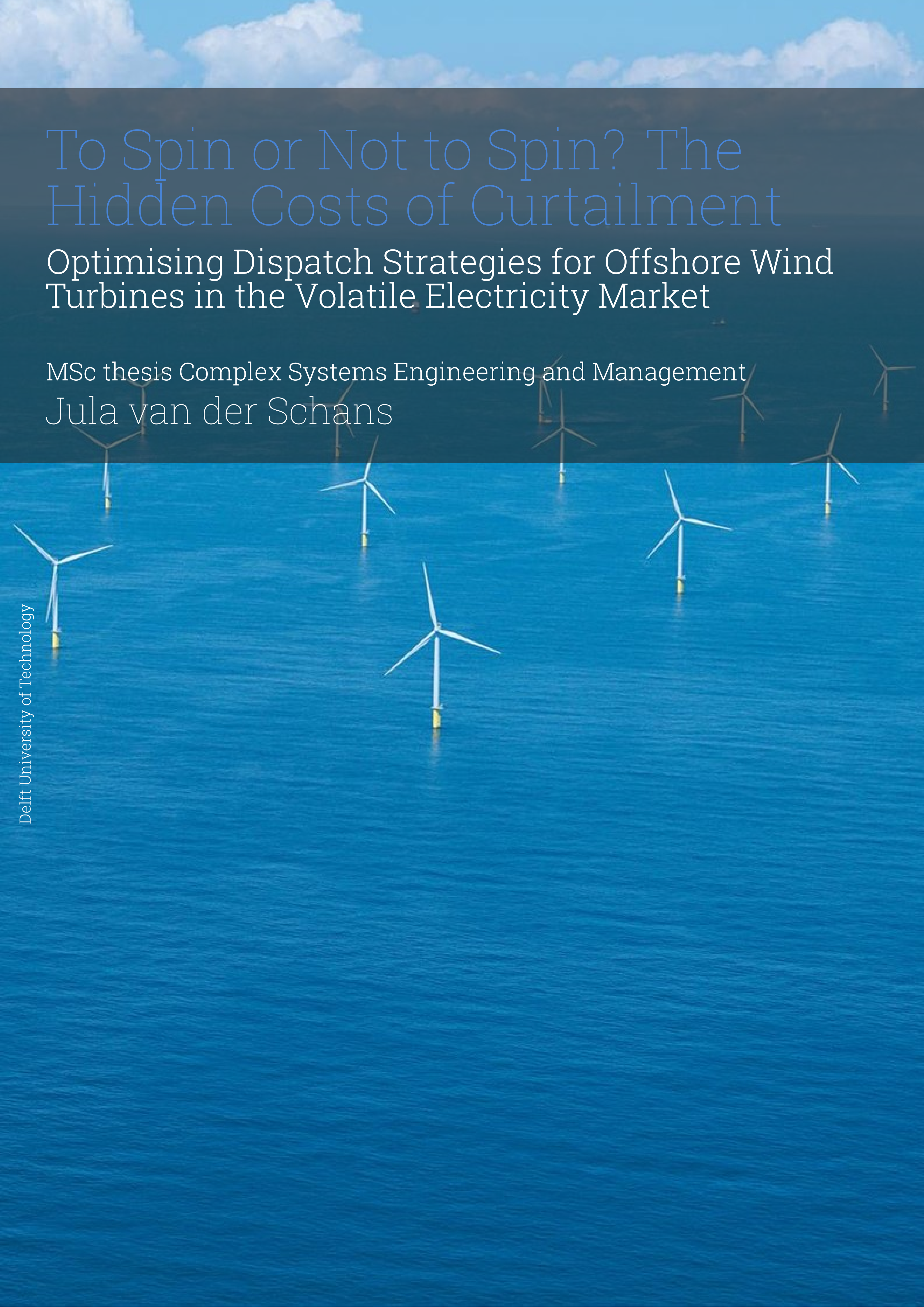
To Spin or Not to Spin? The Hidden Costs of Curtailment

Optimising Dispatch Strategies for Offshore Wind Turbines in the Volatile Electricity Market

MSc thesis Complex Systems Engineering and Management

Jula van der Schans



Delft University of Technology

”A designer knows he has achieved perfection not when there is nothing left to add, but when there is nothing left to take away.”

by

Antoine de Saint-Exupéry [1]

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by

Jula van der Schans

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Cover: Offshore Wind Farm Luchterduinen by Eneco [2]

Acknowledgement

I am now nearing the end of my graduation project, which marks the final step in completing my MSc in Complex Systems Engineering and Management at TU Delft. Looking back, I do so with a sense of nostalgia. I began this process without knowing exactly where it would take me, and at times, it felt like swimming without knowing the destination. That is why I am incredibly proud of the work before you. However, I could never have achieved this alone.

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I hope that those who read this work will be as inspired by the topic as I was. It has been a great privilege to explore this field in such depth. Wishing you an enjoyable and insightful read.

Jula van der Schans
Delft, April 2025

Executive summary

The large-scale integration of variable renewable energy sources (vRES) has led to a growing reliance on curtailment as a tool to manage electricity price volatility. While curtailment can mitigate short-term financial risks, its long-term impact on offshore wind turbine (OWT) degradation remains largely overlooked. This research explores the hidden costs of curtailment and proposes a coordinated framework which internalises asset health in dispatch strategies while maximising financial performance.

Market-driven curtailment is a relatively new trend, emerging as negative electricity prices become more frequent with the growing share of vRES. In a low-electrification scenario and with limited flexibility resources within the power system, negative prices could persist well beyond 2030. Coupled with rising material costs, the phasing out of subsidies, high interest rates, and inflation, these factors have intensified concerns about the economic viability of wind farm development.

Curtailment decisions in offshore wind are currently driven by short-term market incentives, often neglecting the long-term consequences for turbine health. The stakeholders, namely the dispatcher, maintenance parties, and wind farm owners, hold conflicting interests regarding curtailment strategies. While dispatchers focus on minimising immediate financial losses in volatile electricity markets, maintenance teams seek to balance cost-efficient operation with asset availability, and wind farm owners prioritise asset longevity. This misalignment leads to suboptimal outcomes, increasing operational expenditure (OpEx) and reducing the OWT operational lifespan. Through the development of a mathematical optimisation framework, the study incorporates the perspectives of the dispatcher, maintenance teams, and wind farm owners while modelling the degradation of critical OWT components. The central research question guiding this work is: *To what extent can integrating asset health improve the value of offshore wind power through coordinated curtailment strategies?*

To address this question, three different optimisation models were developed, each providing a distinct perspective on curtailment decision-making. A baseline scenario was established to evaluate the current situation, serving as a reference for comparison. The study then proposed two alternative frameworks: a centralised and a decentralised coordinated curtailment strategy. To enable decentralised decision-making, this study applies the Alternating Direction Method of Multipliers (ADMM). Specifically, the problem formulation follows the general global variable consensus optimisation framework introduced by Boyd et al. [3]. Notably, this research is the first to apply ADMM to curtailment strategies, demonstrating its potential in this domain.

The study focuses on three critical OWT components affected by curtailment: the gearbox, the blades, and the support structure. The impact of curtailment depends on turbine design, wind farm location, prevailing environmental conditions, and the levels of both power production and power curtailment. Deep curtailment, where an OWT is completely shut down and produces 0 MWh, increases the stress on the foundation compared to partial curtailment. To mitigate this, long-term agreements typically include a curtailment cap, ensuring that turbines continue to generate 10-25% of their rated power output. While idling has minimal impact on onshore turbines, offshore turbines experience complex interactions between aerodynamic and hydrodynamic forces, complicating the analysis of degradation.

Currently, dispatchers prioritise short-term market conditions, whereas wind farm owners and maintenance teams focus on long-term asset health. This fragmentation results in inefficient curtailment practices that fail to minimise wear on components, resulting in increased expenses to reinforce and replace components. In addition, the inability to scale down power output beyond curtailment limits leads to financial setbacks for dispatchers.

By incorporating asset health into a centralised coordinated curtailment strategy, the financial viability of wind power is significantly enhanced. The results show a 57% reduction in investment costs, and a 439% increase in system-wide profit, reflecting a notable increase from 0.38 M€ to 2.06 M€. The return on investment (ROI) also increases sharply from 5.82% in the base case to 73.31% in the centralised scenario, representing a gain of 67.49 percentage points, clearly demonstrating the considerable added value of coordination. Strategic curtailment can extend component lifespans, potentially delaying expensive replacements and reducing maintenance costs. While a centralised coordination strategy can yield substantial benefits, its feasibility depends on contractual structures. In fragmented ownership models, concerns over data-sharing and operational autonomy may hinder full implementation. A decentralised coordination strategy, as explored in this study, offers a theoretically viable alternative, though further research is needed to assess its practical scalability.

Despite its simplified structure, the model successfully demonstrates the potential value of incorporating asset health into curtailment strategies. While the proposed frameworks offer clear insights, several uncertainties remain. The degradation models are simplified representations of wear processes, and future research could improve their accuracy through more detailed fatigue analysis. The substantial profit increase can be partially attributed to a modelling artefact, where the remaining component health is directly converted into monetary value. Therefore, the 439% system-wide profit increase should be viewed as a theoretical upper bound rather than a realistic financial outcome. Lastly, the scalability of the decentralised approach should be further tested in larger datasets and longer forecasting horizons to evaluate its feasibility in real-world applications.

In conclusion, integrating asset health into curtailment strategies enhances the long-term value of offshore wind power. While centralised coordination remains the ideal benchmark, decentralised frameworks offer a feasible alternative for optimising curtailment decisions. It is important to acknowledge that implementing a fully optimised solution is not a requirement for realising operational improvements. A pragmatic approach, via integrating a simplified assessment of the marginal cost of curtailment into the existing bidding strategy, could already prove to be rewarding. Additionally, wind farm developers should account for market-driven curtailment when designing OWTs to prioritise long-term financial sustainability over short-term material cost reductions. This could be reflected in adjusted terms in the Power Purchase Agreement (PPA). A combination of these practical price incentives to integrate asset health in curtailment strategies has the potential to enhance the long-term value of offshore wind power.

Looking ahead, the value of centralised coordination has proven to be most effective in an electricity market characterised by negative price hours and greater price volatility. As these trends are expected to intensify with an increasing share of vRES, the case for coordinated curtailment becomes even stronger. Internalising asset health will become increasingly valuable in future energy systems.

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Abbreviations and symbols

Abbreviation	Definition
ADMM	Alternating Direction Method of Multipliers
BLD	Blades
BoP	Balance of Plant
CapEx	Capital Expenditure
CfD	Contract for Difference
CoSEM	Complex Systems Engineering and Management
CPPA	Corporate Power Purchase Agreement
DEL	Damage Equivalent Load
GBX	Gearbox
GoO	Guarantee of Origin
LCOE	Levelised Cost of Energy
LEE	Leading-Edge Erosion
LGC	Large-scale Generation Certificates
LP	Linear Programming
MCP	Market Clearing Price
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
NLP	Non-Linear Programming
O&M	Operation and Maintenance
OpEx	Operational Expenditure
OWT	Offshore Wind Turbine
PIF	Profile and Imbalance Factor
PPA	Power Purchase Agreement
RFC	Rainflow Counting
RPM	Rotations per Minute
RUL	Remaining Useful Lifetime
RTU	Remote Terminal Unit
SCADA	Supervisory Control And Data Acquisition
SDE++	Incentive Scheme for Sustainable Energy Production and Climate Transition within the Netherlands
SHM	Structural Health Monitoring
SS	Support Structure
TSO	Transmission System Operator
TSR	Tip Speed Ratio
vRES	Variable Renewable Energy Sources
WTG	Wind Turbine Generator

Symbol	Definition	Unit
B	Total replacement cost with 20% margin	[€]
C^{bld}	Blade replacement cost	[€]
C^{gbx}	Gearbox replacement cost	[€]
C^{ss}	Support structure reinforcement cost	[€]
f_t^{bld}	Blade degradation function	[-]
f_t^{gbx}	Gearbox degradation function	[-]
f_t^{ss}	Support structure degradation function	[-]
H_t^s	Significant wave height	[m]
I_t^{rain}	Rain intensity	[mm/hr]
k	Penalty factor included in NLP	[-]
P_t^{Curt}	Power curtailed	[MW]
P_t^{DA}	Power sold in the day-ahead market	[MW]
$P_{i,t}^{DA}$	Local decision variable of stakeholder i	[MW]
$P_{z,t}^{DA}$	Global consensus variable in ADMM	[MW]
P_t^{Th}	Theoretical wind turbine power	[MW]
P_{rated}	Maximum power output 15 MW turbine	[MW]
r	Rotor radius	[m]
r^k	Primal residual at iteration k	[-]
s^k	Dual residual at iteration k	[-]
S_t^{bld}	Blade health state	[-]
S_t^{gbx}	Gearbox health state	[-]
S_t^{ss}	Support structure health state	[-]
S_{min}	Minimum permissible health state	[-]
S_{max}	Maximum permissible health state	[-]
T	Time horizon of the simulation	[time steps]
T_{fail}^m	Time step of component m failure	[time steps]
T_{stop}^m	Time step at a replacement decision has to be made	[time steps]
T_t	Thrust force on turbine blades at time t	[MN]
V_t^w	Wind speed at 150m hub height	[m/s]
V_{cut-in}	Cut-in wind speed 15 MW turbine	[m/s]
$V_{cut-out}$	Cut-out wind speed 15 MW turbine	[m/s]
$V_{cut-rated}$	Rated wind speed 15 MW turbine	[m/s]
Y	Simulation period in years	[years]
$y_{i,t}$	Dual variable (Lagrange multiplier)	[€/MW]
z_t^m	Binary replacement variable for component m	[-]
$\alpha^{gbx}, \alpha^{ss}, \alpha^{bld}$, $c_{damping}, b_{wave}, b_{rain}$	Degradation scaling factors	[-]
ρ	ADMM penalty parameter	[-]
λ_t^{DA}	Electricity price of the day-ahead market	[€/MWh]
λ_t^{PPA}	Predefined price in the PPA	[€/MWh]

1
Introduction

1.1. Problem introduction

The Netherlands is undergoing a major transformation in its energy sector, driven by the transition to a market increasingly dominated by variable renewable energy sources (vRES). In particular, offshore wind is playing a crucial role in this transition, with installed capacity increasing from 2.5 GW in 2022 to 4.5 GW in 2023 [4], and further expansion targets set at 23 GW by 2030 and 70 GW by 2050 [5]. In 2023, offshore wind energy contributed 16% to the national electricity demand [6], which is expected to increase in the coming years. While the rapid expansion of offshore wind is necessary to reduce reliance on fossil fuels, integrating large-scale vRES into the electricity market is not without challenges.

The increasing share of vRES has led to more frequent occurrences of periods with excess electricity supply. Combined with low demand and inflexible power plants, this can result in the formation of negative electricity prices [7, 8, 9]. For example, on July 2, 2023, electricity prices dropped to a record low of -500 €/MWh for 15 consecutive hours. Without the harmonised price caps under the pan-European Market Coupling, which limits the day-ahead market clearing price to -500 €/MWh and to -9999 €/MWh on the intraday market [10], prices could have been even lower. Negative price formation is a recent trend, as illustrated in Figure 1.1, which provides an overview of the number of negative price hours per month from 2016 to 2024 [11]. Figure 1.1 shows that the number of negative price hours increased sharply from 0 in 2016 to 316 in 2023 and up to 456 in 2024. In addition, Figure 1.2 shows the average level of negative prices per month from 2016 to 2024, which highlights an increasing trend in the magnitude of negative prices.

While these figures focus on the Netherlands, similar trends are observed in other markets with increasing vRES penetration. In Germany, negative price hours rose from 70 in 2014 [12] to 459 in 2024 [11]. In Finland, they surged from 0 in 2016 to over 460 in the first three months of 2025 [11].

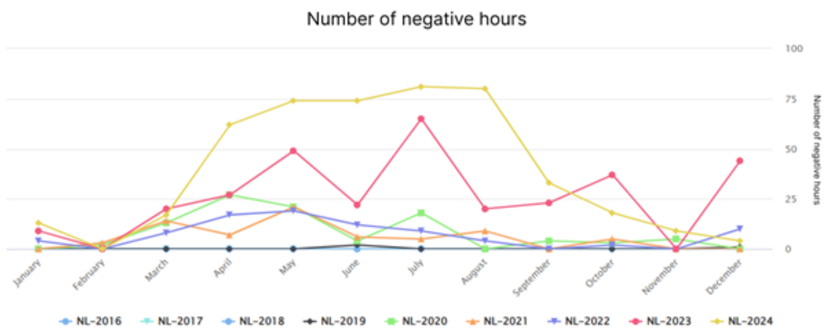


Figure 1.1: The number of hours with negative prices in the Netherlands from 2016 to 2024 [11]

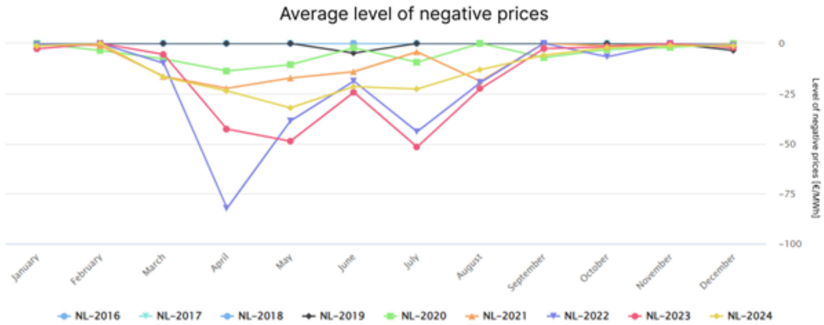


Figure 1.2: The average level of negative prices in the Netherlands from 2016 to 2024 [11]

As negative electricity prices are becoming more frequent, market-driven curtailment is more commonly adopted. Curtailment involves the intentional reduction of wind turbine power output to limit electricity generation, thereby avoiding the necessity to sell produced electricity at a financial loss. While further growth in the vRES share may exacerbate the trend illustrated in Figures 1.1 and 1.2 [13], this could be impacted by the level of electrification of the Dutch industry as outlined by Gonzales-Aparicio et al. [14]. Gonzales-Aparicio et al. have developed a model for the profitability of offshore wind energy based on two scenarios: one scenario assuming high electrification of the industry and the other assuming low electrification. The high-electrification scenario is expected to reduce both the frequency and magnitude of negative prices over time [14]. However, in a low-electrification scenario and with limited flexible resources within the power system, this study suggests that offshore wind energy is expected to be unprofitable in 2030, resulting in a curtailment rate of approximately 13% of offshore wind energy production [14]. According to the Eurelectric report, this low-electrification scenario could be realistic, considering the electrification of the European industry is stagnating, having remained stable at approximately 23% over the past decade [15].

At first glance, curtailing wind turbine power in response to negative electricity prices appears to be a straightforward solution for offshore wind assets. However, in reality, this is more complex. To safeguard turbine health, long-term Power Purchase Agreements (PPAs) often include curtailment limits that restrict full power reduction to 0 MWh. In practice, these agreements typically require a minimum power output of 15–20% of the turbine capacity. Before delving deeper into curtailment strategies, it is important to first understand the broader context in which offshore wind operates. The next section provides an overview of the economic and market dynamics shaping the offshore wind energy sector.

Economic viability under pressure

Besides lower profitability in the electricity market due to more volatile electricity prices, the economic viability of offshore wind is no longer self-evident [16]. Initially, subsidy schemes such as SDE++ ensured financial stability despite market fluctuations [17]. However, over the past two years, investment conditions have worsened due to a gradual reduction in subsidies [17], changes in tendering policies [18, 19, 20], and a sharp increase in the Levelised Cost of Energy (LCOE) driven by rising interest rates and inflation [21]. Subsidies have been scaled back in several countries (e.g. Netherlands [22, 19], Germany [23], and Denmark [24]), and tendering processes now require developers to make financial contributions. While these changes increase costs for developers, the reduction in governmental support is intended to limit excessive profits and ensure compensation for the use of natural resources, such as offshore space. The rise in LCOE has further worsened investment conditions, which is driven by both an increase in interest rates, particularly affecting capital-intensive projects, and inflation, which has driven up material and labour costs. In light of these developments, economic viability has become a primary concern for wind farm developers.

Hidden costs

While curtailment is primarily seen as a market-driven response (i.e., due to negative electricity prices), its implications extend beyond revenue losses. Negative prices aim to discourage energy producers from supplying electricity to the grid, and encourage consumers to increase consumption, as they are effectively paid to use electricity [25]. However, not all energy producers possess the flexibility to adapt the power output in the short term. Fossil fuel generators, for instance, face ramping constraints that limit how quickly they can adjust their output. Additionally, the high start-up and shutdown costs associated with ramping often restrict their ability to react efficiently to price fluctuations.

Offshore wind turbines (OWTs), in contrast, can technically reduce their output more quickly by curtailing. However, frequent transitions between maximum production and zero output introduce additional stress on critical turbine components, such as the gearbox, pitch system and foundation [26]. The magnitude of these loads depends on the occurring environmental conditions. Unlike onshore wind turbines, OWTs must withstand a combination of wind and wave-induced forces. This particular combination can accelerate fatigue of the foundation.

From the perspective of a wind farm owner, preserving turbine health is crucial as it offers the potential to extend the operational lifespan. In this light, a turbine's structural integrity can be viewed as a finite resource, much like fossil fuel is for a conventional power plant, that gradually degrades over time. This degradation of asset health represents the hidden costs of OWTs. While the price of electricity from fossil fuel power plants is largely determined by fuel costs [27], a similar principle should apply to vRES. Asset degradation and associated maintenance expenses should be factored into market pricing strategies.

The need for an integrated curtailment strategy

In the current curtailment strategies, decisions are fragmented. Dispatchers make curtailment decisions based purely on market signals, while maintenance teams and asset owners remain focused on physical longevity. This misalignment can result in unnecessary financial losses and increased component degradation.

For example, negative prices can occur in case of excess solar energy production and mild wind conditions (a sunny, windless summer day). Under the current strategy, which includes minimum power outputs in the PPA, the dispatcher incurs financial losses due to the offloading of excess wind energy. From the dispatcher's perspective, managing a 1 GW wind farm can be costly in this scenario. For example, if prices drop to -100 €/MWh and the PPA includes a minimum power output of 20%, the dispatcher incurs a loss of €20,000 per hour. In this scenario with mild wind conditions, the minimum power output could yield unwanted results as shutting down turbines completely would have resulted in minimal stress on foundations while minimising financial losses. On the other hand, in extreme wind and high wave conditions, the curtailment limit is crucial. Without this, additional environmental loads would accelerate foundation fatigue, potentially shortening the operational lifespan of the wind farm.

An integrated curtailment strategy should internalise long-term asset health considerations while maximising short-term market performance. Strategic curtailment could minimise loads on the foundation during low wind and wave conditions while preventing excessive fatigue during more severe conditions. Without proper coordination, dispatchers face financial losses due to curtailment limits, while wind farm owners bear increased costs for the reinforcement and replacement of components.

A coordinated curtailment strategy would integrate the perspectives of the dispatcher, maintenance team, and wind farm owner, potentially improving the current market-driven approach. Yet, internalising asset health in dispatch decisions has not been common practice. This is largely due to the historical context in which PPAs were negotiated: electricity prices were stable and closely tied to fossil fuel prices, with little need for curtailment. As a result, degradation effects were not seen as economically relevant at the time the PPA negotiations took place, and asset health was excluded from contractual agreements. Even now, reluctance to change persists driven by perceived transaction costs and the complexity of defining degradation under varying environmental conditions. As electricity markets become increasingly volatile, the need for integrated curtailment strategies grows. This thesis seeks to quantify the added value of internalising asset health into dispatch strategies.

1.2. Research objective

Curtailment decisions in offshore wind are often made with a narrow focus on short-term market conditions, prioritising immediate financial returns while neglecting the hidden costs of turbine degradation. Over time, this trade-off jeopardises asset longevity, increases operational expenditures (OpEx), and reduces the overall value of wind energy generation. This study challenges that approach by redefining curtailment as more than just a market-driven constraint. When optimised, curtailment can internalise asset health considerations while still maximising financial performance.

The objective of this research is to develop a decision-making framework for dispatch strategies that internalise the long-term degradation effects of offshore wind turbines while ensuring profitability in a volatile electricity market. A mathematical optimisation approach will incorporate insights from key stakeholders and account for the degradation of critical turbine components. While a centralised framework enables system-wide coordination, it may be impractical due to contractual complexity and data-sharing limitations. Therefore, this research also explores distributed optimisation methods that support independent decision-making by stakeholders. Specifically, it investigates the potential of consensus-based algorithms, in particular the use of the Alternating Direction Method of Multipliers (ADMM), to coordinate decentralised curtailment strategies. Further detail on ADMM and the sub-questions are provided in Chapter 2.

To guide the research, the following main question is explored:

To what extent can integrating asset health improve the value of offshore wind power through coordinated curtailment strategies?

The question will be addressed through answering four sub-questions, namely:

1. What effect does curtailment have on the degradation of critical OWT components?
2. What are the objectives of different stakeholders (dispatchers, asset operators, and wind farm owners) regarding curtailment strategies?
3. How can curtailment strategies be formulated as an optimisation problem?
4. Can a global consensus framework, such as ADMM, be utilised to achieve coordinated decision-making in a decentralised curtailment strategy?

1.3. Report outline

This study examines market-driven curtailment in offshore wind, revealing its hidden costs and inefficiencies. Through a structured approach, it builds towards an optimisation framework that redefines curtailment decision-making.

In Chapter 2, the existing literature on curtailment strategies is analysed. The findings will identify gaps in current research and shape the research questions. Chapter 3, introduces the research methodology. Here, the scope of the system is presented in a conceptual model, which details the roles of the most important stakeholders, namely, the energy dispatcher, maintenance party, and wind farm owner. Following, Chapter 4 dives into the technical aspects of market-driven curtailment. Critical components are selected and the degradation effects of curtailment are determined. Next, Chapter 5 presents the stakeholder perspectives, including their objectives, financial incentives and opposing interests in curtailment decisions. Both Chapter 4 and 5 feed into Chapter 6, which formulates curtailment strategies as an optimisation problem. It introduces mathematical models and proposes a decentralised coordination framework. Chapter 7 discusses the results of the three optimisation scenarios: the baseline scenario, a centralised coordinated strategy, and a decentralised coordinated strategy. The findings provide insights into the value of coordination. Next, Chapter 8 investigates the robustness of the proposed scenarios under different market conditions. The broader implications of the main research findings are explored in Chapter 9, where the discussion assesses the practical feasibility, study limitations, and recommendations for future research. Finally, the conclusions are listed in Chapter 10.

2
Literature review

As discussed in Chapter 1, while offshore wind plays a crucial role in achieving the Netherlands' renewable energy targets, its large-scale integration into the energy system presents significant challenges. Periods of excess energy supply and the associated financial losses underscore the need to transform offshore wind into a flexible and deployable asset [28]. This chapter begins by examining the most important concepts of the electricity market and the challenges related to the integration of offshore wind in Section 2.1. Next, an overview is given of the drivers of curtailment and the associated mitigation strategies in Section 2.2. This is followed by a review of the technical impact of curtailment on the OWT in Section 2.3. Section 2.4 examines the use of distributed consensus algorithms, particularly ADMM, in wind power optimisation and their potential for coordination of multi-stakeholder decisions. Finally, Section 2.5 summarises the knowledge gaps identified in the literature, forming the basis for the research objectives.

2.1. Electricity markets with high penetration of vRES

This section first explores the fundamental concepts of the electricity market, followed by an examination of the challenges posed by high penetration of vRES. It concludes by emphasising the need for flexible energy resources and the changing role of offshore wind.

The day-ahead electricity market operates on a market-clearing principle, where supply and demand determine the market price through the highest accepted bid, illustrated in Figure 2.1. The market-clearing price (MCP) is typically set by the most expensive marginal technology required to meet demand, often natural gas-fired plants [7]. In contrast, offshore wind, with its near-zero marginal costs, is generally dispatched first.

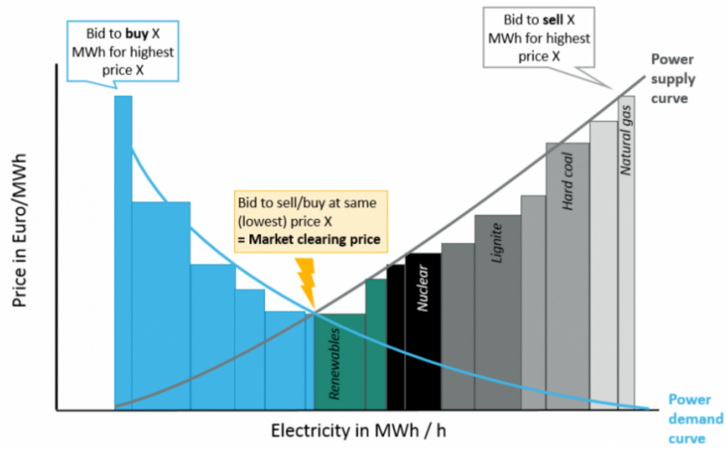


Figure 2.1: The merit order with supply and demand curves, with a positive MCP [29]

As the share of vRES increases, prices decrease through the merit-order effect, where cheaper renewable energy displaces more expensive fossil-based generation [30, 31]. In addition, with the increasing penetration of wind and solar, the cannibalisation effect is introduced, in which the high availability of renewables lowers overall market prices to the point where their own profitability is reduced [16].

At times of high renewable generation combined with low demand and inflexible power plants, market prices may even turn negative [7, 8, 9], as shown in Figure 2.2. This occurs when excess electricity supply cannot be absorbed by the system, and producers must pay consumers or storage operators to take the surplus power out of the system. A study by Johanndeiter et al. suggests that renewable energy producers, such as wind and solar farms, may bid at zero marginal costs or even at negative prices [32]. Systems with high shares of vREs increasingly contain volatile electricity prices, with large extends of near-zero or negative market prices when there is excess energy production, followed by periods with high price surges when vRES output is low [33].

