Md Jahirul Alam

From Prediction to Prescription: Integrating Risk Estimation with Optimization for Offshore Wind Farm Maintenance

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Use of Artificial Intelligence

During the preparation of this thesis, I used OpenAI (ChatGPT) to support language improvement, grammar correction, text refinement, and formatting of academic writing. I take full responsibility for the content of this thesis and confirm that all analyses, interpretations, methodology development, experimental implementation, results, and conclusions were developed and verified by me.

UNIVERSITY OF VAASA	
School of Technology and Innovation	
Authors:	Md Jahirul Alam
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ABSTRACT: Offshore wind farms are crucial in the transition to renewable energy. But their operation and maintenance (O&M) tasks remain costly and difficult. Maintenance planning is challenging due to harsh weather, limited accessibility, vessel requirements, and crew shortages. Predictive maintenance methods can identify possible equipment failures, but many of the studies that are now available focus mainly on prediction and offer little assistance for maintenance decision-making.

This thesis presents a predictive-prescriptive maintenance framework for offshore wind farms that integrates predictive maintenance alerts with maintenance scheduling. The system prioritizes maintenance tasks and evaluates the urgency of maintenance using Remaining Useful Life (RUL) and failure probability data. The tasks are then assigned with respect to real-life constraints like weather accessibility, crew availability, vessel capacity, and maintenance time.

Two scheduling strategies, a Mixed-Integer Linear Programming (MILP) optimizer and a Greedy heuristic scheduler, were tested. Predictive maintenance data was used to test the framework under various workforce availability conditions. The results show that the vessel capacity becomes increasingly important as workforce resources increase, but manpower availability is the key constraint in maintenance operations. By achieving higher maintenance completion rates, lower operational costs, and better resource use, the MILP optimizer consistently outperformed the Greedy scheduler.

The result shows that predictive maintenance is not enough to improve offshore maintenance performance. Effective scheduling is also necessary to convert predictive data into useful maintenance operations. Therefore, this thesis concludes that smart scheduling is as important as accurate prediction for improving the efficiency and cost-effectiveness of offshore wind farm maintenance.

KEYWORDS: Offshore Wind Energy, Predictive maintenance, Mixed-Integer Linear Programming (MILP), Greedy Heuristic, Remaining Useful Life (RUL), offshore maintenance, resource optimization, Operation and Maintenance (O&M)

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Abbreviations

LSTM	Long Short-Term Memory
MILP	Mixed-Integer Linear Programming
O&M	Operation and Maintenance
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
SCADA	Supervisory Control and Data Acquisition
XGBoost	Extreme Gradient Boosting

1 Introduction

1.1 Background

The global adoption of renewable technology has accelerated due to the shift to sustainable energy systems. Because of its technological maturity, scalability, and low generating costs, Offshore wind energy has become one of the major parts of the global transition to a sustainable energy system. Since wind speeds are higher and more stable in the ocean area than on land, offshore wind farms offer huge potential for large-scale renewable energy production. Offshore wind energy has grown significantly during the past ten years (International Energy Agency (IEA)).

It is anticipated that offshore wind energy will be essential to meeting global climate goals and facilitating the shift to low-carbon energy systems. Because offshore wind has the potential to provide significant amounts of renewable electricity while lowering greenhouse gas emissions, many countries have included it in their national energy strategies. The International Energy Agency (2023) predicts that as governments look for dependable and sustainable energy alternatives, offshore wind capacity will continue to rise rapidly.

Offshore wind energy has several operational and financial difficulties despite its benefits. Offshore wind projects confront more complicated operating conditions and demand a larger capital investment than onshore wind farms. Accessibility, logistics, severe weather, and maintenance activities provide special difficulties in the offshore setting. However, with those benefits, offshore wind energy requires high operational & maintenance (O&M) costs. Generally, this cost can be around 20% to 30% of the total life cycle cost (Dinwoodie et al., 2013).

There are several major challenges behind this high cost. These include the severe marine environment, restricted accessibility, the need for specialized ships, and weather-related limitations. As offshore wind farms continue to grow in size and distance from shore, effective maintenance planning is critical to ensuring turbine availability and maintaining the economic feasibility of the project. Failure of critical components such as gearboxes, generators, and blades can cause serious downtime and revenue loss. Consequently, it is essential to plan maintenance activities properly, as delays increase turbine downtime and operational risk. Therefore, improving maintenance planning and decision-making processes is essential to make this sector economically sustainable. This is why Predictive Maintenance has emerged as a promising alternative in this field.

As offshore wind farms continue to grow in size and distance from shore, effective maintenance planning is becoming increasingly important. These strategies help reduce operating expenses, increase turbine availability, and improve the overall financial performance of offshore wind projects. Therefore, maintenance optimization has been considered an important research area to ensure the long-term viability and financial success of offshore wind energy systems.

1.2 Offshore Wind Farm Challenges

Compared to maintenance activities for traditional industrial facilities, maintenance management for offshore wind farms is much more complex. Offshore wind turbines operate in isolated marine environments, where high wind speeds, saltwater exposure, humidity, wave loading, and challenging accessibility exist. These environmental factors increase the risk of equipment failures and accelerate component degradation (Carroll et al., 2016).

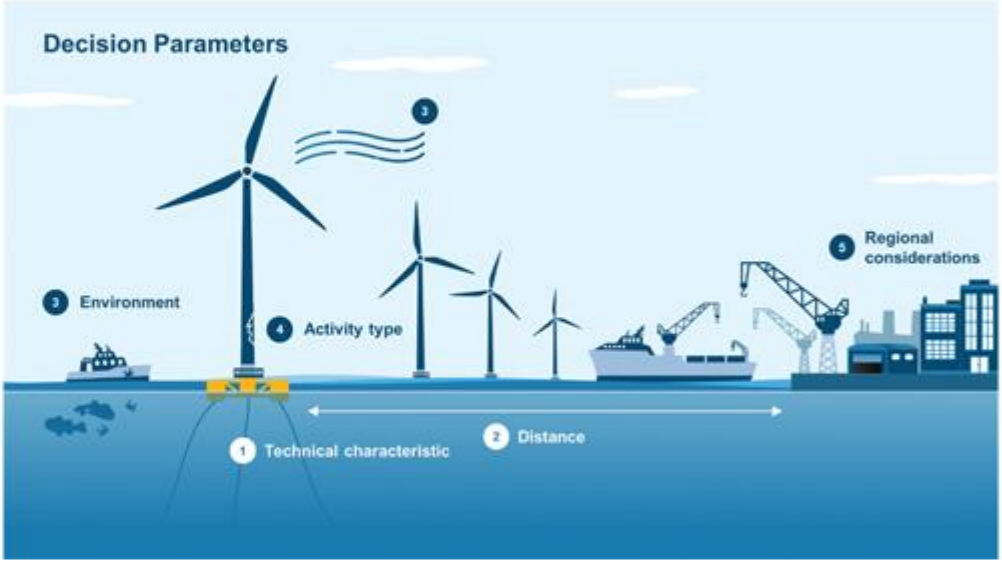

Figure 1. Maintenance challenges of offshore wind farms (Windtech International, 2022).

The gearbox, generator, and blade systems are among the important subsystems of the turbine that are most vulnerable to failure. Failures in these components can cause significant disruption to operations and require costly maintenance interventions.

Compared to onshore wind farms, offshore maintenance operations often require specialized equipment and highly skilled workers. This results in higher maintenance costs and longer repair times.

Weather is one of the biggest obstacles to offshore maintenance operations. Maintenance activities can only be successfully conducted when weather conditions ensure safe vessel movement and turbine access. Large waves, high winds, and poor visibility often limit maintenance opportunities and can cause delays in important repair work (Hofmann, 2011).

Offshore maintenance planning requires coordination of environmental resources as well as various operational resources. Spare parts, repair equipment, support vessels, and maintenance staff must be available at the same time to perform maintenance activities. Since these resources are expensive and limited, maintenance planners need to allocate and manage them effectively to reduce operating costs while maintaining high turbine availability.

The larger and more widely distributed offshore wind farms, the more difficult it is to coordinate these resources. As a result, more sophisticated and data-driven maintenance management frameworks are being developed in response to the growing inadequacy of traditional maintenance planning techniques.

1.3 From Predictive Maintenance to Operational Decision-Making

In recent times, Predictive maintenance has gained immense importance in increasing maintenance efficiency. By using Data-Driving models and machine learning technologies, these methods are used to diagnose the condition of components and predict potential failures in advance (Zhang et al., 2019).

Modern offshore wind turbines continuously generate large amounts of operational data through condition monitoring sensors and SCADA (Supervisory Control and Data Acquisition) systems. These systems provide important information about electrical activity, temperature changes, vibration levels, turbine performance, and other operational characteristics. Predictive Maintenance systems analyze this data to identify component degradation and predict potential failures (Qiu et al., 2012).

Commonly used techniques include:

(1) Remaining Useful Life (RUL) estimation,
(2) Time series forecasting using LSTM networks,
(3) Classification models such as XGBoost.
(4) Deep learning anomaly detection methods.

These methods normally work based on SCADA (Supervisory Control and Data Acquisition) data from wind turbines and give maintenance alerts about potential component failures (Zhang et al., 2019).

The main purpose of Predictive Maintenance is to provide early warning of component deterioration. With this information, maintenance planners can take necessary measures before potential faults occur. As a result, downtime is reduced, and the reliability of the entire system is increased. Predictive Maintenance is currently considered one of the most active and important areas of research in offshore wind energy.

However, although Predictive Maintenance provides important information, most research only focuses on prediction accuracy. These studies usually end with determining a risk score or probability of failure, and it doesn't consider how this information will be used in actual operational decision-making. In the offshore environment, these decisions are often more complex than the forecasting process. As a result, the effectiveness of Predictive Maintenance does not only depend on the accuracy of the forecast, but also on how effectively future maintenance scheduling can be planned and implemented. Therefore, the true value of Predictive Maintenance is achieved when information obtained from forecasts can be successfully linked to effective maintenance planning and decision-making.

1.4 Research Gap

A review of the literature shows that there is a clear gap between predictive maintenance research and maintenance scheduling research. The main subject of Predictive Maintenance research is the condition monitoring of machine parts, providing potential failure identification and failure forecasting. Research in this field investigates data-driven methods, condition-monitoring systems, and machine learning models for measuring equipment deterioration and forecasting future failures. (Lei et al., 2018; Zhang et al., 2019). These studies' main contributions are the creation of maintenance-related data and failure forecasts.

Resource optimizations, logistical planning, and maintenance scheduling are the key topics of the second research area. Workforce distribution, vessel scheduling, repair routing, and operational planning under resource restrictions are all examined in this research (Dinwoodie et al., 2013; Hofmann, 2011). The research's main goals are to save operating costs and increase maintenance effectiveness.

Even though both fields of study make significant contributions to maintenance management, they are often studied separately. After maintenance alerts or Remaining Useful Life estimates are produced, predictive maintenance studies frequently come to an end. On the other hand, scheduling studies usually assume that maintenance duties are already understood and may be optimized.

Because of this, there is a big gap between maintenance execution and maintenance projection. Predictive maintenance systems may successfully identify high-risk components, but maintenance planners still need efficient decision-making processes to decide how to spend limited resources.

This thesis refers to this gap between operational action and predicted information as the decision gap. The primary goal of this thesis is to close this decision gap.

1.5 Problem Statement

There is a notable gap remaining between Predictive analytics output and its integration into operational decision-making. Predictive risks are not included in maintenance schedules, and that’s why they are unable to determine:

1. Which job should be prioritized
2. When maintenance should be performed
3. How the limited vessels and crew should be assigned
4. How weather affects the scheduling feasibility.

These gaps limit the practical applicability of predictive maintenance systems in offshore wind operations.

1.6 Research Objective

The main objective of this thesis is to develop a framework that integrates predictive maintenance results into operational scheduling decisions. This research is designed to:

1. To develop a risk-based maintenance alerts framework.
2. Formulate a scheduling model that explicitly incorporates predictive maintenance output.
3. To develop and evaluate a Mixed-Integer Linear Programming (MILP) optimization model for offshore maintenance scheduling.
4. Evaluate the impact of operational constraints such as weather, crew, and vessel availability.
5. Compare heuristic and optimization-based scheduling approaches under different operational scenarios.

1.7 Scope and Contribution

The main contributions of this thesis can be summarized as follows.

Firstly, a predictive-prescriptive offshore maintenance framework is developed to close the gap between predictive maintenance outputs and operational maintenance decision-making.

Second, alerts from Predictive Maintenance are converted into effective offshore maintenance schedules using a Risk-Aware Greedy Scheduling Framework, taking into account real operational constraints.

Third, a Mixed-Integer Linear Programming (MILP) Optimization Framework has been developed to determine the optimal (globally optimized) maintenance schedule.

