0)	Final (t=500)	Initial (t=0)	Final (t=500)	Difference [%]
Compressor	1	0.527	0.8	0.676	-15.5
Turbine	0	0.001	1	0.999	-0.1
Exhaust Valve	0	0.001	1	0.999	-0.1
Intake Valve	0	0.001	1	0.999	-0.1
LT Pump Engine	0	0.106	1	0.704	-29.6
HT Pump Engine	0	0.108	1	0.704	-29.6
LT Pump	0	0.106	1	0.704	-29.6
HT Pump	0	0.108	1	0.697	-30.3
Filter 1	0	0.001	1	0.965	-3.5
Filter 2	0	0.527	1	0.965	-3.5

Figure 6.13 presents the dynamic evolution of criticality over time. As it is expected with different initial conditions, different criticality evolution is expected compared to the new condition scenario. Initially, the compressor, starting from a degraded state, is assigned the highest criticality due to its potential to cause a complete system shutdown upon failure. This is visually represented by a criticality value starting at one. As operating time advances, the criticality of the compressor exhibits a gradual decline, which can be attributed to the increasing criticality of other components, such as the cooling water pumps. This increase in pumps criticality should highlight a shift in focus areas for maintenance and monitoring. The figure distinctly contrasts with the results observed under new condition scenario, where components like the cooling water pumps presented the highest criticality.

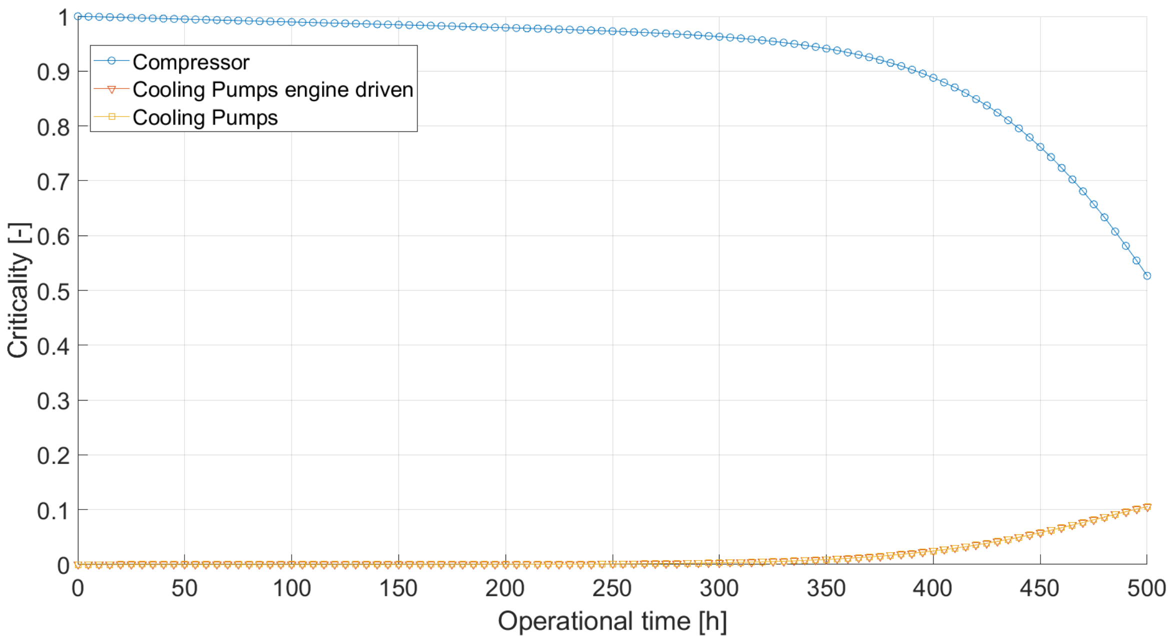

Figure 6.13: Component criticality importance measure time variation at compressor in degraded region.

Table 16 presents the results concerning subsystems. As it is expected all the subsystems apart from the intake subsystem remain in the healthy region. It is observed that the intake subsystem reliability has very close values to compressor reliability. This can be attributed to the fact that the failure of the compressor leads to a complete breakdown of the intake subsystem and subsequently the engine.

Table 16: Compressor in degraded region subsystem results.

Subsystem	Initial (t=0)	Final (t=500)	Difference [%]
Lubrication	1	0.970	-3.0
Cooling	1	0.806	-19.4
Fuel Gas	1	0.997	-0.3
Intake	0.85	0.676	-15.5
Exhaust	1	0.998	-0.2
Mechanical Parts	1	0.996	-0.4
Battery	1	0.999	-0.1
Electrical Propulsion	1	0.999	-0.1

In Figure 6.14, the reliability evolution of the lubrication and cooling subsystems are once again plotted, and they exhibit behavior similar to that observed under new condition, due to their identical initial reliability values. However, in this figure the intake subsystem reliability is plotted, which includes the compressor. The intake subsystem has also transitioned into the degraded region, mirroring the reliability values of the compressor. This behaviour significantly impacts the entire intake subsystem, underscoring the criticality that the ship operator must manage. In this case the ship operator can be informed about the criticality of components that do not have redundant arrangements, which can lead to the unavailability of the subsequent system. Nevertheless, the electrical propulsion subsystem, which has the electric machine and the battery inside, remains unaffected which can offer a reserve to supply certain propulsive and electrical demands.

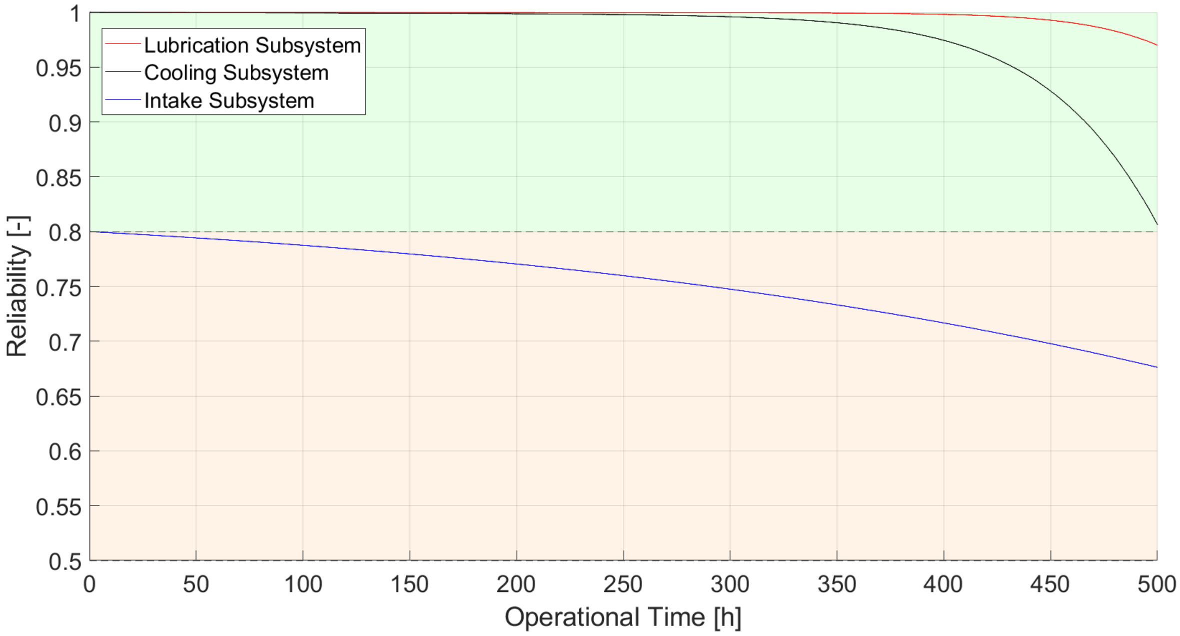

Figure 6.14: Subsystem reliability time variation at compressor in degraded region.