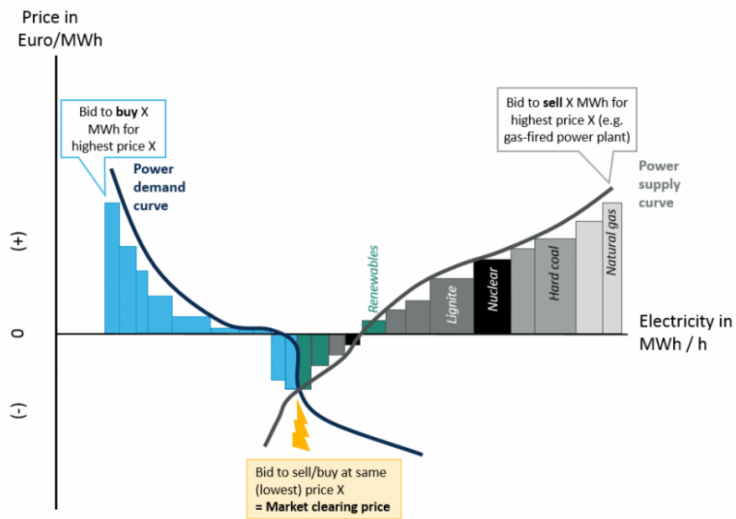


Figure 2.2: The merit order with supply and demand curves, with a negative MCP [29]

Renewable energy generators may bid at negative prices due to government support schemes like, subsidies that ensure revenue regardless of market prices. While such subsidies are gradually being phased out, as discussed in Chapter 1, older wind farms still benefit from these mechanisms.

In contrast, conventional power plants, such as gas-fired units, base their bids on opportunity costs. Due to ramping constraints, these plants cannot adjust output rapidly in response to price fluctuations. To avoid costly shutdowns and restarts, they may bid at negative prices, reflecting the anticipated peak revenue they would forgo if they were to reduce production.

Besides the previously discussed challenges of price cannibalisation and the merit-order effect, both of which impact the profitability of renewable energy producers, large-scale integration also introduces greater price volatility and the risk of Dunkelflautes. Market volatility increases due to the strong correlation between electricity prices and weather-dependent renewable generation. Unlike conventional power plants, which can produce electricity as long as fuel is available, wind and solar power generation fluctuates with environmental conditions. This results in highly dynamic market prices, with frequent periods of negative prices due to excess generation, followed by price spikes when renewable output is low. Additionally, the reliance on vRES heightens the risk of system imbalances, particularly during periods of low wind and solar generation, commonly referred to as 'Dunkelflaute' [34]. During such events, renewable output drops to critically low levels, jeopardising the stability of the electricity supply and triggering extreme price surges. The inability of inflexible conventional power plants to respond rapidly further exacerbates these challenges.

These challenges underscore the growing need for flexibility in electricity markets. The next section explores the necessity of flexible energy resources to address these challenges.

Need for more flexible resources

The integration of vRES into the electricity system necessitates a greater share of flexible resources to cope with their inherent variability and uncertainty [35, 36]. Flexibility in a power system refers to its ability to effectively respond to unforeseen operational changes, driven by the variability and inherent uncertainty in both supply and demand, as well as external constraints [37].

Several studies explored flexibility solutions to mitigate the curtailment of excess vRES. Utility-scale batteries, for instance, have been analysed for their cost-effectiveness [38]. Similarly, the research analysed the optimal duration of energy storage required to absorb curtailed wind energy [39]. Demand-side flexibility, such as demand response, has also been proposed as a mitigation strategy [35, 40, 41]. However, its effectiveness is hindered by several challenges, including the temporal mismatch between peak generation and consumer demand, locational constraints, and the reliance on consumer willingness to shift consumption patterns. In addition, the unpredictable nature of curtailment makes large-scale deployment of demand response even more difficult.

Research suggests that the economic feasibility of curtailed power utilisation is limited. A study analysing the use of curtailed power for methanol production found that while the initial reuse of curtailed renewable energy power reduces the costs, the economic viability quickly diminishes as the variability of the curtailed power increases [42]. This is largely due to the high capital costs of electrolysers [43], which are required to process an increasingly intermittent power supply, therefore, reducing the overall efficiency and financial viability. However, achieving a viable business case solely with the curtailed wind power might be difficult, as electrolysers require operation during a large number of hours per year. Additionally, electrolysers are not as flexible as often assumed. Many systems require a minimum baseload operation of 10-15%, limiting the immediate ramp down to zero production. In cases where they must shut down completely, all residual gases must be purged, leading to further inefficiencies and increased operational costs.

Despite ongoing research, the development of flexible capacity remains uncertain. While emerging solutions promise to mitigate curtailment, they are not mature enough to fully alleviate excess wind generation. It is important to acknowledge that waiting for the widespread deployment of flexible resources does not resolve the immediate challenge faced by offshore wind curtailment today. Without a high level of electrification and significant flexible resources in the power system, another study stated that a curtailment rate of approximately 13% of offshore wind energy production will remain in 2030 [14]. The persistence of curtailment highlights the need for further research into offshore wind as a flexible asset. With limited alternatives to absorb excess generation, offshore wind will either continue facing curtailment or take on a more active role in balancing the system. To keep offshore wind viable as the energy market changes, it is crucial to know how curtailment affects turbines and when it's worth doing.

Evolving role of wind

The role of wind power in electricity markets is changing as the share of vRES increases. Traditionally, fossil-fuel-based power plants participated across multiple trading markets, selling energy on the spot market, where electricity is traded for immediate use, while also providing reserve capacity to maintain grid stability through the balancing market. In contrast, offshore wind has primarily focused on energy generation in the day-ahead market, where prices are set one day before delivery based on supply and demand forecasts [44]. However, the increasing need for system flexibility is reshaping the role of wind power in the electricity market. While the intermittent nature of offshore wind power output poses a challenge for participation in the reserve market [45], wind turbines are nowadays equipped with fast control schemes that enable them to rapidly adjust power output [46, 47]. If wind power generating companies were to be incentivised properly, wind power could play a more active role in providing system flexibility beyond the day-ahead market [45].

According to Tang et al. [48] offshore wind producers rely on three main revenue sources: (1) long-term contracts, (2) spot electricity market sales, and (3) green energy incentives. These incentives vary by country and region, with examples including Renewable Energy Certificates (REC) in the United States, Guarantees of Origin (GoO) in Europe, and Large-scale Generation Certificates (LGC) in Australia. Despite regional differences, the underlying objectives of these incentives are similar worldwide [48]. As a result, the role of wind power in electricity markets is applicable across different countries and market structures.

To provide a clearer understanding of the different trading platforms, this section outlines the structure of the Dutch electricity market. It comprises multiple trading markets, ranging from long-term contracts established up to four years before delivery to real-time balancing mechanisms [49].

The forward market facilitates long-term agreements, such as PPAs and Contracts for Difference (CFDs), which provide energy producers with a stable income and protection against market volatility. As Wolak [50] explains, forward contracts typically specify a fixed price and an associated capacity commitment, indicating the volume of electricity (in MWh) a company agrees to sell at a predetermined price. These contracts are usually private.

All trading platforms include:

- **Futures and forward market**: Allows electricity to be sold up to four years before delivery, enabling producers to minimise their exposure to volatile prices by securing a pre-defined price and volume of electricity [51].
- **Day-ahead market**: Here, the prices are determined one day before delivery based on supply and demand forecasts. Offshore wind primarily participates in this market [44].
- **Intraday market**: Allows continuous trading from after the day-ahead market is closed up to 5 minutes before delivery, enabling participants to adjust positions based on updated forecasts. Thereby, allowing for short-term trading.
- **Balancing market**: Is activated after the closing of the intraday market, enabling trade in real-time. The market is managed by the transmission system operator (TSO) to ensure real-time grid stability by deploying flexible reserves to correct imbalances [49].
- **Imbalance settlement**: Provides additional capacity reserves to maintain system security in case of unforeseen fluctuations in supply or demand.

Wind farms primarily focus on the day-ahead market. However, now some renewable producers use price arbitrage, where generators intentionally bid lower in the day-ahead market to reserve capacity for higher balancing market prices to optimise their revenue [32]. Another study by Hosseini et al. [45] proposed the value of a joint strategy for bidding offshore wind power on the day-ahead and reserve market. This evolving trend suggests that offshore wind could play a more active role in providing flexibility services in the future.

Wind power is a unique energy source with inherent variability, and its large-scale integration into the electricity market presents challenges beyond trading strategies. As offshore wind capacity increases, the risk of overproduction, grid congestion, and ecological impacts can lead to increased curtailment. The next section explores the various drivers of curtailment and potential mitigation strategies.

2.2. Drivers of curtailment and mitigation strategies

In response to these challenges, wind farms may be forced to reduce output, even though they are capable of generating more energy. Curtailment is primarily driven by physical constraints, technical limitations, ecological considerations and economic factors. Understanding these drivers is essential for developing an integrated, market-driven curtailment strategy.

Physical constraints

The stability of the electricity grid requires supply and demand to remain in balance at all times. When excess generation exceeds the grid's capacity to absorb the power, system operators may enforce curtailment [52]. This driver referred to as a physical constraint, arises when the grid is physically unable to transport or accommodate the generated electricity.

As the share of vRES in the energy mix increases, maintaining system frequency stability becomes more challenging. Traditionally, conventional power plants provided grid inertia, helping stabilise frequency fluctuations. However, as reliance on fossil-based generation declines, alternative balancing mechanisms are required. Villamor et al. [52] proposes to reduce vRES curtailment by relaxing inertia floor requirements, thereby decreasing reliance on traditional power plants for grid balancing. While the approach addresses physical constraints, it does not account for the economic implications of curtailment.

Technical limitations

Technical limitations can also necessitate curtailment. Wind turbines require regular maintenance, and extreme weather conditions, such as storms or typhoons, may lead to temporary curtailment as a precautionary measure to protect turbine components from excessive mechanical stress [53]. Wang et al. propose an ordered curtailment strategy to manage wind power during such events, ensuring grid stability while minimising unnecessary power reductions [53].

Another emerging strategy is the erosion-safe mode, which adjusts turbine operation based on rotation speed and rain intensity. As blade maintenance and replacement costs are a large part of the OWT expenses, mitigating leading-edge erosion (LEE) is needed. The erosion-safe mode reduces tip speed during extreme rain events, lowering the impact of raindrops on the blade surface [54].

Ecological considerations

Beyond technical constraints, ecological factors increasingly influence curtailment decisions. Wind turbines can pose risks to wildlife, particularly birds and bats, leading to curtailment measures designed to minimise fatalities [55, 56, 57]. A study by Bureau Waardenburg analysed the trade-off between minimising bird collisions and reducing power losses due to curtailment [55]. The study found that peak bird migration occurs at low wind speeds. Another study by Whitby et al. [56] recommended raising the cut-in from 3 to 4 m/s to 5 m/s to prevent bird collisions. This strategy contrasts with market-driven curtailment, where surpluses on the grid and resulting negative prices coincide with higher wind speeds, resulting in potentially greater reductions in power output.

Economic factors

As increasingly more negative price events occur, curtailment due to economic constraints has gotten a more important role, forcing operators to curtail production to avoid selling power at a loss [7]. Unlike physical or ecological curtailment, economic curtailment is often voluntary, as operators weigh the cost of continued generation against potential revenue losses.

Some literature exists on market-driven curtailment strategies. The study by Brandstätt et al. [7] suggests that the German system seems to have reached its limit of integrating vRES, as the wholesale electricity market experiences serious negative prices at times of high wind and low demand. The study proposes the use of flexible voluntary curtailment agreements as a response to these negative price spikes. These agreements allow offshore generators to receive compensation for reducing their output during periods of excess electricity generation, thereby helping to maintain grid stability. Such agreements are negotiated between the TSO and the generators.

Further research is needed to evaluate the applicability of this approach in the Dutch electricity market. Despite extensive research into curtailment due to ecological and physical factors, limited studies so far address the implications of curtailment due to economic factors. The highly context-dependent nature of curtailment means that strategies designed to mitigate ecological impacts, such as reducing bird collisions, cannot simply be transferred to address market-driven curtailment.

The increasing occurrence of curtailment raises concerns beyond market economics and grid reliability. The next section examines the technical impact of curtailment on OWTs, particularly its effects on turbine lifespan and asset health.

2.3. Technical impact of curtailment on OWTs

A recent study by Robbelein et al. [58] assesses the effect of curtailment on monopile support structures of offshore wind turbines. The study highlights the significant effect of curtailment on the structural integrity of the monopile and the lifespan of OWTs. Frequent curtailment increases load cycles, accelerating fatigue on critical components like foundations and support structures, potentially shortening turbine lifespans. Adjustments of the curtailment strategy may reduce or increase the remaining useful lifetime (RUL) of the monopile depending on chosen curtailment intervals. The study acknowledges the importance of lifetime extension of OWFs, which means that detrimental long-term effects of curtailment on the structural lifetime should be taken into account when discussing short-term curtailment strategies.

Building on this, Ziegler et al. [26] examine the impact of curtailment on loads and wear of tower, blade and pitch system. The study acknowledges the importance of lifetime extension of wind farms and states that the impact of idling on asset life should not be neglected. Ziegler et al. optimise the length of curtailment levels on load neutrality. The impact mostly depends on factors like the control settings of the turbine, structural conditions (structural design and importance of wind/wave loads, etc.), environmental conditions during curtailment (wind, waves, current), and the length of curtailment (duration of idling). For offshore turbines, idling can increase tower loads due to wave excitation and reduced aerodynamic damping. The study concludes that blades benefit from curtailment, as it reduces edgewise blade loads and blade erosion. As a recommendation for future work, the paper identifies the necessity to add the costs or benefits of load and wear caused by curtailment in the optimisation of curtailment strategies.

Kjeld et al. [59] studied the effects of idling on OWTs. The research showed that during idling, variations in wind speed and wave height can lead to fluctuations in the natural frequency and damping. Resulting in additional loads experienced by the turbine. These changing loads introduce uncertainties in fatigue life predictions. This suggests that idling, though reducing aerodynamic loads, can contribute to increased fatigue and wear on tower and support structures. The study highlights the importance of considering these effects in curtailment strategies to prevent long-term damage and extend the operational lifespan of turbines.

While significant progress has been made in understanding curtailment strategies related to ecological and physical constraints, the economic implications of curtailment, particularly during periods of negative or volatile prices, remain under-explored. The additional costs associated with increased load and wear due to curtailment have yet to be integrated into existing curtailment strategies. Addressing this gap requires further research to develop curtailment strategies that internalise these operational costs while ensuring both the technical integrity and economic viability of offshore wind energy.

2.4. Use of distributed consensus algorithm

To enable the integration of diverse stakeholder perspectives in curtailment strategies, this thesis explores both centralised and decentralised optimisation methods. Centralised optimisation methods are applied to ensure system-wide efficiency. However, centralised strategies can become infeasible in practice as they require data transparency and have a high computational burden. To overcome these limitations, distributed optimisation frameworks are proposed, allowing local agents to optimise their objectives independently while maintaining global consensus through an iterative coordination mechanism. A general framework for such distributed coordination, specifically using ADMM, will be introduced in Section 3.3.3.

Several studies have successfully applied ADMM in the power systems domain. For example, Rostampour et al. [60] use ADMM to solve stochastic reserve scheduling in AC power systems with uncertain wind generation. Given the scale and complexity of such problems, a distributed approach was essential to ensure computational flexibility. In this setup, each region optimises its own power dispatch and reserve allocations, while ADMM iteratively enforces consensus across regional boundaries. A similar structure is adopted in earlier works by Molzahn [61] and Lam [62], which also target distributed optimal power flow problems.

A more recent example is provided by Xu et al. [63], who use ADMM to optimise power output at the level of individual turbines in large wind farms. Their approach explicitly accounts for wake effects, which occur when upstream turbines reduce the wind available to downstream turbines. By coordinating control decisions among turbines, the method enhances overall power output. In this context, distributed control is preferred over centralised optimisation, which does not scale well and becomes too slow when dealing with large wind farms or rapidly changing wind conditions.

Despite its previous application in wind power systems, ADMM has not yet been used in the context of bidding strategies for offshore wind that aim to integrate multiple stakeholder objectives. Prior literature focused on physical system coordination (e.g. balancing and/or reserve allocation), rather than negotiation among stakeholders with divergent interests.

2.5. Knowledge gap and research questions

The literature review reveals a significant gap in understanding the long-term impacts of curtailment on OWTs, particularly in the context of market-driven curtailment during periods of negative electricity prices. While studies, such as Brandstätt et al. have examined flexible curtailment agreements [7], and Robbelein et al. have investigated the structural impacts on turbine components [58], limited research has investigated the direct relationship between curtailment, turbine degradation, and the resulting economic costs.

Several gaps are identified. Firstly, there exists limited research on the quantification of additional loads imposed on (non-) replaceable components during extended curtailment periods. Likewise, knowledge about the long-term impact of curtailment on the lifespan of key OWT components is scarce, primarily because offshore wind farms have not been in operation long enough to provide extensive empirical data. Secondly, while previous research addresses curtailment driven by ecological considerations or grid constraints, the physical and economic implications of market-driven curtailment remain underexplored. Lastly, no framework exists to guide offshore wind operators in optimising their curtailment strategy to account for both turbine wear and volatile electricity prices.

These gaps reveal a need to develop an integrated curtailment strategy that internalises operational costs arising from wear, tear and fatigue of critical components of an OWT. This research aims to bridge this gap by developing a strategy that optimises economic performance while preserving turbine longevity.

The project targets of this research include:

- Identify critical components which are impacted by additional curtailment,
- Develop a model in Python to simulate the impact of curtailment on these components and evaluate their degradation,
- Develop a curtailment strategy which optimises short-term financial losses and operational longevity of OWTs using Python,
- Provide insights to inform energy traders and wind farm operators when negotiating curtailment agreements, such as PPAs, to internalise long-term asset health while maximising short-term financial performance.

Combing above targets leads to the following main research question:

To what extent can integrating asset health improve the value of offshore wind power through coordinated curtailment strategies?

The focus of the thesis is on understanding the described issues within the offshore wind energy industry and providing an initial framework for how these additional costs can be internalised into curtailment strategies.

Research sub-questions

Developing a curtailment strategy that internalises long-term asset health while maximising short-term financial performance first requires a clear understanding of how curtailment affects the structural integrity and cost structure of OWTs. This involves identifying the critical turbine components affected by curtailment. This selection will be informed using academic literature and semi-structured expert interviews. Once identified, degradation functions will be developed to quantify the effects of production and curtailment on these components. These functions will be formulated using simplified mathematical equations to assess the aerodynamic and hydrodynamic loads experienced by the turbine. Before integrating them into the extended optimisation model, simulations will be conducted to verify their accuracy and ensure they reflect real-world degradation behaviour. Beyond this technical analysis, a cost evaluation of the selected components will be performed. For this section and the remainder of this research, a 15 MW offshore reference turbine will be used, as it is the largest turbine currently in use in the Netherlands [64, 65] and with extensive open-source data available [66]. This leads to the first sub-question:

SQ1: What effect does curtailment have on the degradation of critical OWT components?

Beyond the technical effects, curtailment decisions are shaped by varying stakeholder perspectives, each with its own financial, operational and regulatory constraints. This results in the second sub-question:

SQ2: What are the objectives of different stakeholders (dispatchers, asset operators, and wind farm owners) regarding curtailment strategies?

To internalise turbine longevity while maximising financial performance, an optimisation model will be developed using mathematical programming in Python. To establish the most suitable problem formulation, this analysis leads to the third sub-question:

SQ3: How can curtailment strategies be formulated as an optimisation problem?

However, while a centralised model sounds good in theory, it could face some challenges in practice. Stakeholders may be unwilling to share sensitive data on degradation functions or financial insights. Therefore, an alternative approach is to explore decentralised decision-making, which allows for coordination without full information sharing. The use of a global consensus framework will be explored. This approach is based on the work of Boyd et al. [3] on ADMM. The technique is widely used for solving optimisation problems involving multiple perspectives. ADMM enables decentralised decision-making while ensuring convergence to a globally optimal solution, making it a suitable method for balancing operational and financial trade-offs in curtailment strategies in a structured manner. An important question is whether a decentralised method can achieve results comparable to the centralised framework while preserving individual autonomy. This leads to the fourth sub-question:

SQ4: Can a global consensus framework, such as ADMM, be utilised to achieve coordinated decision-making in a decentralised curtailment strategy?

Building on the findings from these sub-questions, the integrated coordination mechanism will be analysed and translated into practical price incentives. Ultimately, this research aims to explore how aligning the perspectives of the dispatcher, wind farm owner, and maintenance provider can enhance the overall value of offshore wind power.

3
Research methodology

This chapter outlines the methodology used in the research. The primary goal of the research is to develop an optimisation-based framework that integrates financial incentives and turbine degradation effects while taking into account the perspectives of dispatchers, wind farm owners, and asset operators. The optimisation-based framework is complemented by semi-structured interviews to gain insights into stakeholder perspectives on curtailment strategies. Additionally, an expert feedback session serves to refine preliminary model outcomes and ensures practical applicability. Section 3.1 introduces the system diagram, defining the scope of the research. Section 3.2 introduces the research approach, which presents the main methodologies and their role in addressing the research objectives. Section 3.3 lays the foundation for the optimisation models used in this study. Section 3.4 describes the model implementation, detailing computational setup and the selection of the solver. Section 3.5 outlines the semi-structured interviews used to validate degradation functions and stakeholder perspectives.

3.1. System diagram

Figure 3.1 represents a schematic overview of the scope of the system investigated in this work. The main stakeholders involved include the dispatcher, manufacturer, maintenance party and wind farm owner.

This research focuses on the day-ahead market, as it is generally assumed that this is where the majority of the offshore wind volume is sold, as outlined in Section 2.1. Participation in other markets, such as intraday or ancillary services, falls outside the scope of this study. For instance, as noted by Yasuda et al. [28], curtailed energy could be used in the balancing market, allowing the dispatcher to offer upward reserves when needed [28].

Based on price incentives, the dispatcher may issue a curtailment schedule to limit power output, particularly when prices are negative. Curtailment is restricted to a minimum set point, typically 10-25% of the farm's capacity [44]. The manufacturer defines the minimum set point based on the design of the OWT, as the design determines the loads the turbine can withstand during the operational phase [67]. Once the dispatcher has communicated this production schedule, the park controller determines how power adjustments at farm level are applied to the turbines, which could be either equally divided among all turbines or divided on individual turbine levels [67]. Offshore wind farms use either a Remote Terminal Unit (RTU) or a control box to process the production schedule. RTUs are the standard in the Netherlands as they better suit large-scale operations [68].

The wind farm owner monitors the health of the wind farm asset and collaborates with the maintenance party to decide on component replacements. A longer operational lifespan benefits the owner as it increases the return on investment. The maintenance party is responsible for the maintenance and replacement of the replaceable components.

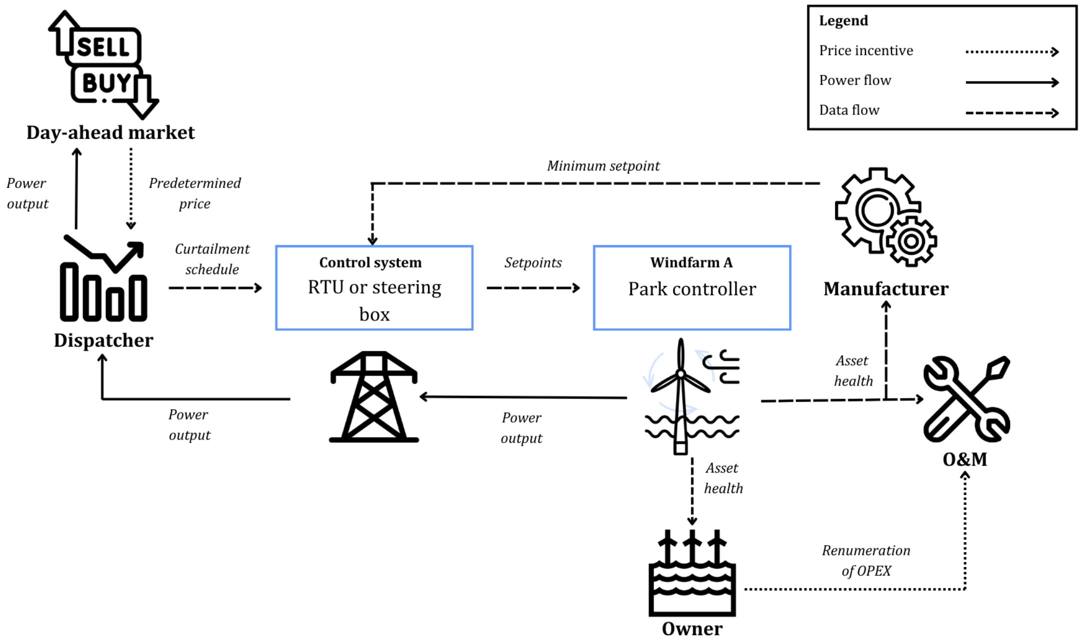


Figure 3.1: System diagram containing all the key elements of the system [69], [70], [71], [72], [73], [74], [75]

3.2. Research approach

This research investigates the value of coordination in offshore wind curtailment strategies. To assess this, the study compares three distinct systems: the current approach, a centralised coordinated strategy, and a decentralised coordinated strategy. Given their differences in decision-making structures and objectives, a modelling approach is adopted as the primary research method. The model aims to optimise a dispatch strategy that integrates financial incentives and turbine degradation effects while considering the perspectives of dispatchers, wind farm owners, and asset operators.

The optimisation problems are formulated using Pyomo in Python [76]. Pyomo is used due to its modular structure, which allows for easy extension and modification of the problem. The research involves various problem formulations, all of which are supported by Pyomo. Its compatibility with different solvers enhances computational efficiency [77]. However, the overall performance is dependent on the solver selected. Nevertheless, the researcher's prior experience with Pyomo accelerates model development, making it the preferred choice.

Figure 3.2 shows an overview of the most important elements in the optimisation framework, illustrating how various inputs, stakeholder perspectives, optimisation models, and outputs interact to develop a coordinated curtailment strategy. The flowchart follows a structured process where:

- The degradation functions are detailed in Chapter 4.
- Different stakeholder perspectives from the dispatcher, maintenance party and owner contribute their objectives to the optimisation framework, which are outlined in Chapter 5.
- These objectives feed into an optimisation model that consists of different scenarios: a baseline model, a centralised coordination approach, and a decentralised coordination approach. The formulation of these are outlined in Chapter 6, each exploring a different level of coordination:
  - **Current situation:** Establish a baseline based on existing curtailment strategies.
  - **Centralised coordination framework:** Evaluates the value of coordination.
  - **Decentralised coordination framework:** Investigate whether coordination is feasible without requiring full data sharing. This is formulated using the ADMM global consensus framework, which will be introduced in Section 3.3.3.

- The model generates optimisation results, consisting of a dispatch strategy, which is formed based on the decision on whether to produce or curtail.
- The results are then assessed using both stakeholder-specific and system-wide economic performance metrics, such as revenue, cost, and profit. The calculation of these will be discussed in Chapter 5.
- The final step involves evaluating whether the strategy has improved, followed by a qualitative assessment of practical price incentives. The results will be discussed in Chapter 7, and the practical price incentives in Chapter 9.

In terms of flow:

- Arrows crossing dashed lines indicate inputs specific to particular models or steps.
- Inputs not passing the dashed boundary apply to all variables within the boundary.

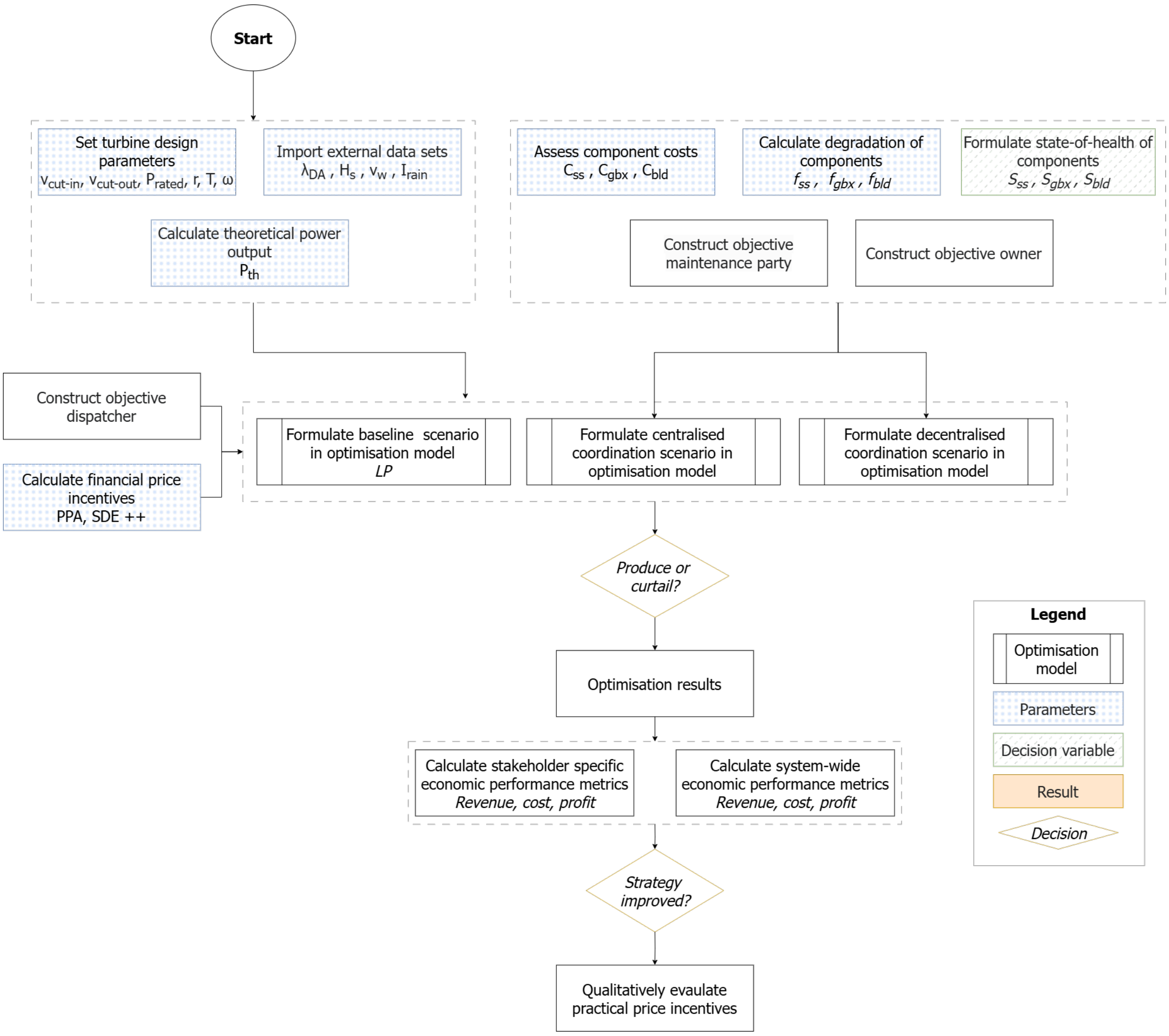


Figure 3.2: Research approach illustrating data inputs, stakeholder perspectives, and outputs of the optimisation model

3.3. Optimisation models

This study focuses on an optimisation modelling method, which uses mathematical programming. This section aims to introduce key mathematical programming concepts, explain different optimisation problem types, and introduce decentralised optimisation, its limitations and general formulation.