Fourth, the effectiveness of this framework has been evaluated under different workforce availability scenarios to analyze the behavior of resource utilization and operational obstacles.

Finally, the study shows that Maintenance Scheduling is crucial for the real usefulness of Predictive Maintenance systems. That is, simply predicting failures is not enough; formulating effective and realistic maintenance plans based on that information is the key to the success of Predictive Maintenance.

1.8 Thesis Structure

The remaining of this thesis is structured as follows:

In Chapter 2, the relevant literature on offshore scheduling optimization and predictive maintenance is reviewed.

Chapter 3 presents the suggested methodology, including the risk simulation engine, scheduling framework, and optimization formulation.

Chapter 4 covered the experimental setup, scenario analysis, and comparative evaluation results.

Chapter 5 summarizes the main findings, discusses limitations, and concludes the thesis with some suggestions for future research.

2 LITERATURE REVIEW

Due to the rapid growth of offshore wind energy industries, the effective operation and maintenance (O&M) strategies have increased massively. As a result, improving turbine availability and lowering the maintenance cost have become major research priorities.
Promising methods for enhancing offshore maintenance operations have been made possible by recent advancements in predictive maintenance and optimization. While optimization approaches focus on the effective distribution of operational resources such as vessels and maintenance crews. The predictive maintenance methods use data-driven methodology to estimate component degradation and predict failures.
This chapter reviews the existing literature on:

1. Offshore Wind Maintenance Challenges
2. Predictive Maintenance approaches
3. Remaining Useful Life (RUL) estimation
4. Machine learning methods in wind turbine maintenance
5. Offshore maintenance scheduling optimization
6. Mixed-Integer Linear Programming (MILP)
7. Research gaps between prediction and operational decision-making

This chapter is concluded by how these research gaps motivate this thesis.

2.1 Offshore Wind Farm Maintenance Challenges

Offshore wind farms mostly operate in challenging and highly unpredictable environments. Long travel distance, weather conditions, crew, and vessel availability have a significant impact on maintenance operations. (Carrol et al., 2016)

Compared to onshore systems, offshore logistics considerably raise operating costs because offshore turbines are often located far from shore and require specialized vessels and trained personnel for maintenance. The maintenance cost is mainly impacted by turbine downtime, weather delays, and vessel mobilizations. For offshore wind farm operations, maintenance scheduling is considered a crucial economic factor (Hofmann, 2011).

According to Dinwoodie et al. (2015), Operation and maintenance costs (O&M) make up about 20-30% of offshore wind farms' overall lifecycle costs. These costs arise from turbine downtime, vessel operation, crew deployment, and spare parts logistics. Additionally, energy production and revenue generation are directly impacted by turbine downtime.

The main operational challenges are listed below:

1. Harsh marine environment
2. Restricted accessibility due to weather
3. Vessel dependency
4. Limited maintenance crew availability
5. Long maintenance times for critical components

Due to these difficulties, effective maintenance scheduling is crucial to ensure the profitability of offshore wind farms.

2.2 Critical Offshore Wind Turbine Components

Several components of wind turbines are particularly vulnerable to degradation and failure.

Gearbox

One of the most expensive and error-prone components is the gearbox. Repairing gearbox faults often takes a long time and requires the use of heavy maintenance vessels.

Generator

Generator failures can cause loss of power generation and significant downtime. Over time, the performance of a generator gradually deteriorates due to thermal and electrical stress.

The Blade System

Environmental loads, erosion, and structural fatigue are related to blade failure. Although blade repairs require less manpower than gearbox replacement, accessibility issues remain a major challenge in the offshore environment.

Research on predictive maintenance often focuses on these elements because they have a very high operational importance and have a significant impact on maintenance costs.

2.3 Predictive Maintenance Approaches

One of the most promising strategies for improving maintenance efficiency in offshore wind farms is predictive maintenance. Corrective maintenance responds to failures after they occur, and preventive maintenance relies on a fixed maintenance schedule. But predictive maintenance aims to estimate components' health and identify the failures before they occur. (Lei et al, 2018)

Predictive maintenance techniques have replaced corrective maintenance in industrial systems.

2.3.1 Corrective Maintenance

In corrective maintenance, a component is repaired only after it fails. Although this approach is easy to employ, it frequently results in unplanned downtime and expensive repairs.

2.3.2 Preventive Maintenance

Regardless of the actual state of the component, preventive maintenance carries out servicing at predetermined times. It may lead to needless maintenance production even while it decreases unplanned breakdowns.

2.3.3 Predictive Maintenance

According to Zhang et al. (2019), predictive maintenance makes use of operational data to assess the condition of equipment and anticipate potential malfunctions before they happen. The primary goal of predictive maintenance is to reduce unexpected failures and improve maintenance timing. Early degradation detection enables proactive intervention, which lowers the system downtime and increases system reliability. As a result, one of the most active research areas in wind energy systems is predictive maintenance.

Predictive maintenance has shown a great deal of promise, but how the data is used in maintenance decision-making ultimately determines its usefulness. The integration of predictive maintenance outputs with operational scheduling has become more popular as a result of this problem.

2.4 SCADA-Based Monitoring Systems

Supervisory Control and Data Acquisition (SCADA) systems are used by modern offshore wind turbines to gather operational data continuously. SCADA systems continuously monitor parameters like temperature, vibration, rotational speed, power output, oil condition, wind speed, and generator performance. With its information, machine learning models can identify abnormal operational trends related to component degradation.

Qiu et al. (2015) claim that SCADA-based monitoring offers an affordable option for large-scale condition monitoring in offshore wind farms.

2.5 Remaining Useful Life (RUL) Estimation

The remaining operational time until a component fails is predicted via Remaining Useful Life (RUL) estimation. Because the RUL estimate offers quantitative degradation data for maintenance planning, it has become one of the most popular methods in predictive maintenance systems. It can be expressed by,

$$RUL = t_f - t_c$$

Where,

$t_f =$ predictited failure time,

$t_c =$ current operational time.

Lower RUL levels show that components are on the verge of failure and need immediate maintenance. Maintenance planners can prioritize maintenance jobs based on operational urgency by using the RUL estimate.

2.6 Machine Learning Methods for Predictive Maintenance

2.6.1 Long Short-Term Memory (LSTM)

A specific kind of recurrent neural network (RNN) created for sequential time-series analysis is the Long Short-Term Memory (LSTM) network. Because LSTM models can identify long-term temporal relationships in operational data, they are very useful for SCADA-based degradation prediction.

The LSTM model has been used in several studies for RUL estimation, gearbox degradation monitoring, and turbine fault predictions. Even in noisy operating conditions, Zhang et al. (2019) showed that LSTM models exhibit strong predictive performance in wind turbine fault detection.

2.6.2 Extreme Gradient Boosting (XGBoost)

A popular supervised machine learning technique for classification and regression issues is Extreme Gradient Boosting (XGBoost). XGBoost is a supervised machine learning algorithm widely recognized for its predictive performance and computational efficiency. (Chen & Guestrin, 2016) In predictive maintenance, XGBoost is well-liked due to robustness against noisy data, quick training speed, interpretability, and high predicted accuracy. XGBoost models have been effectively used for anomaly identification, fault categorization, and turbine health tracking. Compared with deep learning methods, XGBoost uses less computing power than deep learning techniques.

However, similar to many LSTM-based studies, most XGBoost research concentrates on producing maintenance alerts rather than supporting maintenance execution. Because of this, predictive output often remains disconnected from operational decision-making processes.

2.6.3 Deep Learning and Hybrid Methods

In an effort to increase reliability, recent research has increasingly combined several predictive techniques. Examples consist of:

1. CNN-LSTM hybrid models,
2. Autoencoder-based anomaly detection,
3. Attention-based neural networks, and
4. Ensemble learning techniques.

Despite the fact that these techniques increase prediction capacity, the majority of research focuses mainly on prediction performance indicators like precision, recall, accuracy, and F1-score. The operational use of predicted outputs following prediction receives very little attention.

2.7 Maintenance Scheduling and Operations Research

2.7.1 Maintenance Scheduling Problem

Under operational restrictions, maintenance scheduling establishes how maintenance jobs should be distributed across time. Scheduling choices in offshore wind systems involve:

1. Weather feasibility
2. Crew distribution
3. Vessel assignment, and
4. Maintenance scheduling.

Usually, the goal is to reduce maintenance costs, resource consumption, and turbine downtime.

2.7.2 Heuristic Scheduling Methods

Heuristic techniques are frequently employed because of their ease of use and computational effectiveness. The Greedy algorithm, which assigns jobs step by step based on urgency, is one of the most popular heuristic techniques. Heuristic methods offer advantages such as fast scheduling, easy implementation, and low computational complexity.

However, heuristic methods do not guarantee a globally optimal solution. Rather, they depend on local decision-making. This can result in increased overall operating costs, increased downtime, and inefficient resource allocation.

2.7.3 Operations Research Approaches

In the case of complex scheduling problems, Operations Research (OR) techniques provide mathematically optimal solutions and solve resource allocation problems within operational constraints (Nemhauser & Wolsey, 1988). These techniques are widely used in transportation, manufacturing, logistics, and maintenance planning.

In offshore wind maintenance, Operations Research (OR) techniques are used to improve resource utilization, manpower allocation, vessel assignment, and maintenance scheduling. The main objective is to maximize maintenance effectiveness and turbine availability while keeping operational costs to a minimum.

While predictive maintenance models emphasize information generation, operations research (OR) methods focus on decision-making and resource management. This distinction is crucial because maintenance planners need both accurate predictive data and effective scheduling decisions to achieve real operational benefits.

Various optimization techniques have been used in offshore maintenance research, such as:

1. Mixed-Integer linear programming (MILP),
2. Dynamic programming,
3. Genetic algorithms, and
4. Particle Swarm Optimization.

MILP is especially applicable among these techniques since it permits formal modeling of global optimization, binary scheduling choices, and operational restrictions.

2.8 Mixed-Integer Linear Programming (MILP)

A mathematical optimization method called Mixed-Integer Linear Programming (MILP) limits certain decision variables to binary or integer values. MILP has been used extensively in scheduling maintenance, transportation systems, production planning, and logistics optimization.

Binary variables are frequently used in offshore maintenance scheduling to represent decisions about task distribution, vessel activation, and maintenance scheduling. MILP models are able to satisfy intricate operational limitations while concurrently optimizing several cost components.

MILP combines continuous and binary decision variables, enabling a realistic representation of maintenance assignment decisions and operational constraints (Nemhauser and Wolsey, 1988). They claim that MILP offers globally optimal solutions within bounds of computing feasibility. MILP provides an appropriate framework for combining predictive maintenance data with operational scheduling choices since offshore maintenance involves multiple interacting constraints.

2.8.1 Weather-Constrained Offshore Maintenance

One of the biggest obstacles to offshore maintenance operations is the weather. Turbine accessibility and vessel mobility may be prevented by strong winds and rough seas. Several studies portray offshore feasibility windows using probabilistic weather models or weather accessibility masks. In real-world offshore systems:

The efficiency of maintenance planning is significantly impacted by weather unpredictability, and maintenance can only be carried out within accessible weather windows. Thus, for practical offshore scheduling, weather feasibility modeling is crucial.

2.8.2 Decision Gap Between Prediction and Scheduling

Predictive maintenance systems and operational schedule optimization are significantly out of sync, according to the literature. Research on Predictive Maintenance focuses on:

1. RUL estimation,
2. Anomaly detection,
3. Fault prediction, and
4. Predictive accuracy.

Research on Scheduling Optimization focuses on:

1. Logistical optimization,
2. Maintenance scheduling,
3. Resource allocation, and
4. Vessel routing.

However, only a small number of studies incorporate predicted outcomes into maintenance schedule choices. For this reason, Operational planners continue to use reactive or manually prioritized scheduling techniques, even though predictive systems produce alarms. This results in a crucial decision-making gap between anticipating malfunctions and carrying out the best possible maintenance. The main goal of this thesis is to close this gap.

2.9 Summary of Literature Review

The literature on machine learning techniques, scheduling optimization strategies, predictive maintenance systems, and offshore wind maintenance was evaluated in this chapter. Several significant findings were noted in the review.

Weather, vessels, and crew availability all have a significant impact on offshore maintenance operations. Component deterioration and failure risk can be accurately estimated using predictive maintenance techniques. Strong scheduling capabilities are offered by optimization strategies like MILP. Predictive alarms are infrequently included in operational scheduling decisions in current research.

Integrated predictive-prescriptive frameworks that can convert predictive maintenance results into workable offshore maintenance schedules are, therefore, obviously needed. By creating a risk-aware MILP-based offshore maintenance scheduling framework, this thesis fills this research gap.