6.3.4. Lubrication Filter in Degraded Region – 500 Hours Operation

This section presents the scenario in which a single lubrication oil filter has entered the degraded region, with all other components preserved in a new condition. Analogous to the scenario involving the compressor, the initial reliability of this particular filter is set at 0.80, signifying its entry into the degraded region. However, this scenario differs from the one involving the compressor in a crucial aspect: while the failure of the compressor could result in the entire subsystem becoming unavailable, the lubrication system is designed with redundancy. Here, the presence of a second filter, serving an identical function, provides a layer of resilience against system failure.

Table 17 presents the reliability and criticality findings for the power plant components. At the beginning of the operating profile, the compressor remains the component with the highest criticality. However, as the operational period extends, the filters demonstrate an elevated increase in criticality, compared to their behaviour under new conditions. Notably, by the end of the operating profile, one of the lubrication filters is observed to enter the failure region. This behaviour can be linked to the inherently high failure rates of lubrication filters, as recorded in the OREDA database, compounded by an increasing rate of failure projected by the WPM. The transition of the filter into the failure region is a clear indication that maintenance actions are required, specifically the replacement of the affected component. The ship operator must prioritise attention on this filter, as its compromised function could have detrimental impacts on the lubrication system's performance.

Table 17: Lubrication filter in degraded region components results.

Component	Criticality		Reliability		
	Initial (t=0)	Final (t=500)	Initial (t=0)	Final (t=500)	Difference [%]
Compressor	0.117	0.012	1	0.996	-0.4
Turbine	0.056	0.004	1	0.999	-0.1
Filter 1	0.054	0.081	0.8	0.241	-69.9
Filter 2	0.054	0.081	1	0.965	-3.5
Exhaust Valve	0.049	0.003	1	0.999	-0.1
Intake Valve	0.049	0.003	1	0.999	-0.1
LT Pump Engine	0	0.306	1	0.684	-31.6
HT Pump Engine	0	0.304	1	0.704	-29.6
LT Pump	0	0.306	1	0.708	-29.2
HT Pump	0	0.304	1	0.690	-31.0

Furthermore, Figure 6.15 presents the variation over time of the criticality importance measure for each component. Consistent with the new condition scenario, the majority of components exhibit similar behaviour due to identical initial reliability values, except for the lubrication filters. It becomes apparent that the criticality of the lubrication filters is increasing in parallel, reflecting an identical increase in criticality, even though their reliability values differ. This pattern underscores the significance of redundancy within the system; the two filters are deemed equally critical because they fulfil the same operational role.

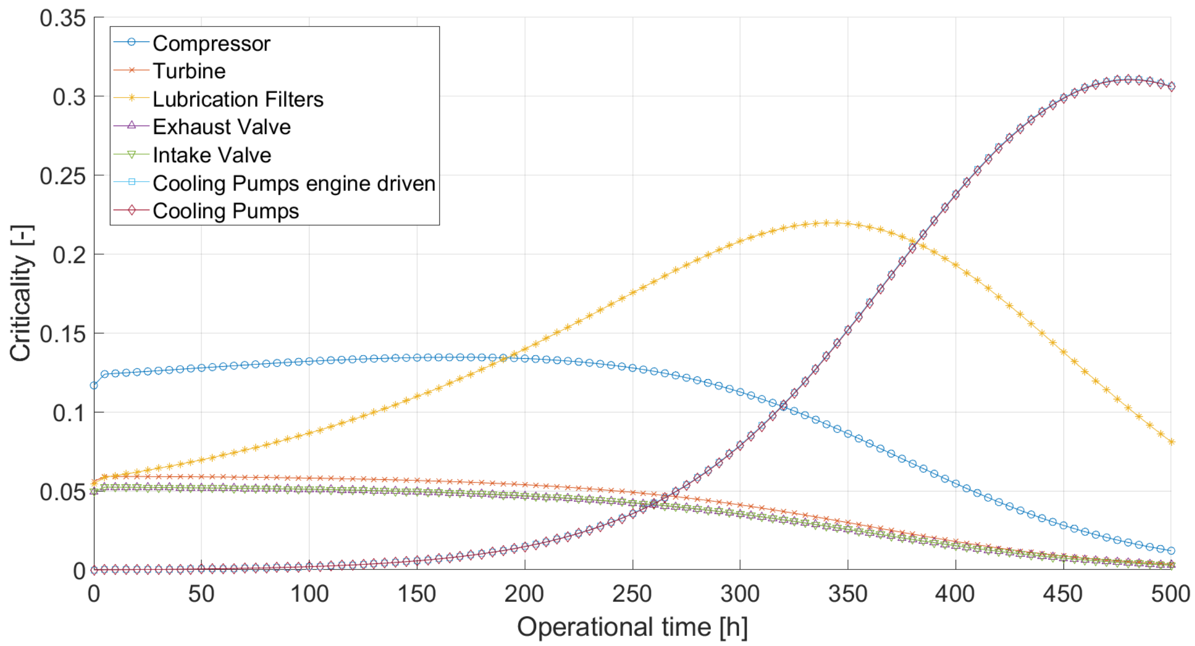

Figure 6.15: Component criticality importance measure time variation at lubrication filter in degraded region.

Table 18 provides a detailed breakdown of the results related to the subsystems. According to the guidelines for autonomous operations, systems designed with redundancy should be able to maintain or restore their operation following a single failure. The system's design should ensure that one component's failure does not impact other components' functionality. This design principle is essential to ensure that the overall system resilience is upheld, allowing for continued operation even in the face of unexpected failures.

Table 18: Lubrication filter in degraded region subsystem results.

Subsystem	Initial (t=0)	Final (t=500)	Difference [%]
Lubrication	1	0.950	-5.0
Cooling	1	0.801	-19.9
Fuel Gas	1	0.997	-0.3
Intake	1	0.996	-0.4
Exhaust	1	0.998	-0.2
Mechanical Parts	1	0.996	-0.4
Battery	1	0.999	-0.1
Electrical Propulsion	1	0.999	-0.1

Figure 6.16 presents a comparison in subsystem reliability between this condition scenario and the new condition of the power plant. It is evident that the deviation in reliability is marginal, with a decrease of only approximately 2%, even in the presence of a component

within the failure region. As anticipated, the redundancy engineered into the filter configuration does not impede the lubrication subsystem's functionality. This underlines the effectiveness of redundancy as a strategy to improve resilience, particularly when components are operating in degraded states.

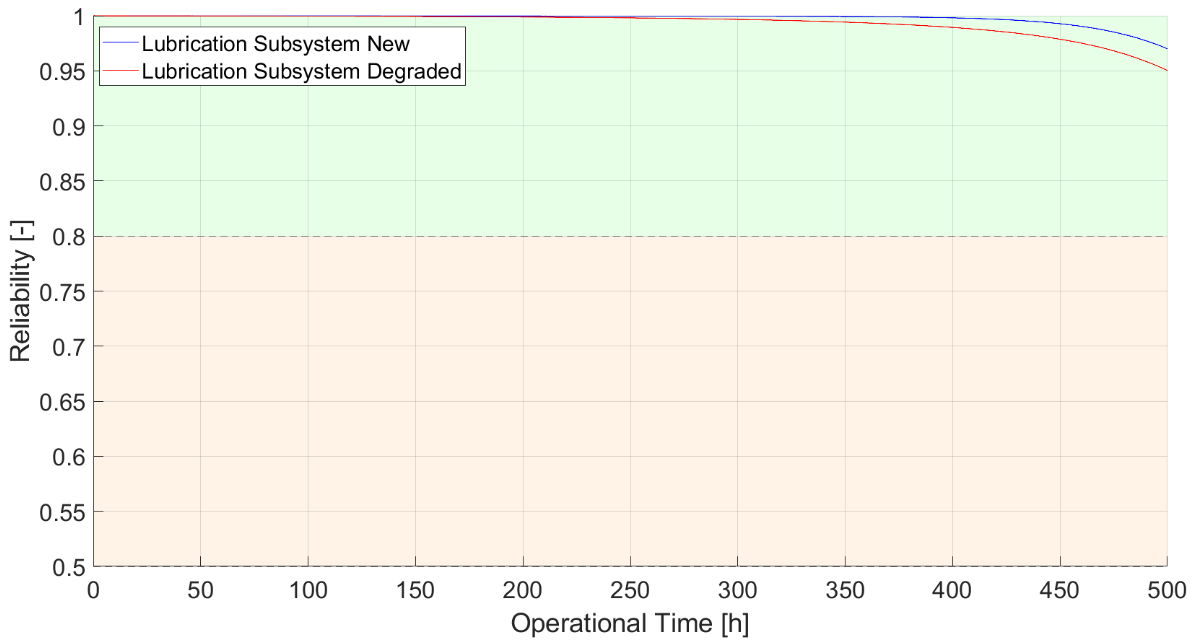

Figure 6.16: Subsystem reliability time variation at lubrication filter in degraded region.