3.3.1. Key concepts of mathematical programming

Mathematical programming provides a structured framework for formulating and solving optimisation problems. This section introduces key concepts in mathematical programming. The formulations follow the principles outlined by Morales et al. [78], addressing the challenges of integrating large-scale renewables into electricity markets through mathematical programming. Additionally, Kallrath [79] defines a mathematical optimisation problem consisting of four fundamental components:

- **Parameters:** Fixed numerical values that serve as inputs to the model. These include datasets representing deterministic factors, such as electricity prices or environmental conditions.
- **Decision variables:** These variables are controlled by the optimisation model, and represent the possible choices within the system. Decision variables are often characterised as continuous, semi-continuous, binary, or integer values.
- **Constraints:** A set of equations with equalities or inequalities that impose limitations on the solution space, defining feasible solutions within the model.
- **Objective function:** The goal of the optimisation, which will be maximised or minimised (e.g., maximising benefits like revenue or minimising costs like maintenance expenditures).

This structure serves as the foundation for formulating the optimisation problems in this study.

3.3.2. Different optimisation problem types

Mathematical optimisation models typically fall into structured problem categories such as linear programming (LP), mixed-integer linear programming (MILP), non-linear programming (NLP), or mixed integer non-linear programming (MINLP) [79]. The appropriate classification depends on the problem's complexity and the nature of the decision variables involved. An LP consists only of continuous variables, which can take any value between zero and a specified upper limit. If a problem includes both integer and continuous variables, it becomes a MILP. Integer variables are restricted to take on whole number values within a defined range, while binary variables (a subset of integer variables) can only take values of 0 or 1. If the objective or any constraints contain quadratic or other non-linear functions, the problem is classified as non-linear.

When constructing an optimisation model, it is important to navigate between simplicity and accuracy. As Kallrath [79] states: "Make the model as simple as possible, but as complex as necessary". This is particularly relevant in large-scale curtailment strategies, as overly complex models may become computationally expensive, while overly simplistic models may fail to capture the dynamics of wind turbine degradation and market fluctuations. Thus, a trade-off arises between model accuracy and computational efficiency. This work focuses on three of the explained optimisation categories:

1. A **LP model**, in which the optimisation only included continuous variables for the degradation of components.
2. A **MILP model**, which incorporates binary variables to represent discrete replacement decisions for critical turbine components.
3. A **NLP model with penalty function**, replacing binary decision variables with a continuous penalty function to simplify the model formulation. This approach retains the computational advantages of NLP over MILP while still enforcing replacement decisions through the penalty function.

Each formulation presents distinct challenges in computational complexity, which determines the time and resources required to solve the problem, and applicability, which reflects how accurately the model represents the real-world optimisation problem [78]. These aspects will be further examined in Section 6.3, where the state of health variable will be formulated.

3.3.3. Decentralised optimisation

A fully centralised optimisation approach may be impractical, as it requires complete data sharing and joint decision-making, which is often unfeasible. The involvement of multiple stakeholders, including competitors, makes it unlikely that sensitive technical data, asset health insights, or economic performance metrics will be shared. Decentralised optimisation offers an alternative, enabling each stakeholder to optimise their decisions independently while still achieving a coordinated curtailment strategy.

To enable decentralised decision-making, this study applies ADMM. Specifically, the problem formulation follows the general framework of ADMM introduced by Boyd et al. [3]. Notably, this research is the first to apply ADMM to curtailment strategies, demonstrating its potential in this domain.

ADMM is particularly suitable for this application as it is an optimisation framework designed to solve large-scale, distributed problems. It achieves this by decomposing a centralised problem into smaller, independent sub-problems, which can be solved in parallel while maintaining consistency in shared decision variables. These variables can be categorised into local and global variables. Local variables represent decisions made independently by each stakeholder, while global variables capture shared quantities that must remain consistent across all entities. ADMM enforces agreement between local and global variables, ensuring coordination without requiring full centralisation.

This makes ADMM especially relevant for applications where multiple entities must collaborate while preserving decision-making autonomy.

In practice, the decentralised problem would function as an iterative negotiation process, where:

- Stakeholders propose dispatch strategies based on their individual objectives.
- These strategies are shared and evaluated.
- Adjustments are made in successive rounds until a mutually beneficial agreement is reached.

Limitations of the framework

Despite its advantages, ADMM presents several challenges when applied to curtailment optimisation. One key difficulty is handling non-convex constraints and objective functions, which can hinder convergence and affect solution feasibility. Additionally, the choice of the penalty parameter (ρ) is crucial in determining the speed and stability of convergence. ADMM relies on the penalty parameter to regulate the divergence of global decision variables across stakeholders [3], and improper tuning can result in slow convergence or suboptimal solutions.

Overall, the decentralised ADMM approach provides a powerful framework for optimising curtailment decisions while maintaining the autonomy of individual stakeholders. By enforcing a global consensus through local decision-making, it offers a scalable and flexible alternative to fully centralised models.

General framework for global variable consensus optimisation

The general form of the global variable consensus optimisation contains local variables x_i and a common global variable z. The general framework is based on the reader 'Distributed Optimisation and Statistical Learning via the ADMM' from S. Boyd et al. [3]. This general framework can be written as:

$$\begin{aligned} \text{minimise} \quad & \sum_{i=1}^{N} f_i(x_i) \\ \text{subject to} \quad & x_i - z = 0, \quad i = 1, \dots, N. \end{aligned}$$

Here, $f_i(x_i)$ represents the local objective functions, x_i are the local variables, and z is the global consensus variable. The constraint states that all the local variables should agree, i.e. be equal to the common global variable. Hence, the goal is to find a common z that minimises the collective objective.

The augmented Lagrangian for this problem is:

$$L_\rho(x_1, \dots, x_N, z, y) = \sum_{i=1}^{N} \left(f_i(x_i) + y_i^T (x_i - z) + \frac{\rho}{2} \|x_i - z\|_2^2 \right),$$

Where y_i^T are the dual variables of each sub-problems, and ρ is the penalty parameter. The parameter ρ penalises the difference between the local and the global consensus variables.

Selecting an appropriate value for the penalty parameter ρ is a complex process, with a significant impact on convergence and numerical stability. A high ρ, corresponding to a strong penalty for deviations from the global consensus variable, has fast residual convergence but comes with the risk of numerical instability. On the other hand, a low ρ, corresponding to a weak penalty to deviations from the global consensus variable, allows flexibility in the optimisation of the local problems and faster dual residual convergence, while having the risk of slower primal residual convergence due to the solutions of the sub-problems deviating too much from the consensus.

For the global consensus variable in ADMM, the residual updates follow the general form:

Primal residual

$$r^k = x^k - \bar{x}^k, \tag{3.1}$$

Where x^k represents the local decision variables and $\bar{x}^k$ is the global consensus variable. The squared norm is given by:

$$\|r^k\|_2^2 = \sum_{i=1}^{N} \|x_i^k - \bar{x}^k\|_2^2. \tag{3.2}$$

Dual residual

$$s^k = -\rho(\bar{x}^k - \bar{x}^{k-1}), \tag{3.3}$$

Where ρ is the penalty parameter. The squared norm of the dual residual is given by:

$$\|s^k\|_2^2 = N\rho^2\|\bar{x}^k - \bar{x}^{k-1}\|_2^2. \tag{3.4}$$

The primal residual r^k measures the deviation of the local variables from the consensus, while the dual residual s^k tracks the difference between consecutive consensus iterations. The convergence of ADMM is often monitored by ensuring that both residuals decrease over iterations.

3.4. Model implementation

This section details the choice for Pyomo, the selection of the solver, and the computational setup.

The optimisation model is implemented using Pyomo, a Python-based modelling language, within the Visual Studio Code interface. Pyomo provides a flexible and structured approach to defining optimisation problems, allowing for the formulation of LP, MILP and NLP models [76].

Since different solvers are designed for specific types of optimisation problems, a comparison is conducted to determine the most suitable option for this study. The selected solvers represent two distinct approaches:

- **Gurobi**: A powerful commercial solver specialised in MILP, accessed via the academic license of the Technical University of Delft,
- **Ipopt (Interior Point Optimiser)**: An open-source solver designed for large-scale NLP problems. It finds local solutions by solving a continuous relaxation of the problem, ensuring efficiency in handling non-linear constraints and large-scale datasets.

Given the non-linear nature of the optimisation problem in this thesis, Ipopt is selected for its ability to efficiently handle complex degradation functions and large-scale datasets. Unlike Gurobi, which is limited to linear and mixed-integer formulations, Ipopt can accommodate non-linear constraints, making it a more suitable choice. Although Ipopt does not strictly enforce integer constraints, it offers computational advantages, particularly when solving problems with continuous penalty functions.

All computational tasks are executed on a Windows Surface 5 device, with the following specifications:

- Processor: 2.70 GHz
- RAM: 16.0 GB

This ensures sufficient computational power to handle extensive optimisation calculations. However, due to the computational intensity of large-scale optimisation problems, the input data is reduced when necessary to ensure feasible run times while preserving model accuracy.

3.5. Interviews

Due to limited academic literature on market-driven curtailment, semi-structured interviews were conducted with industry experts to validate assumptions and gain insights into this relatively unexplored area. The main objectives of these interviews were to:

- **Validate degradation functions and model assumptions:** Experts provided technical insights into how curtailment strategies influence asset health to enable a realistic representation of degradation effects within the model.
- **Understand market-driven curtailment practices:** Interviewees shared practical experiences and market knowledge, clarifying how financial incentives impact curtailment decisions in the day-ahead market.
- **Gain multiple stakeholder perspectives:** Interviews included a diverse range of stakeholders, such as dispatchers, wind farm owners, and operation and maintenance teams, to ensure that diverse viewpoints were accurately represented.
- **Ensuring practical applicability** of findings

The insights from these interviews serve as a foundation during the scoping phase, shape stakeholder objectives, refine degradation functions, and inform model assumptions. A concise summary of the interviewees, interview dates, and discussed topics is provided in Appendix A.

Once the model is developed and initial results are analysed, the findings are reviewed during an expert feedback session. The goal is to evaluate the results, discuss their practical applicability, and explore price incentives that enhance collaboration and improve curtailment strategies.

3.6. Concluding remarks

This chapter outlined the methodology used in the research, which combines mathematical optimisation with expert interviews. As identified in the literature review in Chapter 2, the impact of market-driven curtailment on the long-term economic performance of offshore wind assets remains an under-explored area. Given the limited availability of empirical data on operational OWT degradation, expert interviews provided a crucial foundation for constructing representative degradation functions.

While more detailed empirical methods exist, they fall outside the scope of this thesis due to time constraints and data accessibility. Instead, simplified degradation models were developed in collaboration with industry experts to enable the internalisation of asset health within dispatch strategies. The next chapter will analyse the impact of market-driven curtailment on critical components of the OWT.

4 Market-driven curtailment

Market-driven curtailment has become an increasingly important tool for enhancing the flexibility of offshore wind assets. While curtailment reduces short-term economic risks, its long-term impact on turbine longevity remains uncertain. This chapter delves into market-driven curtailment, its effects on OWT degradation and the associated costs.

Curtailment is defined as the intentional reduction of a wind turbine's power output below its theoretical maximum under given environmental conditions [25, 58]. It can be measured in two ways: (1) as the share of the turbine's operational lifetime spent curtailed, or (2) as the reduction in power output relative to its full capacity under available environmental conditions. This work adopts the latter approach, where, for instance, a 20% curtailment indicates that the turbine is generating only 20% of its potential output at that moment. While curtailment results in direct production losses [58], its broader implications on turbine wear and replacement costs require further investigation.

The impact of curtailment on turbine longevity depends largely on the turbine's operational state. OWTs operate in three distinct phases: normal production, idling, and standstill. In the normal production phase, the turbine actively generates power, with blades set at an optimal pitch angle to harness wind efficiently. During idling, the turbine produces no power but blades continuously rotate at low speeds (1-2 rpm) to maintain lubrication. As the turbine is idling, the blades are feathered, meaning they are pitched parallel to the wind direction to reduce aerodynamic loads [59]. In contrast, the standstill phase involves complete rotor stoppage using brakes, typically occurring during maintenance or extreme weather conditions. Each operational phase affects the turbine differently due to variations in aerodynamic and hydrodynamic loads experienced by the turbine. While the impact of idling has been studied to some extent, further investigation is needed to understand the impact of curtailment on different components. Previous research suggests that frequent transitions between states caused by curtailment may accelerate fatigue and degradation [58].

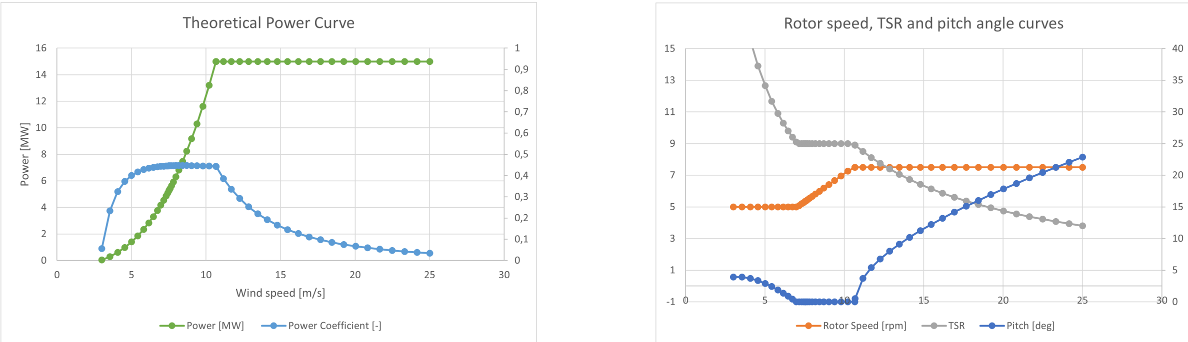
Thus, this chapter aims to answer the following sub-research question: *What effect does curtailment have on the degradation of critical OWT components?*

To build a foundation for the analysis, Section 4.1 provides an overview of wind power fundamentals. Next, Section 4.2 examines how curtailment affects component stress, influenced by aerodynamic and hydrodynamic loads. Section 4.3 identifies the critical components affected by curtailment, followed by Section 4.4, which outlines the investment and replacement costs associated with these components. Afterwards, Section 4.5 introduces degradation functions to quantify curtailment-induced wear. These functions are simulated in Section 4.6, offering insights into how curtailment shapes the health evolution of critical components. Finally, Section 4.7 concludes the main insights from the chapter.

4.1. Introduction to wind power fundamentals

To understand the impact of curtailment on OWTs, it is first important to understand the fundamentals of producing electricity from wind. The kinetic energy from the wind pushes the turbine blades to move, generating mechanical power in the rotor. This mechanical power is then converted into electrical power through a generator and ultimately fed into the grid. Several parameters influence this process, including power output, power coefficient, thrust, torque, rotor speed, tip speed ratio, and pitch angle. Each of these factors influences the efficiency of the turbine and the structural loading experience by the turbine.

This section provides an overview of these fundamental concepts using a 15 MW reference turbine [80]. Figures 4.1a and 4.1b illustrate the relation between these parameters under normal operating conditions.



(a) Power curve (P) (green) and power coefficient (c_p) (blue)

(b) Rotor speed (rpm) (orange), Tip speed ratio (TSR) (grey) and pitch angle ($^\circ$) (blue)

Figure 4.1: Wind turbine operational parameters for a 15 MW reference wind turbine [80]

Power output

Power output is the main metric for evaluating the performance of OWTs. It directly translates the energy captured from the wind into usable electricity, which determines the turbine's efficiency and profitability. The power extracted from the wind is determined by:

$$P_{Turbine} = \frac{1}{2}\rho A v^3 C_p \tag{4.1}$$

Where:

- P_{Turbine} is the electrical power extracted from the wind by the turbine, also referred to as the power output $[W]$,
- ρ is air density $[kg/m^3]$,
- A is the rotor swept area $[m^2]$,
- v is the wind speed $[m/s]$, and
- C_p is the power coefficient [-], representing the efficiency of energy capture.

As indicated by the equation, power output scales with the cube of wind speed, v^3, meaning that even small variations in wind speed have a substantial impact on energy generation. However, beyond the rated wind speed (v_{rated}), power output is regulated to maintain a constant rated power output (P_{rated}). This regulation is achieved by adjusting the blade pitch angle to a less aerodynamically efficient orientation, preventing excessive loading.

When curtailment is applied, power output is intentionally reduced, typically to a predefined limit. Figure 4.2 illustrates an example of a turbine operating at 20% of its rated capacity due to curtailment. The way in which this reduction is achieved, whether through adjustments in the pitch angle or rotor speed, affects turbine degradation and is explored further in later sections.

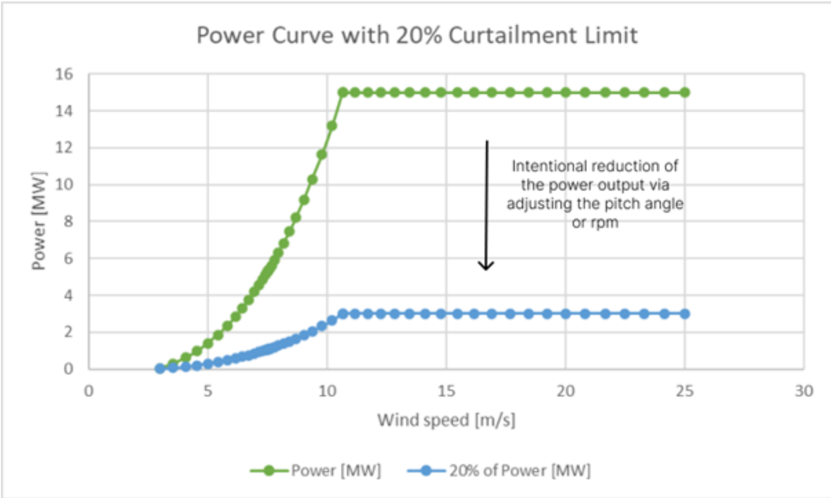


Figure 4.2: The intentional reduction of the power production, production at rated power (P_{rated}) is depicted with a green line

Power coefficient

The efficiency in wind power extraction is quantified by the power coefficient (C_p), which is the ratio of power extracted by the turbine to the total power of the wind resource [81]. This metric is important for understanding overall performance as it is directly related to the proportion of usable electrical power.

$$C_p = \frac{P_{Turbine}}{P_{wind}} \tag{4.2}$$

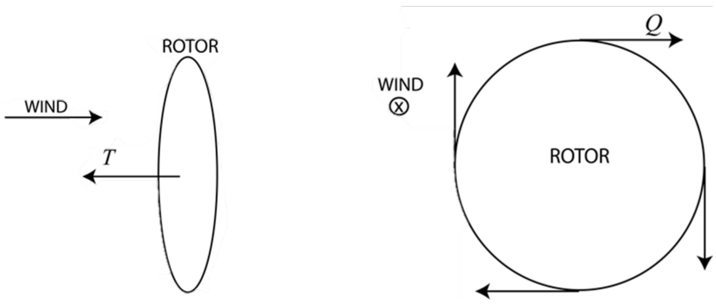
Where:

- P_{turbine} is the electrical power produced $[W]$,
- P_{wind} is the available wind power $[W]$.

The efficiency of wind power extraction peaks at moderate wind speeds and declines beyond (v_{rated}) due to aerodynamic and mechanical limitations.

Thrust

Thrust force is the reaction force exerted by the rotor as it pushes against wind flow. It acts as the counterforce to the pressure the wind applies on the turbine. Understanding thrust force is important, as it directly impacts the mechanical stress on components and the stability of the turbine. This reactional force can be seen in Figure 4.3a, which acts in the opposing direction of the wind flow to balance the system.



(a) Thrust force acts in the opposite direction of the wind

(b) Torque force acting tangent to the rotor plane

Figure 4.3: Visualisation of thrust and torque force, visuals from [82]

A thrust curve represents the variation of the thrust force (T) over varying wind speeds, this is schematically shown in Figure 4.4. As wind speed increases, the thrust force initially rises and then levels off near the turbine's rated wind speed (v_{rated}), beyond which it decreases due to active blade pitch control. The blade pitch control reduces aerodynamic forces on the blades.

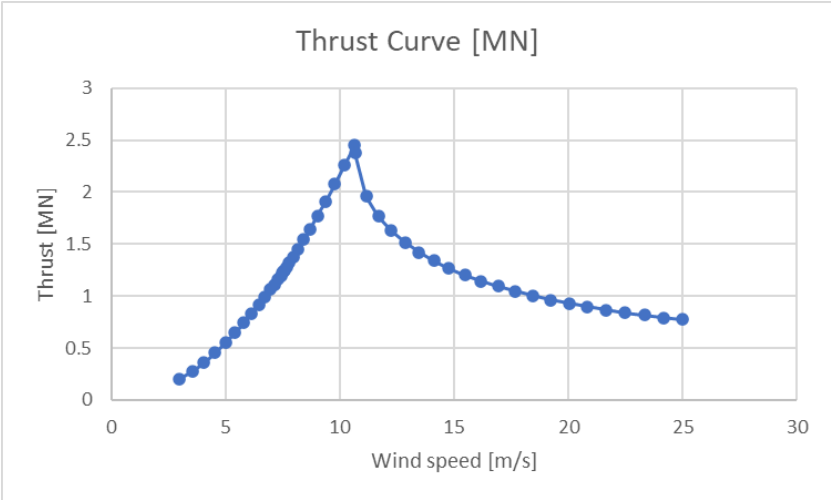


Figure 4.4: Thrust curve for a 15 MW reference wind turbine [80]

In the context of curtailment, a reduction in power output is often accompanied by a decline in thrust force, which can significantly influence the fatigue behaviour of structural components such as the tower and foundation.

Torque

The torque forces enable the turbine to convert wind energy into rotational energy, essential for driving the generator to produce electricity. It serves as a direct link between aerodynamic forces and mechanical energy conversion. The torque force is illustrated in Figure 4.3b.

$$Q = \frac{P}{\omega} \tag{4.3}$$

Where:

- Q is torque [Nm],
- P is the power generated by the turbine [W],
- ω is the angular velocity of the rotor [rad/s].

From this equation, it can be concluded that torque scales linearly with power output at a constant rotor speed. This relationship can be visually represented as:

$$Q \propto P \quad \text{(for constant } \omega\text{)} \tag{4.4}$$

Consequently, when curtailment is applied by reducing rotor speed, torque decreases, altering the loading conditions on the drivetrain, particularly on the gearbox and bearings. Repeated fluctuations in torque due to intermittent curtailment can accelerate fatigue damage in these critical components.

Rotor speed and tip speed ratio

The rotor speed, measured in rotations per minute (rpm), determines the blade tip speed, which is a crucial factor in aerodynamic performance.

The Tip Speed Ratio (TSR), defined as the ratio of blade tip speed to wind speed, is a fundamental control parameter:

$$TSR = \frac{\omega \cdot R}{v} \tag{4.5}$$

Where:

- ω is rotor speed [rad/s],
- R is the radius of the blade [m],
- v is the wind speed $[m/s]$.

At wind speeds below v_{rated}, TSR remains relatively stable as rotor speed increases proportionally to wind speed. However, beyond v_{rated}, as rotor speed is held constant while wind speed continues to increase, TSR decreases.

Curtailment influences TSR by reducing rotor speed, which alters the balance of aerodynamic forces and affects energy conversion efficiency [83]. This has potential implications for blade loading.

Blade pitch angle

The blade pitch angle is the orientation of the turbine blades relative to the incoming wind direction. It is a primary control mechanism for regulating power output and protecting the turbine from excessive loads.

At wind speeds exceeding v_{rated}, the pitch angle is actively adjusted to maintain a constant power output (referred to as P_{rated}). This adjustment reduces aerodynamic efficiency by orienting the blades to a less optimal angle, limiting aerodynamic forces and protecting the turbine from excessive loads.

In the context of curtailment, power output reduction is typically achieved by either adjusting the pitch angle or lowering the rotor speed. Figure 4.5 illustrates these operational zones. In this study, the focus is on curtailment strategies that involve adjustments in rotor speed rather than pitch adjustments.

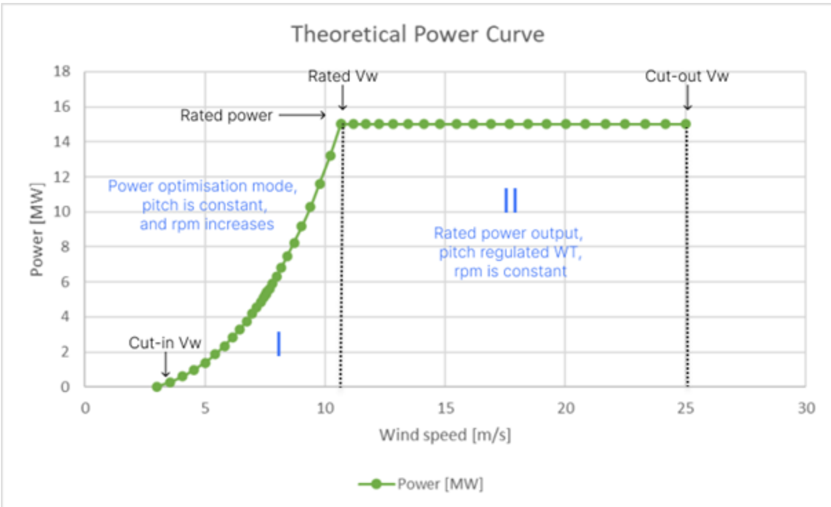


Figure 4.5: The power curve with the two operational phases are visually explained

This section has outlined the fundamental principles concerned with wind turbine operation, providing the necessary context for analysing the impact of curtailment. The next section will explore how reductions in power output influence aerodynamic and hydrodynamic loads, ultimately affecting the degradation of critical turbine components.

4.2. Impact of curtailment on turbine performance

Now that the fundamental concepts of wind turbine operation have been established, the next step is to examine how curtailment affects the aerodynamic and hydrodynamic loads acting on the turbine. A schematic representation of the wind- and wave-induced loads on the turbine is shown in Figure 4.6. These loads are critical drivers of the structural integrity of turbine components and, consequently, the overall turbine longevity.

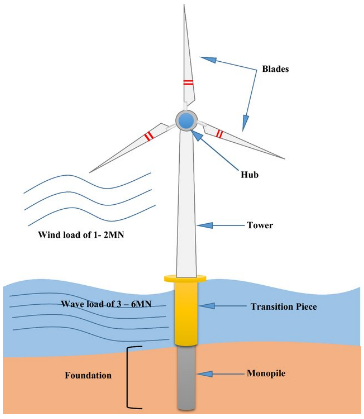


Figure 4.6: Schematic representation of an OWT and associated wind and wave loads [84]

Aerodynamic load

The aerodynamic load (L_{aero}) is the force exerted by the wind on the rotor and influences the thrust force, which acts in the opposite direction. It scales proportionally with thrust:

$$L_{\text{aero}} \propto T \tag{4.6}$$

During normal operation, the thrust force increases with wind speed but reaches a peak near the rated wind speed v_{rated}, as shown in Figure 4.4. Beyond this point, the turbine's pitch control system adjusts the blade angles to regulate power output and prevent overloading. This adjustment reduces thrust and, consequently, aerodynamic load.

Aerodynamic damping is a stabilising mechanism that counteracts oscillations induced by wind and waves. It depends on blade rotation: as blades spin, they generate counteracting forces that reduce structural strain. However, curtailment reduces the rotor loading, diminishing aerodynamic damping.

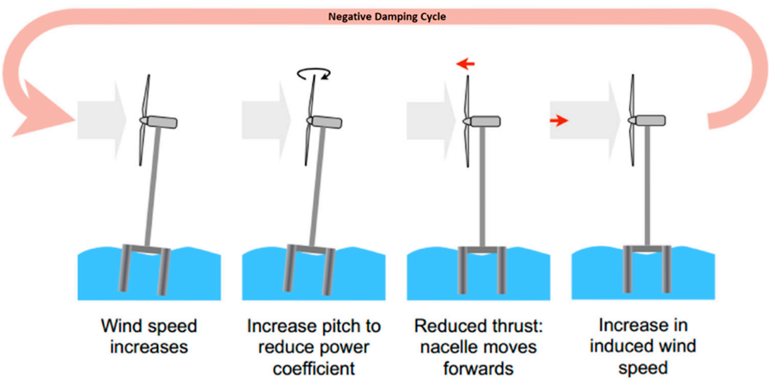


Figure 4.7: Damping cycle schematic explanation [85]

Figure 4.7 presents a schematic explanation of the damping cycle for a floating OWT (FOWT). Unlike monopile OWTs, which are fixed directly into the seabed, FOWTs are anchored to the ocean floor with mooring lines, allowing them to move with more degrees of freedom. As a result, the damping cycle differs significantly, as FOWTs manage aerodynamic loads differently compared to monopile-based OWTs. However, the figure provides a useful illustration of a damping cycle. In monopile-based OWTs, blade rotation reduces the thrust force acting on the turbine, thereby lowering structural loads and minimising fatigue accumulation.

As curtailment reduces thrust force, aerodynamic damping weakens as well. This makes the tower and foundation vulnerable to damaging oscillations, for example, when certain wave periods are close to the structure's natural frequency. As a result, they experience higher fatigue loads. Figure 4.8 illustrates this linear decrease in thrust, consistent with the findings of Guillore et al. [86], further reinforcing this effect.