3 Methodology

This chapter presents the core methodological approach of this thesis for combining offshore maintenance scheduling decisions with predictive maintenance output. The primary goal of this proposed framework is to convert predictive maintenance alerts into workable, resource-conscious offshore maintenance schedules within practical operational limits.

The methodology uses a predictive-prescriptive maintenance architecture with two primary phases:

1. Risk Simulation Engine
2. Prescriptive Scheduling Model

The first step is to generate a maintenance alert that indicates component degradation and failure urgency. While considering offshore operating constraints, including weather accessibility, crew availability, vessel capacity, and component-specific maintenance requirements, the second stage transforms these alerts into actionable maintenance schedules.

The operational scheduling environment of the implemented scheduling framework is essentially a risk-aware Greedy heuristic scheduler. In addition, as an advanced optimization extension for enhancing global scheduling optimality, a Mixed-Integer Linear Programming (MILP) formulation is proposed.

Predictive maintenance alerts can have a direct impact on operational maintenance planning decisions due to the overall framework.

3.1 Risk Simulation Engine

3.1.1 Purpose of the Risk Simulation Engine

The risk simulation engine’s goal is to produce maintenance alerts with an urgency ranking that resembles the results of predictive maintenance systems. Predictive maintenance systems assess component degradation and failure likelihood in real-world offshore wind farms by using SCADA and condition-monitoring data. However, this thesis focuses on how predicted outputs might be converted into operational scheduling decisions rather than on creating new machine learning models. Therefore, the predictive layer in this study serves as an input engine that produces maintenance alerts for the scheduling framework.

Two categories of predictive inputs are supported by the framework:

1. Degradation simulation is used to create artificial predictive maintenance alerts.
2. Real predictive maintenance alerts obtained from the dataset certified by ERA-5.

Both are made possible by this dual-input strategy, such as realistic operational validation as well as controlled experimental study.

3.1.2 Fake Alert Generator

To simulate predicted maintenance outputs for offshore wind turbine components, a fake alert generator was created. Each generated alert represents a maintenance task related to degraded turbine components. The operational and maintenance-related characteristics needed for scheduling are included in the generated alerts.

The major turbine components are the gearbox, generator, and blade system. These elements were chosen because they have a significant impact on offshore maintenance costs and crucial operational downtime.

Each maintenance task i is represented by the following feature vector:

$$Xi \; = \; [\, di, pi, crew\ req\ i, distance\ i, deadline\ i, \ldots]$$

Where,

di = maintenance duration

Pi = predicted failure probability

crew req i = required workforce

distance i = travel distance

deadline i = latest preferred maintenance slot

The complete task matrix is represented as:

$$\mathrm{X} \in R^{N \times F}$$

Where,

N = number of maintenance tasks

F = number of task features

For controlled experimental evaluation, a total of 3000 synthetic maintenance alerts were generated across different component categories.

3.1.3 Remaining Useful Life (RUL) Generation

Remaining Useful Life (RUL) values were created at random to simulate various degradation conditions in order to create a synthetic task. The generated RUL values satisfy:

$$RULi \; \epsilon \; [5,60]$$

Where,

Lower RUL values indicate severe degradation,

Higher RUL values indicate healthier components.

RUL values are later converted into failure probability using a Potential-to-Functional Failure (P-F) curve.

3.1.4 P–F Curve-Based Failure Probability Estimation

The failure probability was estimated from component degradation data using a linear Potential-to-Functional Failure (P-F) curve. For maintenance task i, the failure probability is defined as follows:

$$Pi \; = \max\left(0,1 \; - \; \frac{RULi}{H} \right)$$

Where,

Pi = predicted failure probability

RULi = remaining useful life

H = degradation horizon

This formulation ensures that healthy components are given less maintenance priority while components that are on the verge of failure are given more urgency. The priority of maintenance scheduling is directly impacted by the calculated failure probability. Instead of being produced via simulation, failure probabilities for the actual dataset are directly derived from predictive maintenance outputs.

3.1.5 Real Predictive Dataset Integration

An actual predictive maintenance dataset validated using ERA5 offshore weather data is used to assess the framework in addition to synthetic alarms. The actual dataset includes:

1. Turbine identification
2. Component type,
3. Expected failure probability,
4. Urgency of maintenance,
5. Task duration, and
6. Earliest possible maintenance slot.

This makes it possible to assess the scheduling framework realistically in offshore operations. This proposed framework's practical applicability is enhanced by the incorporation of both synthetic and actual predictive datasets.

3.2 Prescriptive Scheduling Model

3.2.1 Scheduling Objective

Predictive maintenance alerts are converted into workable offshore maintenance plans via the prescriptive scheduling layer. The scheduling framework determines:

1. Which maintenance task should be carried out,
2. When maintenance should take place,
3. Which vessel should be assigned, and
4. How the crew should be distributed.

The overall objective is to maximize practical maintenance execution while minimizing offshore operating costs. The scheduling process considers several practical offshore operating restrictions, such as weather viability, crew availability, operational capacity of the vessel, and maintenance duration.

3.2.2 Operational Constraints

3.2.2.1 Crew Availability Constraint

Trained technical workers are needed for maintenance activities. The available maintenance workforce is limited during each scheduling slot. The definition of crew capacity limitation is:

$$\sum_{i=1}^{N} r_{i,c} d_i \, y_{i,t} \ \leq \ R_{c,t}$$

Where,

$r_{i,c} = workforce\ requirement\ of\ task\ i$

$d_i = maintenance\ duration$

$R_{c,t} = available\ crew\ capacity\ at\ slot\ t$

Three workforce scenarios are tested:

1. Low crew availability
2. Baseline crew availability
3. High crew availability

3.2.2.2 Vessel Capacity Constraint

Specialized maintenance vessels are required for offshore maintenance operations. Also, during every schedule slot, the operational working-hour capacity of each vessel is limited. The definition of the vessel capacity constraint is:

$$\sum_{i=1}^{N} d_i \, x_{i,v,t} \ \leq \ H_v \, z_{v,t}$$

Where,

$H_v = vessel\ working - hour\ limit$

$d_i = maintenance\ duration$

$z_{v,t} = vessel\ activation\ variable$

This ensures that vessel workload remains operationally feasible.

3.2.2.3 Weather Feasibility Constraint

Offshore maintenance operations are significantly impacted by weather accessibility. Only when the weather is suitable can maintenance operations be carried out. A binary weather accessibility mask is defined as:

$$w_t \in \{ 0,1 \}$$

Where,

$$w_t = \begin{cases} 1, & weather\ feasible \\ 0, & weather\ restricted \end{cases}$$

Maintenance tasks must satisfy,

$$y_{i,t} \leq w_t$$

This prevents maintenance scheduling during inaccessible offshore conditions.

3.2.2.4 Component-Specific Maintenance Rules

The amount of time and crew needed for maintenance varies depending on the turbine components.

Table 1. The operational maintenance rules used in the framework

Components	Duration (hours)	Crew required
Gearbox	12	3
Generator	8	2
Blade	6	2

Gearbox maintenance requires the highest operational effort due to its complexity.

3.3 Baseline Method: Risk-Aware Greedy Heuristic

A risk-aware Greedy heuristic scheduler is the main scheduling strategy used in this thesis. While taking into account offshore operating restrictions, the scheduler assigns maintenance jobs to the earliest possible maintenance slot based on the projected failure probability. This implemented scheduler clearly demonstrates that predictive maintenance alerts can be converted into a workable maintenance schedule.

3.3.1 Scheduling Procedure

Four sequential steps make up the scheduling logic:

1. Sort maintenance tasks according to the failure probability,
2. Look for workable maintenance times,
3. Check crew and vessel availability, and
4. Assign the earliest maintenance window that is practical.

As a result, the scheduler gives priority to

$$P_i^{high} \rightarrow higher\ scheduling\ priority$$

This ensures that highly degraded components get priority maintenance attention.

3.3.2 Scheduling Variable

The binary scheduling variable is defined as:

$$y_{i,t} = \begin{cases} 1, & task\ i\ assigned\ to\ slot\ t \\ 0, & otherwise \end{cases}$$

The greedy scheduler attempts to assign:

$$\arg\min_t (t)$$

This is subject to:

$$w_t = 1$$

$$\sum_i r_{i,c} d_i \, y_{i,t} \ \le \ R_{c,t}$$

$$\sum_i d_i \, x_{i,v,t} \ \le \ H_v$$

That’s how each task is assigned to the earliest operationally feasible maintenance slot.

3.3.3 Advantages and Limitations

Advantages:

1. Fast computation,
2. Easy installations,
3. Interpretable scheduling patterns,
4. Low computational complexity.

Limitations:

1. Make locally optimal decisions,
2. Global optimality cannot be guaranteed,
3. Could result in higher long-term operating costs.

Despite these limitations, the Greedy Scheduler successfully exhibits risk-aware offshore maintenance scheduling behavior.

3.4 Proposed Solution: MILP Optimizer

A Mixed-Integer Linear Programming (MILP) formulation is suggested as an advanced optimization extension of the developed framework to further enhance scheduling optimality. The MILP model simultaneously optimizes all maintenance tasks throughout the planning horizon while meeting offshore operational limitations, in contrast to the Greedy heuristic scheduler, which makes sequential local decisions.

The proposed optimization framework minimizes vessel activation costs, labor costs, and maintenance costs associated with downtime.

3.4.1 Decision Variables

Task scheduling variable

$$y_{i,t} \in \{ 0,1 \}$$

Where,

$$y_{i,t} = \begin{cases} 1, & task\ i\ assigned\ to\ slot\ t \\ 0, & otherwise \end{cases}$$

Task assignment variable

$$x_{i,v,t} \in \{ 0,1 \}$$

Where,

$$x_{i,v,t} = \begin{cases} 1, & task\ i\ assigned\ to\ vessel\ v\ in\ slot\ t \\ 0, & otherwise \end{cases}$$

Vessel activation variable

$$z_{v,t} \in \{ 0,1 \}$$

$$z_{v,t} = \begin{cases} 1, & vessel\ active\ at\ slot\ t \\ 0, & otherwise \end{cases}$$

3.4.2 Objective function

The objective function minimizes total offshore operational cost:

$$min \sum_{v,t} c_v z_{v,t} + \sum_{i,t} \sum_{c} c_c r_{i,c}\, d_i y_{i,t} + \sum_{i,t} c_d d_i y_{i,t}$$

Where,

$C_v = vessel\ activation\ cost$

$C_c = workforce\ operational\ cost\ coefficient$

$r_{i,c} = workforce\ requirement$

$d_i = maintenance\ duration$

$C_d = down\ time\ cost\ coefficient$

3.4.3 MILP Constraints

Constraint (1): Task execution exactly once (assignment).

$$\sum_{t=1}^{T} y_{i,t} = 1 \qquad for\ all\ i \in I$$

Justification by definition: $y_{i,t}$ is defined as a binary indicator that equals 1 only if task i is executed in period t. Therefore, summing $y_{i,t}$ over all periods and setting it equal to 1 enforces that each task is executed exactly once (not skipped and not duplicated). This is a standard assignment structure in integer programming models (Nemhauser & Wolsey, 1988).

Constraint (2): Linking vessel assignment to task execution.

$$\sum_{v=1}^{V} x_{i,v,t} = y_{i,t} \qquad for\ all\ i \in I, t \in T$$

This linking constraint ensures that a task is executed only if a vessel is assigned in that period, and that exactly one vessel is selected when the task is executed. Linking constraints of this type are standard in MILP formulations (Nemhauser & Wolsey, 1988).

Constraint (3): Vessel working-hour capacity.

$$\sum_{i=1}^{N} d_i\, x_{i,v,t} \leq H_v\, z_{v,t} \qquad for\ all\ v \in V, t \in T$$

This constraint prevents infeasible assignments where a vessel is allocated more service time than its available working hours in a period. Capacity constraints of this form are common in offshore O&M scheduling and logistics models (Dinwoodie et al., 2015).

Constraint (4): Weather feasibility (weather window)

$$y_{i,t} \leq w_t \quad for\ all\ i \in I, t \in T$$

Justification by definition: w_t is defined as a binary feasibility indicator. If w_t =0, maintenance access is not possible in period t, so $y_{i,t}$ must be 0. This matches the weather-window concept for offshore access and avoids scheduling tasks during unsafe conditions (Hofmann, 2011; Haensch et al., 2025).

Constraint (5): Crew availability

$$\sum_{i=1}^{N} r_{i,c} d_i \, y_{i,t} \;\leq\; R_{c,t} \quad for\ all\ c \in C, t \in T$$

This constraint ensures that the total crew workload required by scheduled tasks does not exceed available crew capacity. Workforce capacity constraints are standard in scheduling and resource allocation models (Nemhauser & Wolsey, 1988).