6.4. Chapter Summary

In this the results generated from the case studies were presented and discussed in detail. In the first case study, it was demonstrated that the health aware energy management tool can find a balance between the trade-off operation of fuel consumption and system reliability, achieving higher reliability levels at the expense of a slight increase in fuel consumption. In the second case study, it was demonstrated that in the different scenarios of the power plant inside the short-sea shipping cargo vessel, criticality changes dynamically with time depending on the initial conditions. This tool can help provide warnings to the ship operators about the investigated system health condition.

7. Final Remarks & Conclusion

7.1. Chapter Outline

In this Chapter, a reflective discussion is conducted along with the presentation of the novelty and the research contribution to the academia and the maritime industry. The accomplishment of the aim and objectives of this research are discussed. Finally, the limitations of this study are highlighted whereas recommendations for future work are suggested.

7.2. Reflective Discussion

The proposed methodology was verified with two case studies by employing two reference power plants. These case studies concerned two hybrid power plants while the MUNIN project's target of autonomy concerning unmanned operation for 500 hours was investigated. The first case study concerns the health-aware energy management tool for the hybrid power plant of a pilot boat and the second case study the health monitoring tool for the hybrid power plant of a short-sea shipping cargo vessel.

The health-aware energy management tool has proven effective, particularly in managing the trade-off between fuel consumption and system reliability. By employing the utopia point method, it achieves a balance between these two conflicting objectives. As demonstrated by the case study results, enhancement of system reliability can be achieved with a marginal increase in fuel consumption by 1.5% compared to ECMS. The overall system failure rate was reduced almost 4 times at 300 h of operational time compared to ECMS, where components with greater contribution to reduction of system reliability are used less than the others.

It was demonstrated that the hybrid configuration brings substantial fuel savings of around 17% compared to the baseline configuration that has mechanical propulsion powered by a diesel engine. In addition, a rapid decrease in engine reliability was observed in the baseline configuration compared to the hybrid plant. For the engine, which is the most critical component, operation in more reliable regions can be achieved, which is expected to result in enhanced safety levels, avoiding rapid degradation.

The effectiveness of the tool is most pronounced in operating profiles characterised by high power demand variations, where multiple operating points can satisfy the power demand.

Conversely, for power plants with constant power demands, the tool's benefits may be less effective.

Additionally, the tool can potentially be effective in power plants with multiple components, as it allows for various configurations to meet power demands. This flexibility indicates potential applicability to a range of other power systems. Nonetheless, the tool does not account for emergency scenarios, where something unexpected might happens like the failure of a component, which requires further improvement to incorporate actions for reconfiguration planning.

The tool incorporates the effect of elapsed time and operational point to update component failure rate using the WPHM. However, it simplifies the failure rate to follow a Weibull distribution, which may not reflect the stochastic nature of real-world applications. Actual sensor measurements from ship operation could refine reliability estimates.

For successful shipboard implementation, it is crucial to develop methods that can accurately assess the health state of components and the system based on real ship performance data. Integrating this data into the energy management strategy could lead improve reliability improvement as well as prolonged system lifetime expectancy and reduction of maintenance costs.

In the second case study, a health monitoring tool was used to decompose the power plant into various components and subsystems while the ECMS was utilised to perform the energy management of the power plant. Since the operating profile of the short-sea shipping cargo vessel has different operational modes, the ECMS has been modified by changing the target battery SOC in each operational mode to improve performance.

It has been observed that in the hybrid configuration, engine operation in more efficient BSFC regions has been achieved while the fluctuations of the propulsive and electrical demands have been managed effectively by the electrical part of the power plant. In this way, the engine can operate in constant load which can prolong lifetime expectancy and improve maintainability. Additionally, the hybrid configuration has been benchmarked with the original power plant in terms of fuel consumption. Nevertheless, the fuel consumption improvement has been negligible, as a controllable pitch propeller is used which optimises the engine load given the propeller’s rotational speed.

Apart from the performance results, the focus of this case study concerns the health monitoring of the power plant to serve as a decision support tool to give information to ship operators about the criticality of components and provide an overview of how subsystem health is affected given an operating profile. Four different scenarios have been investigated where the initial component conditions have been set accordingly.

It has been observed that the criticality importance measure changes dynamically throughout the power plant's operation and depending on the initial conditions different components arise as critical.

In the first scenario the power plant's operation ends at 500 hours, which has been set as an autonomous operation target proposed by the MUNIN project. However, it was observed that the cooling water subsystem enters the degraded region. This is attributed to the low reliability values of the low and high temperature cooling circuit pumps, as by entering the degraded region criticality is increasing, affecting cooling water subsystem health. As a result, the mechanical part of the power plant concerning the engine operation can be critical after 500 hours of operation, posing challenges towards autonomous operation using existing setups.

In the second scenario, the compressor has been set to be in the degraded region while other components are in new condition. The compressor is a single component in the system without redundant arrangements, a its failure can result in engine shutdown. As it was expected, compressor reliability significantly affects the intake subsystem, which also enters the degraded region.

Lastly, in the third scenario, a redundant arrangement was tested. One of the two lubrication oil filters was set to be in the degraded region. It was inferred that the power plant remains unaffected as all the subsystems remain the healthy region. As a result, even though one of the components can be in the failure region, where the ship operator can be notified about its criticality and its health state, by having sufficient redundancy the power plant can continue its normal operation.

Unlike the previous case study, the health-aware energy management was not effective for two reasons. This ship primarily operates in a consistent sailing mode, characterised by a lack of diversity in the operating profile. Unlike the pilot boat where the power demands can vary between low and high loads during the operating profile, in the short-sea shipping cargo vessel this pattern is not observed as during sailing, which account for the biggest part of the operating, the power demand remains in a constant region. Additionally, most of the components inside the DBN are modelled without the operating point affecting component reliability, as an explicit relationship between the load and the low-level components cannot be easily established. Unlike fuel consumption, which varies and can be optimised, reliability remains identical across the evaluated operating points.

While reliability served as an effective health indicator in this case study, other health metrics can be investigated. By considering alternative indicators like risk and component RUL, the tool could provide a more comprehensive assessment of the power plant's health, potentially enhancing its predictive capabilities.

The adaptability of the tool is highlighted by its potential for deployment in various power plant configurations. By inputting the specific structure of subsystems and components, the tool can be used for system health monitoring across different types of power plants.

For practical shipboard application, integrating real-time sensor data presents an opportunity to accurately reflect the health status of subsystems and components. This data-driven approach can provide an overview of the power plant's condition which can help the ship operator as a decision support tool.

7.3. Novelty & Research Contribution

In this section, the novel aspects and contributions of this research are discussed, addressing the research gaps which were identified during the literature review. The novel aspects of this thesis are included both the in proposed methodology and in the developed tools.