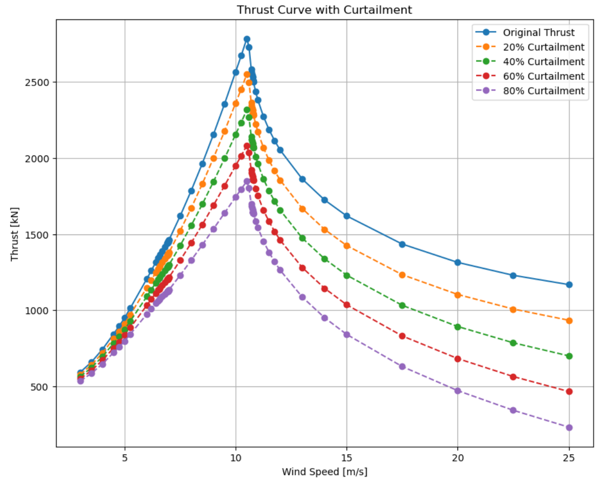


Figure 4.8: Thrust curve with curtailment for a 15 MW OWT

Hydrodynamic load

The hydrodynamic load (L_{hydro}) consists of forces exerted by waves and currents on the support structure. The primary driver of the hydrodynamic load is the significant wave height (H_s) [87], which is defined as the average height of the highest one-third of waves in a given sea state. As wave forces scale with wave height, the hydrodynamic load L_{hydro} is assumed to be proportional to (H_s):

$$L_{\text{hydro}} \propto H_s \tag{4.7}$$

This assumption provides a simplified representation of the relationship between hydrodynamic forces and environmental conditions, allowing for an approximate estimation of component wear with minimal data.

Figure 4.9 illustrates the expected behaviour of aerodynamic and hydrodynamic loads as a function of wind speed. As previously discussed, aerodynamic loads are directly influenced by the thrust force exerted on the turbine, aligning with the thrust curve shown in Figure 4.4. In contrast, hydrodynamic loads increase more significantly at higher wind speeds due to the linear relationship between wave height and wind speed.

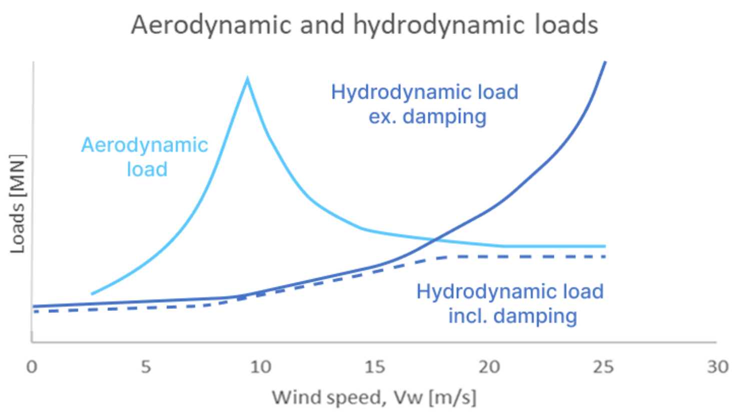


Figure 4.9: Dependence of the significant aerodynamic and hydrodynamic load and wind speed (V_w)

4.3. Selection of components

As the impact of curtailment in terms of aerodynamic and hydrodynamic loads becomes clearer, this work shifts its focus towards the examination of the impact on specific components of the turbine. This section provides an overview of the turbine's components, their functions, and how curtailment might influence them. Based on the analysis as set out below, a selection of three critical components will be made, which are focussed on in the remainder of the research.

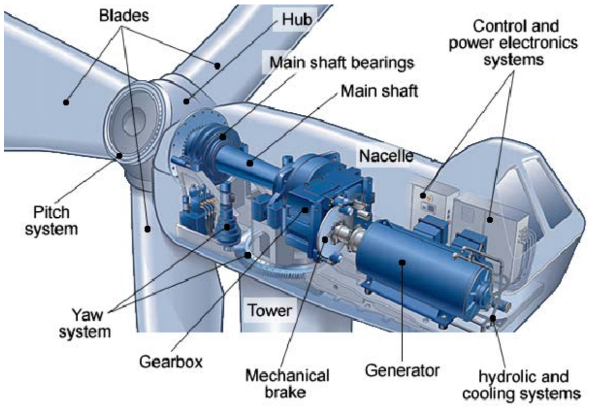


Figure 4.10: Overview of the components within the nacelle [88]

Tchakoua et al. [88] provides an overview of component-specific failure modes which is used as input for the overview of the subsystems below.

- **Rotor**: Includes blades, bearings, and the main shaft. The rotor captures wind energy and transmits it to the drivetrain. Blades, in particular, are prone to leading-edge erosion (LEE) and cracking.
- **Drivetrain**: Consists of the gearbox, main shaft, and mechanical brake. The gearbox increases rotational speed to match the generator's requirements. Gearboxes are vulnerable to wear, fatigue, and oil leakage, while main shaft bearings experience high loads and vibrations. The mechanical brakes are used to stop the turbine, these experience wear due to repeated breaking because of potential head build-up.
- **Generator**: The generator transforms mechanical energy into electrical energy. Possible failures are electrical issues, overheating, and rotor asymmetry.
- **Support Structure**: Consists of the foundation and the tower. The tower supports the nacelle and rotor while transferring aerodynamic and hydrodynamic loads to the foundation.
- **Auxiliary Systems**: These include the yaw system, pitch system, and hydraulic system, which are essential for aligning the rotor, adjusting blade angles, and maintaining turbine operations.
- **Electrical System**: This subsystem includes control systems, power electronics, and transformers that ensure grid-compatible power output. Possible failures are short circuits and component faults.

Most failures occur within the electrical system or plant control system [88, 89]. However, this does not capture the full context. For example, while gearboxes have a lower failure rate, the downtime and associated replacement or repair costs are high [90]. Long replacement durations result in substantial electricity loss. Additionally, drivetrain bearings endure high mechanical and thermal stresses, making bearing failures among the most common and costly in terms of downtime [91].

This thesis focuses on three distinct and critical components: the support structure, the gearbox, and the blades. Each component is further detailed below, and an explanation is given as to why this component is important in the research of curtailment.

Support Structure

The support structure, including the tower and foundation, forms the backbone of the OWT. Most OWT towers are constructed from steel [83], with the amount of steel used influencing the loads the tower can withstand throughout its operational lifetime. However, as steel prices have increased, the amount of steel is reduced to minimise costs. Modern OWTs are designed for an operational lifespan of 30 years, whereas older turbines were typically designed for 20 years. During the design phase, downtime due to technical non-availability is typically estimated at 5-10% over the turbine's lifetime [92]. Therefore, market-driven curtailment has to be incorporated into support structure design considerations to account for its impact on structural loading and fatigue accumulation.

Curtailment significantly impacts the support structure by reducing aerodynamic damping. When blade rotation slows down, the reliance on the support structure to counteract wave-induced hydrodynamic loads increases. At higher wind speeds, curtailment increases structural stress, resulting in high wave-induced vibrations and fatigue loads, as illustrated in Figure 4.9. The additional stress can cause material fatigue and accelerate structural wear.

The support structure is a non-replaceable component, meaning that the turbine's operational life ends once it reaches its critical fatigue threshold. Consequently, the support structure is one of the limiting factors when considering lifetime extension strategies for OWTs.

The support structure is considered a crucial focus of this study because it has a critical function in ensuring turbine stability, endures fatigue loads from both operational and environmental conditions, and is non-replaceable.

Gearbox

The gearbox transfers rotational energy from the rotor to the generator by increasing rotational speed [93]. It is one of the most fragile components in a wind turbine due to its exposure to alternating loads from wind speed variations and impulsive forces from frequent braking, leading to poor reliability [94].

Gearbox failures result in significant downtime due to the complexity of repairs and replacement, which require specialised equipment, such as jack-up vessels to be able to reach hub height offshore [95]. The high cost of maintenance and replacement, combined with revenue losses from non-operating gearboxes, make the gearbox one of the most expensive components to manage in offshore wind farms [93, 95]. The component is impacted by high curtailment levels as this introduces irregular loads and increased torque fluctuations, resulting in additional fatigue damage and misalignment issues [83].

The gearbox is designed for a 20-year lifespan [96]. But in practice, major maintenance is scheduled every 7 to 10 years, typically for the replacement of the bearing [97]. Actual lifespans are often shorter than the design expectations. In this study, a design life of 15 years is assumed for the gearbox.

While replacement is possible, it is not desirable due to the associated downtime and expenses. Therefore, the gearbox is critical in this study, as understanding its degradation may help reduce maintenance costs.

Blades

Wind turbine blades are directly exposed to aerodynamic loads and environmental conditions, which make them susceptible to leading edge erosion (LEE) [98]. LEE is caused by high wind and rain intensities in combination with high tip speeds, increasing the impact of rain droplets on the leading edge.

Curtailment has been identified as a potential strategy to mitigate LEE by reducing rotational speed during periods of heavy rain [99]. Nevertheless, curtailment also results in annual energy production losses, creating a trade-off between erosion mitigation and energy output.

Although blade replacement is possible, frequent replacement is undesirable. Replacement is not assumed in standard operations due to high costs, logistical challenges, and long downtime. This study focuses on blades because of their direct exposure to erosion, the high cost of maintenance, and the potential for optimised curtailment strategies to extend their lifespan.

4.4. Cost breakdown

Understanding the cost breakdown of the selected components is necessary for evaluating the financial implications of the degradation of these components. The cost structure of OWTS depends heavily on turbine size and capacity. In this study, a turbine of 15 MW is used as the baseline for cost estimation [66]. Wind farm costs span multiple phases, including development expenditures (DevEx), upfront CapEx for construction, installation and commissioning costs, OpEx for maintenance and repairs, and decommissioning costs at the end of the turbine's lifespan [100]. However, this study focuses solely on the cost of replacing the specific turbine components, as installation and transport costs, even though significant, require a separate, more comprehensive financial analysis, which is beyond the scope of the research.

To estimate component costs, data from an offshore wind farm cost analysis from 2019 is used [101]. Given the rise in material and labour costs, a 27% cost increase over five years is applied, based on AFRY's projection of CapEx growth from 2020 to 2025 [102]. To maintain consistency, this study assumes a similar 27% increase to reflect 2024 price levels. Table 4.1 provides an overview of the updated component costs.

Table 4.1: Cost breakdown of wind turbine components [101, 102]

Component	CapEx per MW		CapEx for 15 MW OWT
	[£/MW] (2019)	[€/MW] (2024)	[€] (2024)
Gearbox	70,000	88,900	1,333,500
Blades	130,000	165,100	2,476,500
Tower (steel + tower internals)	70,000	88,900	1,333,500
Steel	60,000	76,200	1,143,000
Turbine foundation	280,000	355,600	5,334,000
Support structure (tower + foundation)	350,000	490,000	7,350,000

4.5. Impact of curtailment on components

The previous sections covered the fundamentals of wind power, the impact of curtailment on turbine performance, and the selection of critical components. These insights provide the foundation for determining how curtailment affects component degradation. To quantify the impact, degradation functions are formulated for the selected components: support structure (ss), gearbox (gbx) and blades (bld).

OWT components experience complex aerodynamic and hydrodynamic loads, and degradation typically requires detailed fatigue analysis, such as Rainflow Counting (RFC) or Damage Equivalent Load (DEL) methods. However, these techniques are computationally expensive, may require several iterations between multiple parties, and are often based on confidential and project-specific data. Instead, simplified degradation functions are developed to approximate the impact of curtailment on component lifetime. It is important to note that this study does not consider stochastic failure rates or additional reliability metrics. Instead, the degradation functions focus solely on deterministic, progressive wear of components due to operational and environmental factors. The functions are formulated based on assumed relationships between aerodynamic and hydrodynamic loading, as outlined in Section 4.1. Additionally, they incorporate engineering insights from expert interviews (see Appendix A) and account for the effects of curtailment on turbine performance, as discussed in Section 4.2.

Support structure degradation

The degradation of the support structure is influenced by aerodynamic and hydrodynamic loads, which vary based on wind speed, thrust force, and wave height. Additionally, aerodynamic damping plays an important role in reducing structural fatigue when the turbine operates, as shown in Figure 4.9.

The aerodynamic load is assumed to scale with thrust force, as defined in Equation 4.6, while the hydrodynamic load scales with significant wave height, as shown in Equation 4.7. The aerodynamic damping experienced by the support structure depends on the ratio of actual power production to theoretical power output under given environmental conditions.

Additionally, thrust force scales linearly with curtailment, as visualised in Figure 4.8. The degradation function is therefore expressed as:

$$f_{\mathrm{t}}^{\mathrm{ss}} = \alpha^{\mathrm{aero}} \cdot F_{\mathrm{t}}^{\mathrm{thrust}} \cdot \frac{P_t^{\mathrm{DA}}}{P_t^{\mathrm{Th}}} + \alpha^{\mathrm{hydro}} \cdot H_s(v_w) - \alpha^{\mathrm{damp}} \cdot F_{\mathrm{t}}^{\mathrm{thrust}} \cdot \frac{P_t^{\mathrm{DA}}}{P_t^{\mathrm{Th}}} \tag{4.8}$$

Where:

- P_t^{DA}: Power delivered to the day-ahead market,
- P_t^{Th}: Theoretical power output at given environmental conditions,
- $F_{\mathrm{t}}^{\mathrm{thrust}}$: Thrust force in Mega Newtons (MN),
- α^{aero}: Scaling factor for aerodynamic loading on the support structure,
- α^{hydro}: Scaling factor for hydrodynamic loading,
- α^{damp}: Scaling factor for damping due to rotations,
- $H_s(t)$: Significant wave height at time t in meters (m).

The scaling parameters ($\alpha^{\mathrm{aero}}, \alpha^{\mathrm{hydro}}, \alpha^{\mathrm{damp}}$) are be determined in Section 4.6.

Gearbox degradation

The degradation of the gearbox is primarily driven by wind speed variations and the ratio of power production and the theoretical power output. The load experienced by the gearbox is assumed to be linearly dependent on the thrust force, therefore, the degradation function of the gearbox is as follows:

$$f_{\mathrm{t}}^{\mathrm{gbx}} = \alpha^{\mathrm{gbx}} \left(\frac{P_t^{\mathrm{DA}}}{P_t^{\mathrm{Th}}} \cdot F_{\mathrm{t}}^{\mathrm{thrust}} \right) \tag{4.9}$$

Where:

- α^{gbx}: Scaling factor for gearbox degradation,

Blade degradation

Blade degradation is influenced by aerodynamic forces and rain droplet impact on the leading edge. At high tip speeds, rain droplets can cause LEE, as discussed in Section 4.5.

In a so-called erosion-safe mode, curtailment also reduces blade tip speed, which in turn lowers the impact velocity of rain droplets, mitigating LEE damage. The aerodynamic forces experienced by the blades scale with thrust force (Equation 4.6) and vary with the level of curtailment, as illustrated in Figure 4.8.

The degradation function for the blades is given by:

$$f_{\mathrm{t}}^{\mathrm{bld}} = \alpha^{\mathrm{aero}} \cdot \left(\frac{P_t^{\mathrm{DA}}}{P_t^{\mathrm{Th}}} \cdot F_{\mathrm{t}}^{\mathrm{thrust}} \right) + \beta^{\mathrm{rain}} \cdot \left(\frac{P_t^{\mathrm{DA}}}{P_t^{\mathrm{Th}}} \cdot v_{\mathrm{tip}} \right) \cdot I_t^{\mathrm{rain}} \tag{4.10}$$

Where:

- α^{aero}: Scaling factor for aerodynamic loading on the blades,
- β^{rain}: Scaling factor for additional loading on the blades due to rain,
- v_t^{tip}: Defined as the blade tip speed and depends upon the operational mean wind speed v_w,
- I_t^{rain}: Rainfall intensity, could be measured in [mm/h].

Where:

$$v_t^{\text{tip}} = \omega \cdot r \tag{4.11}$$

$$\omega = \frac{rpm \cdot 2\pi}{60} \tag{4.12}$$

- $\omega[rad/s]$: angular velocity of the rotor in radians per second
- $r[m]$: rotor radius (distance from the centre of the turbine to the tip of the blade), $r = 120m$.

4.6. Implementation of the degradation functions

To be able to calibrate the degradation function parameters a simulation is conducted. This section visualises how degradation functions affect component health over time. This process follows an iterative approach, where initial values are arbitrarily chosen and refined to align with the expected lifespans of the components. Parameters are determined based on the following design life assumptions:

- **Support structure:** Designed to last 30 years, with an optional 5-year extension,
- **Gearbox:** Assumed design life of 15 years,
- **Blades:** Designed for a lifespan of 20-35 years, where replacement is possible but typically unnecessary.

The simulation does not focus on optimising power production but rather on understanding the effects of curtailment. Assumptions used for the simulation include:

- With negative prices, the power delivered to the day-ahead market (P_t^{DA}) is set to zero:

$$P_t^{\text{DA}} = 0$$

- If electricity prices are positive, power production follows the theoretical power output:

$$P_t^{\text{DA}} = P_t^{\text{theoretical}}$$

The simulation employs the IEA 15 MW reference OWT [103]. In addition, two, hourly-based data sets from 2023 are used, one for the electricity prices and one for the environmental conditions, namely:

- **Electricity prices:** Data from 2023 is used due to its high frequency of negative price hours, ensuring realistic curtailment scenarios [104].
- **Environmental conditions:** Data on wind speeds, significant wave heights and precipitation are gathered from the ERA5 hourly dataset provided by the Copernicus Climate Change Service [87].

Given the simplified nature of the simulation, an hourly temporal resolution over a 30-year period is used. To construct the full simulation dataset, the datasets from a single year are repeated annually. This approach is justified as the absolute price values do not directly influence power production, rather, only the occurrence of negative price hours and environmental conditions impact the operational decisions. While this assumption is suitable for the simulation, subsequent chapters incorporate alternative datasets adjusted for the optimisation models, as detailed in Section 6.1.

Sets and parameters

The simulation spans a 30-year modelling period and uses the following sets:

$$T = \{t_1, t_2, \ldots, t_{8760}\},\ Y = \{y_1, y_2, \ldots, y_{30}\},\ M = \{\text{ss},\ \text{gbx},\ \text{bld}\}$$

Where:

- T represents the time steps, defined as hours per year, with a total of 8,760 hours annually.
- Y refers to the simulation period in years, spanning a total of 30 years.
- M refers to the set of selected components for degradation analysis, including the support structure (ss), gearbox (gbx), and blades (bld).

The minimum permissible health factor S_{min} is set at 0.2. Additional degradation parameters are detailed in Appendix B. The degradation functions, defined in Section 4.5, influence the component's state of health through the following equation:

$$S^{\text{m}}_{t+1} = S^{\text{m}}_{t} - f^{\text{m}}_{t}, \quad \forall t \in T, \quad \forall y \in Y, \quad \forall m \in M \tag{4.13}$$

Where:

- S^{m}_{t}: Representing the health state of each of the components, initialised at 1.

Visualisation

The results of the health evolution of the three components, based on the input parameters as stated above, are illustrated in Figure 4.11.

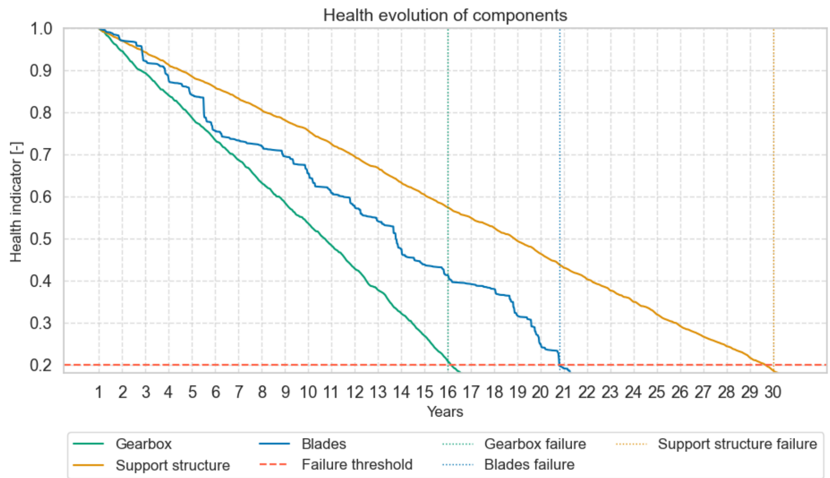


Figure 4.11: Health evolution of components, with a failure threshold (S_{min}) equal to 0.2 and an hourly time resolution over 30 years

The figure includes a failure threshold (S_{min}) set at 0.2, marking the point at which a component reaches its end-of-life and requires replacement. Component failure requires replacement to maintain turbine operation or, if this proves to be economically unattractive, prompt the decommissioning of the OWT. Since the gearbox is relatively inexpensive (see Table 4.1), replacing it could be economically viable. Conversely, due to the higher cost of blade replacement, blade failure could lead to the turbine's premature end-of-life. An extensive comparison of replacement decisions is discussed in Section 7.1.1.

4.7. Concluding remarks

This chapter examined the effects of market-driven curtailment on the degradation and cost structure of critical OWT components. By analysing aerodynamic and hydrodynamic loads, it has been shown that the impact of curtailment depends on the turbine's operational state.

The study focused on three key components: the support structure, gearbox, and blades. The support structure is influenced by changes in aerodynamic damping, which impact the distribution of external loads on the tower and foundation. The gearbox experiences variations in loading conditions due to fluctuations in rotor speed and power output, while blade degradation is linked to aerodynamic forces and environmental exposure, such as leading-edge erosion caused by rain.

To estimate the impact of curtailment on component wear, degradation functions were developed and applied in a 30-year simulation. The resulting degradation parameters will serve as a reference for further analysis in Section 6.4.1, where they will be used to establish a centralised coordinated curtailment strategy that internalises the impact of curtailment on asset health. Once a component reaches the failure threshold, a decision has to determine whether to replace components or decommission the turbine. This trade-off compares maintenance costs against the economic benefits of continued turbine operation.

5 Stakeholder perspectives

This chapter examines the perspectives of the stakeholders on market-driven curtailment. Specifically, it addresses the following research question: *What are the objectives of the three most important stakeholders (namely dispatchers, maintenance party and wind farm owners) regarding curtailment strategies?* To answer this, the chapter analyses the operational, financial, and regulatory incentives driving decision-making in market-driven curtailment strategies.

While a wind farm owner might prioritise long-term asset health to maximise return on investment, dispatchers are primarily concerned with short-term market dynamics, focussed on optimising profits through energy trading [44]. Manufacturers and maintenance parties add further complexities as turbine design limitations and operational constraints may impose curtailment caps. These conflicting objectives create inefficiencies in the current curtailment strategy.

The contractual structure of offshore wind farms varies depending on the type and number of stakeholders involved. Figure 5.1 provides an example of a common contractual arrangement. The structure of ownership differs per project, ranging from single-owned farms, such as Prinses Amalia, which is owned by Eneco [105], to multi-stakeholder consortia, such as Blauwwind [106]. In the case of Prinses Amalia, the owner, dispatcher, and maintenance party are all part of the same company, which simplifies coordination. Typically, ownership consists of a mix of insurance companies, pension funds, banks, and energy suppliers, with greater stakeholder involvement in consortia leading to increased complexity in decision-making.

There are currently only two main offshore wind turbine manufacturing companies active in the Netherlands, namely, Vestas and Siemens. The next biggest manufacturer is General Electric (GE), which is mostly active in the United Kingdom, Denmark, and France. These companies design the turbines and are usually responsible for O&M during the warranty period, which ranges from 5 to 15 years. Maintenance contracts are based on availability guarantees, where owners compensate the maintenance party based on uptime. These availability guarantees will be explained in more detail in Section 5.1. After the warranty period, owners may either extend contracts, hire external service providers, or do the O&M in-house.

The PPA, which is a long-term contract between a wind farm owner and the dispatcher, includes a predefined price at which the power output is sold to the dispatcher. The responsibility of dispatching varies as it may be shared among owners, assigned on a rotating basis, or handled by an external entity. As outlined in the rapport by Bird et al. [25], PPAs increasingly address the use of curtailment hours and more explicitly share the risk between the owner and dispatcher. End users purchase electricity through Corporate PPAs (CPPAs), though they fall outside the scope of the study as their role does not directly influence the contractual decisions related to curtailment.

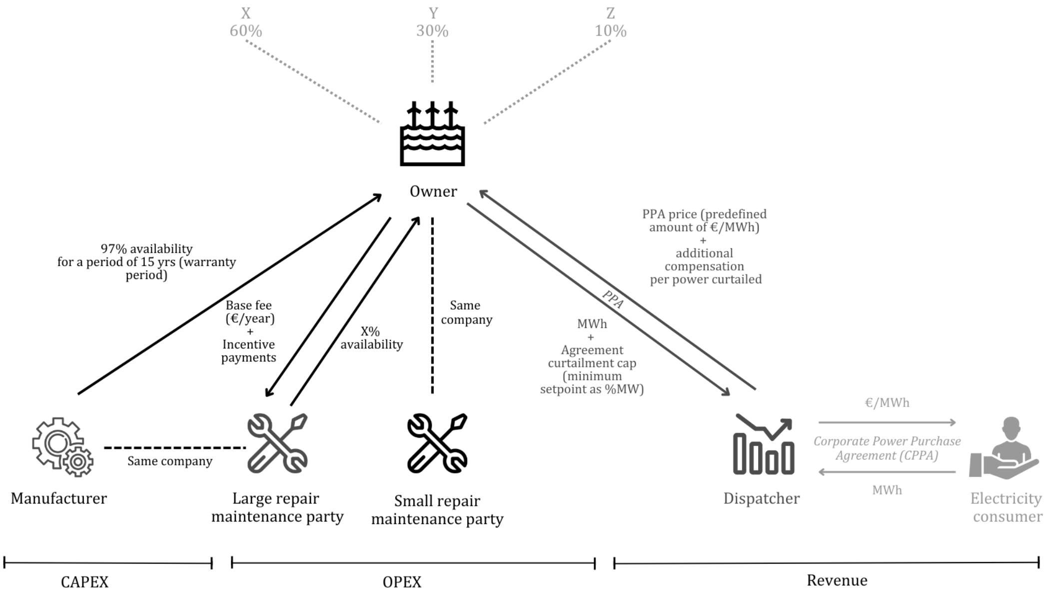


Figure 5.1: Conceptual overview of contractual relationships [70], [72], [74], [75]

5.1. Perspective of the dispatcher

The dispatcher determines when curtailment or production is financially beneficial, as they can reduce power output up to the minimum set point. This decision is shaped by contractual agreements, market conditions, and financial incentives. The decision space within the dispatcher is able to operate is outlined in the PPA. The PPA defines a price for each MWh produced. As traders bear the financial risk of negative electricity prices, they aim to curtail power when selling electricity is becoming unprofitable. Therefore, traders often advocate for the ability to curtail to 0% of the potential power output during negative price hours.

5.1.1. Strike price

Curtailment decisions are guided by the strike price, which represents the economic threshold below which it becomes more profitable to curtail production than to continue generating electricity. This is influenced by two factors, the Guarantees of Origin (GoOs) and the subsidy height. GoOs certify that the electricity production is renewable [107]. The value of these certificates typically ranges between three and seven euros per MWh and are only issued when electricity is actively generated. As a result, curtailing output leads to a loss of GoO revenue, which can influence bidding strategies. To account for this potential loss, wind farms may engage in negative bidding.

In addition to GoOs, offshore wind farms may receive subsidies (e.g., in the Netherlands through the SDE ++ scheme), which are adjusted annually based on the previous year's market conditions [108]. These subsidies provide an additional revenue stream, resulting in the following strike price determination:

$$\text{Strike price} = -\text{GoO} - \text{Subsidy} \tag{5.1}$$

5.1.2. Role of subsidy in curtailment decisions

To incentivise renewable energy investment, the SDE ++ subsidy scheme compensates producers for revenue shortfalls, ensuring they can cover their costs [44]. The subsidy level varies based on the type of vRES and the specific tender under which a wind farm was developed. Notably, wind farms awarded subsidies from 2023 onwards do not receive support during periods of negative electricity prices if their installed capacity exceeds 200 kW [17].

The subsidy level is determined by market conditions and is based on the average electricity price in the day-ahead market, adjusted using a Profile and Imbalance Factor (PIF). The PIF is a correction factor that reflects deviations between forecasted and actual production, accounting for costs incurred in the imbalance market [108]. The expected subsidy is calculated as:

$$\text{Expected subsidy} = \text{Subsidy (base value)} - \bar{\lambda}_t^{\text{DA}} \times \text{PIF} \tag{5.2}$$

Where:

- Subsidy (base value): The maximum financial compensation allocated to produces before market revenues are accounted for.
- $\bar{\lambda}_t^{\text{DA}}$: The average electricity price over previous year [10].
- PIF: The profile and imbalance factor, correcting for imbalance market costs.

Subsidies help ensure financial viability by covering the gap between market revenues and break-even costs, thereby incentivising producers to minimise OpEx. The type of vRES also influences the subsidy level, with solar energy often receiving higher compensation than offshore wind. This discrepancy reflects solar energy's frequent role in driving electricity prices into negative territory, requiring greater support to maintain profitability. Similarly, subsidies for wind farms ensure that expected revenue levels are met by compensating for the shortfall between break-even revenue and actual market earnings, adjusted using the PIF [109]. Historically, subsidies have been approximately €200/MWh for older wind farms, but they have decreased to around €55–60/MWh for newer projects [44].

Additionally, subsidy calculations exclude periods where negative electricity prices persist for more than six consecutive hours, further impacting the financial context for curtailment decisions [17]. Consequently, the strike price calculation is extended to account for these factors:

$$\text{Electricity bid} = \text{Strike price} = -\text{GoO} - \text{Subsidy} - \bar{\lambda}_t^{\text{DA}} \times \text{PIF} \tag{5.3}$$

5.1.3. Determining the PPA price

The order in which the dispatcher decides to curtail is influenced by the strike price, with assets that have a lower strike price being curtailed first [44]. The current curtailment strategy prioritises curtailing the asset with the lowest strike price entirely before moving to the next rather than distributing curtailment across multiple assets with similar strike prices. In cases where strike prices are close to each other, this approach may not be optimal. A strategy in which partially curtailing multiple assets would be used instead of fully curtailing just one could ensure a more balanced curtailment strategy across the energy portfolio.

In many cases, the PPA price is set to align with the average EPEX price and is adjusted annually in April to reflect the market conditions of the previous year. Throughout the year, dispatchers estimate expected subsidy payments, with partial payments made in advance based on forecasts and final corrections applied in April [44].

The price at which the dispatcher purchases electricity from the wind farm is determined by the following equation:

$$\lambda^{\text{PPA}} = \bar{\lambda}_t^{\text{DA}} \times \text{PIF} \tag{5.4}$$

Where:

- λ^{PPA}: The fixed PPA price per MWh, which remains constant throughout the year.