3.4.4 Characteristics of the MILP Model

The suggested MILP model offers:

1. Risk-aware maintenance priority,
2. Integrated resource allocation, and
3. Globally optimized scheduling choices.

The MILP formulation offers a more robust theoretical foundation for optimizing offshore operational cost under limited maintenance settings when compared to the Greedy heuristic scheduler.

3.5 Chapter Summary

In this chapter, a methodological framework for combining predictive maintenance alerts with offshore maintenance schedule decisions was described. Using P_F curve-based failure estimation and fake warning generation, a risk simulation engine was created to provide urgency-ranked maintenance alerts. The generated alerts were then used as inputs to the prescriptive scheduling framework.

The implemented scheduling framework uses a risk-aware Greedy heuristic scheduler under practical offshore operational limitations such as weather viability, crew availability, and vessel capacity. Furthermore, as an advanced optimization extension to enhance global scheduling optimality, a Mixed-Integer Linear Programming (MILP) formulation was proposed.

The experimental setup, scheduling outcomes, and operational analysis under various resource scenarios are presented in the next chapter.

4 EXPERIMENTS AND RESULTS

This chapter presents the experimental evaluation and operational analysis of the proposed predictive–prescriptive offshore maintenance scheduling framework. The tests are designed to understand how predictive maintenance alerts can be converted into feasible offshore maintenance schedules within realistic operational constraints. Workforce availability, vessel utilization, urgency of maintenance, and total operating costs are all given special consideration.

The evaluation focused on two main objectives. The first part focuses on scenario analysis, where Operational bottleneck analysis is conducted under different workforce availability scenarios. Three workforce scenarios are considered, namely low crew availability, baseline crew availability, and high crew availability. The objective of this analysis is to identify operational bottlenecks and understand how resource limitations influence maintenance execution.

The second part focuses on a comparative evaluation between the implemented Greedy heuristic scheduler and the proposed MILP optimization framework. The tests used a synthetic predictive maintenance alert and a real ERA5-validated predictive maintenance dataset.

The analysis tested:

- maintenance task execution,
- crew utilization,
- vessel utilization,
- task urgency prioritization, and
- operational cost performance.

Both strategies are assessed using the same predictive maintenance alerts, operational constraints, and planning horizon. The comparison looks at personnel utilization, vessel utilization, operational cost, penalty reduction, and maintenance task completion.

All financial results are provided in Euros (€) to ensure consistency with European offshore energy studies. This chapter’s findings highlight the usefulness of combining intelligent scheduling techniques with predictive maintenance data.

4.1 Experimental Setup

4.1.1 Scheduling Configuration

The scheduling framework has been evaluated in multiple operational scenarios using predictive maintenance alerts generated from offshore wind turbine components.

Table 2. The real alert dataset experiment was used

Parameter	**Value**
Tasks	112
Turbines	5,16,30,59
Time horizon	98 slots (two-winter window)
Workable slots	75 / 98 (76.5%) ERA5 feasibility mask
Component mix	Gearbox 43%, Generator 27%, Blade 30%
RUL range	0.0 to 6.9 days
p_fail_14d range	0.507 to 1.000 (majority > 0.90)
Fleet	2 vessels, 12 vessel-hours per slot

The main turbine components considered were the gearbox, generator, and blade system. The ERA5-validated predictive maintenance dataset was used in the real scheduling experiment, which included a total of 112 maintenance tasks for turbines 5, 16, 30, and 59.

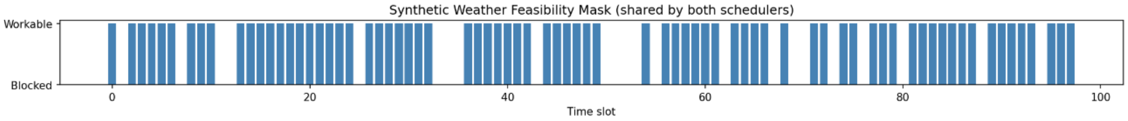

Figure 2. Synthetic Weather Feasibility Mask

The planning horizon consists of 98 discrete time slots representing a two-winter operational duration. To improve realism, weather accessibility constraints are included using ERA5 weather data. Figure 2 illustrates the resulting weather feasibility mask used during the experiment. The mask identifies periods in which offshore maintenance activities can be safely performed. Blue regions suggest accessible windows for maintenance, while blocked durations represent weather conditions that prevent ship deployment and maintenance operations. Out of 98 available time slots, 75 are diagnosed as viable maintenance windows, equivalent to approximately 76.5% occupancy at a given point in the planning horizon.

4.1.2 Crew Availability Scenarios

Three crew headcount scenarios were evaluated, each converting crew count to crew-hours per slot (crew counts x 12). Both schedulers operated under identical valid slots per task windows and the same ERA5 weather mask.

Table 3. Three workforce scenarios were assessed

Scenario	Crew Availability
Low crew	Limited workforce
Baseline	Moderate workforce
High crew	High workforce

Table 4. For real dataset experiments

Scenario	Crew Headcount	Crew-Hours Per Slot
Low Crew	3	36
Baseline	5	60
High Crew	10	120

All scenarios used the same predictive alert, the same weather feasibility mask, and the same vessel configuration. This ensures fair comparison across all scheduling experiments. In this experiment, two maintenance vessels were available in all scenarios, each providing a capacity of 12 vessel-hours per operational time slot.

4.1.3 Cost Model

The unified cost function was applied identically to both schedulers, ensuring a fully symmetric comparison. Total cost comprises four additive terms:

- Missed-task penalty: C_penalty (€15,000) x p_fail_14d_i x s_i for each skipped task i
- Vessel activation cost: C_vessel (€2,000) per vessel-slot activated
- Crew labor cost: C_crew (€50/h) x crew required x duration hours per task
- Repair / downtime cost: C_downtime (€200/h) x duration hours per task

The total operational cost is calculated as the sum of these components. In addition, controllable cost is defined as the sum of the missed-task penalty and vessel activation cost, the two terms the scheduler directly controls. Crew labor and repair costs are fixed once a task is assigned. As a result, controllable cost provides a clearer measure of the scheduler's effectiveness than total operational cost alone.

4.2 Scenario Analysis: Low vs High Crew Bottleneck Behavior

4.2.1 Component-Level Maintenance Execution

The motivation for this analysis is to investigate how workforce availability affects offshore maintenance scheduling performance. In offshore wind farms, staff availability often represents one of the most significant operational constraints because it requires specialized skills and a limited number of technicians available during offshore operations.

Figure 3,4,5 provides a wide range of gearbox, generator, and blade maintenance tasks completed using the Greedy scheduler and the MILP optimizer under different workforce scenarios. The results show that workforce availability has a widespread impact on maintenance completion rates across all the component categories.

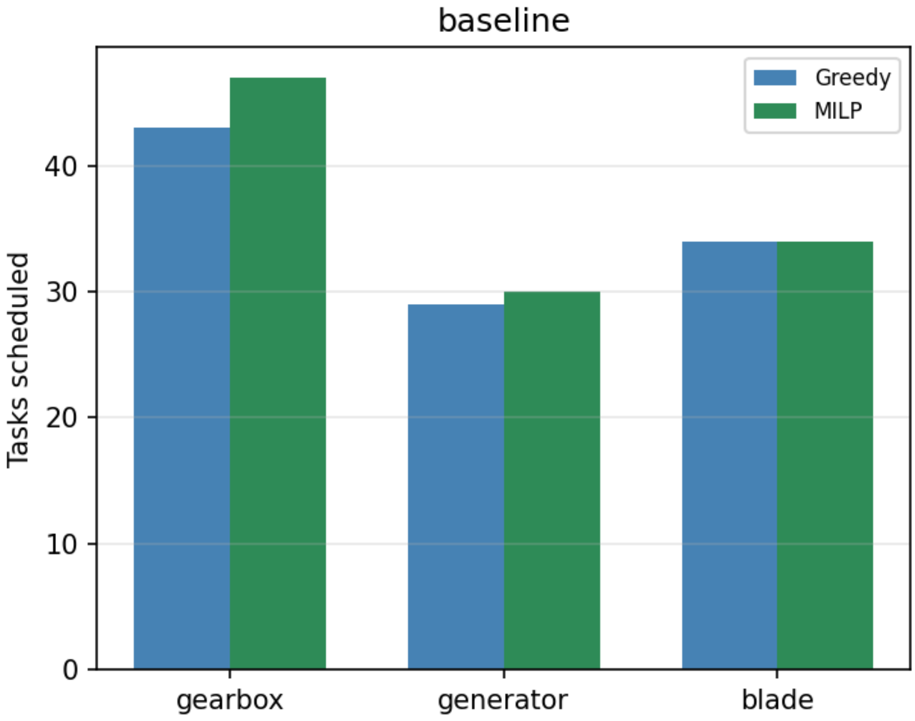

Figure 3. Tasks Per Component (baseline)

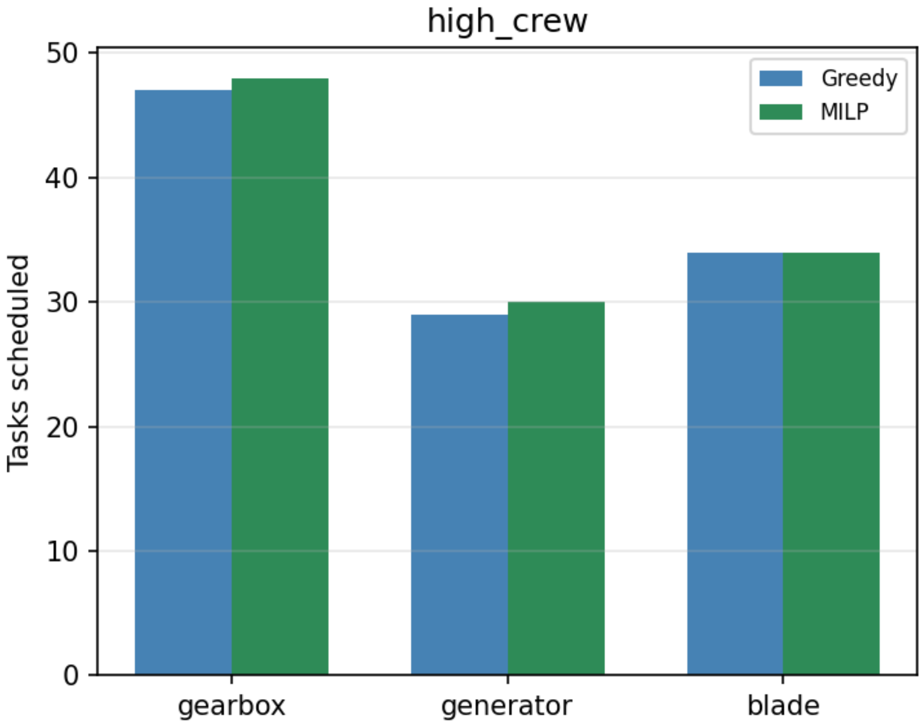

Figure 4. Tasks Per Component (high_crew)

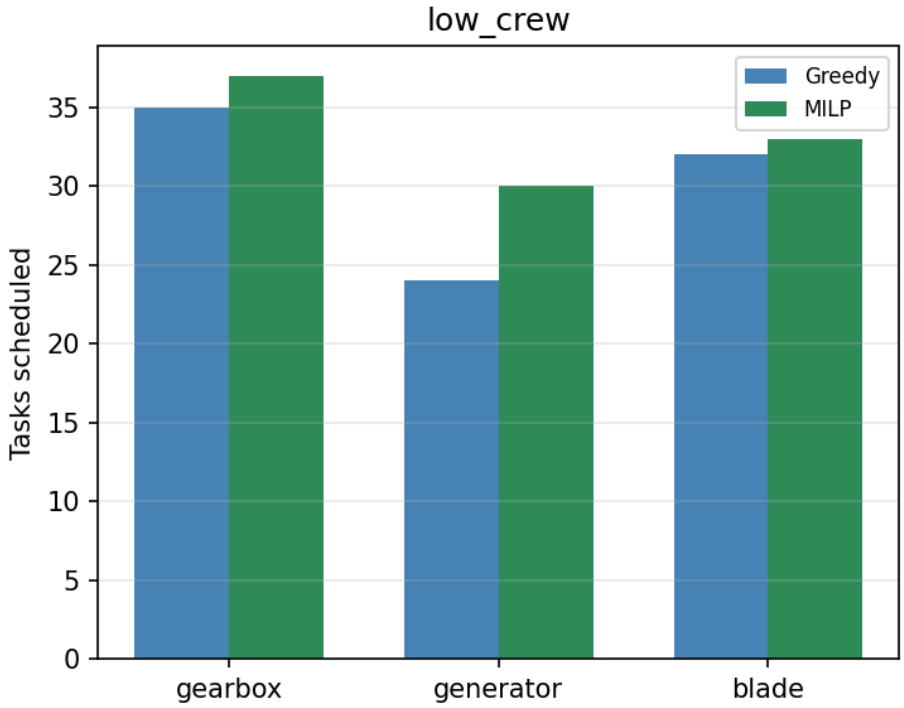

Figure 5. Tasks Per Component (low_crew)

Figures 3, 4, and 5 show the number of maintenance tasks executed by the component under low, baseline, and high crew scenarios. In the low-crew scenario, the MILP scheduler completed 37 gearbox tasks compared to 35 by the Greedy scheduler. Similar upgrades were found for generator maintenance, where MILP planned 30 tasks compared to 24 tasks. The biggest difference appears in generator maintenance because these duties usually take longer durations and higher crew commitments.