The concept of autonomic systems was exploited to provide motivation towards developing the proposed methodology to transition into autonomous operation. By emphasising both performance optimisation and health monitoring, the proposed methodology integrates these concepts to achieve the health-aware operation of hybrid power plants.

Based on this integration, system health consideration was incorporated into the high-level control of the power plant. This was accomplished by incorporating the health monitoring module's output into the energy management of the hybrid power plant. To the best of the author's knowledge, it is the first time that such an approach is presented in the pertinent literature concerning marine applications.

As for the tools, a health-aware energy management tool was developed which demonstrated the operation of hybrid power plants considering a trade-off between fuel consumption and system health consideration. This was achieved by using a decision-making method that adequately considers the trade-offs between conflicting objectives.

Additionally, this tool can capture the influence of operating points using component reliability. This was achieved by updating the failure rate based on both elapsed time and operating conditions.

Another significant contribution is the development of an advanced health monitoring tool that dynamically assesses the power plant's health condition. This tool considers the interactions between components, providing a comprehensive understanding of system-level health assessment. It has the capability to calculate and rank components in terms of criticality and offer estimations regarding subsystem health throughout the power plant’s operation. By specifying an operating profile, this tool can be used to make predictions about future health condition.

Finally, the health monitoring tool uses sensor measurements to update failure rates and component reliability. This integration can help represent system health within the power plant by using operational data.

Regarding the applicability of the proposed methodology, Figure 7.1 presents a high-level graph for the actual shipboard application. The boxes in the flowchart, highlighted with different colours, present the boundaries between the proposed methodology and the components for the shipboard implementation. The output of the proposed methodology concerns the setpoints of the various components included within the power plant. The setpoints must be given to the actual components in the physical power plant, which are undergone under low-level controllers to give the actual operating points. All the necessary parameters are then fed back to the tools of the proposed methodology to update the setpoints at the next time step, based on the requested power and the power plant’s condition.

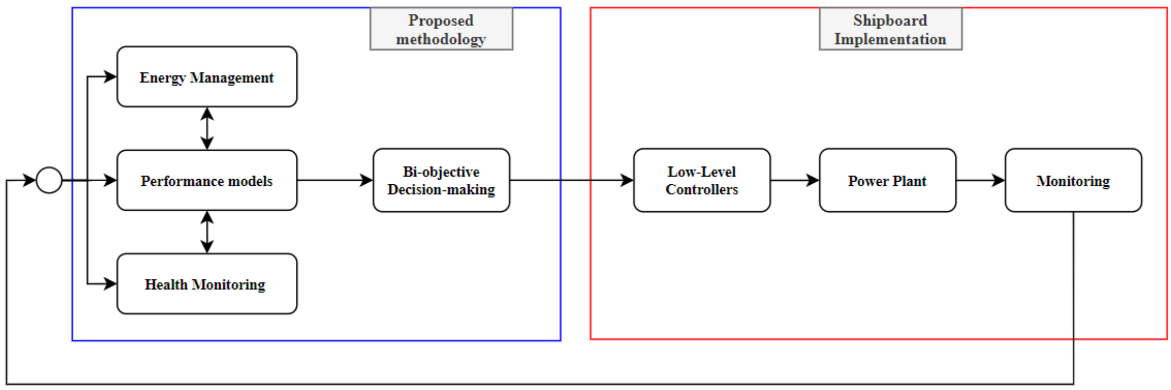

Figure 7.1: High-level control process framework for shipboard implementation.

Regarding the implications in academia, this study introduces the concept of health-aware control, which is a subject that has remained relatively unexplored in marine applications. Traditionally, energy management studies mainly focus on optimising performance metrics, such as minimising fuel consumption and reducing emissions. Additionally, the integration of high-level control and reliability engineering into the power plant's operation is one of the essential steps towards autonomous operations. This study is expected to contribute towards the development of supervisory control of autonomous power plants, with the gradual adoption of more sophisticated supervisory control strategies to conventional power plants.

As for the wider industrial implications, the developed health monitoring tool can serve as a decision-support tool for ship operators. This tool can display warnings and potential risks by informing the ship operator about critical components and the power plant's health state. This information can potentially help in maintenance planning, by providing estimations of the component health state to prioritise maintenance tasks and potential replacements, both in normal operation and emergency situations. By utilising real sensor measurements this tool can be further developed to allow for precise system-level health estimation and predictions and serve as a product for intelligent system health monitoring.

7.4. Review of Research Objectives

In this section, a discussion is presented on how effectively the research objectives have been covered in this study.

The first objective concerns the literature review on autonomous ship power plants. In Chapter 2, existing research and industrial projects were reviewed and a critical consideration of autonomous ship power plant requirements was performed. From the requirements, it was inferred that hybrid power plants can be a viable solution towards autonomy and consequently their advantages were discussed. Afterwards, the areas of energy management strategies, prognostics and health management, system-level dependability analysis and health-aware control were explored to give insights regarding the development of the proposed methodology.

The second objective concerned the development of a methodology that integrates energy management with health monitoring to enable health-aware energy management of hybrid ship power plants. This objective combines the output of the energy management, which prioritises energy efficiency by minimising fuel consumption, with the output of the health monitoring module which prioritises system reliability. This was achieved by using the utopia point method for the decision-making between two conflicting objectives, which demonstrated its effectiveness at the first case study, by increasing slightly the fuel consumption but significantly improving system reliability.

The third objective was the refining and adapting models to simulate and analyse the performance of hybrid ship power plants. This was achieved by adapting appropriate mathematical and computational models to represent the behaviour and interactions of the power plant components. The components of the investigated power plants include electric machines, ICEs and batteries which were modelled using efficiency maps, fuel consumption maps, and first principles models. Although these models are simplified, they offered a balance between accuracy and computational cost to perform rapid evaluation of the operating points during the control process execution.

The fourth objective concerns the deployment and evaluation of energy management strategies for hybrid ship power plants. In this study the ECMS was used as the main energy management strategy for both investigated hybrid power plants. Although, ECMS offers suboptimal results, it is less computationally heavy, and does not rely on detailed information about future operating conditions which can offer robustness to unknown power demands. This robustness was demonstrated, at the second case study where ECMS was modified by changing the battery's SOC target to account for the influence of the different operational modes. Additionally, to verify that ECMS achieves close to optimal results for fuel consumption a comparison was performed with DP at first case study, which is a widely used method that guarantees optimality.

The fifth objective was the implementation of health monitoring on ship power plants that are based on reliability. This was achieved by using DBNs to decompose the power plants into components and subsystems. One of the significant advantages of using DBNs was to gain a better understanding of how different components and subsystems influence the overall health and reliability of the power plant. This is accomplished through the utilisation of criticality importance measure, which assess the importance of individual components, and the investigation of individual component and subsystem reliability values, as demonstrated at the second case study. Additionally, two different methods were used in each case study to update component reliability based on the failure rate. At the first case study, the WPHM model was used to update the failure rate to account for both the operational time and operating point of the component, whereas at the second case study a method based on WPM was used to update the failure rate to account for random effects in component reliability.

The sixth objective concerns the selection of reference power plants. In this study the two reference power plants were selected based on the discussion of the applicability of ship types, considering the advantages of short-sea shipping applications discussed in Section 2.4.1. As a result, the power plants of a pilot boat and short-sea shipping cargo vessel were selected based on the transferring of non-hazardous cargoes and a simplified operational framework.

Finally, the effectiveness of the proposed methodology was demonstrated through the investigated case studies at the final objective. Overall, through the above objectives the aim was addressed by developing health-aware energy management strategies for hybrid ship power plants, integrating advanced monitoring capabilities and decision-making methods. However, it's important to note that this study has several limitations, and there is room for further improvements, as discussed in the following sections.