The dispatcher's priority is to optimise financial performance by strategically managing curtailment, primarily to minimise losses during negative electricity prices. Greater operational flexibility enhances the dispatcher's ability to respond to market fluctuations. Curtailment decisions are driven by PPAs, strike prices, and prevailing market conditions. While the dispatcher is responsible for executing curtailment schedules, the maintenance party and owner influence the extent to which curtailment can be applied by setting operational constraints.

5.2. Perspective of the maintenance party

The maintenance party is responsible for ensuring the operational reliability of the turbines. Their primary focus is on minimising wear and tear, managing O&M costs, and complying with contractual availability guarantees (e.g., maintaining uptime of 97%). While market-driven curtailment is a financial decision made by dispatchers, it directly impacts the components' health that maintenance teams must account for. Maintenance teams can put turbines in standstill mode (with locked rotors) during scheduled maintenance, however, they do not have the authority to curtail output due to negative electricity prices.

Manufacturers of offshore wind turbines typically offer warranties of up to 15 years. Most often, the manufacturing party is also responsible for regular maintenance and component replacements as long as the warranty period lasts. Contracts between project developers often contain availability guarantees, with a target of 97% uptime for newer projects. This level is reviewed every five years. This arrangement usually includes a base fee for O&M activities along with incentive payments tied to meeting availability benchmarks.

As explained in more detail in chapter 4, curtailment impacts the fatigue and stress endured by components like blade bearings, the gearbox, and the drivetrain. Frequent curtailment cycles, especially in short intervals (e.g. every 5-10 minutes), accelerate fatigue loads, which can shorten the component lifespan. To mitigate this, manufacturers impose minimum curtailment durations (e.g. 10 minutes) to limit excessive load cycles [110].

An aggressive curtailment or production strategy can significantly increase O&M costs, as repairs are expensive. For instance, gearbox replacements exceed €1 million, with jack-up vessel costs reaching €400,000 per day [110]. Offshore logistics further complicate repairs, particularly in harsh weather conditions.

The maintenance party's priority is to maximise turbine availability through continuous maintenance and component replacements. Therefore, their focus lies on the impact of dispatch strategies on replaceable components. The OWT also contains non-replaceable components, in which the owner holds a greater stake.

5.3. Perspective of the wind farm owner

The wind farm owner is often the stakeholder involved for the longest period, potentially from tendering to decommissioning, a period that may exceed 30 years. Unlike other stakeholders, whose interests may be short- or medium-term, the owner prioritises long-term asset health to maximise financial return on investment. Mostly due to the need to protect the resale value of the wind farm. This preservation of asset health is challenged with excessive curtailment and idling, as frequent start-stop cycles can accelerate structural wear, particularly on the foundation and drivetrain components [111].

Wind farm ownership often involves a consortium of developers and investors who collectively oversee the project's financial and operational performance. In some cases, the wind farm owner is also the developer, where the same party is responsible for both the development of the farm and the management throughout its operational life. In other cases, the ownership is shared with or transferred to external investors, such as pension funds, infrastructure funds, or energy companies, who provide financial resources but may not be directly involved in day-to-day operations. Regardless of the ownership structure, their focus is on reducing the LCOE, which is a decisive factor in securing tenders and ensuring economic viability.

5.3.1. Turbine design and cost considerations

To achieve cost reductions, wind farm developers aim to minimise CapEx, particularly by reducing the amount of steel used in the foundation and tower. This design choice is made before the wind farm becomes operational and includes an assumption about the expected number of idle hours over the turbine's lifetime, often in the range of 5-10%. This reduction in the thickness of steel can potentially make the turbine more susceptible to fatigue loads caused by curtailment and extended idling periods. By contrast, wind farms with heavier steel foundations can withstand long-term curtailment impacts better but have a higher CapEx [111].

5.3.2. Negotiating curtailment agreements

To mitigate the impact of curtailment on asset longevity, wind farm owners increasingly incorporate curtailment restrictions in the PPAs with dispatchers. Aggressive curtailment strategies can accelerate component wear, increase O&M costs, and shorten turbine lifespan, ultimately reducing the wind farm's resale value. To protect turbine longevity, these agreements introduce operational constraints, such as:

- **Curtailment limit:** Wind farm owners may prohibit full power reduction to 0 MW, requiring a minimum output of 15-20% to reduce mechanical stress. They can also limit how often dispatchers adjust turbine output to prevent excessive load cycles [111].
- **Penalty for deep curtailment:** A financial penalty is imposed when power output is reduced to 0 MW, compensating owners for increased turbine fatigue while allowing dispatchers flexibility in balancing curtailment. These penalties can be substantial, around €100/MWh, significantly impacting profitability compared to electricity prices in Figure 1.2 [111].

The owner's decision-making is driven by long-term asset health, PPA prices, and potential lifetime extension. To maximise returns, the owner has a vested interest in preserving the health of both replaceable and non-replaceable components. By minimising excessive wear, the owner can extend the operational lifespan of the wind farm, increasing the financial viability and resale value.

5.4. Economic performance

This section details the mathematical equations included in the optimisation model to reflect the different perspectives of each stakeholder. More specifically, it shows how each stakeholder's revenue, costs and corresponding profit are being calculated. Figure 5.2 represents a simplified version of the contractual overview presented earlier in Figure 5.1 to highlight the most important relations for this research.

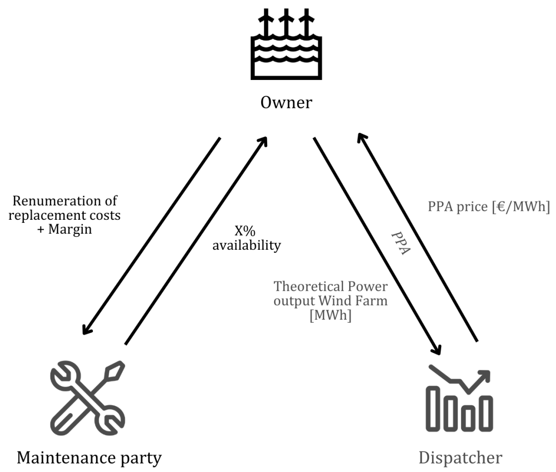


Figure 5.2: Contractual relations considered in optimisation [72], [70], [74]

Dispatcher

The dispatcher's revenue is calculated by multiplying the amount of power sold in the day-ahead market by the corresponding day-ahead market price for each time step t. Similarly, the dispatcher's costs are determined by multiplying the PPA price by the theoretical power output over the same time series. The resulting profit is the difference between revenue and costs.

$$\text{Revenue} = \sum_{t \in T} \left(\lambda_t^{\text{DA}} \cdot P_t^{\text{DA}} \right) \tag{5.5}$$

$$\text{Cost} = \sum_{t \in T} \left(\lambda^{\text{PPA}} \cdot P_t^{\text{Th}} \right) \tag{5.6}$$

$$\text{Profit} = \text{Revenue} - \text{Cost} = \sum_{t \in T} \left(\lambda_t^{\text{DA}} \cdot P_t^{\text{DA}} - \lambda^{\text{PPA}} \cdot P_t^{\text{Th}} \right) \tag{5.7}$$

Where:

- P_t^{DA}: Power sold in the day-ahead market.
- λ_t^{DA}: Day-ahead market price.
- λ^{PPA}: Predefined price in the PPA, assumed constant over time.
- P_t^{Th}: Theoretical power output possible under prevailing environmental conditions.

Maintenance party

The revenue of the maintenance party primarily consists of a base remuneration for O&M services, which is expressed as follows:

$$\text{Revenue} = B = \text{Margin} \cdot (C^{\text{gbx}} \cdot (1 - S_T^{\text{gbx}}) + C^{\text{bld}} \cdot (1 - S_T^{\text{bld}})) \tag{5.8}$$

In this calculation, it is assumed that the maintenance party is fully reimbursed for its costs. While this may not always hold in practice, this simplification allows for a clearer comparison of cost structures and profitability without introducing additional uncertainties from specific agreements.

$$\text{Cost} = C^{\text{gbx}} \cdot (1 - S_T^{\text{gbx}}) + C^{\text{bld}} \cdot (1 - S_T^{\text{bld}}) \tag{5.9}$$

$$\text{Profit} = B - C^{\text{gbx}} \cdot (1 - S_T^{\text{gbx}}) - C^{\text{bld}} \cdot (1 - S_T^{\text{bld}}) \tag{5.10}$$

Where:

- B: Base remuneration for O&M services.
- Margin: Margin assumed at 20%.
- C^{gbx}: Replacement cost of gearbox.
- C^{bld}: Replacement cost of blades.
- S_t^{gbx} and S_t^{bld}: Gearbox (gbx) and blade (bld) health state, both initialised at 1.

Wind farm owner

For the wind farm owner, revenue is calculated by multiplying the PPA price by the theoretical power output over a series of time steps t. Costs consist of the base remuneration for O&M services, as well as investment costs for support structures if replacements are required. As before, profit is determined as the difference between revenue and costs.

$$\text{Revenue} = \sum_{t \in T} \left(\lambda^{\text{PPA}} \cdot P_t^{\text{Th}} \right) \tag{5.11}$$

$$\text{Cost} = C^{\text{ss}} \cdot (1 - S_T^{\text{ss}}) - B \tag{5.12}$$

$$\text{Profit} = \sum_{t \in T} \left(\lambda^{\text{PPA}} \cdot P_t^{\text{Th}} \right) - C^{\text{ss}} \cdot (1 - S_T^{\text{ss}}) - B \tag{5.13}$$

Where:

- λ^{PPA}: Predefined price in the PPA, considered constant over time.
- P_t^{Th}: Theoretical power output possible at occurring environmental conditions at that time.
- C^{ss}: Investment cost of the support structure.
- S_t^{ss}: Support structure (ss) health state, initialised at 1.
- B: Base remuneration for O&M services, includes the replacement costs of the gearbox and blades and a margin.

5.5. Trade-off

As has become evident from the previous sections, curtailment decisions are shaped by the competing objectives of stakeholders, resulting in a trade-off. The lack of coordination among these stakeholders can lead to suboptimal decision-making. In the baseline scenario, each party seeks to optimise its own objective without considering the broader impact on the overall system.

A practical example of such inefficiencies can be observed in the current dispatch strategy, where neither equipment wear and tear nor environmental factors are considered. This can lead to unfavourable economic outcomes. For instance, on a particularly sunny day, electricity prices may turn negative, yet the dispatcher is still required to feed 20% of production into the grid. Consider a wind farm with a capacity of 1 GW facing a price of -€100/MWh, under the existing dispatch strategy, the operator would incur a loss of €20,000 per hour. If factors such as turbine wear or low wind speeds were accounted for, the more optimal decision might be to shut down the turbine entirely rather than adhering rigidly to the curtailment limit.

Furthermore, the relationship between the wind farm owner and the maintenance party reflects a classic principal-agent problem [112, 113]. The owner, as the principal, aims to maximise long-term asset value, while the maintenance party, acting as the agent, may be incentivised by short-term performance metrics such as uptime. This creates the notion of asymmetric information, as the maintenance party holds more detailed knowledge on degradation risks and wear patterns but may be hesitant to share it with the owner as it could potentially backfire via contractual disputes.

The insights from this chapter form the foundation for the optimisation frameworks introduced in Chapter 6. These include a baseline scenario where curtailment strategies focus solely on market-based incentives, a centralised strategy that integrates all objectives into a unified framework, and a decentralised strategy that allows for coordination without requiring full disclosure of sensitive information.

6

Formulation of curtailment strategies

To internalise turbine longevity within the dispatch strategy while maximising financial performance, an optimisation model will be developed using mathematical programming techniques. Selecting the right model is crucial as each type of formulation has different trade-offs in terms of accuracy, computational efficiency, and real-world applicability. Unlike textbook problems, where the correct mathematical technique is often evident, real-world optimisation requires careful consideration of multiple approaches to determine which best captures the problem at hand [79]. To establish the most suitable problem formulation, this analysis leads to the third sub-question: *How can curtailment strategies be formulated as an optimisation problem?*

The chapter begins with an overview of the data collection process in Section 6.1, defining the external data collected, the temporal resolution and modelling period and the example dataset used in the decentralised optimisation problem. It then introduces the baseline scenario in Section 6.2, which serves as a reference point. To incorporate asset health into the optimisation, different modelling approaches are considered in Section 6.3. Linear programming (LP), mixed-integer linear programming (MILP), and nonlinear programming (NLP) each provide a different way of integrating degradation effects into decision-making. Furthermore, Section 6.3.5 provides refined cost calculations that explicitly incorporate replacement decisions. Finally, the chapter formulates two curtailment strategies: a centralised approach, where all decisions are optimised collectively, and a decentralised approach, in which stakeholders make independent decisions while maintaining global coordination. These approaches are detailed in Sections 6.4.1 and 6.4.2, respectively.

6.1. Data collection

This section describes the data collection process, detailing the turbine specifications, electricity price data, and environmental conditions used in the optimisation models.

Turbine specifications

The optimisation model is based on a 15 MW reference turbine [103]. The technical operating conditions used in the model are set out below [103]:

- **Wind speed thresholds [m/s]:** Defines the operational limits of the turbine:
  - Cut-in wind speed: $v_{cut-in} = 3$ m/s
  - Rated wind speed: $v_{rate} = 10.6$ m/s
  - Cut-out wind speed: $v_{cut-out} = 25$ m/s
- **Rated power [MW]:** Maximum power output under optimal wind conditions:
  - $P_{rate} = 15$ MW
- **Rotor radius [m]:** Distance from the centre of the rotor to the tip of the blade, which is used to determine the swept area A of the turbine blades:

- $r = 120$ m (for a 240 m diameter turbine)
- Swept area: $A = \pi r^2$

- **Thrust force [MN]:** Determines the aerodynamic load acting on the turbine:
  - Derived based on the wind speed
  - Used in all degradation functions to determine the aerodynamic force acting on the components
- **Rotor speed [rpm]:** Rotational speed of the turbine blades:
  - Dependent on wind speed, derived from Equation 4.12
  - Required for evaluating blade degradation

These parameters define the operational behaviour of the turbine and determine the degradation mechanisms, forming the foundation of the curtailment optimisation model. Another static variable is the air density ($\rho = 1.225$ kg/m³), which is used when determining the theoretical power output following Equation 4.1.

External datasets

The optimisation model incorporates historical market and environmental data to simulate real-world operating conditions. However, the dataset assumes deterministic values for electricity prices and environmental conditions. While these values are inherently uncertain in reality, this assumption simplifies the optimisation model and reduces computational complexity. By removing uncertainty, the focus remains on optimising decision-making rather than modelling stochastic fluctuations.

For the environmental conditions the coordinates of the upcoming Dutch tender [114] are used, which is shown in Figure 6.1. The coordinates are: $53°32'$N, $4°13'$E.

Figure 6.1: Location of upcoming tender, IJmuiden Ver Gamma-A, IJmuiden Ver Gamma-B and Nederwiek 1-A [114]

- **Electricity prices [€/MWh]:** Hourly market prices are sourced from Ember [104]. The year 2023 is selected as the base period because, at the start of this study, it was the most recent full year available. In addition, it included a significant number of negative price hours, which are relevant for analysing curtailment strategies.
- **Wind speed [m/s]:** Hourly historical wind data at 150 meters hub height is sourced from the ERA5 reanalysis dataset [87]. The wind speed data is used to estimate the theoretical power output of the turbine.
- **Significant wave height [m]:** The average height of the highest one-third of waves (H_s), which is sourced from the ERA5 hourly reanalysis dataset [87], and used to evaluate hydrodynamic forces on the turbine.
- **Total precipitation [mm/h]:** This parameter represents the total liquid and frozen water accumulation per hour, including rain and snow. Precipitation is relevant for computing blade degradation, as leading-edge erosion is strongly influenced by the impact of raindrops on the turbine blades at high rotational speeds. The data is sourced from the ERA5 hourly reanalysis dataset [87].

Temporal resolution and modelling period

The initial data set is based on an hourly resolution, consistent with the day-ahead spot market on which this study is based. Electricity price data from ENTSOE-E and Ember is also available at an hourly level, ensuring alignment with day-ahead trading conditions [104, 115]. To realistically capture the relation between electricity prices and environmental factors, the corresponding environmental data is included for each hourly time step.

Since new offshore wind farms are typically designed for a 30-year operational lifetime [116], the optimisation model should ideally cover the same period. However, incorporating an hourly dataset for 30 years, equivalent to 262.800 time steps, is computationally infeasible within the constraints of this thesis and standard computing resources. To reduce computational complexity while preserving essential temporal patterns, the dataset is sorted and reduced.

The selected methodology ensures that both daily and seasonal variations in electricity prices and environmental conditions are retained. Daily variations need to be taken into account as both electricity prices and environmental conditions fluctuate significantly between day and night. Monthly variations are also included to capture seasonal effects, for example, wind availability is typically higher in autumn and spring, potentially affecting electricity prices due to increased wind power generation.

To achieve this, a representative dataset of 8640 hours is constructed:

- Year 1: The first 24 hours of each month (e.g. January 1st 00:00-00:00, February 1st 00:00-00:00, etc.) are selected, resulting in 288-time steps (24 x 12),
- Year 2: The second day of each month is selected (February 2nd 00:00-23:00, March 2nd 00:00-23:00, etc.), again resulting in 288-time steps,
- This process is repeated for 30 years, ensuring a total dataset of 8640 representative hours while maintaining consistency between price trends and environmental conditions.

The dataset represents a model period of 30 years, from the years 2023 to 2052.

Degradation and cost parameters

The degradation parameters are derived from the simulation presented in Section 4.6, which operates at an hourly resolution over 30 years. To ensure compatibility with the new dataset resolution, these parameters require an adjustment, which is detailed in Appendix B.2. The final degradation parameter values are:

$$\begin{aligned} a_{\text{gbx}} &= 1.462 \times 10^{-4}, & a_{\text{ss}} &= 1.246 \times 10^{-5} \\ c_{\text{damping}} &= 8.558 \times 10^{-6}, & b_{\text{wave}} &= 9.414 \times 10^{-6} \\ a_{\text{bld}} &= 1.096 \times 10^{-5}, & b_{\text{rain}} &= 1.086 \times 10^{-5} \end{aligned}$$

The corresponding replacement costs for the selected components, derived from Section 4.4, are:

$$\begin{aligned} C^{\text{gbx}} &= €1,333,500, \\ C^{\text{ss}} &= €7,350,000, \\ C^{\text{bld}} &= €2,476,500 \end{aligned}$$

Due to the computational complexity of solving the decentralised optimisation model, a reduced dataset was used containing 11 time steps. This text dataset was selected to maintain the feasibility of the simulation. Although this represents a simplification, it allows to evaluate the theoretical feasibility of the decentralised coordination framework before scaling to larger datasets. For a detailed explanation of the test dataset, refer to Appendix B.3.

This section provided the overview of the collected data which serves as input for the optimisation models discussed in the next sections.

6.2. Baseline scenario

First, a baseline scenario is established as a reference for evaluating centralised and decentralised optimisation strategies. This scenario represents an uncoordinated curtailment strategy where the dispatcher maximises revenue from selling electricity in the day-ahead market while complying with constraints imposed by the wind farm owner and maintenance party. Unlike the centralised approach, this scenario does not incorporate the long-term impact of curtailment on turbine component degradation. It assumes independent decision-making without coordination between the dispatcher, owner and maintenance party. For the baseline scenario, the mathematical programming concepts used in the optimisation model are set out below, including the used sets, parameters, decision variables, objective function, and constraints.

Sets

$$T = \{t_1, t_2, \ldots, t_{288}\}, \quad Y = \{y_1, y_2, \ldots, y_{30}\}$$

Where:

- T represents time steps, with 288 hours annually as explained in Section 6.1.
- Y refers to the optimisation period, spanning 30 years.

Parameters

Table 6.1: Model parameters for the baseline scenario

Parameter	Description	Unit
P_t^{Th}	Theoretical power output at given environmental conditions.	MW
λ_t^{DA}	Electricity price in the day-ahead market.	€/MW
P_{rate}	Rated turbine power (15 MW).	MW

Decision variables

Table 6.2: Decision variables for the baseline scenario

Variable	Description	Unit
P_t^{DA}	Power sold in the day-ahead market.	MW
P_t^{Curt}	Power curtailed.	MW

Objective function

$$\max \sum_{t \in T} \lambda_t^{\text{DA}} \cdot P_t^{\text{DA}} \tag{6.1}$$

Constraints

$$P_t^{\text{DA}} + P_t^{\text{Curt}} = P_t^{\text{Th}}, \quad \forall t \in T \tag{6.2}$$

$$P_t^{\text{Curt}} \leq \text{curtailment\_cap} \cdot P_{\text{rate}}, \quad \forall t \in T \tag{6.3}$$

The objective function, defined in Equation 6.1, seeks to maximise revenue from selling electricity in the day-ahead market without considering the impact of curtailment on component degradation.

Equation 6.2 ensures that the sum of power sold and curtailed equals the theoretical power output.

Equation 6.3 limits curtailment to a predefined fraction of the turbine's rated power, in alignment with the assumption that the PPA includes an agreement on such a curtailment limit.

While the baseline scenario provides a useful benchmark for understanding the current curtailment strategy, its focus is solely on maximising short-term profit. In the next section, a comparison is made with different optimisation approaches to incorporate degradation-aware decision-making into the curtailment strategy.

6.3. Formulating the state of health

To integrate the perspectives of the wind farm owner and maintenance party, a state of health factor is introduced for each critical component. The state of health represents the RUL of critical components, it represents whether components would need to be replaced, once they have reached the minimum failure threshold. The state of health degrades based on the degradation functions as detailed in Section 4.5. This factor is formulated as either a continuous or an integer decision variable. Other options like semi-continuous versions exist, but are not considered in this study.

To determine the most appropriate formulation, three approaches are compared based on computational efficiency and applicability:

- A LP without replacement decisions.
- A MILP including replacement decisions.
- A NLP with a penalty function approximating replacement behaviour.

6.3.1. Linear problem without replacement

The formulation extends the baseline scenario by introducing a continuous decision variable for the health state of each component. The mathematical programming concepts are extended from the baseline scenario. Besides the time series, the sets now also include specific wind turbine components. Furthermore, the parameters are extended to include environmental conditions, component replacement costs, and health state limits.

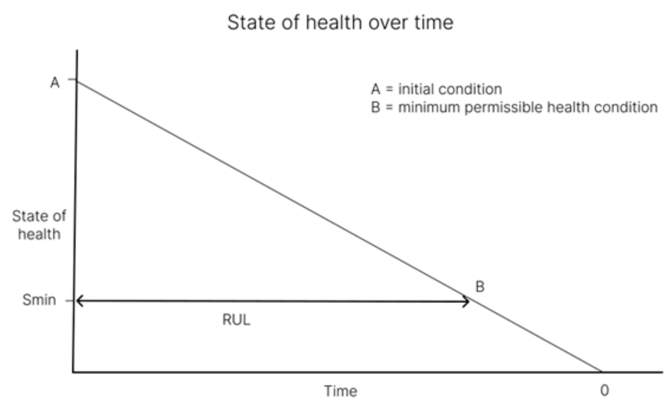


Figure 6.2: Visualisation of the state of health variable [S_t^m] for the linear problem

The health state represents the turbine's RUL, as schematically visualised in Figure 6.2.

The extension of the baseline scenario includes the following mathematical programming concepts used in the optimisation model:

Sets

$$T = \{t_1, t_2, \dots, t_{288}\}, \quad Y = \{y_1, y_2, \dots, y_{30}\}, \quad M = \{\text{ss, gbx, bld}\}$$

Where:

- M represents the selected components: support structure (ss), gearbox (gbx), and blades (bld).

Parameters

Table 6.3: Model parameters for the linear problem

Parameter	Description	Unit
P_t^{Th}	Theoretical expected power output at occurring environmental conditions.	[MW]
λ_t^{DA}	Electricity price of the day-ahead market.	[€/MW]
T_t	Thrust force on turbine blades at time t.	[MN]
V_t^w	Wind speed at 150m hub height.	[m/s]
H_t^s	Significant wave height.	[m]
I_t^{rain}	Rain intensity impacting blades.	[mm/hr]
$S_{\min}$	Minimum permissible health factor.	[-]
$S_{\max}$	Maximum health state (initial state = 1).	[-]
C^m	Replacement cost of component m.	€
$a_{\text{gbx}}, a_{\text{ss}}, a_{\text{bld}}$	Degradation scaling factors for gearbox, support structure, and blades.	[-]
$c_{\text{damping}}, b_{\text{wave}}, b_{\text{rain}}$	Additional degradation scaling coefficients.	[-]
r	Rotor radius (120m).	[m]
P_{rate}	Rated turbine power (15MW).	[MW]

Decision variables

Table 6.4: Decision variables for the linear problem

Variable	Description	Unit
S_t^m	Health state of component m at time t.	[-]

Objective function

$$\max \sum_{t \in T} \left(\lambda_t^{\text{DA}} \cdot P_t^{\text{DA}} - \sum_{m \in M} C^m \cdot (1 - S_t^m) \right) \tag{6.4}$$

Constraints

$$P_t^{\text{DA}} + P_t^{\text{Curt}} = P_t^{\text{Th}}, \quad \forall t \in T \tag{6.5}$$

$$0 \leq P_t^{\text{Th}} \leq P_{\text{rated}} \tag{6.6}$$

$$P_t^{\text{Curt}} \leq \text{curtailment\_cap} \cdot P_{\text{rate}}, \quad \forall t \in T \tag{6.7}$$

$$S_{t+1}^m = S_t^m - f_t^m, \quad \forall t \in T, \forall m \in M \tag{6.8}$$

$$S_t^m \geq S_{\min}, \quad \forall t \in T, \forall m \in M \tag{6.9}$$

Equation 6.4 shows the extended objective of the linear problem, including the maximisation of revenue from the power sold in the day-ahead market and a penalty for degradation of the components.

The power production constraint, in Equation 6.5, shows that the sum of the power sold in the day ahead and the amount of power curtailed has to be equal to the theoretical power output. In addition, Equation 6.6 shows that the theoretical power output is limited up to the rated power output. The rated power output is the maximum amount of power that a turbine can produce under optimal operating conditions.

Equation 6.7 ensures that curtailment does not exceed 20% of the turbine's rated power.

Equations 6.8 track the degradation of the main components over time. This ensures the model will not decide to produce or curtail if this would cause degradation to drop below this failure threshold, to prevent failure of components. The next health state is degrading at the rate equal to the degradation value of the current time step. The degradation value is calculated using the degradation function as determined in Section 4.5.

Equation 6.9 ensures that the component health does not drop below a critical threshold.

6.3.2. Mixed-integer problem with replacement

The MILP formulation extends the linear problem by introducing binary replacement decisions. When a component's health state reaches its minimum threshold (i.e. component is completely degraded), the model allows for replacement, restoring it to full capacity. While using the same sets and parameters, the addition of integer variables increases computational complexity but enables a realistic representation of discrete maintenance actions.

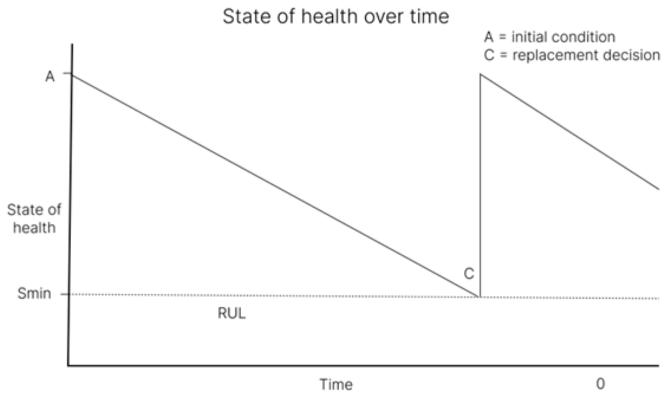


Figure 6.3: Conceptual overview of the health state in the MILP model

In this formulation, turbine health gradually degrades over time. When S_t^m reaches the minimum threshold, the model can choose to replace the turbine ($z_t^{\mathrm{m}} = 1$), restoring the health to a predefined maximum level.

Corresponding mathematical programming concepts in the MILP model that are added or adjusted compared to the LP model from Section 6.3.1 are:

Decision variables

Table 6.5: Decision variables of the MILP

Decision Variable	Description	Unit
S_t^{m}	Health state of component m, initialised at $S_{\max}$.	[-]
z_t^{m}	Binary replacement variable for component m, initialised at 0.	[-]

Objective function

$$\max \quad \sum_{t \in T} \left(\lambda_t^{\mathrm{DA}} \cdot P_t^{\mathrm{DA}} - \sum_{m \in M} C^{\mathrm{m}} \cdot z_t^{\mathrm{m}} \right) \tag{6.10}$$

The objective function in Equation 6.10 includes the cost of replacement. If a replacement occurs, the objective subtracts the associated replacement costs.

Constraints

Equations 6.5, 6.7, 6.6, and 6.9 are also part of the MILP formulation. The health state is adjusted to include a binary replacement term compared to Equation 6.8, and additional constraints are introduced, formulated as follows:

$$S_{t+1}^{m} = S_t^{\mathsf{m}} - f_t^{\mathsf{m}} + z_t^{m} \cdot (S_{\max} - S_{\min}), \quad \forall t \in T, \forall m \in M \tag{6.11}$$

$$z_t^{m} \in \{0, 1\}, \quad \forall t \in T, \forall m \in M \tag{6.12}$$

Equation 6.11 ensures that the health state degrades over time according to the degradation function. Additionally, it restores the health state to its initial value after a replacement has taken place.

Equation 6.12 defines the binary replacement variable, restricting it to either 0 (indicating no replacement) or 1 (indicating replacement).

6.3.3. Non-linear problem with a penalty function

The MILP optimisation model increases computational complexity due to the necessity to handle of binary variables. As a result, this work investigates another method using an NLP model which can overcome this computational issue.

This extension of the linear optimisation problem introduces a continuous replacement variable to explore the impact of integrating replacement into a linear framework. Since this variable is continuous rather than binary, a penalty function is introduced to enable the model to select discrete replacement decisions (either full replacement or none at all). The penalty function discourages fractional replacement values by applying a quadratic penalty to any deviation from 0 or 1. This model uses a quadratic penalty function as shown in Figure 6.4.