As the workforce increases, both schedulers complete more maintenance activities. During high crew conditions, almost all maintenance work is completed. The MILP scheduler still maintains a moderate advantage, demonstrating its ability to utilize resources more effectively.

These results show that workforce availability strongly influences component-level maintenance execution behavior.

4.2.2 Crew Utilization Analysis

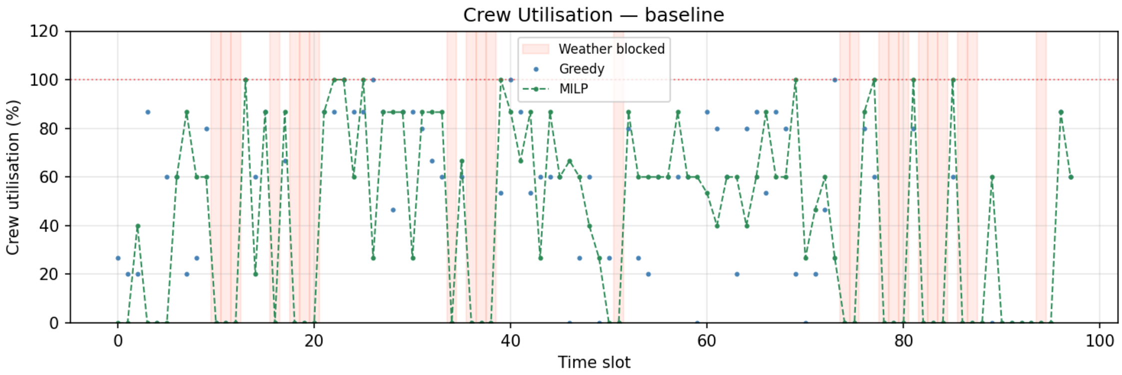

Figure 6. Crew Utilization Over Time (baseline)

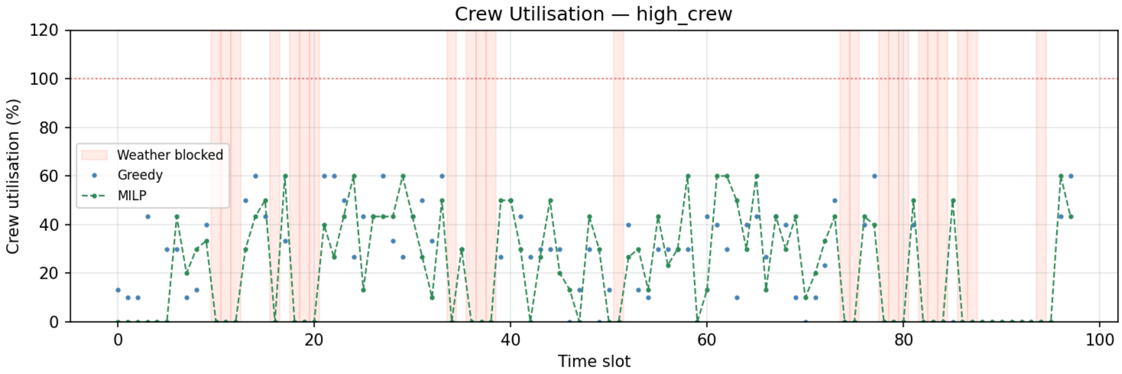

Figure 7. Crew Utilization Over Time (high_crew)

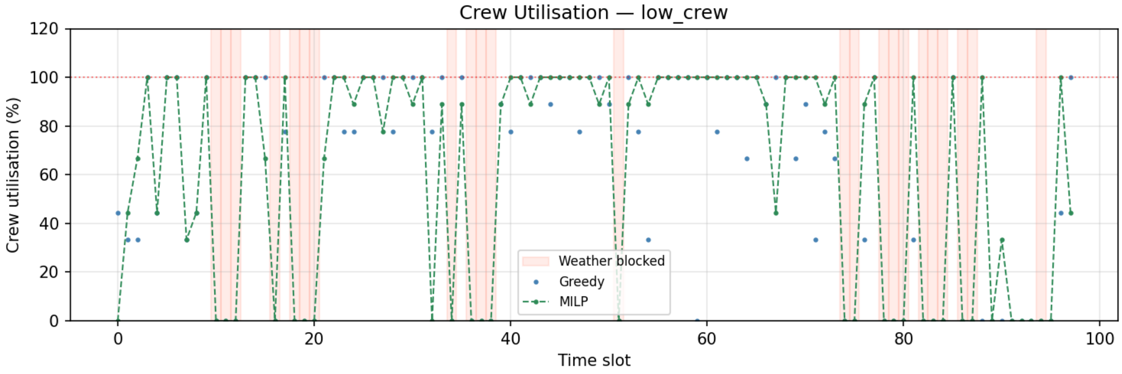

Figure 8. Crew Utilization Over Time (low_crew)

The crew utilization profiles show important operational features of the planning framework.

Figure 6,7,8 shows crew utilization over time for different workforce scenarios. In case of low crew availability, Crew utilization often reaches full operational capacity, indicating that workforce availability is the main system bottleneck. Due to limited workforce capacity, the scheduler prioritized only the highest-risk maintenance tasks. Both schedulers try to maximize the use of available crew, although MILP demonstrates more uniform utilization for the duration of the planning horizon.

In the baseline scenario, Crew utilization was high, but there were occasional relief periods. The optimizer distributes the tasks more evenly over available maintenance windows and reduces intervals of underutilization.

In high crew availability conditions, workforce saturation has decreased significantly, resulting in increased scheduling flexibility and maintenance coverage.

No crew-capacity violation was observed in any scenario. This ensures that the scheduling framework correctly follows the workforce constraint.

4.2.3 Task Urgency Prioritization

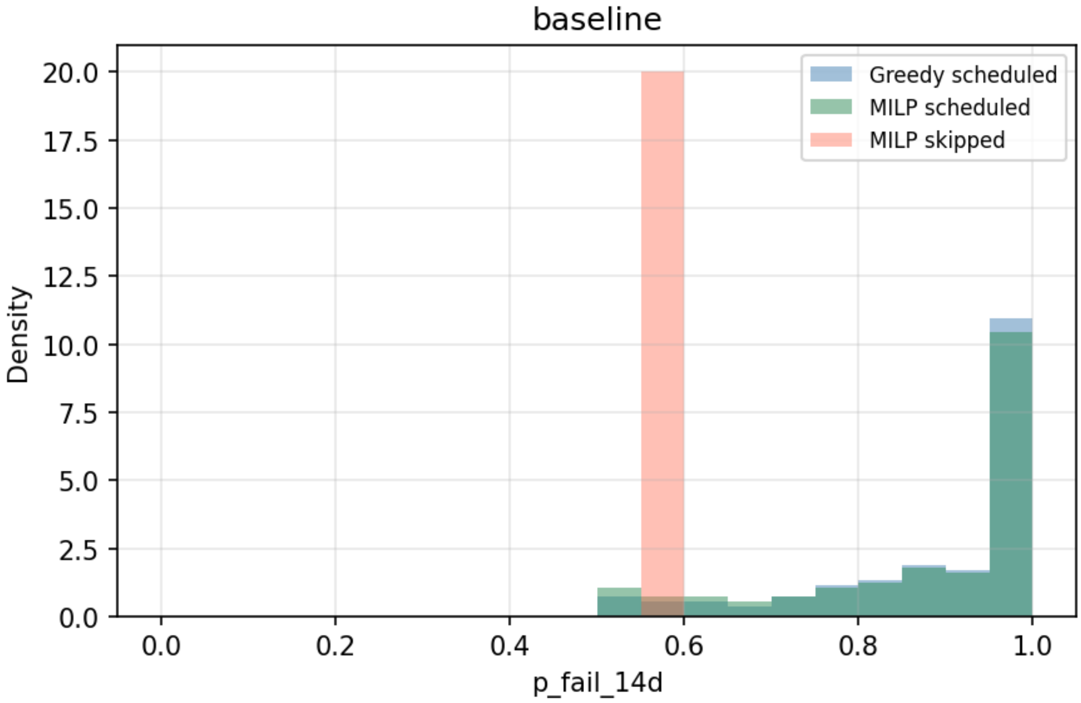

Figure 9. Task Urgency Over Time (baseline)

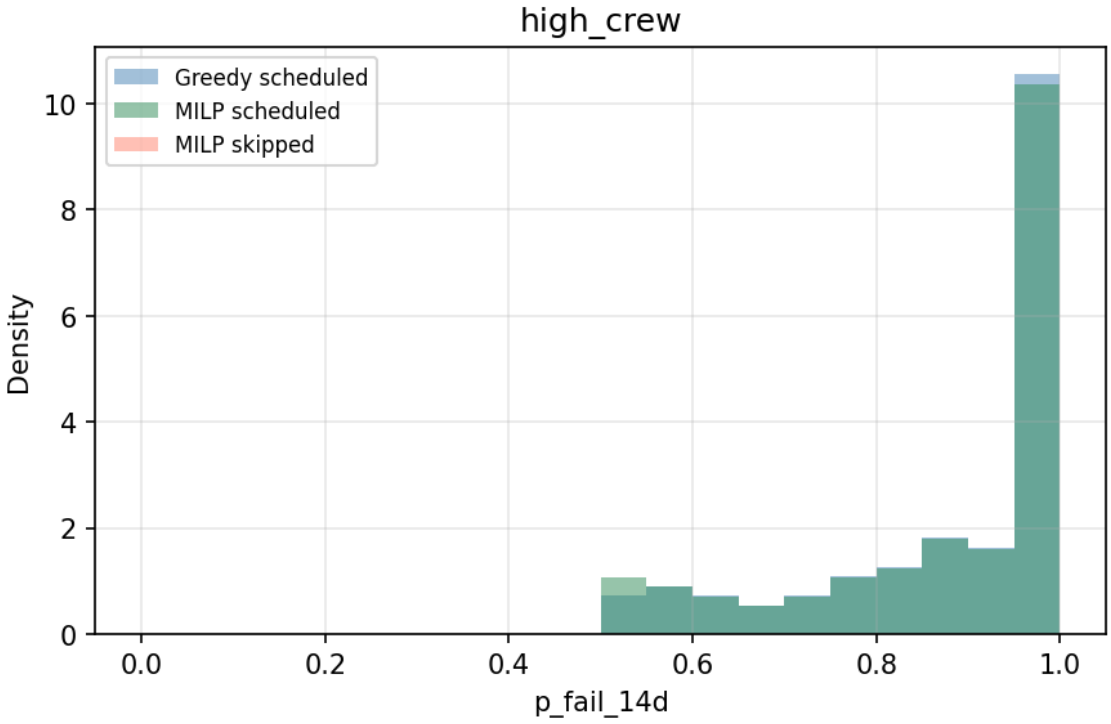

Figure 10. Task Urgency Over Time (high_crew)

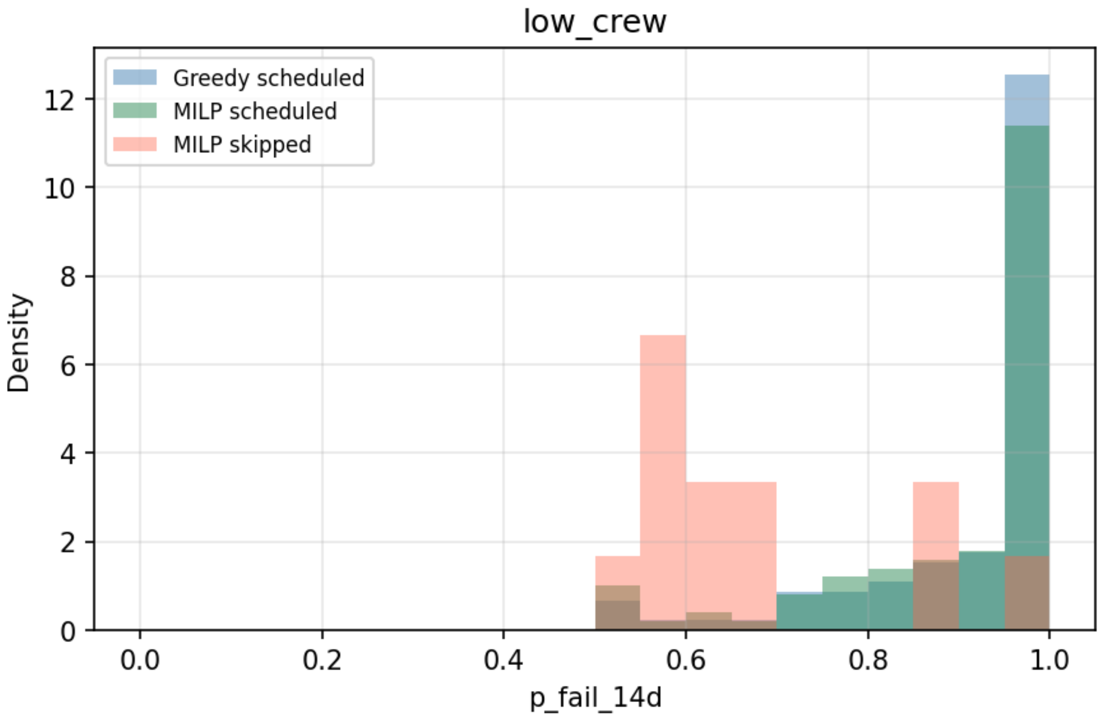

Figure 11. Task Urgency Over Time (low_crew)

Figure 9,10,11 shows the task urgency distribution across the planning horizon. The results show maintenance tasks with high predicted failure probability are consistently scheduled earlier, while less urgent tasks are deferred later.