7.5. Limitations

In this research, especially in emerging fields like autonomous ships, limitations exist. These limitations encompass aspects of methods, models, assumptions, and data used.

The models considered do not directly influence the performance behaviour of the system. As a result, the performance models remain intact throughout the control process execution. In practice, component degradation often leads to reductions in performance, such as increased fuel consumption.

The models employed in this study encompass uncertainties (both epistemic and aleatory), which were not explicitly integrated into the control process. The performance models are idealised, and the output from real-world applications presents deviations. Additionally, the models used to update failure rates do not account for the influence of uncertainty in estimations.

The ECMS utilised a constant equivalence factor, tuned according to the employed operating profile. However, in real-world scenarios with variable operating profiles, this strategy may not guarantee optimal fuel savings. Adaptive methods with varying equivalence factors could be employed to address this limitation, requiring estimates of future power demands (Kalikatzarakis et al., 2018).

The reliability calculations relied on historical databases with population-based component reliability values. Although failure rates were updated to account for the effects of operational time and load, actual reliability may differ significantly in real conditions with noisy environments.

System complexity can impact health estimation. The case study of the pilot's boat power plant in this study had a relatively simple structure, whereas real applications often involve complex topologies with interdependent systems, subsystems, and components.

Most components in the developed health monitoring tool were mechanical parts, and the influence of software was not explored sufficiently. In autonomous operations, software can significantly impact system reliability. Additionally, BNs although capable of capturing multi-state systems and complex relationships, were employed with noisy gates and two states in this study.

7.6. Future Research Directions

Building upon the developed methodology, the insights from the identified research gaps, and the findings in the case studies, it becomes evident that there is room for further advancements in the field of health-aware control for autonomous ships.

While the proposed methodology focused on health-aware control, there is an opportunity to expand its scope to include risk in the control process of power plants. Emerging trends in autonomous operation emphasise the importance of supervisory risk control (Parhizkar, 2022), (Utne et al., 2017). Integrating risk can enhance the system's decision-making abilities, enabling it to evaluate and manage risks during operation.

To further improve health-aware control as more objectives are incorporated, future research can delve into multi-objective optimisation and multi-criteria decision-making. In this respect the power plant operation can be expanded by incorporating multiple criteria, allowing for more comprehensive decision support systems that aid operators in managing power plants efficiently.

This study did not explore responses to faults and emergencies. Future work should include fault management, effective failure propagation measures, and simulation of failure scenarios. Actions for reconfiguration can be developed to ensure the power plant continues its operation even in the event of a failure.

Autonomous ships face unique hazards and risks that require identification and assessment (Poikonen et al., 2016). Conducting failure simulations can help unveil previously unidentified risks and provide insights to enhance ship designs for increased safety and reliability.

Concerning the components inside hybrid power plants, certain components, such as batteries, experience performance degradation over time. This degradation can be divided into cyclic and lifetime degradation, influenced by the number and nature of charging/discharging cycles. Future research can employ ageing and temperature models to consider the impact of these cycles, providing more accurate predictions of battery health (Rosewater et al., 2019).

The extensive use of real sensor measurements can be exploited further. Continuous measurement data can be recorded and stored for real-time or historical analysis, allowing for the early detection of impending faults or to analyse the correlation of past failures by using recorded data. This approach can significantly enhance the ability to predict the health state of the system by relying on actual information compared to historical databases.

Finally, apart from addressing solely the power plant operation, future research can shift towards the synthesis and design aspects of power plants. This includes calculating optimal battery sizes for hybrid configurations and determining the optimal configuration based on metrics related to redundancy, availability, and maintenance. This can help introduce power plant configurations that are tailored to autonomous operation given the requirements.

7.7. Chapter Summary

In this concluding chapter, a reflective discussion is conducted. The novelty is presented, as well as the research contributions that are made to both academia and the maritime industry. A discussion is performed on how the set aim and objectives were achieved. The limitations of this research in the aspects of methods and models are highlighted. Finally, based on these limitations and the lessons learned, directions for future research are recommended.

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Appendix A Subystems Layout

The Bayesian Networks for the subsystems in the short-sea shipping cargo vessel are provided through figures A.1-A1.13.

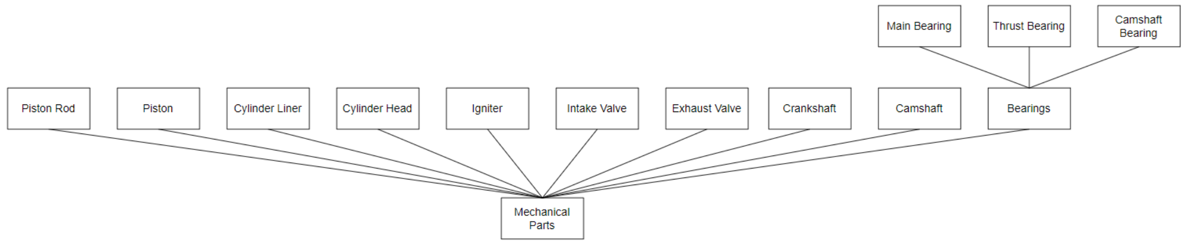

Figure A.1: Mechanical Parts Subsystem.

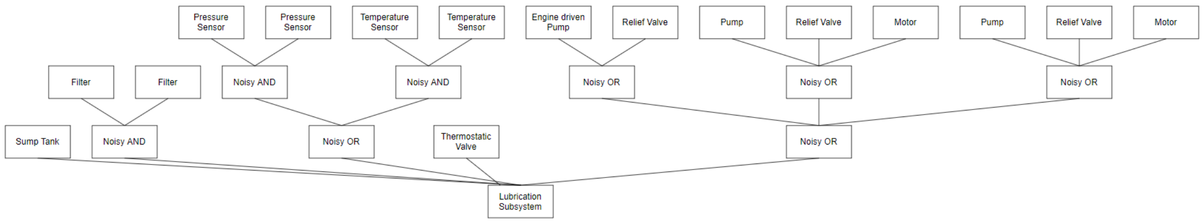

Figure A.2: Lubrication Subsystem.

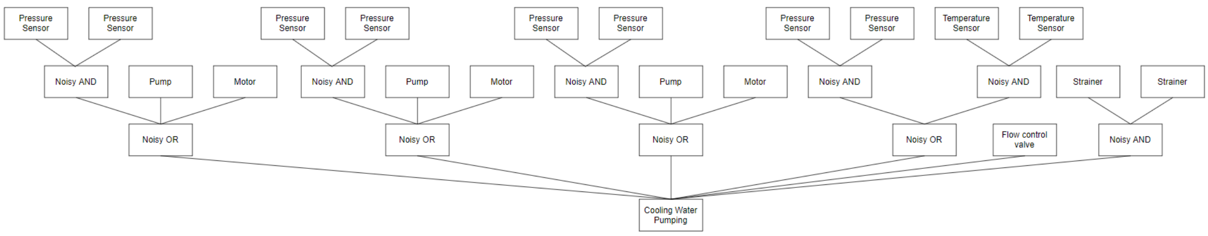

Figure A.3: Cooling Water Pumping Subsystem.

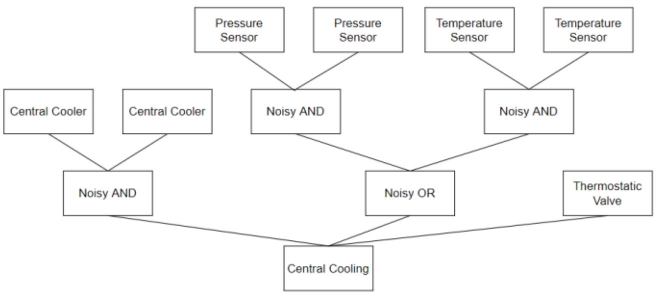

Figure A.4: Central Cooling Subsystem.