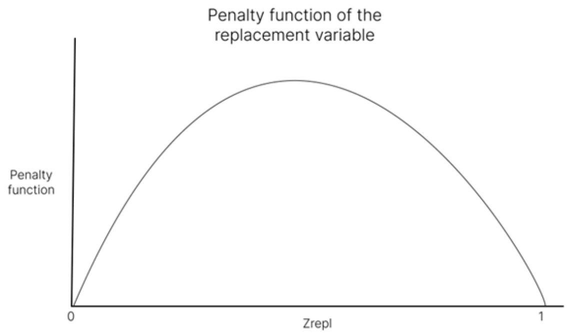


Figure 6.4: Quadratic penalty function example

Corresponding mathematical programming concepts in the NLP model that are added or adjusted compared to the LP model from Section 6.3.1 are:

Parameters

The parameters from the linear problem are used and extended with a penalty factor k.

Table 6.6: Additional parameters NLP

Parameter	Description	Unit
k	Penalty factor to enforce binary-like replacement decisions.	[-]

Decision variables

Table 6.7: Decision variables for the NLP

Decision Variable	Description	Unit
S_t^m	Health state of component m at time t.	[-]
z_t^{m}	Continuous replacement variable of component m at time t (ideally 0 or 1).	[-]

Objective function

$$\max \quad \sum_{t \in T} \left(\lambda_t^{\mathsf{DA}} \cdot P_t^{\mathsf{DA}} - \quad \sum_{m \in M} (C^{\mathsf{m}} \cdot z_t^{\mathsf{m}} - k \cdot (1 - z_t^{\mathsf{m}}) \cdot z_t^{\mathsf{m}}) \right) \tag{6.13}$$

The objective function in Equation 6.13 contains a quadratic penalty term ($k \cdot (1 - z_t^{\mathsf{m}}) \cdot z_t^{\mathsf{m}}$ which discourage intermediate values for z_t^{m} , pushing it towards either 0 or 1.

Constraints
Equations 6.5, 6.7, 6.6, and 6.9 are again part of the NLP formulation as well. In contrast, the calculation of the health state is adjusted as it contains a continuous replacement term compared to Equation 6.8. The additional constraints are introduced, and formulated as follows:

$$S_{t+1}^m = S_t^m - f_t^m + z_t^{\mathsf{m}} \cdot (S_{\max} - S_{\min}), \quad \forall t \in T, \forall m \in M \tag{6.14}$$

$$0 \leq z_t^{\mathsf{repl}} \leq 1, \quad \forall t \in T \tag{6.15}$$

Equation 6.14 ensures that the health state degrades over time and is restored upon replacement.

Equation 6.15 keeps replacement within the realistic range but does not strictly enforce binary values.

6.3.4. Selecting the optimisation method

The explored optimisation methods provide insights into the trade-off between computational complexity and applicability in formulating replacement strategies. where the linear problem without replacement presents a computationally efficient and scalable framework. The advantage of this approach is the availability of shadow prices, which offer insights into the sensitivity of constraints. However, its limitation lies in its simplification of the problem by excluding replacement decisions.

The MILP with replacement extends the LP formulation by introducing a binary replacement variable. While it allows for a more realistic representation of maintenance strategies, it does come with disadvantages. While LP enables the calculation of shadow prices, this advantage is lost when applying the MILP model as explained by Crema, A. [117]. Because the marginal analysis in MILP, needed for calculating marginal shadow prices, may not be useful because the objective function is neither concave nor convex [117]. In addition, the inclusion of binary decision variables increases the computational complexity compared to a standard LP. For small-scale problems, this remains manageable, however, for solving MILPs with larger time horizons or more constraints, this may become computationally expensive [79].

The linear problem with the penalty function approximates replacement decisions without using binary variables, thus avoiding the computational burden of a MILP formulation. However, with the introduction of a quadratic penalty function, the problem becomes non-linear. Solving quadratic optimisations requires additional computational effort, particularly for larger optimisation problems. Regarding applicability, the penalty function ensures replacement decisions remain continuous, but it does not guarantee truly discrete (0 or 1) replacement. This can lead to partial replacement values, which are not desired in the optimisation model. In addition, the effectiveness of the approach depends on properly tuning the penalty factor (k). A too-small penalty may allow intermediate replacement values, while a too-large penalty may distort the optimisation results.

While incorporating replacement decisions leads to a more realistic representation of maintenance strategies, it also increases computational complexity. Among the three formulations, the LP problem without replacement is selected in this work. The main reason is its scalability and computational efficiency, which are essential for developing an optimisation framework that handles long-term decision-making and large-scale problems. Although the approach simplifies the problem by excluding explicit replacement decisions, it retains the ability to analyse the impact of degradation, which is the most critical aspect of this research. Given the simplification within the optimisation problem, the necessity arises to refine cost calculations to better reflect the economic impacts associated with additional component replacements.

6.3.5. Updated cost calculations

As the linear method is selected, the model must account for additional replacement costs once a component reaches its end-of-life. While this is not incorporated within the decision space of the optimisation model, the calculations can account for additional replacement decisions.

Within the comparison of the base scenario and centralised scenario two important assumptions are used:

- A component is replaced once it reaches its end-of-life, defined by a minimum state of health, $S_{\min}$.
- The replacement cost is not applied in full. Instead, the cost is scaled by the remaining useful life of the component at the time of replacement.

This approach ensures that replacement costs are fully incorporated in the base case while adjusting costs to reflect the RUL of the component. By accounting for the RUL, the analysis recognises that components with residual life can extend the operational period of the OWT or provide additional value upon resale.

$$C^m = \begin{cases} C^m \cdot \left(1 - S_T^m\right) + C^m \cdot \left(\frac{T_{\text{stop}}^m}{T}\right), & \text{if } S_t^m \leq S_{\min} \\ C^m \cdot \left(1 - S_T^m\right), & \text{otherwise} \end{cases} \tag{6.16}$$

Where:

- T_{stop}^m: This is the time step at which component m reaches its failure threshold, causing the turbine to replace the component or discontinue operation.

The LP approach has been selected to integrate the state of health of components into the curtailment strategy. Additionally, cost calculations have been refined to account for the extra expenses associated with component replacements. With these improvements in place, the coordinated curtailment strategies are formulated next. The following section introduces both centralised and decentralised approaches. With the goal to investigate how different stakeholders can align their objectives with a unified framework.

6.4. Coordinated curtailment strategies

The previous sections explored the various methods to optimise curtailment strategies with or without replacement decisions and formulated the baseline scenario. In this section, the coordinated curtailment strategies will be established. First, a centralised version of the coordinated curtailment strategy will be formulated in Section 6.4.1, representing an ideal scenario where the dispatcher, wind farm owner, and maintenance party are willing to cooperate and share sensitive data. After this, Section 6.4.2 will formulate a decentralised version of the coordinated curtailment strategy as fully cooperating might not be realistic in practice. This decentralised optimisation problem will be formulated using the general framework defined in Section 3.3.3.

6.4.1. Centralised problem

The centralised optimisation problem aims to maximise financial returns from power sold in the day-ahead market while minimising the degradation costs of key wind turbine components. This approach assumes a central decision-maker with full access to all relevant data, including market prices, turbine degradation models, and operational constraints.

The model operates over the same time horizon as in the baseline scenario, given in Section 6.2. However, the parameter set is extended to include environmental conditions, component replacement costs, and health state limits. Additionally, the decision variables include the continuous health state of each component. The mathematical programming concepts used in the centralised problem are set out below.

Parameters

Table 6.8: Model parameters for the centralised dispatch strategy

Parameter	Description	Unit
P_t^{Th}	Theoretical expected power output at occurring environmental conditions.	[MW]
λ_t^{DA}	Electricity price of the day-ahead market.	[€/MW]
T_t	Thrust force on turbine blades at time t.	[MN]
V_t^w	Wind speed at 150m hub height.	[m/s]
H_t^s	Significant wave height.	[m]
I_t^{rain}	Rain intensity impacting blades.	[mm/hr]
$S_{\min}$	Minimum permissible health factor.	[-]
$S_{\max}$	Maximum health state (initial state = 1).	[-]
C^{ss}	Replacement cost of the support structure.	[€]
C^{gbx}	Replacement cost of the gearbox.	[€]
C^{bld}	Replacement cost of the blades.	[€]
$a_{\text{gbx}}, a_{\text{ss}}, a_{\text{bld}}$	Degradation scaling factors for gearbox, support structure, and blades.	[-]
$c_{\text{damping}}, b_{\text{wave}}, b_{\text{rain}}$	Additional degradation scaling coefficients.	[-]
r	Rotor radius (120m).	[m]
P_{rate}	Rated turbine power (15MW).	[MW]

Decision variables

Table 6.9: Decision variables for the centralised dispatch strategy

Variable	Description	Unit
P_t^{DA}	Power sold in the day-ahead market.	[MW]
P_t^{Curt}	Power curtailed.	[MW]
S_t^{ss}	Support structure health state.	[-]
S_t^{gbx}	Gearbox health state.	[-]
S_t^{bld}	Blade health state.	[-]

Objective function

$$\max \sum_{t\in T} \left(\lambda_t^{\text{DA}} \cdot P_t^{\text{DA}} - C^{\text{ss}} \cdot (1 - S_t^{\text{ss}}) - C^{\text{gbx}} \cdot (1 - S_t^{\text{gbx}}) - C^{\text{bld}} \cdot (1 - S_t^{\text{bld}}) \right) \tag{6.17}$$

The objective function maximises the profit from electricity sold in the day-ahead market while accounting for the degradation costs of critical components.

Constraints

$$P_t^{\text{DA}} + P_t^{\text{Curt}} = P_t^{\text{Th}}, \quad \forall t \in T \tag{6.18}$$

Equation 6.18 ensures that the sum of power sold and curtailed equals the theoretical power output.

$$P_t^{\text{Curt}} \leq \text{curtailment\_cap} \cdot P_{\text{rate}}, \quad \forall t \in T \tag{6.19}$$

Equation 6.19 ensures that curtailment does not exceed 20% of the turbine's rated power.

$$S_{t+1}^{\text{ss}} = S_t^{\text{ss}} - f_t^{\text{ss}}, \quad \forall t \in T \tag{6.20}$$

$$S_{t+1}^{\text{gbx}} = S_t^{\text{gbx}} - f_t^{\text{gbx}}, \quad \forall t \in T \tag{6.21}$$

$$S_{t+1}^{\text{bld}} = S_t^{\text{bld}} - f_t^{\text{bld}}, \quad \forall t \in T \tag{6.22}$$

Equations 6.20, 6.21 and 6.22 track the degradation of the support structure, gearbox, and blades over time, respectively.

$$S_t^{\text{ss}}, S_t^{\text{gbx}}, S_t^{\text{bld}} \geq S_{\min}, \quad \forall t \in T \tag{6.23}$$

Equation 6.23 that the component health does not drop below a critical threshold.

The centralised optimisation problem will help to determine the value of coordinated decision-making. While theoretically optimal, full centralisation may be impractical. The next section explores the decentralised coordination framework.

6.4.2. Decentralised problem

The problem uses the same sets and decision variables as in the centralised problem (Section 6.4.1), but the objectives of individual stakeholders are now optimised separately in an iterative process. To enable consensus between the subproblems, the variables are classified as follows:

- **Global variable** ($P_{z,t}^{\text{DA}}$): Represents the consensus day-ahead power schedule at time t and is initialised at 0.
- **Local variable** $P_{i,t}^{\text{DA}}$: Represents each stakeholder's i (dispatcher, maintenance party and, owner) individual day-ahead power schedules at time t and is initialised at 0.

Furthermore, the penalty parameter ρ is set equal to 0.3, the number of iterations k is initialised from 1 to a maximum of 50, and the tolerance is set at 2. The process of tuning these values is explained in Section 8.1.3:

$$\begin{aligned} \rho &= 0.3, \\ k &= 1, \\ k_{\text{max}} &= 50, \\ tolerance &= 2 \end{aligned}$$

Reformulated decentralised optimisation

The overall objective function can be derived from the general form of the global consensus optimisation as detailed in Section 3.3.3, and is decomposed as follows for the decentralised curtailment optimisation:

$$\begin{aligned} \text{Max} \sum_{i \in I} \sum_{t \in T} f_i(P_{i,t}^{DA}), \qquad & (6.24) \\ \text{s.t} \sum_{i \in I} \sum_{t \in T} P_{i,t}^{\text{DA}} - P_{z,t}^{\text{DA}} = 0 \end{aligned}$$

Where the constraint of the global problem formulation as given in Equation 6.24 states all local decision variables (i.e. objectives of dispatcher, owner, and asset operator) are equal to the global decision variable as follows:

$$P_{\text{i, t}}^{\text{DA}} = P_{z,t}^{\text{DA}}$$

Local objectives for each of the stakeholders

The main goal for each of the stakeholders is as follows:

- **Dispatcher:** Aims to maximise energy market profits.
- **Maintenance party:** Optimises replacement costs for components like the gearbox and blades.
- **Owner:** Seeks to minimise degradation costs of non-replaceable structures.

The mathematical concepts used in the optimisation model, further detailing the respective stakeholder objectives, are set out below.

Dispatcher sub-problem

The dispatcher maximises profit while adhering to power balance constraints, resulting in the following problem formulation:

$$f_1(P^{\text{DA}}_{\text{dispatcher, t}}) = \sum_{t\in T} \left(\lambda_t^{DA} \cdot P_t^{DA} - \lambda^{PPA} \cdot P_t^{\text{Th}}\right) \tag{6.25}$$

$$\text{s.t} \sum_{t\in T} P_t^{DA} + P_t^{\text{Curt}} = P_t^{\text{Th}}$$

Owner sub-problem

The owner minimises the degradation costs of the support structure, therefore, their local optimisation problem can be written as:

$$f_2(P^{\text{DA}}_{\text{owner ,t}}) = \sum_{t\in T} \left(\lambda_t^{DA} \cdot P_t^{\text{Th}} - C^{ss} \cdot (1 - S_t^{ss}) - B\right). \tag{6.26}$$

$$\text{s.t} \sum_{t\in T} P_t^{DA} + P_t^{\text{Curt}} = P_t^{\text{Th}}$$

$$S^{\text{ss}}_{t+1} = S^{\text{ss}}_t - f^{\text{ss}}_{\text{t}}, \quad \forall t \in T$$

$$S_{\min} \leq S^{\text{ss}}_t, \quad \forall t \in T$$

Maintenance party sub-problem

The maintenance party minimises degradation costs for replaceable components, therefore, their optimisation problem can be written as:

$$f_3(P^{\text{DA}}_{\text{maintenance, t}}) = \sum_{t\in T} \Big(B - C^{gbx} \cdot (1 - S_t^{gbx}) - C^{bld} \cdot (1 - S_t^{bld})\Big) \tag{6.27}$$

$$\text{s.t} \sum_{t\in T} P_t^{DA} + P_t^{\text{Curt}} = P_t^{\text{Th}}$$

$$S^{\text{gbx}}_{t+1} = S^{\text{gbx}}_t - f^{\text{gbx}}_{\text{t}}, \quad \forall t \in T$$

$$S_{\min} \leq S^{\text{gbx}}_t, \quad \forall t \in T$$

$$S^{\text{bld}}_{t+1} = S^{\text{bld}}_t - f^{\text{bld}}_{\text{t}}, \quad \forall t \in T$$

$$S_{\min} \leq S^{\text{bld}}_t, \quad \forall t \in T$$

Where B is calculated as:

$$B = \sum_{t} \Big(C^{gbx} \cdot (1 - S_t^{gbx}) + C^{bld} \cdot (1 - S_t^{bld})\Big) \cdot 1.2 \quad \text{(20\% margin)}. \tag{6.28}$$

ADMM formulation

The augmented Lagrangian, introduced in general form in Section 3.3.3, can be written as follows by implementing the decentralised optimisation problem from Equation 6.24:

$$L_\rho(P_{i,t}^{DA}, P_{z,t}^{DA}, y_i) = \sum_{t\in T}\sum_{i=I}(f_i(P_{i,t}^{DA}) + y_i^T(P_{i,t}^{DA} - P_{z,t}^{DA}) + \frac{\rho}{2}\|P_{i,t}^{DA} - P_{z,t}^{DA}\|^2) \tag{6.29}$$

Where:

- y_i: Dual variable (Lagrange multiplier) for each stakeholder.
- ρ: Penalty parameter encouraging consensus.

The resulting ADMM update equations for the decentralised optimisation problem are stated below.

The primal residual, as defined in Equation 3.2, and the dual residual, as defined in Equation 3.4, can be rewritten to reflect the specific case of this problem involving three stakeholders.

1. **Local variable updates ($P_{i,t}^{DA}$):**
   Each stakeholder updates its local decision variable by solving the following optimisation problem:

   $$P_{i,t}^{k+1} = \arg\max_{P_{i,t}} \left(f_i(P_{i,t}) + y_{i,t}^k \cdot (P_{i,t} - P_{z,t}^k) + \frac{\rho}{2}\|P_{i,t} - P_{z,t}^k\|^2\right) \quad \forall t \in T \tag{6.30}$$

   This equation ensures that each stakeholder optimizes its local objective while aligning with the global consensus variable.
2. **Global consensus variable update ($P_{z,t}^{DA}$):**
   The global consensus variable is updated by taking the average of the local variable updates while incorporating the scaled dual variables:

   $$P_{z,t}^{k+1} = \frac{1}{3}\sum_{i=1}^{3}\left(P_{i,t}^{k+1} + \frac{1}{\rho}y_{i,t}^k\right) \quad \forall t \in T \tag{6.31}$$

   This step ensures that the global consensus variable is consistent across stakeholders by averaging their local decisions.
3. **Dual variable updates (y_i):**
   The dual variables, which enforce consensus between local and global variables, are updated as follows:

   $$y_{i,t}^{k+1} = y_{i,t}^k + \rho \cdot (P_{i,t}^{k+1} - P_{z,t}^{k+1}) \quad \forall t \in T \tag{6.32}$$

   This update strengthens the agreement between the local and global variables by adjusting the Lagrange multipliers accordingly.
4. **Primal residual updates:**
   The primal residual measures the deviation of local variables from the consensus variable:

   $$\|r^k\|_2^2 = \sum_{i=1}^{3}\|P_{i,t}^k - P_{z,t}^k\|_2^2 \quad \forall t \in T \tag{6.33}$$

   This residual is monitored to assess whether the local and global variables are converging.
5. **Dual residual updates:**
   The dual residual tracks the changes in the global consensus variable across iterations:

   $$\|s^k\|_2^2 = I\rho^2\|P_{i,t}^k - P_{z,t}^{k-1}\|_2^2, \quad \forall t \in T \tag{6.34}$$

   A decreasing dual residual indicates that the consensus updates are stabilising.

By iteratively performing these updates, the ADMM framework ensures that all stakeholders reach a coordinated decision while maintaining their individual autonomy.

6.5. Concluding remarks

This chapter introduced a baseline scenario as a reference point for evaluating the added value of coordinated curtailment strategies. Within the baseline scenario, the dispatcher decides to curtail based on day-ahead market prices. This decision causes long-term degradation to the turbine, which affects the asset owner and maintenance team, but not the dispatcher. Creating an externality that is not accounted for in the current dispatch strategy.

To address this, a centralised coordination framework is developed that internalises asset health into the optimisation problem. The state of health S_t^m is internalised in the optimisation problem as a continuous decision variable to ensure the scalability and computational efficiency of the problem.

Finally, a decentralised coordination framework was formulated using a distributed consensus approach to assess whether similar outcomes as the centralised approach can be achieved without full data centralisation. This allows for a more realistic implementation in a context with fragmented ownership and many stakeholders, which results in reluctance to share sensitive data.

The next chapter will compare the results of the baseline, centralised and decentralised scenarios, to determine the value of coordination within offshore wind power generation.

7 Results

This chapter reveals the findings from the research. The value of coordination emerges clearly when comparing the baseline scenario with the centralised approach, as detailed in Section 7.1. Given the simplified nature of the model, it is important to interpret the numerical findings not as precise predictions but as comparative benchmarks that assess the relative advantages of coordinated curtailment strategies. Although the centralised approach is theoretically effective and feasible under certain contractual structures, it may not always be practical in real-world projects. Therefore, an alternative decentralised approach is explored in Section 7.2. The results will indicate whether a decentralised curtailment strategy can achieve outcomes comparable to those of the centralised framework.

7.1. Value of coordination

To quantify the value of coordination, this section compares two distinct curtailment strategies. The base case represents the conventional market-driven scenario. Here, curtailment decisions are solely based on short-term revenue maximisation in the day-ahead market. Long-term component degradation is not considered. Whereas the centralised coordination strategy integrates the objectives and constraints of the dispatcher, maintenance party, and wind farm owner into one optimisation framework. The main advantage of the centralised strategy is its ability to incorporate degradation into operational decision-making.

The comparison begins by evaluating economic performance at the system level using the equations discussed in Section 6.3.5. Next, the impact on individual stakeholders is examined, along with a comparison of health trajectories of critical components and an illustration of power production and curtailment patterns. In the initial comparison, it is assumed that any component reaching its end-of-life will be replaced to maintain turbine operation. Section 7.1.1 challenges the assumption of full replacement by exploring alternative strategies within the base case, comparing scenarios with (1) no replacement, (2) gearbox replacement only, and (3) replacement of both gearbox and blades once. Finally, Section 7.1.2 discusses the practical limitations of centralised coordination.

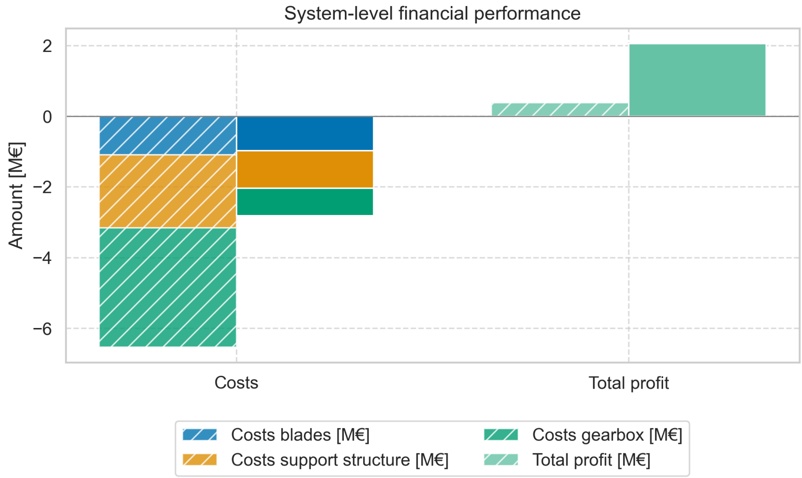


Figure 7.1: System-level costs and profit: base case (hatched) vs. centralised (solid), $T = 8592$, $Y = 30$.

At the system level, the comparison of the investment costs and profit in Figure 7.1 shows a sub-optimal current situation. The substantial costs associated with reinforcing the support structure and replacing the gearbox and blades outweigh the profit generated by the dispatcher in the day-ahead market. This difference indicates that, under the current conditions, the system does not efficiently allocate financial resources to ensure asset longevity and profitability. These results point to areas where the dispatch strategy could be improved.

Centralised coordination reduces global costs and significantly enhances overall profit. This demonstrates the potential value of internalising asset health in curtailment strategies while maximising financial performance.

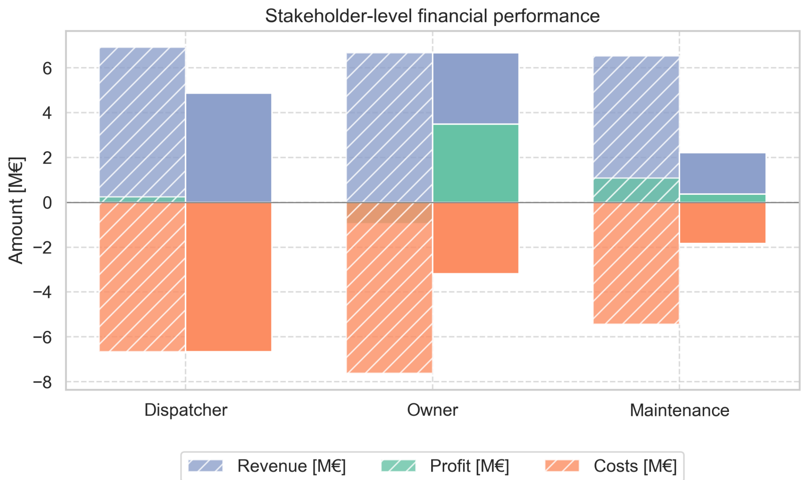


Figure 7.2: Stakeholder-level financial performance: base case (hatched) vs. centralised (solid), $T = 8592$, $Y = 30$.

The financial performance per stakeholder is shown in Figure 7.2. In the base case, the dispatcher focuses on maximising short-term revenue without bearing direct responsibility for replacement or reinforcement costs. These costs are instead reflected in the PPA price, making it an expense for the dispatcher and income for the wind farm owner. The wind farm owner faces substantial costs due to the wear of both replaceable and non-replaceable components. In the base case, the owner is not profitable, raising concerns about the economic viability of the wind farm. Given the limitations in interpreting the numerical values precisely, it is possible that the wind farm remains marginally profitable in reality, but does not yield significant returns. Additionally, the maintenance party incurs considerable costs due to the need to replace major components such as the gearbox and blades.

The centralised strategy mitigates component degradation, leading to reduced costs for both the owner and maintenance party. For the maintenance party, lower component costs result in reduced expenditure, although this also leads to diminished profit margins. Conversely, the owner benefits from extended component lifespans and improved overall profitability. However, the dispatcher experiences a reduction in revenue, which results in negative profitability. This is likely due to dispatch decisions no longer being solely driven by market prices. Unlike in the base case, where curtailment was based purely on financial incentives, the centralised strategy requires curtailment to be applied strategically to reduce component wear. As a result, the dispatcher may be forced to curtail production even when electricity prices are high, prioritising long-term component health over immediate market returns. Such redistribution of costs and benefits might provoke resistance from dispatchers, potentially complicating the implementation of a fully centralised coordination strategy.

Table 7.1: Comparison of financial metrics between current situation and centralised coordination, values in million euros (M€). Red indicates a detrimental change, while green indicates a beneficial change.

Category	Metric	Base case [M€]	Centralised coordinated [M€]
Dispatcher	Revenue	6.91	4.87 (-30%)
	Profit	0.25	-1.80 (-820%)
Maintenance party	Blade costs	3.37	0.58 (-77%)
	Gearbox costs	2.07	1.07 (-48%)
	Total costs	5.44	1.84 (-66%)
Owner	Support structure costs	1.09	0.97 (-11%)
	Total costs	7.62	3.18 (-58%)
Global	Investment costs	6.53	2.81 (-57%)
	Netto profit	0.38	2.06 (439%)
	ROI	**5.82 %**	**73.31 %**

The numerical comparison of financial metrics between the base case and centralised coordination strategies is summarised in Table 7.1. This table focuses on the most important economic indicators for addressing the main research question, with additional details available in Appendix C. Percentage differences are provided to clearly illustrate the relative changes, with detrimental outcomes marked in red and beneficial outcomes marked in green. System-level performance metrics are calculated based on equations detailed in Appendix C.1.

Significant cost reductions are evident under the centralised strategy. Blade costs decrease by 77%, gearbox costs by 48%, and overall maintenance costs by 66%. This substantial decline in costs positively impacts the wind farm owner's profitability, whose overall costs fall by 58%. In contrast, the dispatcher's revenue drops by 30%, leading to a drastic profitability decrease of 820%. This shift illustrates how centralised decisions might integrate asset health at the expense of short-term market-driven revenue.

At system level, the centralised approach improves financial outcomes. Investment costs decline by 57%, and total profit surges by 439%, reflecting a notable increase from 0.38 M€ to 2.06 M€. The large profit increase can primarily be attributed to a modelling artefact where the remaining health of components at the end of the modelling period is directly translated into monetary terms. In reality, converting residual asset health into direct financial gains would be limited, as typically, these components yield only a minimal scrap value. Additionally, the model does not fully capture practical considerations such as the lumpiness of investment expenditures and the irreversibility of certain investments. Therefore, the 439% increase should be interpreted as an indication of potential economic benefit under idealised conditions rather than a direct representation of achievable financial returns.

To illustrate a more comprehensive metric, the Return on Investment (ROI) is calculated using Equation E.2 (see Appendix E). ROI increases sharply from 5.82% in the base case to 73.31% in the centralised scenario. This represents a gain of 67.49 percentage points, clearly demonstrating the considerable added value of strategic coordination.

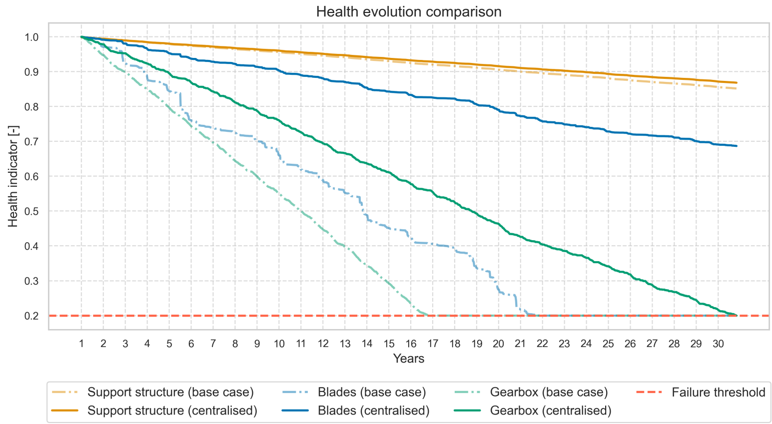
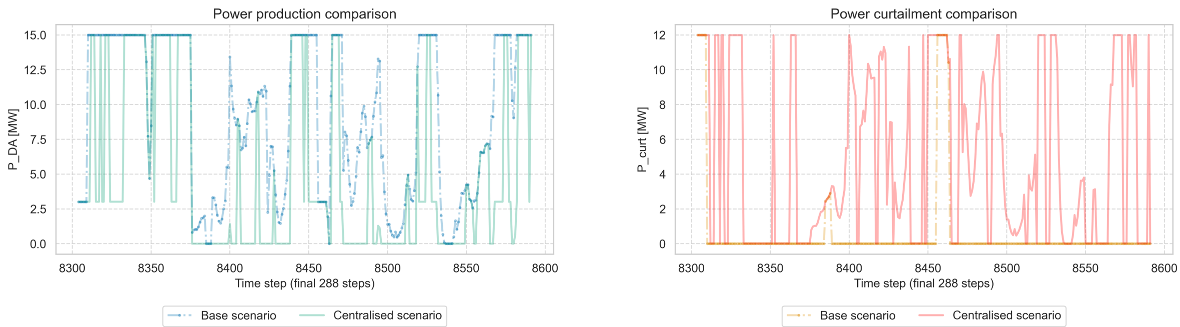


Figure 7.3: Health evolution comparison of critical components: base case (dotted) vs. centralised (solid), $T = 8592$, $Y = 30$.