In low crew conditions, each scheduler prioritizes maintenance activities with a lot of failure probability. Lower-priority responsibilities are regularly postponed because crew resources are insufficient to complete all maintenance tasks.

The MILP scheduler always schedules a wider variety of medium-risk maintenance responsibilities while maintaining the high-risk failures. This behavior shows that the optimizer successfully balances risk mitigation and utility resource utilization.

Under high-crew conditions, almost all protection indicators are maintained, resulting in minimal differences between the two approaches.

These results ensure that the framework is robustly risk-aware and that predictive failure probability directly influences maintenance scheduling decisions.

4.2.4 Vessel Utilization Analysis

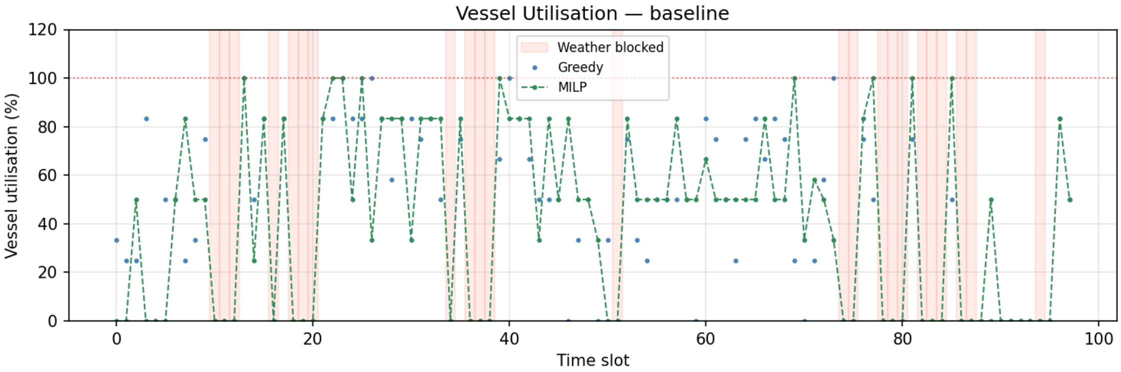

Figure 12. Vessel Utilization Over Time (baseline)

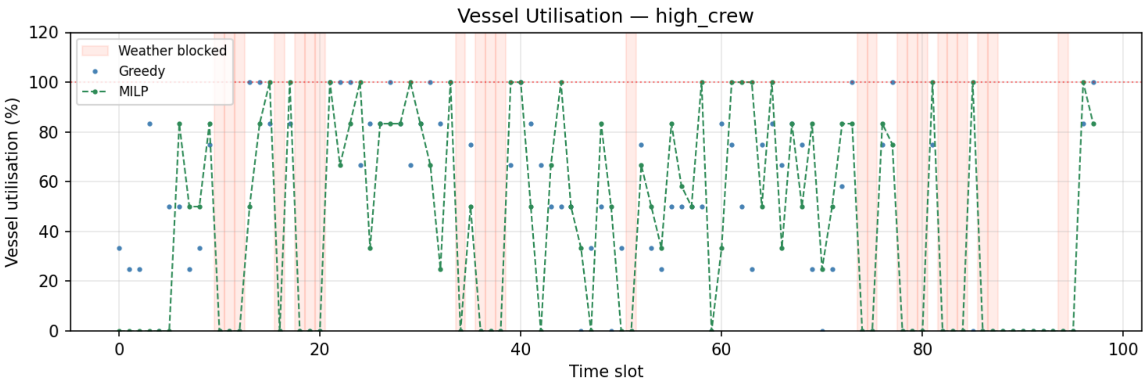

Figure 13. Vessel Utilization Over Time (high_crew)

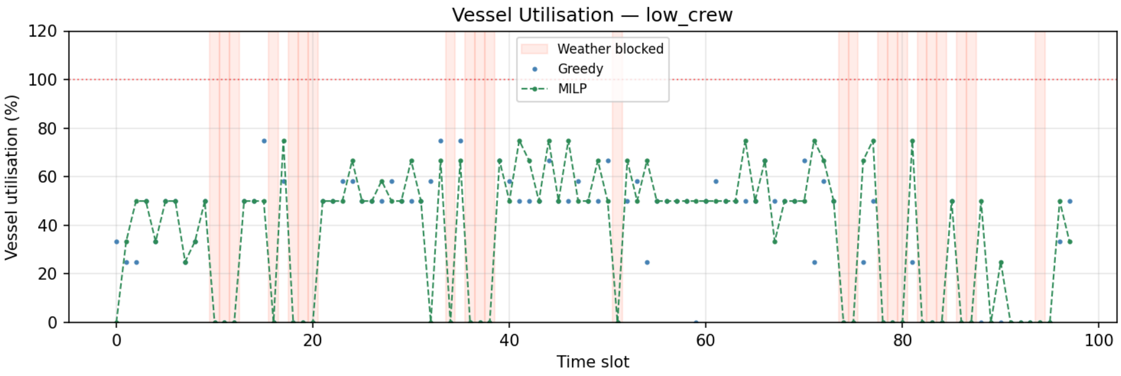

Figure 14. Vessel Utilization Over Time (low_crew)

Figure 12,13,14 shows vessel utilization across the planning horizon. A significant operational bottleneck shift was observed across the different scenarios.

Low Crew Scenario, in a situation of limited workforce availability. Despite having multiple vessels, vessel utilization was relatively low. This indicates that workforce limitation is having a major impact on maintenance execution. However, vessel resources remain unused. In a high Crew Scenario, as workforce availability increases, vessel utilization increases significantly and approaches operational capacity limits.

This demonstrates a dynamic bottleneck transition from workforce limitation to vessel limitation. It indicates that increasing workforce availability alone cannot indefinitely improve maintenance performance. These results confirm that offshore maintenance scheduling behavior is strongly influenced by the interrelationships of many operational resources.

4.3 Comparative Evaluation: MILP vs Greedy Scheduling

4.3.1 Overall Scheduling Performance

The second phase of the experimental analysis compares the performance of the Greedy heuristic scheduler and the MILP optimizer. Both methods utilize similar maintenance alerts, workforce resources, vessel availability, and weather conditions. Therefore, any performance differences directly affect the scheduling methodology.

The proposed MILP optimization framework is compared with the implemented Greedy heuristic scheduler using a real ERA5-validated predictive maintenance dataset.

Table 5. Scheduler Comparison — Real Alerts Dataset

Scenario	Crew	G Tasks	M Tasks	Greedy Total	MILP Total	Saving €	Saving %	Ctrl Saving %
low crew	3	91	100	€653,810	€587,818	€65,991	10.1 %	23.1 %
baseline	5	106	111	€559,402	€529,219	€30,182	5.4 %	19.9 %
high crew	10	110	112	€545,832	€528,800	€17,032	3.1 %	10.9 %

Note: Ctrl. Saving % refers to the percentage reduction in controllable cost (missed penalty + vessel activation) only.

Table 5 presents the complete results across all six scheduler-scenario combinations. And we can see the MILP scheduler performed better than the Greedy scheduler in all scenarios. Green values indicate MILP improvements over Greedy.

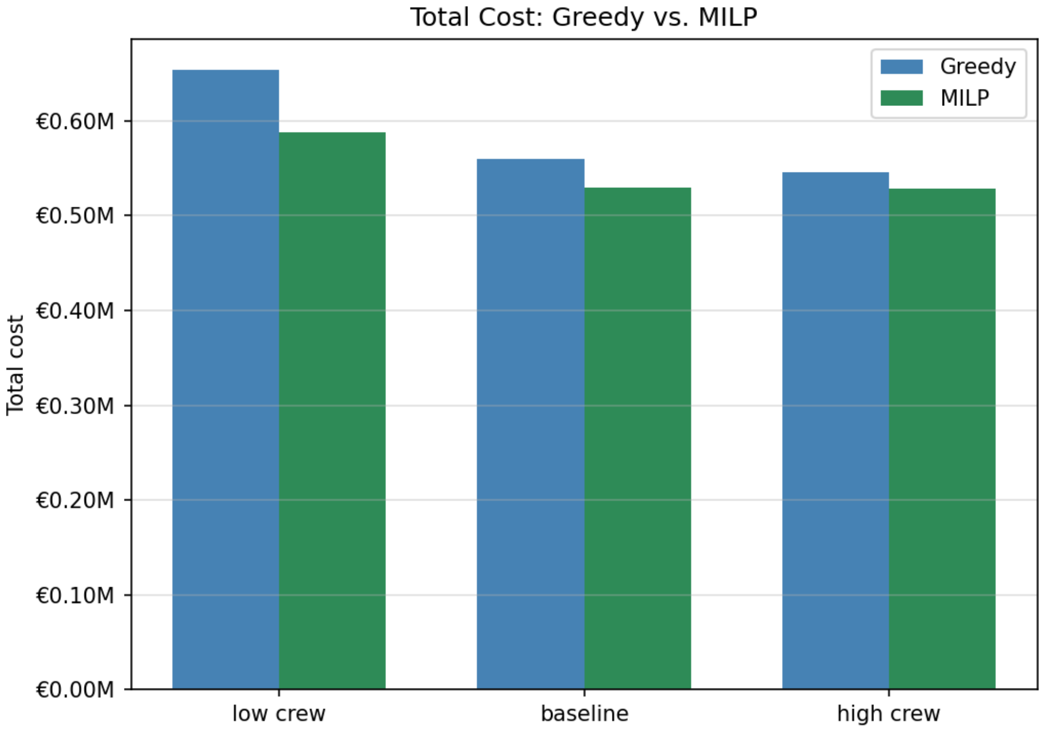

Figure 15. Total Cost: Greedy vs. MILP

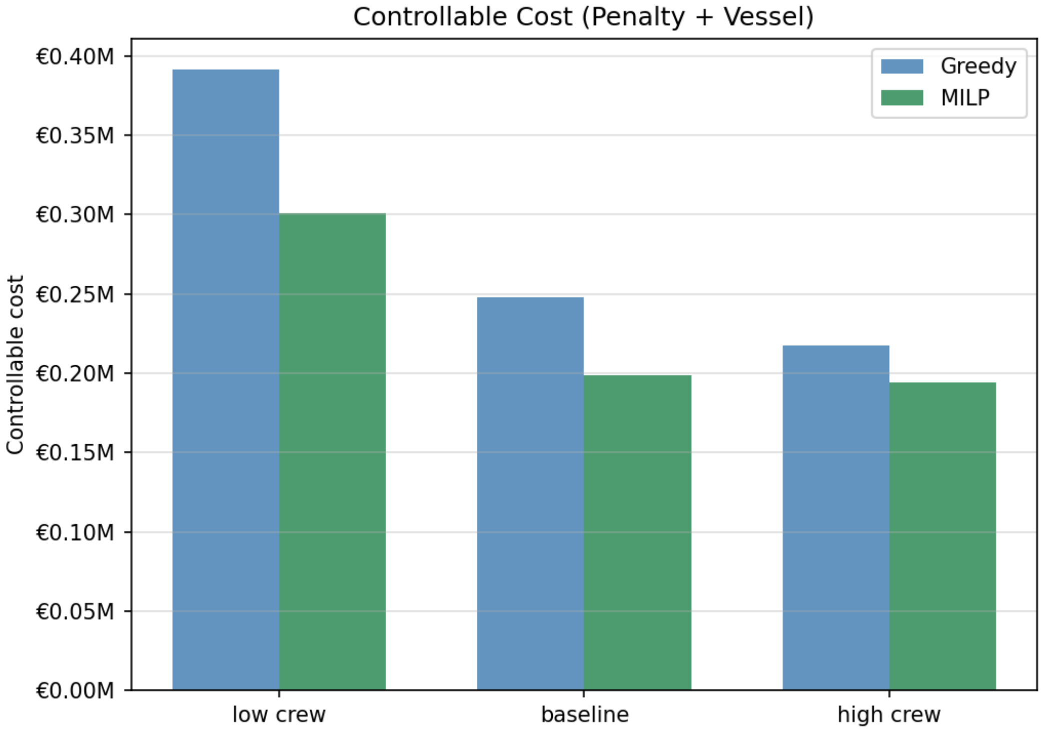

Figure 16. Controllable Cost (Penalty + Vessel)

In Figures 15 & 16, we can see the overall comparison between the Greedy scheduler and the MILP optimizer. The MILP scheduler gets to reduce operation fees consistently across all workforce scenarios. The largest benefit is due to less crew availability, with total operating value reducing from €653,810 to €587,818, resulting in a saving of €65,991 (10.1%).