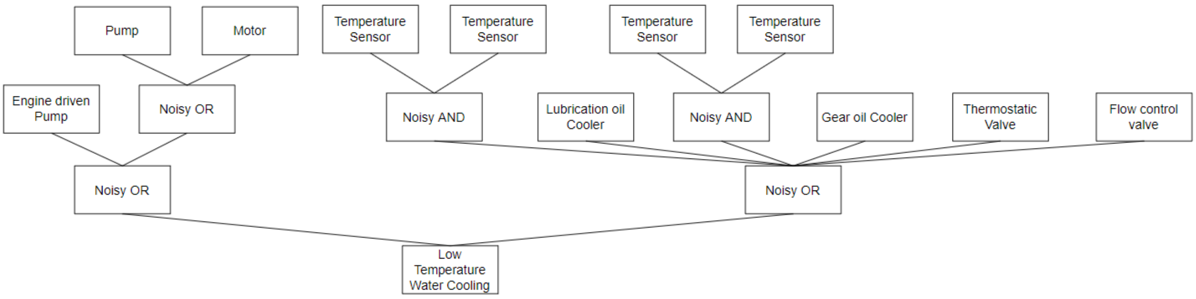

Figure A.5: Low Temperature Water Cooling Subsystem.

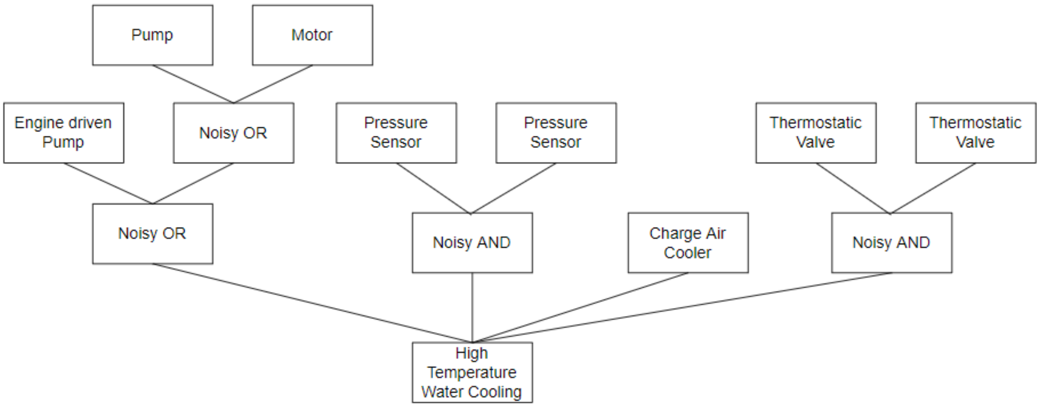

Figure A.6: High Temperature Water Cooling Subsystem.

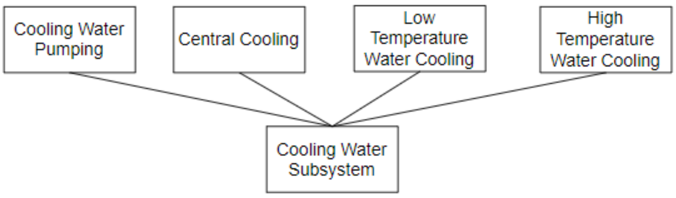

Figure A.7: Cooling Water Subsystem.

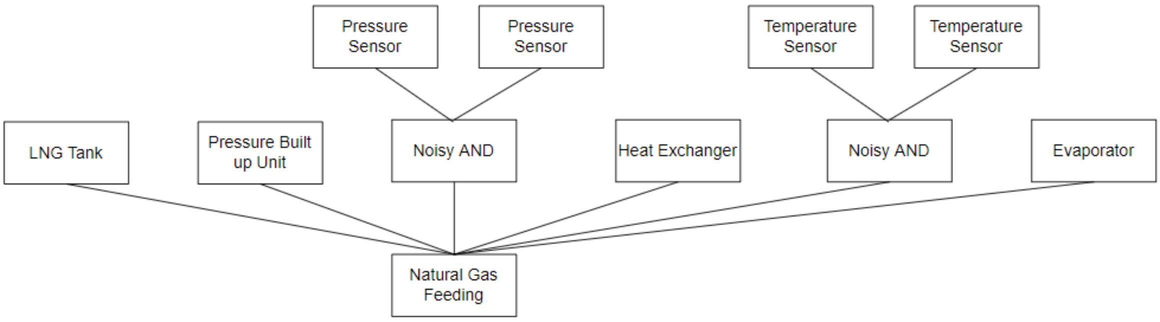

Figure A.8: Natural Gas Feeding Subsystem.

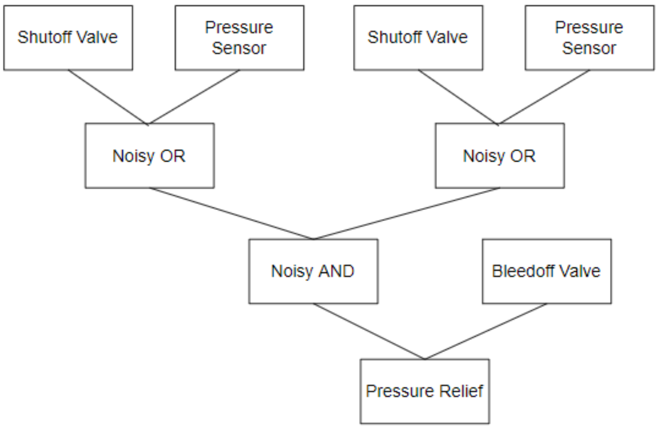

Figure A.9: Pressure Relief Subsystem.

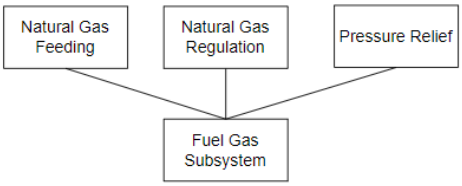

Figure A.10: Fuel Gas Subsystem.

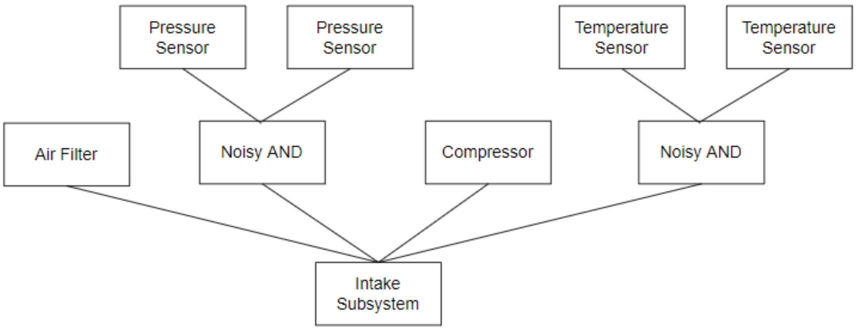

Figure A.11: Intake Subsystem.

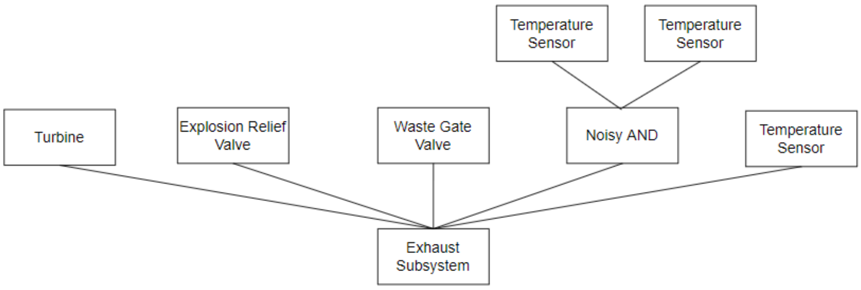

Figure A.12: Exhaust Subsystem.