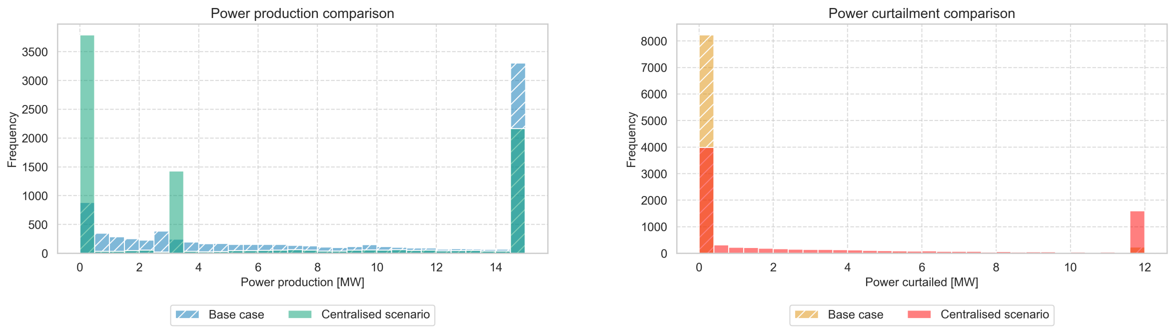
Figure 7.3 further illustrates the advantages of the centralised approach by comparing the health evolution of critical components. The support structure S_{ss} shows minimal to a slight improvement, suggesting limited sensitivity to curtailment decisions within the model. As the support structure is the most expensive component, the optimisation model will aim to conserve the degradation of the component. A more detailed sensitivity analysis regarding component costs is available in Section 8.3.1. Conversely, the gearbox S_{gbx} and blades S_{bld} show slower degradation rates, with an extended component lifespan under the centralised strategy.



(a) Power production final year

(b) Power curtailment final year

Figure 7.4: Comparison of power production and curtailment strategies in the final year: base case (dotted) vs. centralised (solid), $Y = 30 \Longrightarrow t \in \{8304, \ldots, 8592\}$.



(a) Frequency distribution of power production

(b) Frequency distribution of power curtailment

Figure 7.5: Comparison of frequency distributions for power production and curtailment: base case (hatched) vs. centralised scenario (solid), $T = 8592$, $Y = 30$.

Figure 7.4 illustrates the changes in power production and curtailment strategies during the final year of the analysis, while Figure 7.5 presents the frequency distribution of power production and curtailment levels throughout the entire modelling period. The centralised scenario shows more frequent partial curtailment at moderate levels, strategically avoiding high production stress and complete shutdowns. The base case, however, shows more aggressive curtailment extremes, either minimal or maximal.

7.1.1. Incorporating the replacement decision

In the previous comparison between the base case and the centralised coordination strategy, it was assumed that replacement occurs once the components reach their minimum state of health ($S_{\min}$), as defined in Section 6.3.5. This assumption leads to the replacement of the gearbox and blades in the base case. However, in practice, the decision to replace a component is not always straightforward. As outlined in Section 4.6, a wind farm owner must decide whether to continue operating an OWT once a critical component reaches its end-of-life ($S_t^m \leq S_{\min}$). At this point, two options exist: (1) replace the failed component and resume operation, or (2) cease operation and decommission the turbine. If replacement is economically feasible and selected, the costs are updated as follows:

$$\mathsf{C}^m = C^{\mathsf{m}}_{T^m_{\mathsf{fail}}} + C^{\mathsf{m}} \cdot (1 - S^{\mathsf{m}}_{T^m_{\mathsf{fail}}}) \tag{7.1}$$

Where:

- $S^m_{T_{\mathsf{fail}}}$: The state of health of component m at the failure time step.
- C^m: The total replacement or reinforcement cost of component m.
- $C^m_{T^m_{\mathsf{fail}}}$: The actual replacement cost incurred at failure time T^m_{fail}, only added if $S_t^m \leq S_{\min}$.

In contrast, if no replacement is chosen, the turbine is decommissioned, and no revenues are generated from that time onward. Therefore, revenue is computed only until the failure time T_{fail} of the first critical component:

$$T^m_{\mathsf{fail}} = \min_m \{t \mid S_t^m \leq S_{\min}\} \tag{7.2}$$

The resulting revenue and cost functions are in this case calculated using:

$$\text{Revenue dispatcher} = \sum_{t \in T^m_{\mathsf{fail}}} (\lambda_t^{\mathsf{DA}} \cdot P_t^{\mathsf{DA}}) \tag{7.3}$$

$$\text{Cost dispatcher} = \sum_{t \in T^m_{\mathsf{fail}}} (\lambda^{\mathsf{PPA}} \cdot P_t^{\mathsf{Th}}) \tag{7.4}$$

$$\text{Revenue wind farm owner} = \sum_{t \in T^m_{\mathsf{fail}}} (\lambda^{\mathsf{PPA}} \cdot P_t^{\mathsf{Th}}) \tag{7.5}$$

Where:

- T^m_{fail}: The time step at which the first component m reaches its end-of-life and the owner decides to decommission or stop the operation of the OWT.

The comparison considers three replacement strategies:

1. **No replacement:** In this scenario, no component is replaced. The turbine is decommissioned as soon as the gearbox fails.
2. **Gearbox replacement:** Here, the gearbox is replaced upon failure to extend operation, however, if the blades reach their end-of-life, no replacement is performed, and the turbine is stopped.
3. **Selective replacement:** In this strategy, both the gearbox and the blades are replaced once at their initial failure events, but no further (second) replacements are carried out. This approach aims to extend the turbine's operational life.

Appendix D.1 provides a detailed overview of the three replacement scenarios, including insights into their health evolution and financial calculations.

Table 7.2 summarises the financial performance of these replacement strategies, with revenue discounted over the project lifetime using discounted electricity prices. Revenue is discounted over the 30-year model period using a fixed annual discount rate to account for the time value of money. Details on the discounting methodology are provided in Appendix D.2. The optimisation weighs the replacement costs against the discounted benefits from extending the turbine's operational lifespan, capturing the economic trade-off between immediate investment and future income. For results without discounting, please refer to Appendix D.2.

Table 7.2: Financial performance of replacement strategies (in M€ and time steps).

Category	Metric	Scenario 1: No replacement [M€]	Scenario 2: Gearbox replacement [M€]	Scenario 3: Selective replacement [M€]
Dispatcher	Revenue	3.25	4.14	5.30
	Cost	3.59	4.75	6.67
	Profit	-0.34	-0.61	-1.37
Maintenance party	Blade costs	1.98	1.98	4.46
	Gearbox costs	1.07	2.40	2.40
	Profit	0.61	8.76	1.37
Owner	Support structure costs	1.09	0.76	1.09
	Profit	-1.16	-1.26	-2.65
Global	Investment costs	4.14	5.14	7.95
	Netto profit	-0.89	-1.00	-2.65
Operational life time	T_{stop} [time steps]	4553 (T_{fail}^{gbx})	5955 (T_{fail}^{bld})	8592

The comparison indicates that the optimal strategy depends on the owner's priorities. On one hand, the scenario without replacement yields the least negative global profit (-0.89 M€) but comes at the cost of the shortest operational lifetime (4533 time steps, equal to 16 years in the model). On the other hand, while selective replacement extends the turbine's lifetime significantly (8592 time steps, equal to 30 years in the model), it incurs much higher costs and a more negative system-wide profit (-2.65 M€). Partial replacement of only the gearbox offers an intermediate solution, with a modest extension of the operational lifetime to the failure moment of the blades and only a slight increase in negative profit (-1.00 M€). The comparison of these different replacement strategies presents the trade-off between achieving an extended operational lifetime while maintaining favourable financial performance.

While the replacement strategy affects the financial performance at both the stakeholder and system-wide levels, the overall profit remains negative under the base case. In contrast, the centralised approach shows promising results increasing the profit at system level.

7.1.2. Practical limitations of centralisation

Implementing centralised coordination in practice would require a central entity responsible for integrating the objectives of all stakeholders into a unified dispatch strategy. In this model, the wind farm owner could take on the role of the coordinating entity, collecting data from the dispatcher and maintenance party to optimise power dispatch while considering asset degradation and long-term profitability. The wind farm owner is best suited for the role due to their long-term stake in the project. Unlike the dispatcher, focused on short-term market dynamics, or the maintenance party, which prioritises component reliability, the wind farm owner manages the full operational lifecycle of turbines. Additionally, as the contractual hub connecting all stakeholders, the wind farm owner could act as the natural intermediary for a centralised coordination model, as illustrated in Figure 5.2. However, several challenges complicate the feasibility of centralised coordination.

Organisational and contractual complexity

The centralised approach assumes transparent and open collaboration among stakeholders, requiring a trusted, all-knowing entity to manage the coordination. In practice, as discussed in Chapter 5, the contractual structure of offshore wind projects is often highly complex. Multiple entities, including developers, insurers, banks, and investors, form a consortium that manages the wind farm's operation. While these parties collaborate within a single project, they often compete in other ventures, making data sharing and full transparency difficult.

Achieving centralised coordination would require extensive data-sharing across different stakeholders, including:

- The dispatcher would need to share dispatch strategies, price forecasts, and economic performance data.
- The maintenance party would need to disclose failure patterns, which could trigger discussions about serial defects, increasing the risk of the manufacturers being held accountable for large-scale replacements. In addition, disclosing failure rates, comment wear patterns, and repair costs, allows the project owner to closely evaluate maintenance expenses, potentially leading to disputes over compensation or the decision of the owner to develop in-house maintenance capabilities.
- The owner would need to collect and share structural health data, component degradation models, and asset evaluation reports.

However, stakeholders may be reluctant to disclose sensitive data due to concerns over competitive advantage and financial exposure. For example, the dispatcher may not want to reveal trading strategies, which are considered company trade secrets or know-how, to potential competitors. Wind farm owners may fear that structural health disclosures could reduce the market value of assets.

Unequal distribution of benefits

Another challenge in implementing the centralised coordination framework lies in the uneven distribution of financial benefits among stakeholders. While the strategy extends turbine lifespan and reduces long-term costs, it leads to revenue reductions for the dispatcher. In contrast, the wind farm owner gains financial benefits as asset health is preserved. Without appropriate incentive structures to redistribute financial gains, dispatchers may resist participation.

Given these limitations, a fully centralised coordination strategy may not be practical for real-world wind farm operations. Full transparency and trust between stakeholders would be needed, and practical price incentives are required to incentivise all stakeholders before implementation could be considered. As a result, the next section explores an alternative approach with a decentralised coordination framework, which seeks to achieve similar benefits while preserving stakeholder autonomy.

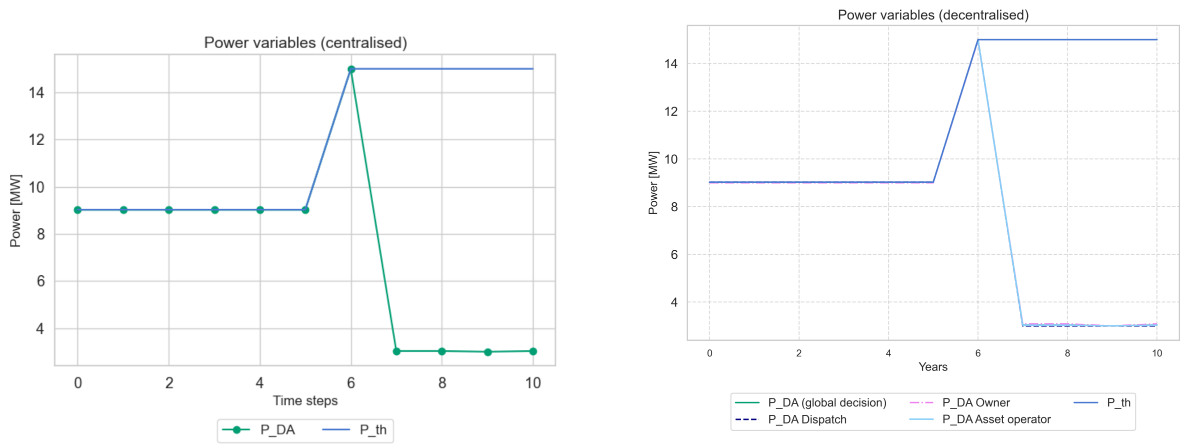
7.2. Assessing the potential of a decentralised approach

The purpose of this section is to analyse the feasibility of a decentralised coordinated curtailment strategy and compare its outcomes with the centralised approach. Unlike the centralised model, where a single entity optimises curtailment strategies on behalf of all stakeholders, the decentralised approach distributes decision-making among individual parties. Each stakeholder optimises its respective objective while iteratively communicating and coordinating with each other to converge toward a mutually beneficial solution.

While decentralised optimisation offers certain benefits, the introduction of inter-temporal constraints significantly increases computational complexity. As optimisation problems grow in size, computational time scales non-linearly, often exponentially, with larger datasets [118]. Due to the complexity of solving interconnected time steps across multiple iterations, a reduced dataset is used in this comparison to assess the theoretical feasibility of the decentralised strategy.

7.2.1. Comparison with the centralised approach

A comparison of the power dispatch strategy between the centralised and decentralised approach is presented in Figure 7.6. The decentralised strategy shows a power dispatch profile that closely resembles the centralised strategy, suggesting that the decentralised method effectively nears the optimal centralised solution for a dataset consisting of 11 time steps. In addition, all local dispatch strategies converge to the global dispatch strategy, indicating consensus among the stakeholders.



(a) Centralised dispatch strategy

(b) Decentralised dispatch strategy

Figure 7.6: Comparison of dispatch strategies with $T = 11$.

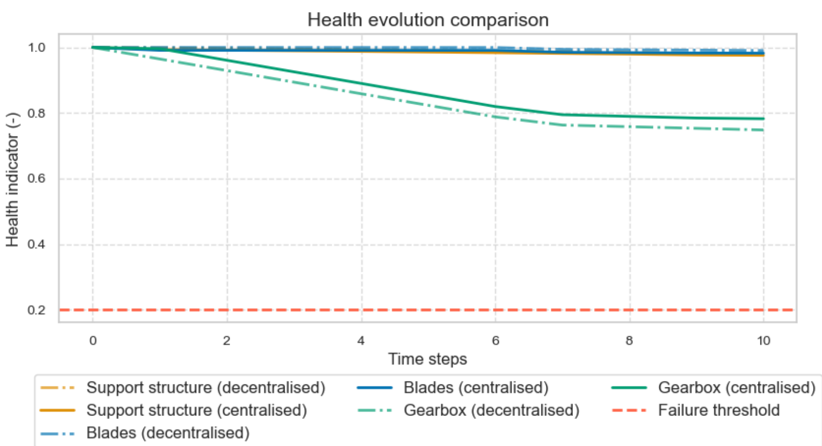


Figure 7.7: Health evolution comparison of critical components: centralised (dashed) vs. decentralised (solid), $T = 11$.

Figure 7.7 illustrates the health evolution of each of the components m incorporated in the analysis for both strategies. The results confirm that the optimal solution in the decentralised coordination framework aligns with the results from the centralised framework.

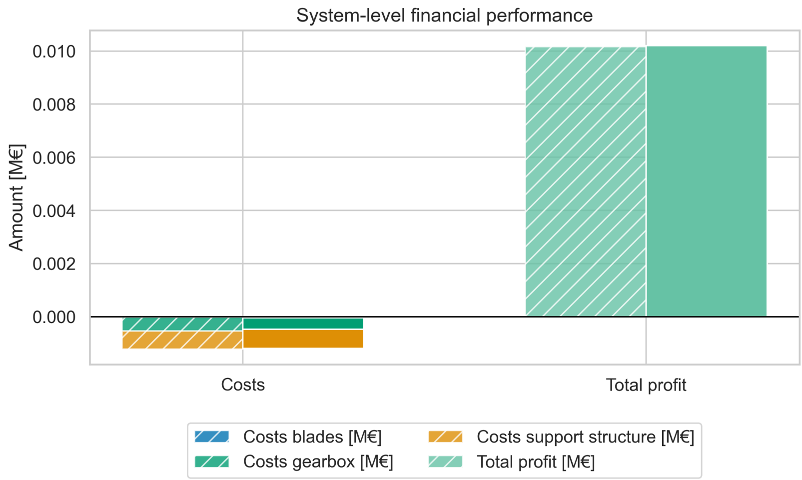


Figure 7.8: System-level costs and profit: centralised (hatched) vs. decentralised (solid), $T = 11$.

The financial performance of the decentralised strategy is comparable to that of the centralised strategy, as shown in Figure 7.8. This indicates that decentralised coordination can achieve similar system-wide benefits without requiring full transparency or centralised control.

7.2.2. Convergence

The effectiveness of a decentralised framework depends on the ability of stakeholders to exchange information iteratively and reach a consensus within a reasonable number of iterations. The penalty parameter ρ and the convergence tolerance both influence the convergence. When properly chosen, these parameters enable the decentralised approach to closely approximate the centralised solution. After iterative tuning, a penalty parameter of $\rho = 2$ and a tolerance of 10^{-4} were selected, as detailed in Section 8.2. As shown in Figure 7.9, which depicts the primal and dual residuals, the solution successfully converges within 25 iterations.

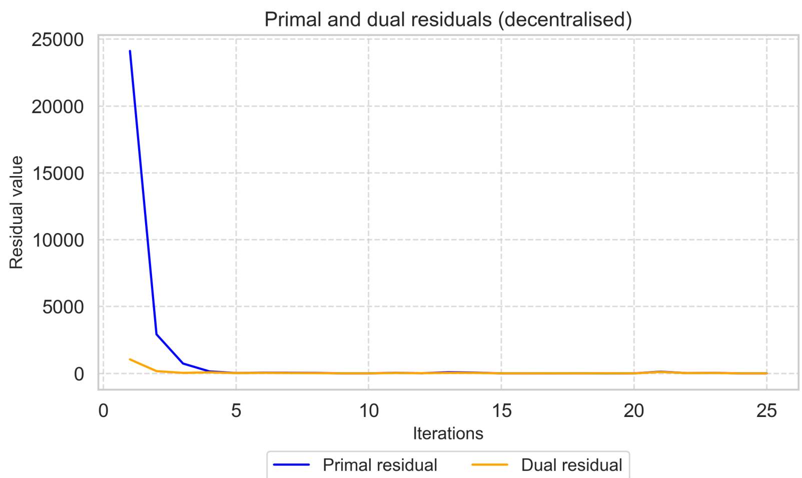


Figure 7.9: Primal and dual residuals over the iterations, under a decentralised scenario $T = 11$.

It can be concluded that if the decentralised framework is tuned correctly, it can converge to the same results as the centralised coordination strategy. As the centralised framework may not function in reality, this decentralised framework could be an alternative approach. But how would a decentralised coordinated curtailment strategy look?

7.2.3. Implementation of the decentralised strategy

A practical way to implement decentralised coordination is through an iterative negotiation process, where stakeholders gradually refine their curtailment strategies in structured bidding rounds. This approach ensures that each party's objectives are considered while working towards a curtailment strategy that benefits all. In general, such a process would follow these steps:

1. **An initial bidding round** - Stakeholders outline their objectives and expectations, sharing insights on replacement and reinforcement costs, PPA prices, and operational constraints. This sets the foundation for negotiations.
2. **Bid adjustments** - Each party adjusts its bids based on changing operational conditions, asset health trade-offs, and financial constraints. If needed, new agreements are added based on maintenance insights (e.g. maximum allowable curtailment level).
3. **Iterative convergence** - The process repeats, with ongoing adjustments, until an agreement is reached that balances revenue generation, cost reduction, and asset longevity.
4. **Final agreement and execution** - The optimised curtailment strategy is formalised in contracts, ensuring all stakeholder interests are reflected and commitments are secured.

This decentralised negotiation process allows stakeholders to maintain control over their data and decision-making while still benefiting from a coordinated curtailment strategy. Refining dispatch strategies through iterative adjustments rather than imposing a centralised approach encourages stakeholder trust and participation, making implementation more practical.

8 Verification, validation and sensitivity analysis

Confirming the robustness and reliability of the developed optimisation model is needed to determine whether it can effectively answer the main research question: *To what extent can integrating asset health improve the value of offshore wind power generation through coordinated curtailment strategies?* This chapter presents the verification, validation, and sensitivity analysis of the model. This chapter begins with verification in Section 8.1, which confirms the model has been correctly implemented, meaning that its mathematical formulation is accurately translated into code and that it produces consistent, logical results. This involves debugging, verifying constraint enforcement, and analysing the convergence of the decentralised framework to ensure the optimisation model performs as intended.

Next, validation in Section 8.2 evaluates whether the model reflects real-world system dynamics. As George Box famously stated, ”All models are wrong, but some are useful” [119]. Since no model can perfectly replicate reality, validation focuses on whether the outputs align with theoretical expectations, empirical insights, and expert knowledge. In this study, model behaviour was iteratively reviewed with industry experts to refine assumptions and enhance its practical applicability.

It is important to acknowledge the trade-off between model accuracy and practicality. While certain elements, such as degradation functions, could always be further refined, the objective of this research is not to predict precise values but rather to develop a structured framework that supports informed decision-making. The true value of the model lies in providing a systematic approach for integrating long-term asset health into dispatch strategies rather than serving as an exact forecasting tool.

Finally, Section 8.3 presents a sensitivity analysis. Given the rapidly evolving nature of electricity markets and offshore wind operations, assessing the sensitivity of the model to changing market conditions is crucial.

8.1. Verification

This section verifies whether the model behaves as expected. First, Section 8.1.1 evaluates the impact of uncertainty in electricity prices and environmental data by comparing results from different base years. Next, Section 8.1.2 examines whether constraints in the centralised optimisation model are correctly enforced in the final solution. Finally, Section 8.1.3 investigates the convergence of the decentralised optimisation model by identifying an appropriate penalty parameter and evaluating its impact on the primal and dual residuals.

8.1.1. Uncertainty in price and environmental data years

The choice of a base year for electricity prices and environmental conditions introduces uncertainty into the model results. This section examines how different base years for electricity price and environmental data impact model outcomes and whether the results are consistent. The year 2015 is used as a reference as it contains no negative price hours, a phenomenon that has only emerged in recent years. As shown in Table 8.1, 2023 saw a total of 315 negative price hours (c. 3.6% of total hours). This increased in 2024 to 458 hours (c. 5.2% of total hours), resulting in a relative growth of 47% compared to 2023. For this study, 2023 was selected as the default base year for electricity prices in the day-ahead market and environmental data.

Comparative distributions in electricity prices and environmental factors

Table 8.1 provides a comparison of statistical values on electricity price and wind speed distribution for the base years 2015, 2023, and 2024. The day-ahead electricity price data is from Ember [104], and environmental data is from ERA5 [87], as detailed in Section 6.1. It is important to note their differences in time steps, as 2024 was a leap year, leading to a dataset with 8,784 time steps, while 2015 and 2023 contained 8,760 time steps.

Table 8.1: Comparison of electricity price and wind speed distribution base year: 2015, 2023 and 2024 [87],[104].

Metric	2015	2023	2024
Total hours	8760	8760	8784
Mean price [€/MWh]	40.0	95.8	77.3
Median price [€/MWh]	39.9	99.2	80.0
Min price [€/MWh]	1.7	-500	-200
Max price [€/MWh]	99.8	463.8	873.0
Negative price hours	0	315	458
Mean wind speed [m/s]	10.4	10.0	9.8
Median wind speed [m/s]	9.8	9.4	9.6
Min wind speed [m/s]	0.1	0.1	0.2
Max wind speed [m/s]	28.0	26.1	29.1

On average, 2015 had lower electricity prices than 2023. Electricity prices were relatively high in 2023 as they were correlated with elevated gas prices [120]. This correlation is expected to weaken as reliance on gas as an energy source decreases. With an increasing share of vRES, the correlation between electricity prices and environmental factors (e.g. wind speed and solar irradiation) will become more important. This makes the comparison between 2024 and 2015 particularly insightful, as the importance of environmental conditions in price formation is significantly higher in 2024 due to the increased installed wind capacity [121].

A visual comparison of electricity prices and environmental data across the years 2015, 2023, and 2024 can be found in Appendix E.1. 2015 contains more stable electricity prices with fewer extreme price fluctuations. While 2024 contains a higher occurrence of near-zero and negative electricity prices, reflecting an increases share of vRES. While both 2023 and 2024 exhibit similar peak prices, 2023 displays greater volatility in the day-ahead market, with more frequent price spikes above 200 €/MWh and with a more negative minimum price of -500 €/MWh compared to -200 €/MWh in 2024. This suggests that while negative pricing became more prevalent in 2024, extreme price fluctuations were more common in 2023.

The wind speed distribution is relatively consistent across all years (Figure E.1b), with only minor differences. 2015 exhibits slightly more occurrences of extreme wind gusts above 20 m/s compared to the later years, potentially influencing turbine stress and curtailment decisions. Wave height (Figure E.1c) and precipitation distributions (Figure E.1d) remain almost identical across all three years.

Economic performance in sorted datasets from different base years

How do economic performance metrics vary across the sorted datasets with different base years? It is important to emphasise that the comparison is based on a sorted dataset, based on the methodology explained in Section 6.1. The underlying data stems from different base years, but the datasets have been re-ordered to represent a simulated 30-year horizon.

This section compares the centralised coordination scenario with the current situation for each sorted dataset. Table 8.2 only presents a subset of metrics to avoid redundancy, a more extensive overview of financial performance can be found in Appendix E.

Table 8.2: Economic performance metrics comparing centralised coordination with the current situation for base years 2015, 2023, and 2024. Red indicates a detrimental change, while green indicates a beneficial change.

Category	2015 [M€]		2023 [M€]		2024 [M€]	
	Baseline	**Centralised**	**Baseline**	**Centralised**	**Baseline**	**Centralised**
Dispatcher						
Revenue	3.24	1.81 (-44%)	6.91	4.87 (-30%)	5.57	3.91 (-30%)
Profit	-3.8	-5.23 (-38%)	0.25	-1.8 (-820%)	-1.18	-2.84 (-141%)
Maintenance Party						
Blade Costs	3.37	0.51 (-85%)	3.37	0.78 (-77%)	3.37	0.68 (-80%)
Gearbox Costs	2.07	0.88 (-57%)	2.07	1.07 (-48%)	2.07	1.07 (-48%)
Total Costs	5.44	1.39 (-74%)	5.44	1.84 (-66%)	5.44	1.75 (-68%)
Owner						
Support Structure Costs	1.13	0.95 (-16%)	1.09	0.97 (-11%)	1.06	0.94 (-11%)
Total Costs	7.66	2.61 (-66%)	7.62	3.18 (-58%)	7.59	3.04 (-60%)
Global						
Investment Costs	6.57	2.34 (-64%)	6.53	2.81 (-57%)	6.5	2.69 (-59%)
Profit	-3.33	-0.53 (84%)	0.38	2.06 (439%)	-0.93	1.22 (231%)
ROI	**-50.68 %**	**-22.65 %**	**5.82 %**	**73.31 %**	**-14.31 %**	**45.14 %**

The results suggest that implementing a centralised coordinated strategy results in a significant increase in profit on a system level in the years in which negative price hours occur: 2023 (+439%) and 2024 (+231%). This could indicate a significant potential for improving the financial viability of wind farms under a coordinated approach.

In 2015, an absence of negative electricity price hours and a lower correlation between wind availability and electricity prices led to a weaker impact of coordination. While the coordinated strategy still leads to a notable profit increase of 84%, the ROI remains negative (-22.65%). This suggests that in a more stable market with fewer extreme price fluctuations, the potential for efficiency gains through coordination is limited.

A closer look at the cost components shows that while investment levels remain relatively stable across years, dispatcher profit, revenue and system-wide profit are highly sensitive to market fluctuations. Where in particular the dispatcher experiences significant revenue losses under a centralised approach. In 2024, dispatcher profit drops by 141%, while the system-wide profit improves by 231%. This underscores the finding that while coordination improves financial performance on a broader scale, not all stakeholder benefits equally.

Value of coordination in sorted datasets from different base years

To be able to quantify the value of coordination, Table 8.3 presents the increase in ROI when comparing the centralised strategy with the current situation.

Table 8.3: Impact of centralised coordination on ROI across different base years.

Metric	2015	2023	2024
ROI Increase [percentage points]	28.04	67.49	59.45

The increase in ROI is greatest in 2023 and 2024, both years characterised by more volatile electricity prices. In contrast, although coordination also led to improvements in 2015, the overall ROI remains negative. This supports the observation that centralised coordination is most effective in electricity markets with negative price hours and greater price variability.

Sensitivity to different base years

The sensitivity analysis evaluates the robustness of the results regarding the economic performance metrics. The methodology and output of the sensitivity analysis can be found in E.3. The main findings are stated here.

While investment costs remain relatively stable across different base years, suggesting that reinforcement and replacement decisions are primarily driven by long-term degradation trends, system-wide profitability fluctuates significantly. This variation can largely be attributed to the strong dependence of system profitability on revenue generated in the day-ahead electricity market. When electricity prices vary significantly between years, it directly impacts the system-wide profit.

Given the sensitivity of the model outcomes, relying on a single base year may not fully capture the broader market trends. A more robust approach would involve using multiple years of data (e.g. a 10- to 20-year dataset) to mitigate the influence of short-term fluctuations in electricity prices and environmental conditions.

Due to computational constraints, this study is limited to 2023 as the base year. Despite inherent uncertainties, the model demonstrates some consistency across different base years, particularly concerning the reinforcement costs of the support structure and the replacement costs of the blades and gearbox. Therefore, the results confirm that while market conditions significantly impact short-term profitability, the underlying optimisation framework remains robust in supporting dispatchers by integrating long-term asset health considerations into their dispatch strategies.

8.1.2. Enforcing constraints

Verification of constraint enforcement is essential to ensure the optimisation model operates within its defined solution space. This process involves a visual inspection of model outputs and an analysis of dual variables. This section focuses on the centralised coordination problem, introduced in Section 6.4.1, as it integrates the evolution of the health of the components into the baseline problem formulation.

Model development

Throughout the model development process, errors were identified and resolved based on code debugging. Each newly introduced component, such as degradation functions or stakeholder perspectives, was systematically tested, and errors were corrected until the model operated as expected.