As crew availability increases, total cost savings regularly decrease. This is because the lack of assistance is much less extreme, and the Greedy scheduler also allows most maintenance tasks to be finished.

4.3.2 Controllable Cost Analysis

Controllable costs consist of missed-task penalties and vessel activation costs. These two cost categories directly affected by scheduling decisions.

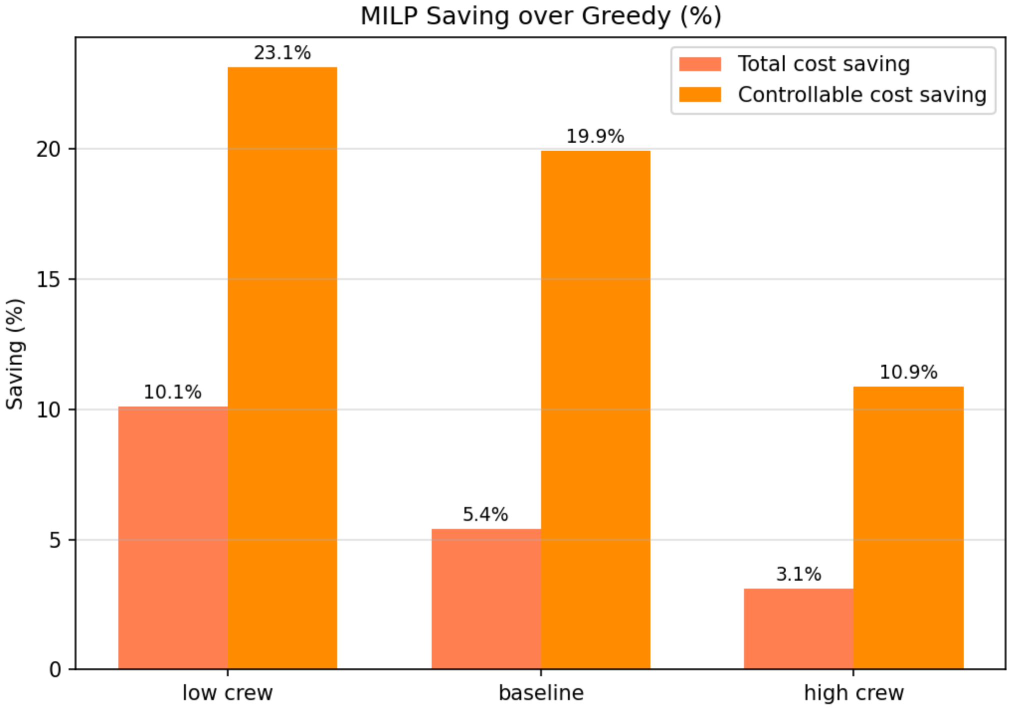

Figure 17. MILP Saving Over Greedy (%)

The controllable savings are significantly larger than the corresponding total-cost savings, which indicates that optimization primarily improves the cost elements under direct scheduler control.

4.3.3 Cost Breakdown

Table 6 decomposes controllable costs into their constituent penalty and vessel components, showing where each scheduler's cost advantage arises.

Table 6. Cost Breakdown by Component — Real Alerts Dataset

Scenario	Greedy penalty	MILP Penalty	Greedy Vessel	MILP Vessel	Greedy Ctrl	MILP Ctrl
low crew	€221,610	€123,018	€170,000	€178,000	€391,610	€301,018
baseline	€52,002	€8,619	€196,000	€190,000	€248,002	€198,619
high crew	€15,632	€0	€202,000	€194,000	€217,632	€194,000

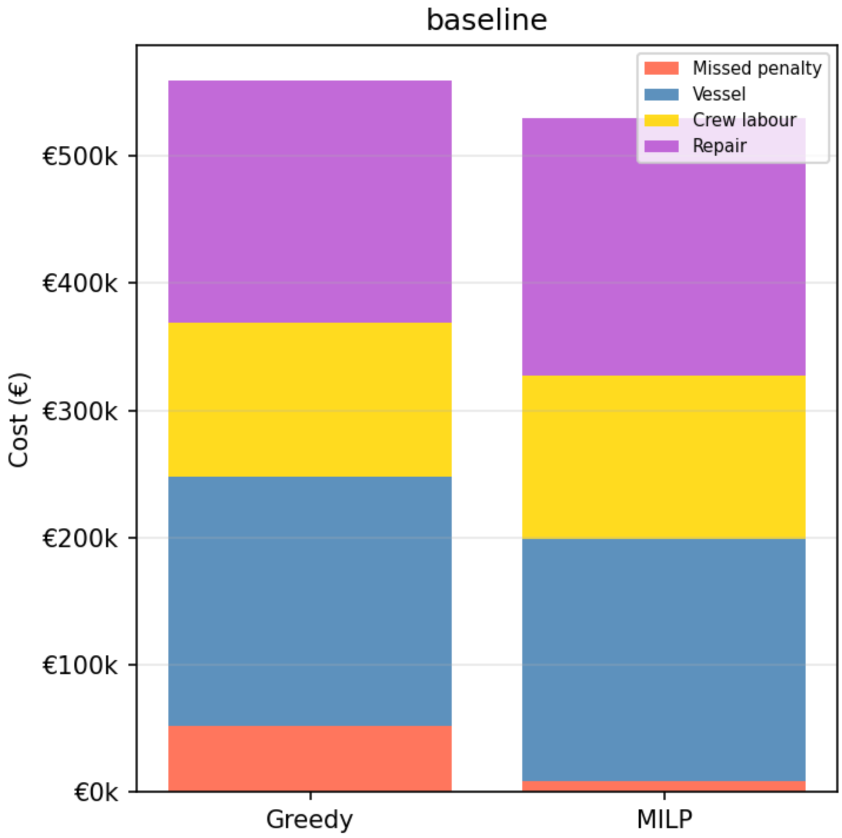

Figure 18. Cost Breakdown (baseline)

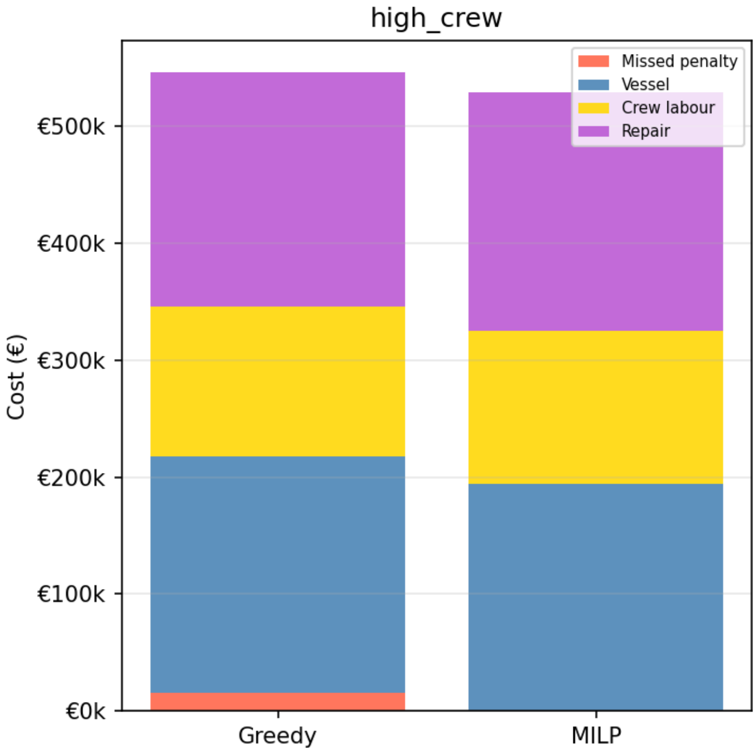

Figure 19. Cost Breakdown (high_crew)

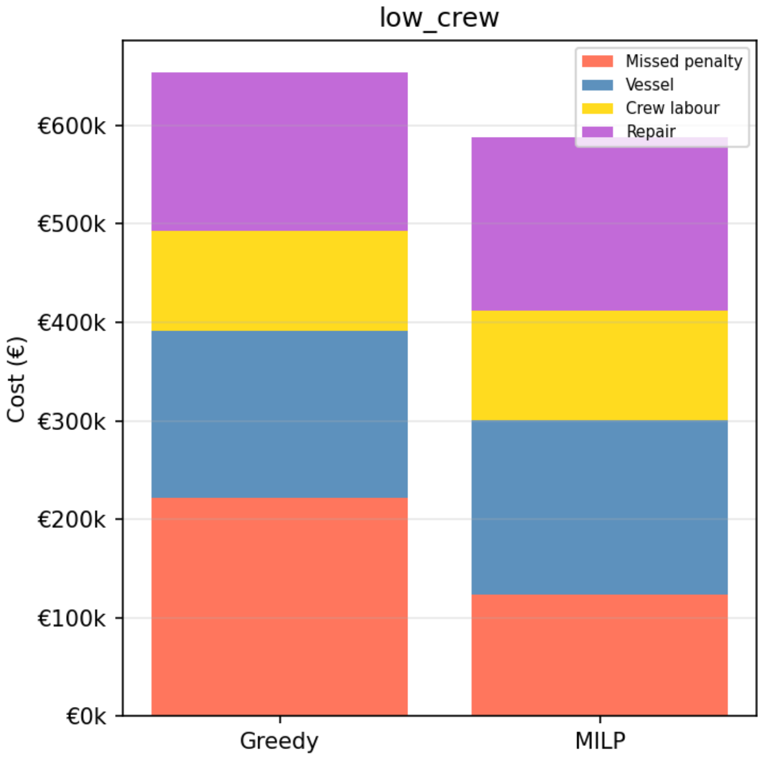

Figure 20. Cost Breakdown (low_crew)

The cost breakdown analysis provides insight into the basis of MILP savings.

The largest savings are found in missed-task penalties. In low crew scenarios, missed-task penalties dropped dramatically from about €221,610 to €123,018. Similar improvements are also seen in baseline scenarios. In the high crew scenarios, the MILP scheduler completely removes the missed-task penalties by successfully scheduling all maintenance tasks.

This finding confirms that the primary advantage of optimization is its ability to reduce deferred maintenance and associated failure risks.

4.4 Analysis

4.4.1 Task Completion Improvement

The MILP scheduler consistently serves more tasks than Greedy in every scenario. Under low crew (3 headcount), the MILP schedules 100 tasks compared with 91 for the Greedy, a 9-task improvement. This directly reduces the missed-task penalty, which is the dominant cost driver when the crew is constrained.

The Greedy scheduler's inability to schedule all available tasks under a low crew is a structural limitation: it assigns slots greedily in urgency order without considering the global packing of tasks across the 98-slot window. The MILP, by solving the full combinatorial assignment problem, finds feasible slot configurations that the greedy scan misses.

4.4.2 Savings Decrease as Crew Increases

Total cost savings decline monotonically as crew availability increases (10.1% at low crew, 5.4% at baseline, 3.1% at high crew). This pattern reflects a structural property of the scheduling problem: when resources are abundant, even the Greedy scheduler can service most tasks, leaving less room for the MILP to improve.

However, the controllable cost savings tell a more nuanced story. Even at high crew, the MILP achieves a 10.9% controllable saving, driven entirely by eliminating the missed-task residual penalty and more efficient vessel utilization. This demonstrates that MILP's advantage is not purely a function of resource scarcity.