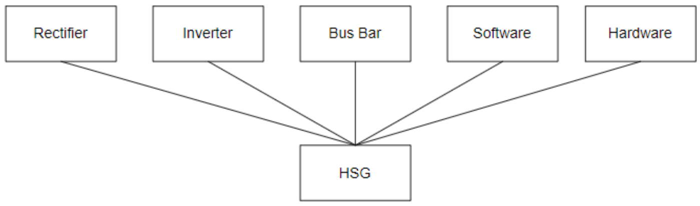

Figure A.13: HSG drive Subsystem.

Appendix B Failure Rate Data

The failure rates that have been used for the short-sea shipping cargo vessel are provided in Table 19 below.

Table 19: Component failure rates.

Component	λ [$\times 10^{-6}$ h^{-1}]	Source
Engine Components		
Centrifugal pump	769.62	(SINTEF and NTNU, 2015)
Lubricating oil filter	457.00	(Dionysiou and Bolbot, 2021)
Heat exchanger	53.89	(SINTEF and NTNU, 2015)
Pump motor	36.51	(SINTEF and NTNU, 2015)
Pressure relief valve	10.85	(SINTEF and NTNU, 2015)
Sump tank	12.70	(Dionysiou and Bolbot, 2021)
Thermostatic valve	39.60	(SINTEF and NTNU, 2015)
Strainer	40.18	(Kirolivanos and Jeong, 2022)
Pressure sensor	0.62	(Hauge and Onshus, 2010)
Flow control valve	39.60	(SINTEF and NTNU, 2015)
Temperature sensor	0.30	(Hauge and Onshus, 2010)
Bleedoff valve	10.85	(SINTEF and NTNU, 2015)
Flowmeter	2.00	(Hauge and Onshus, 2010)
Gas filter	0.42	(Milioulis et al., 2022)
Gas regulator	39.60	(SINTEF and NTNU, 2015)
Shut-off valve	26.43	(SINTEF and NTNU, 2015)
Solenoid valve	39.60	(SINTEF and NTNU, 2015)
Throttle valve	39.60	(SINTEF and NTNU, 2015)
Compressor	196.00	(Milioulis et al., 2022)
Turbine	93.85	(SINTEF and NTNU, 2015)
Pressure built up unit	28.83	(SINTEF and NTNU, 2015)
Heat exchanger LNG	42.75	(Milioulis et al., 2022)

Evaporator	4.51	(Bolbot, 2020)
LNG tank	77.80	(Milioulis et al., 2022)
Piston rod	16.31	(Cheliotis, 2020)
Piston	32.62	(Cheliotis, 2020)
Cylinder liner	16.31	(Cheliotis, 2020)
Cylinder head	16.31	(Cheliotis, 2020)
Igniter	14.85	(SINTEF and NTNU, 2015)
Camshaft	11.85	(SINTEF and NTNU, 2015)
Crankshaft	11.85	(SINTEF and NTNU, 2015)
Bearing	16.31	(Cheliotis, 2020)
Engine valve outlet	83.10	(SINTEF and NTNU, 2015)
Engine valve Inlet	83.10	(SINTEF and NTNU, 2015)
PTO/PTI		
Motor	43.76	(SINTEF and NTNU, 2015)
Electronic components		
Hardware	17.60	(Hauge and Onshus, 2010)
Software	6.18	(SINTEF and NTNU, 2015)
Circuit breaker	0.80	(Hauge and Onshus, 2010)
Inverter	21.31	(Gao et al., 2021)
Bus bar	0.41	(Vedachalam and Ramadass, 2017)
Battery components		
Battery	63.57	(Hauge and Onshus, 2010)
BMS	4.54	(SINTEF and NTNU, 2015)

Appendix C Efficiency Maps

The BSFC maps and the electric machine map used in this study are presented in the figures below.

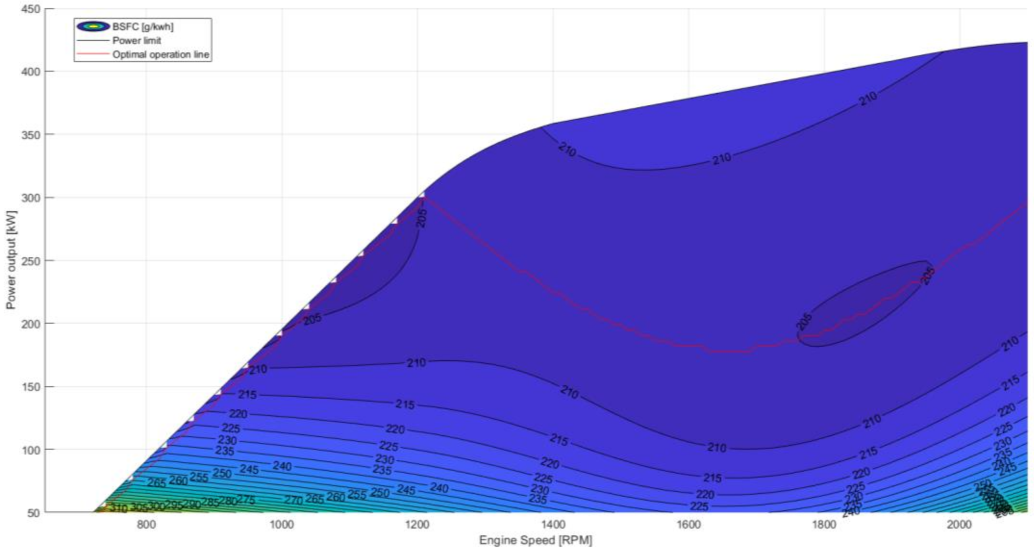

Figure C.1: Scania DI16M BSFC map (with optimal operation line).

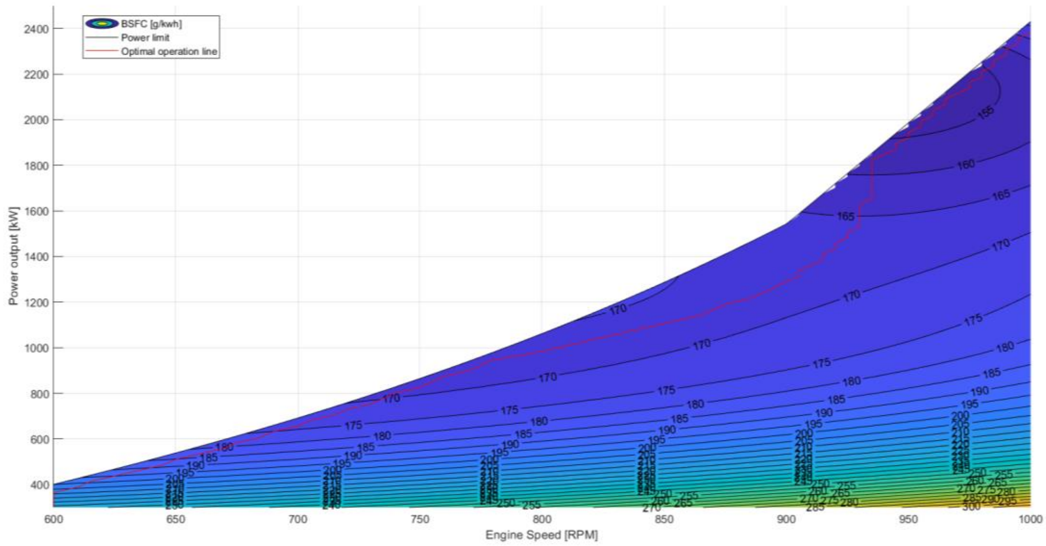

Figure C.2: Bergen C26:33L9PG BSFC map (with optimal operation line).