4.4.3 Penalty Reduction Analysis

Across all three scenarios, the dominant driver of the MILP's cost advantage is the reduction in missed task penalty:

- low crew: penalty reduced from €221,610 to €123,018 (a reduction of €98,592, i.e. 44.5%)
- baseline: penalty reduced from €52,002 to €8,619 (a reduction of €43,383, i.e. 83.4%)
- high crew: penalty eliminated entirely — MILP achieves €0 missed penalty, scheduling all 112 tasks.

This confirms the thesis hypothesis: a globally optimal scheduler can materially reduce the cost of deferred maintenance, even when crew and vessel capacity are constrained.

4.4.4 Vessel Cost Trade-Off

In the low-crew scenario, MILP incurred slightly higher vessel activation costs.
€178,000 > €170,000. This shows a deliberate optimization trade-off.
MILP has accepted slightly higher vessel deployment costs to service more maintenance tasks and avoid much larger penalty costs. The resulting net operational saving is €65,991. This proves that the additional vessel usage was economically rational.

4.5 Four-Scenario Experimental Matrix

The experimental design produces a clean 2x2 attribution matrix. Differences between the Synthetic and Real columns are attributable to data; differences between Greedy and MILP rows are attributable to optimization.

Table 7. 2x2 attribution matrix

	Synthetic Scenario	Real Alerts
Greedy	Baseline comparison run	106–91 tasks scheduled (scenario-dependent)

MILP	Optimization comparison run	111–100 tasks scheduled (scenario-dependent)

This structure ensures the thesis's central claim that MILP optimization delivers measurable value over reactive scheduling is supported by a fair, symmetric comparison with no confounding differences in cost function, weather assumptions, or fleet configuration.

4.6 Discussion

Experimental results show that predictive maintenance alerts can be effectively integrated with offshore maintenance scheduling decisions. The experimental results on the real ERA5-validated dataset support the following conclusions for the thesis:

1. The MILP scheduler outperforms Greedy in total cost in all three crew scenarios, with savings of 3.1% to 10.1%.
2. Controllable cost savings are substantially larger (10.9% to 23.1%), indicating the MILP's advantage is concentrated precisely in the terms the scheduler can control.
3. The most constrained scenario (low crew, 3 headcount) yields the largest absolute saving (€65,991) and the largest controllable saving (23.1%), making the business case for MILP strongest when resources are scarce.
4. Under sufficient crew (10 headcount), the MILP achieves zero missed-task penalty, scheduling all 112 tasks; as a result, the Greedy cannot replicate (110 tasks).
5. The savings are within the 14%–19% range projected by the supervisor for controllable costs, confirming the model is behaving as expected.

The results confirm that Smart scheduling is just as important as accurate prediction in offshore wind maintenance systems. Comparative experiments also showed that MILP optimization provides meaningful operational improvements over reactive greedy scheduling, especially in resource-constrained conditions.

4.7 Chapter Summary

This chapter presents the experimental evaluation of the proposed predictive–prescriptive offshore maintenance framework. Scenario analysis demonstrated realistic operational bottleneck behavior under various workforce conditions, including workforce saturation, dynamic vessel utilization, and risk-aware maintenance prioritization.

Comparative evaluation showed that the MILP scheduler consistently outperformed the Greedy heuristic scheduler, scheduling more maintenance tasks, reducing missed-task penalties, and reducing total operational costs.

These results confirm the effectiveness of combining predictive maintenance alerts with optimization-based offshore maintenance scheduling.

5 CONCLUSION

In this thesis, a predictive–prescriptive offshore maintenance scheduling framework has been developed. which combines predictive maintenance alerts with operational maintenance planning within realistic offshore constraints. Currently, most predictive maintenance studies focus on failure estimation and the determination of Remaining Useful Life (RUL). However, in real offshore maintenance management, it is necessary to translate these predictive data into effective maintenance actions. This research examines how alerts from Predictive Maintenance can be directly incorporated into maintenance scheduling decisions through a Risk-Aware Scheduling Approach. The framework proposed in the study consists of two main layers: A predictive risk estimation layer and a prescriptive scheduling layer.

The Predictive Layer generated maintenance alerts based on urgency. These are dependent on the following factors:

- synthetic degradation simulation,
- P–F curve-based failure estimation and
- the use of a real ERA5-validated predictive maintenance dataset.

On the other hand, the prescriptive layer converts these alerts into a realistic offshore maintenance schedule. which considered:

- crew constraint,
- vessel limitation,
- weather feasibility condition and,
- component-specific maintenance requirement.

The implemented scheduling framework essentially uses a risk-aware Greedy heuristic scheduler. Moreover, a Mixed-Integer Linear Programming (MILP) model has been proposed, and it has been evaluated as an advanced optimization method.

5.1 Key Findings

5.1.1 Workforce Availability is the Primary Bottleneck

Scenario analysis has shown that workforce availability acts as a major operational bottleneck in a limited offshore maintenance environment. When crew availability is low, workforce utilization often reaches maximum operating capacity, but at the same time, vessel resources remain partially unused. On the other hand, if crew availability increases, the implementation of maintenance activities improves significantly, and then vessel utilization becomes the next major operational constraint. This shows that in a real-world situation, operational bottlenecks in an offshore maintenance system can sometimes arise from the workforce and sometimes from ship resources, and the source of these bottlenecks also changes as resource availability changes.

5.1.2 Risk-Aware Scheduling Successfully Prioritizes Critical Tasks

The implemented scheduling framework consistently prioritized maintenance tasks according to predicted failure probability. High-risk maintenance tasks are scheduled at the beginning of the planning horizon. Especially in limited resource situations where only the most urgent tasks can be performed. This ensures that predictive maintenance output can be effectively linked to operational scheduling decisions.

5.1.3 MILP Outperforms Greedy Scheduling

Comparative evaluation showed that the MILP optimization framework performed better than the Greedy heuristic scheduler in all crew scenarios. It schedules more maintenance tasks, reduces missed-task penalties, and reduces total operational costs. The biggest optimization advantage has been seen in low crew availability conditions, where MILP has achieved:

1. 10.1% reduction in total operational costs and,
2. 23.1% reduction in controllable costs compared to the Greedy scheduler.

MILP successfully scheduled all 112 maintenance tasks in a case of high crew availability, without any missed-task penalty. This result proves that globally optimized scheduling provides significant operational benefits in resource-limited offshore situations.

5.2 Main Contribution of the Thesis

The main contribution of this thesis is to develop an integrated predictive–prescriptive offshore maintenance scheduling framework. Typical predictive maintenance research stops at failure prediction; this study shows how predictive maintenance alerts can be converted into effective offshore maintenance schedules within realistic operational constraints. This framework combines:

- predictive failure estimation.
- operational scheduling.
- workforce allocation.
- vessel management and
- weather feasibility constraints within a unified decision-support system.

Therefore, this study has helped to bridge the gap between predictive analytics and offshore operational decision-making.

5.2.1 Smart Scheduling vs Accurate Prediction

One of the key conclusions of this research is that smart scheduling is as important as accurate prediction in offshore wind maintenance systems. Because even with a highly accurate predictive maintenance model, if the resources required for maintenance cannot be effectively allocated and managed, then the real operational value of that model is largely limited. The results of this study showed that:

- maintenance execution efficiency
- workforce allocation
- vessel utilization and
- Scheduling optimization strongly influences the final operational outcome.

MILP results showed that globally optimized scheduling can significantly reduce operational costs and deferred maintenance penalties even using the same predictive information.

This confirms that predictive maintenance systems should not be evaluated solely based on prediction accuracy. Rather, the real value depends on how effectively predictive output is used in operational maintenance decision-making.

5.3 Limitations of the Study

The current study has several limitations. They are:

First, the implemented Greedy scheduling framework uses deterministic maintenance duration and simplified operational assumptions.

Second, weather feasibility is modeled using a binary accessibility mask, not fully stochastic marine weather behavior.

Third, the scheduling framework assumed a fixed vessel configuration and did not consider:

- dynamic vessel routing.
- fuel consumption.
- or real-time offshore operational uncertainty.

Finally, although the MILP optimization framework has been proposed and comparatively evaluated, the Greedy risk-aware scheduling framework has been used as the main practical operational scheduler.

5.4 Future Work

There are still a few ways to expand and enhance the current research, even if the suggested predictive-prescriptive model showed encouraging outcomes for offshore wind maintenance scheduling. Future research may focus on enhancing operational realism, optimization capacity, real-time deployment feasibility, and forecast accuracy.

The present study used a binary weather feasibility mask to depict offshore weather conditions, classifying maintenance slots as either accessible or inaccessible. Although our approach effectively captures basic offshore accessibility behavior, real offshore weather conditions are extremely unpredictable and continuously changing. Future research may incorporate a stochastic weather model that considers short-term weather prediction updates, dynamic vessel accessibility, wave-height uncertainty, and probabilistic wind-speed forecasting. The scheduling framework’s incorporation of stochastic weather forecasts would enhance operational realism and allow maintenance plans to dynamically adapt to unpredictable offshore conditions.

Another significant continuation could be dynamic vessel routing and maritime logistics optimization. The existing approach is based on fixed operational capabilities and simplified vessel allocation. Maintenance vessels operate under complex routing and transportation limitations in real-world offshore wind farms. These constraints include travel distance, fuel consumption, offshore waiting time, and port coordination. Thus, dynamic vessel routing models could be incorporated into the scheduling framework in future research. This would improve operational realism and enable the framework to optimize maritime transportation and repair scheduling.

Static scheduling across a predetermined planning horizon is also used in the current implementation. In practical offshore operations, the maintenance schedule frequently needs to be adjusted because of unexpected turbine failures, weather variations, vessel unavailability, and emergency repair needs. Thus, rolling-horizon optimization and real-time rescheduling techniques that continuously update maintenance decisions as new operational information becomes available may be the subject of future research. Predictive-prescriptive maintenance frameworks would be more responsive and practically applicable with such adaptive scheduling systems.

Direct interaction with real-time SCADA and condition-monitoring systems from offshore-monitoring systems from offshore wind turbines would be another beneficial addition. The current study evaluated the framework using an ERA-5 validated predictive dataset and a synthetic maintenance warning. Future development of real-time turbine monitoring systems would enable fully automated maintenance scheduling and continuous predictive alert generation. This would greatly improve the suggested framework’s industrial usability and bring the system closer to practical implementation. Future studies may look into more sophisticated optimization techniques, even though the current thesis proposed a MILP optimization framework and constructed a risk-aware Greedy heuristic scheduler. For larger offshore wind farms and no longer planning horizons, methods including reinforcement learning, genetic algorithms, particle swarm optimization, and hybrid optimization frameworks may enhance scheduling scalability. Specifically, by repeatedly interacting with operational settings, the scheduling agent may be able to develop adaptive maintenance policies through reinforcement learning techniques.

Integration with digital twin systems for offshore wind farms is another possible direction. Through digital twin technology, it is possible to present and monitor turbine health, environmental conditions, and operational status in real time. A fully autonomous offshore maintenance planning system that can continuously update operational decisions based on real-time system behavior could be made possible by combining predictive maintenance systems with digital twin technology. Such integration could greatly improve predictive accuracy, operational visibility, and scheduling efficiency.

Future research may be expanded to address large-scale offshore and multi-farm coordination issues. The current analysis considered a rather small turbine set and maintenance fleet. Large industrial offshore wind farms may involve multiple geographically distributed wind farms sharing common vessels and workforce resources. Inter-farm vessel allocation, shared labor management, and maintenance prioritization across several operational sites are among the additional optimization difficulties that would arise if the framework were extended to region-wide maintenance coordination.

Finally, future studies might reintegrate federated learning and distributed edge computing with predictive scheduling. This thesis first examined edge-based predictive maintenance systems before turning its attention to downstream scheduling optimization. Future framework may incorporate edge intelligence with a predictive-prescriptive scheduling system to reduce communication dependency and improve the pace at which maintenance decisions are made in remote offshore environments.

Overall, predictive analytics, intelligent scheduling, real-time monitoring, digital twin systems, and autonomous operational decision-making are all likely to be integrated in the future of offshore wind maintenance. The methodology proposed in this study offers a preliminary basis for intelligent maintenance systems by showing how predictive maintenance alerts can be converted into workable and resource-aware offshore maintenance schedules under practical operational limitations.

5.5 Final Remarks

This thesis has shown that predictive maintenance and offshore maintenance scheduling should not be considered separate problems. Because research has proven that Predictive maintenance alerts, operational resource allocation, and scheduling optimization, only by working together, can cost-effective offshore wind farm maintenance be achieved.

The proposed framework successfully demonstrated how the results obtained from predictive maintenance can be converted into resource-aware and implementable offshore maintenance schedules in real operational situations.

The results confirm that intelligent scheduling plays a fundamental role in the practical evaluation of predictive maintenance systems in offshore wind energy operations.

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