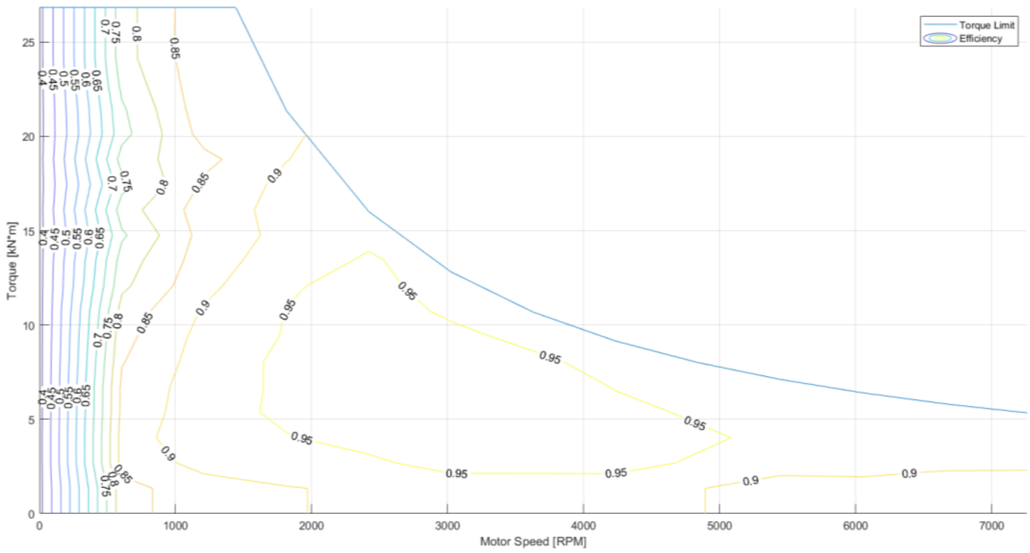

Figure C.3: 1100 kW electric Machine with 1500 RPM nominal speed efficiency map.

Appendix D Feature Maps

The feature maps used for the WPDP using sensor measurements are presented in the figures below.

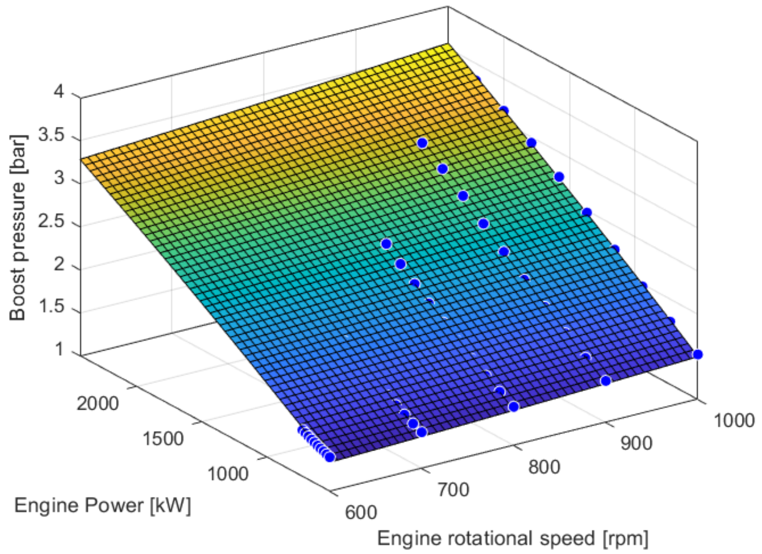

Figure D.1: Boost pressure map.

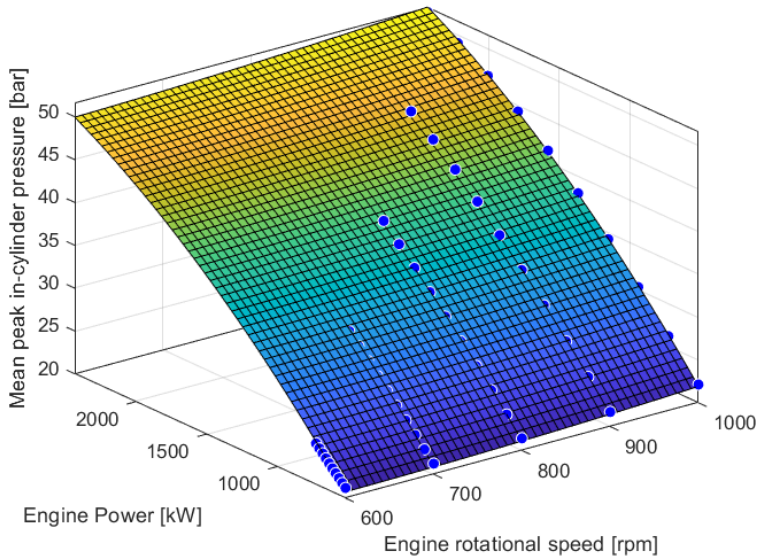

Figure D.2: Mean peak in-cylinder pressure map.

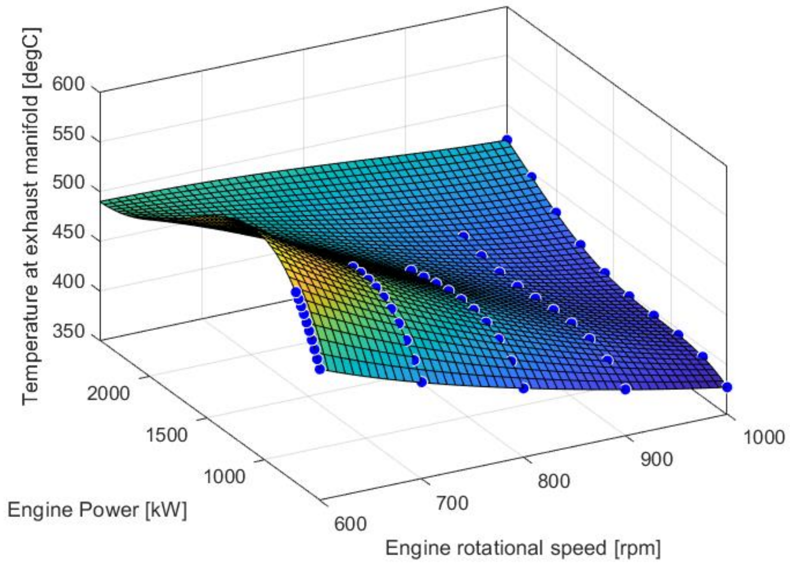

Figure D.3: Temperature at exhaust manifold map.

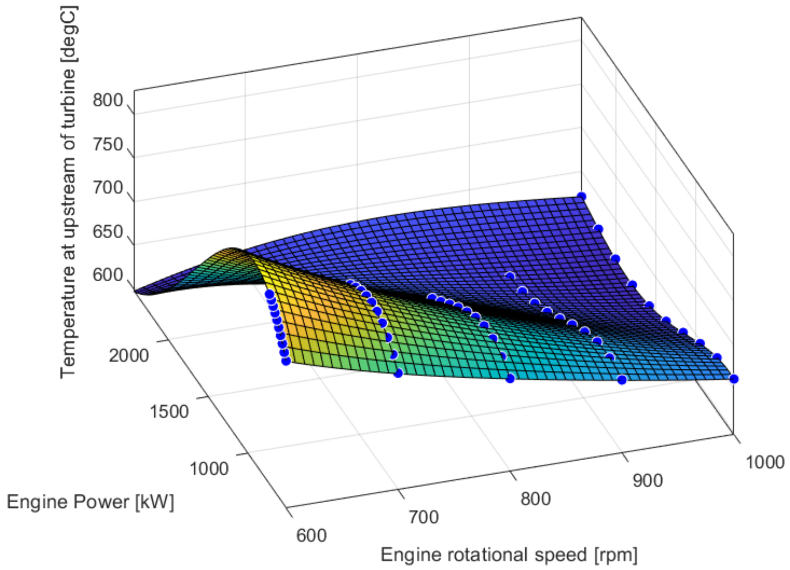

Figure D.4: Temperature at upstream of turbine map.