This study is the first to integrate component health states into dispatch strategies, meaning no prior methodologies exist for formulating health state constraints. To be able to determine how these degradations of health states needed to be modelled, different formulations were tested before the final formulation was selected. The detailed process is explained in Section 6.3. A non-linear penalty function failed to enforce strict replacement constraints, while integer replacement variables significantly increased model complexity. Consequently, the current centralised problem formulation, a linear problem that takes costs related to component degradation into account, was selected as the most suitable.

Once the centralised problem was developed, the enforcement of the added constraints had to be verified, which is addressed in the next section.

Power production and curtailment constraint

The power balance constraint (Equation 6.18) ensures that the sum of dispatched power P_t^{DA} and curtailed power P_t^{Curt} are always equal to the theoretical power output P_t^{Th}. Secondly, the curtailment limit constraint (Equation 6.19) restricts curtailment, ensuring that curtailed power never exceeds 80% of the theoretically available power.

The correct enforcement of both constraints is investigated by including numerical checks in the code. Furthermore, Figure 8.1 provides a graphical representation to show that both constraints are correctly enforced in the solution. In the figure, the green line represents the actual power production P_t^{DA}, the orange dashed line shows the curtailed power P_t^{Curt}, and the blue dashed line represents the theoretical available power P_t^{Th}.

Firstly, the power balance constraint is verified. The data behind Figure 8.2 shows that the sum of dispatched power and curtailed power is always equal to the theoretical power. Hence, the model correctly balances power generation and curtailment decisions.

Secondly, the curtailment limit constraint needs to be correct. Curtailment occurs when the power output is intentionally reduced to protect turbine components or align with market conditions. In this case, the maximum theoretical power is equal to 15 MW. Since the curtailment limit constraint is set to 80%, P_t^{Curt} should have a maximum value of 12 MW of available power that is intentionally not produced. Figure 8.2 confirms that the curtailment never exceeds the predefined 80% limit corresponding to 12 MW, ensuring that operational constraints are met. This verifies that the model adheres to the constraints in the optimal solution under the centralised coordination strategy.

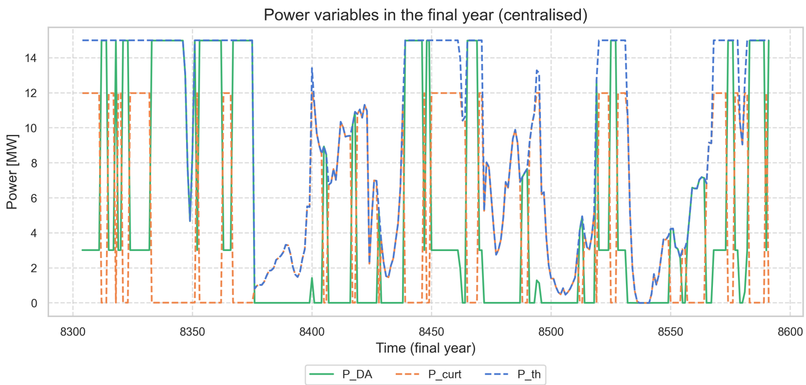


Figure 8.1: Dispatched power in the day-ahead market (green), curtailed amount of power (orange) and theoretical available power (blue) in the final year, $Y = 30 \Longrightarrow t \in \{8304, \dots, 8592\}$.

Health condition constraint

The minimum health constraint, from Equation 6.23, ensures that the health state of component S_t^{m} remains above a defined threshold ($S_{\min} = 0.2$).

As shown in Figure 8.2, the health conditions of the support structure, gearbox and blades decrease over time. The gearbox health reaches the threshold at the final time step, where the constraints become active.

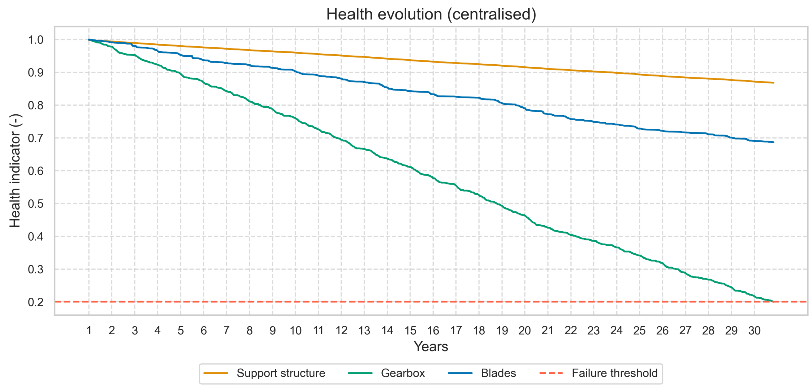


Figure 8.2: Health evolution over time in the centralised scenario, $T = 8592$, $Y = 30$.

Following the confirmation of enforced constraints in the centralised problem, the tuning of the penalty parameter of the decentralised coordinated strategy will be investigated in the next section. This will be explored through a convergence test of the decentralised model in comparison with similar outputs, where the centralised model serves as a benchmark.

8.1.3. Convergence of ADMM

This section analyses the convergence of the decentralised framework to the centralised solution. Convergence in ADMM is assessed through the evolution of primal and dual residuals, which indicate to which extent decentralised sub-problems align with the global solution. Additionally, the evolution of dispatch strategies for each local sub-problem, as formulated in Section 6.4.2, provides further insight into convergence effectiveness.

The primal residual measures the difference between the sub-problems dispatch strategy and the global dispatch strategy. A high primal residual indicates solutions do not align well. The dual residual measures how much the Lagrange multipliers are changing between iterations. A low dual residual means the adjustments have stabilised, and the optimisation has reached a stable state.

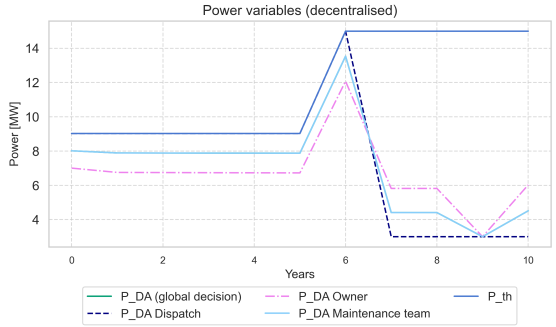
Figures 8.3a and 8.3b illustrate the convergence behaviour when a low penalty parameter ($\rho = 0.02$) is applied. As seen in Figure 8.3a, the decentralised dispatch strategies fail to reach a consensus, with noticeable deviations between the stakeholders and the global dispatch strategy. This lack of agreement is further reflected in 8.3b, where the primal residual shows an increase over the iterations, indicating an unstable convergence process. Consequently, a too-low parameter allows too much flexibility in local sub-problems, preventing the system from reaching a stable consensus.

Increasing the penalty parameter to $\rho = 2$, as shown in Figures 8.3c and 8.3d, improves the synchronisation process, with residuals declining at a more stable rate.

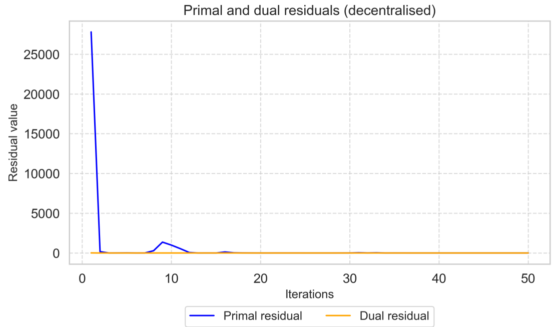
At $\rho = 20$, illustrated in Figures 8.3e and 8.3f, power variables align well with the consensus strategy, but residuals decrease more slowly. A high penalty forces the consensus solution but at the cost of delayed dual residual stabilisation.

This analysis underscores the need for careful tuning of the penalty parameter to balance convergence and stability in the outcomes. A moderate penalty ($\rho \approx 2$) provides the best trade-off, ensuring alignment between stakeholders within reasonable iteration counts.

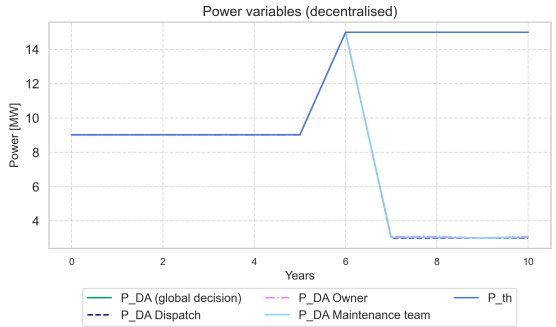
However, due to the complexity of using ADMM and with this research being the first time ADMM has been applied to curtailment strategies in offshore wind, the extension to larger datasets failed to converge properly.



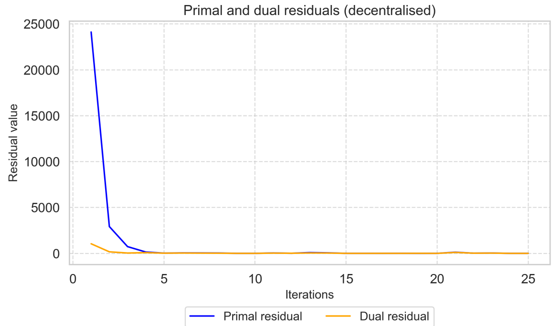
(a) Power variable evolution for $\rho = 0.02$



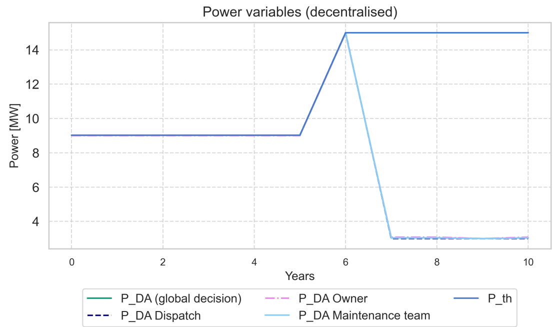
(b) Primal and dual residuals for $\rho = 0.02$



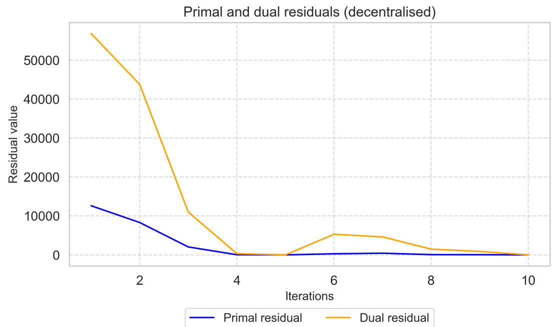
(c) Power variable evolution for $\rho = 2$



(d) Primal and dual residuals for $\rho = 2$



(e) Power variable evolution for $\rho = 20$



(f) Primal and dual residuals for $\rho = 20$

Figure 8.3: Impact of penalty parameter ρ on power variable evolution and residual convergence.

8.2. Validation

This section evaluates the validation of the model and data. First data validity (8.2.1) is assessed to ensure the input dataset contains a realistic distribution of negative price hours and variations in environmental data. Next, the model operation (8.2.2) is validated by examining whether the degradation functions correctly capture expected relations between environmental conditions and component wear. This section ends with explaining the process of qualitatively validating the stakeholder objectives.

8.2.1. Data validity

As the dataset used in the baseline and centralised scenario is reduced to a smaller set, which should represent 30 years, validation of the data is necessary. First, the section will explore whether the amount of negative price hours are representative within the sorted dataset. After which the variations of the input parameters are examined.

The future of negative prices

This section examines the assumption that negative price hours will persist over the next 30 years. As this study aims to remain open-source, publicly available historical data is used instead of proprietary forecasts. Forecasting tools often exclude negative price hours due to modelling complexity and inherent uncertainties, making them unsuitable for this research.

The number of negative price hours in the dataset is expected to significantly influence the model's behaviour, as a higher occurrence of negative prices could result in increased curtailment. Since only a subset of hours from 2023 has been used, potential variations in the number of negative price hours may be larger than expected. Therefore, it is crucial to validate whether the dataset contains a realistic distribution of negative price hours without extreme deviations.

It is important to note that the dataset is in no way predicting the number of negative price hours in the Dutch day-ahead market over the next 30 years. Forecasting long-term electricity prices stays outside of the scope of the research due to inherent uncertainties in price projections. Instead, this dataset serves as a reasonable approximation based on historical data and trends.

The electricity price dataset used in the research, which serves as the basis for the sorted dataset, contains zero negative price hours in 2015, 315 in 2023, and 458 in 2024. These values are consistent with report data from other sources on negative price occurrences in the Dutch day-ahead market [11, 122]. When expressed as a percentage of total hours, this corresponds to 3.6% in 2023 and 5.2% in 2024.

The sorted dataset, which is used for the baseline and centralised scenario, shows a compatible distribution of negative price hour shares across the simulated years. Moreover, the distribution of negative price hours in the dataset varies across simulated years, reflecting the inherent fluctuations of market dynamics. Some years exhibit lower shares of negative price hours, while others show higher values, yet all remain within a realistic range of 0-10%. A summary of the distribution is provided in Table 8.4.

Table 8.4: Negative price hours share per simulated year

Simulated year	Negative price hours share [%]
2023	3.13
2028	0.70
2032	3.81
2037	2.78
2042	4.17
2047	8.68
2052	4.17

The primary driver of negative electricity prices is the subsidy scheme for vRES, which allows producers to bid at negative prices. These subsidies aim to accelerate capacity expansion but are set to phase out over time, as indefinite financial support is unsustainable. As subsidies decrease, the frequency of negative price hours is expected to decline. Another contributing factor is the surplus of low-cost vRES on the grid. Future large-scale energy storage, such as battery systems or hydrogen conversion, is expected to absorb excess supply, further reducing negative price occurrences.

Given these trends, the share of negative price hours is likely to increase over the next years before gradually declining as large-scale storage options mature. Ideally, the dataset should reflect this transition by initially increasing the occurrence of negative price hours before declining. However, for this study, such adjustments are unnecessary, as the timing of negative price hours does not affect turbine degradation calculations. Additionally, asset depreciation and inflation are not accounted for in this model. While these factors would be relevant for economic assessments, they do not impact the technical evaluation of turbine wear.

Daily and seasonal variations in environment conditions

The dataset used in this study is based on historical weather and electricity price data. The 2023 weather data and electricity prices have been combined and extrapolated to construct a representative dataset for 30 years. Since weather conditions and electricity prices are inherently correlated, it is crucial to maintain this relationship in the dataset. However, long-term forecasts of environmental conditions are subject to considerable uncertainty, particularly due to the potential effects of climate change on wind patterns, wave heights, and precipitation intensity. These uncertainties fall outside the scope of this thesis, and no climate change projections are incorporated into the dataset.

Electricity prices and environmental conditions fluctuate on daily and seasonal scales, and the sorted dataset used for optimisation must preserve these variations. The sorted dataset consists of 8640 time steps, significantly fewer than the time steps expected in a full hourly 30-year dataset containing 30 years $\cdot\ 8760$ hours $= 262,800$ time steps. The sorted dataset does not directly reflect the original time steps, as they are not in hours, days or months. The sorted dataset contains 288 time steps per year. Therefore, it is not possible to directly translate it back to recognisable daily or monthly patterns, however, a representative level of variation must still be present in the input parameters, which is assessed in this section.

The method used to sort environmental conditions and their corresponding day-ahead electricity prices ensures that any correlation between these factors stays consistent. See Section 6.1 for a recap of the method used to sort the data. This approach is commonly applied in the industry to approximate realistic market conditions in smaller datasets.

The figures of the dataset's variation are presented in Appendix F, where the electricity price and environmental conditions trends over the simulated year (2052) are visualised. These confirm that essential variations are preserved. Electricity prices include occurrences of both positive and negative price spikes. Furthermore, wind speed and wave conditions show similar variations over time, aligning with the assumption that most often if the wind speed increases, waves follow.

8.2.2. Validation of the model operation

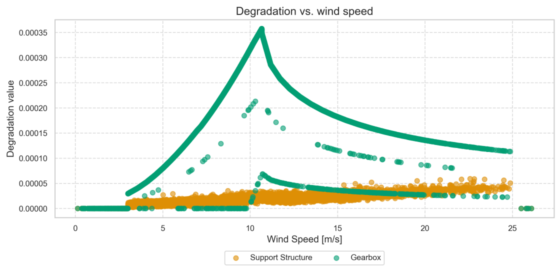
The degradation values are validated through a combination of comparative analysis and expert consultation, as integrating both qualitative and quantitative validation enhances confidence in the model's outputs [123]. Following this, the validation of stakeholder objectives is addressed through qualitative assessment.

Degradation functions

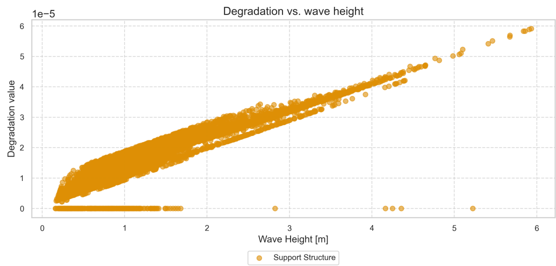
The degradation functions used in this study provide a simplified representation of component wear, as they incorporate the relation with thrust, wind speed, wave height and precipitation. However, as they are not based on empirical field data, their absolute values cannot be validated. Instead, the focus is on assessing whether they correctly reflect expected degradation trends.

To ensure degradation rates are similar to real-world operation the functions are fine-tuned so that each component reaches its assumed end-of-life consistently with real-world design specifications. This process has been validated through expert input from a support structure engineer, yield expert, and operation and maintenance specialist (see Appendix A). For a detailed explanation of the fine-tuning processes used to determine the degradation parameters, see Section 4.6.

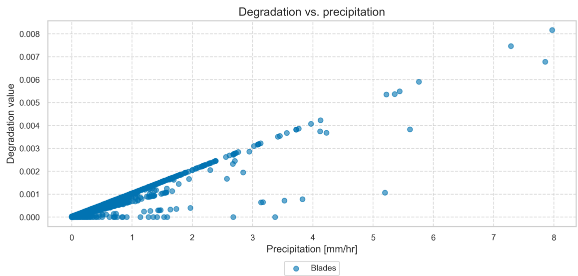
Figure 8.4 presents scatter plots illustrating the relation between degradation values and environmental parameters. Gearbox degradation (green) peaks around rated wind speed ($v_{\text{rated}} = 10.6$ m/s), which is expected as this is where the turbine operates at full load. The degradation of the support structure (orange) remains relatively stable across wind speeds and wave heights, with a slight increase, suggesting lower sensitivity to short-term variations. Blade degradation (blue) increases with precipitation intensity, confirming that rain-induced erosion impacts the degradation of the blades significantly. However, this does not necessarily confirm that blade degradation occurs over time due to precipitation, as research on this topic is still ongoing (e.g., TNO studies on leading-edge erosion [99]).



(a) Degradation values as a function of wind speed



(b) Degradation values as a function of wave height



(c) Degradation values as a function of precipitation

Figure 8.4: Degradation values for each of the components m relative to environmental conditions plotted as scatter plots.

While these functions do not predict exact failure rates, they capture the expected dependencies between environmental stressors and degradation trends. For real-world applications, further validation using field data, structural health monitoring (SHM), and long-term load case simulations would be necessary.

Stakeholder objectives

Validating stakeholder objectives and economic metrics is challenging, as these are typically kept confidential due to competitive sensitivities. As discussed in Chapter 5, stakeholders tend to keep their cards close to the chest as they are collaborating in one project but are competitors in the next. In practice, only trend-based or pseudo-functions are shared during negotiations, rather than exact financial details. Given this limitation, validation in this study focuses on ensuring the model captures realistic economic trade-offs rather than making precise predictions of economic values. Therefore, qualitative validation is deemed sufficient, as it ensures the model aligns with industry expectations.

This validation was conducted iteratively, refining the perspectives of each stakeholder and their respective objectives through expert consultation. The process involved close collaboration with professionals from energy trading, asset development, and maintenance, as well as a technical director from an organisation that owns and operates a wind farm. Their insights helped ensure that the economic trade-offs and decision-making processes reflected in the model are representative of real-world industry practices.

8.3. Sensitivity analysis

The context in which the decision on dispatch strategies for offshore wind power are determined is inherently complex, influenced by fluctuating electricity prices, changing material costs and market dynamics. To assess the robustness of the proposed centralised coordinated curtailment strategy under varying economic conditions, a sensitivity analysis is conducted. This analysis examines how different assumptions about component replacement costs and electricity prices affect the results.

First, the sensitivity to decreasing or increasing costs for components is analysed. Secondly, the impact of different price-time projections on the value of coordination is examined.

8.3.1. Sensitivity to costs of components

The economic viability of offshore wind is dependent on the evolution of the cost of components. Historically, it was widely expected that technological advancements and economies of scale would drive costs down over time [124, 125]. However, recent market trends indicate the opposite, with rising material costs, particularly for steel, alongside increasing labour and logistic expenses, due to the increasing demand for manufacturing and O&M services. This poses a critical question on how robust the proposed centralised coordinated dispatch strategy is to fluctuations in component costs.

To address this, a sensitivity analysis is performed by examining the impact of both cost reductions and increases. The following hypotheses are formulated:

- **Hypothesis 1:** An increase in component costs will lead to a decline in profitability, as component health considerations will play an even greater role in the dispatch strategy.
- **Hypothesis 2:** When components become cheaper, short-term revenue maximisation in the day-ahead market will become more favourable, as reinforcement and replacement costs are lower.
- **Hypothesis 3:** The gearbox, as the cheapest major component, is typically optimised to reach its end-of-life at the end of the simulation period. However, when the cost of other components is varied, the optimal replacement order and prioritisation of component health may shift.

In this analysis, the cost of each component is adjusted separately, while the costs of all other components remain constant. Two distinct scenarios are tested: one with a 25% cost reduction and another with a 25% cost increase.

The results of these variations are shown in Table 8.5, detailing the percentage change in revenue, costs, and profitability across different stakeholders. The colour coding highlights the magnitude of these changes: dark red indicates percentage differences greater than 20% and green denotes differences below 10%, suggesting minimal variation.

Table 8.5: Percentage change in economic performance metrics under 25% cost variation for gearbox, blade, and support structure components.

Metric	Cost gearbox		Cost blades		Costs support structure	
	-25%	+25%	-25%	+25%	-25%	+25%
Dispatcher						
Revenue	-8.21 %	0.00 %	1.23 %	-1.03 %	-8.21 %	0.00 %
Costs	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
Profit	2.78 %	0.00 %	-3.89 %	2.78 %	22.22 %	0.00 %
Maintenance						
Revenue	-14.48 %	14.48 %	-7.24 %	7.69 %	4.52 %	0.00 %
Total costs	-14.67 %	14.67 %	-7.12 %	7.61 %	4.35 %	-0.54 %
Blade costs	-1.28 %	0.00 %	-18.08 %	16.67 %	12.82 %	-2.56 %
Gearbox costs	-25.23 %	24.30 %	0.00 %	0.00 %	-2.80 %	0.00 %
Profit	-13.51 %	13.51 %	-7.84 %	8.11 %	5.41 %	2.70 %
Owner						
Revenue	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
Total costs	-10.06 %	10.06 %	-5.03 %	5.35 %	-1.07 %	7.55 %
Support structure costs	-13.81 %	0.00 %	0.00 %	0.00 %	-13.81 %	24.74 %
Profit	9.17 %	-9.17 %	4.58 %	-4.87 %	0.97 %	-6.88 %
Global						
Investment costs	-9.61 %	9.61 %	-4.66 %	4.98 %	-1.92 %	8.19 %
Netto profit	12.62 %	-13.11 %	9.27 %	-9.22 %	-16.80 %	-11.17 %

The results confirm that profitability declines with rising component costs, validating Hypothesis 1.

Among the components, a 25% increase in gearbox costs has the strongest impact, reducing global profit by 13.11%. Conversely, a 25% reduction in support structure costs results in an even greater global profit reduction (-16.80%), challenging the assumption that cost reductions always lead to higher profits.

Hypothesis 2, which suggested that cost reductions would lead to increased short-term revenue prioritisation, is partially supported. Specifically, when support structure costs (-25%) are reduced the profit of the dispatcher increases sharply (+22.22%).

This suggests that a less expensive support structure allows for greater flexibility in dispatch strategies, reinforcing the idea that short-term market revenue becomes more attractive when CapEx are minimal. However, a 25% reduction in blade costs does not significantly impact dispatcher profits (-3.89%), indicating that blade costs play a less central role in influencing short-term dispatch decisions.

The third hypothesis, predicting a shift in component health prioritisation when varying costs, is not observed under the 25% cost variations. This is likely because the cost differences between components remain too large for a 25% change to significantly alter the prioritisation.

Extreme value test

To further explore whether a shift in component prioritisation can occur, an extreme value test is conducted. For illustrative purposes, the cost of each component is set to a low value (€1000), while all other components retain their standard costs.

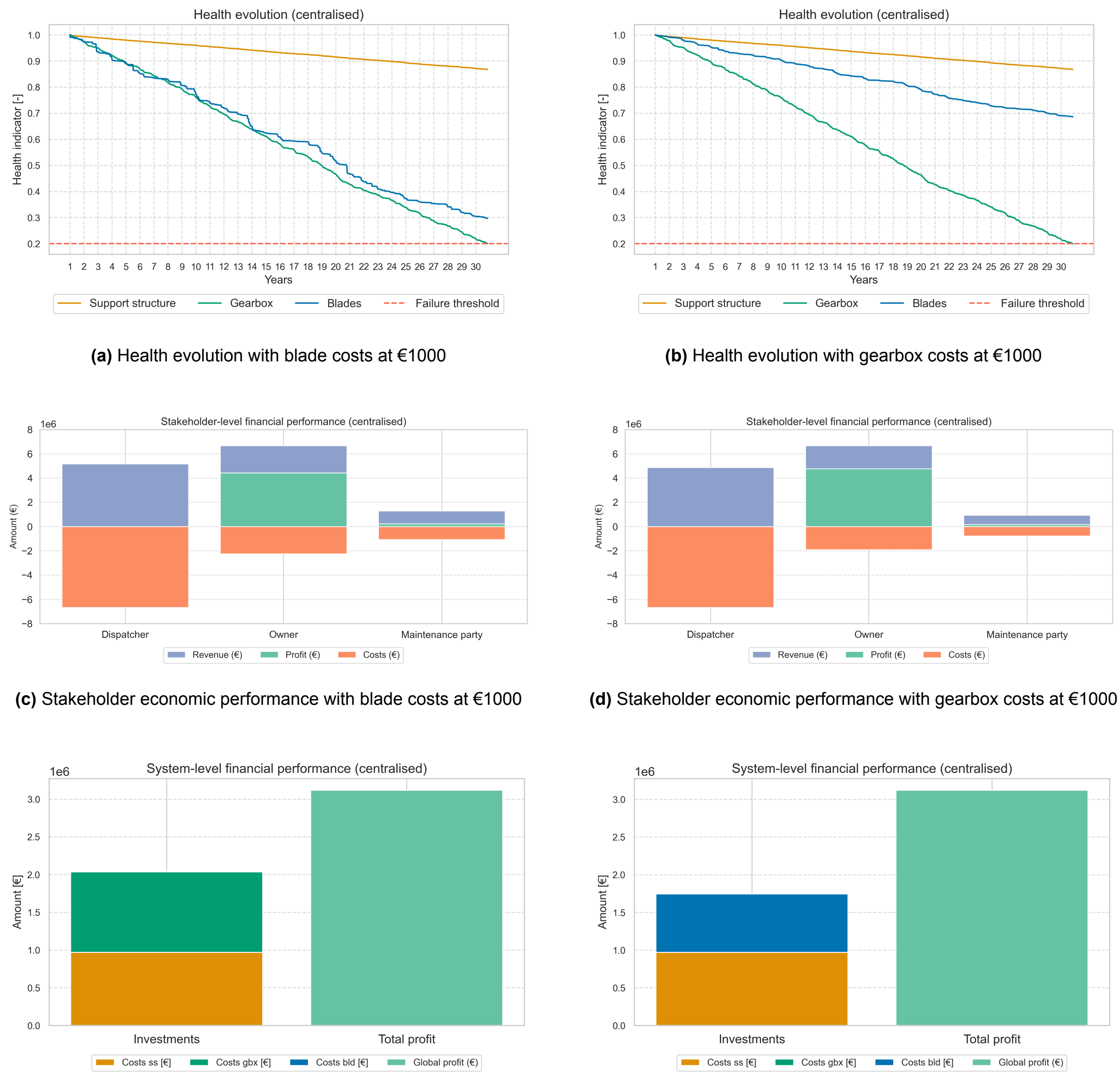
The extreme value test reveals two important insights into the model's behaviour under extreme cost reductions. When the cost of the support structure is set to €1000, the model fails to find a feasible solution, resulting in an infinite runtime. This suggests that the support structure plays an important role in determining the dispatch strategy, however, without realistic values for this component, the model is unable to generate a viable dispatch strategy.

The health evolution of components behaves differently depending on which component cost is reduced. Figure 8.5a illustrates that when blade costs are reduced to €1000, the model allows blade degradation to accelerate. Meanwhile, the health of the gearbox and support structure remain unaffected. This suggests that, in response to low blade costs, the model prioritises frequent blade replacement rather than prolonging their lifespan. Since the cost of replacement is negligible, maintaining blade health is no longer an economic priority.

In contrast, Figure 8.5b shows that when gearbox costs are reduced to €1000, gearbox health follows a similar degradation rate as in previous scenarios. This behaviour might be influenced by constraints on minimum allowable component health, as described in Equation 6.23, preventing gearbox failure even if replacement costs are extremely low.

The economic performance of different stakeholders under extreme cost reduction is shown in Figures 8.5c and 8.5d. In both cases, the economic performances remain relatively stable, indicating that revenue generation is not significantly affected by extreme reductions in component costs.

At the global level, as seen in Figures 8.5e and 8.5f, overall system profit does not increase dramatically under either extreme scenario.



(a) Health evolution with blade costs at €1000

(b) Health evolution with gearbox costs at €1000

(c) Stakeholder economic performance with blade costs at €1000

(d) Stakeholder economic performance with gearbox costs at €1000

(e) Global economic performance with blade costs at €1000

(f) Global economic performance with gearbox costs at €1000

Figure 8.5: Comparison of health evolution, stakeholder impact, and system-wide economic performance when the costs of blades and gearboxes are set to €1000 (while all other component costs remain constant).

8.3.2. Sensitivity to day-ahead electricity prices

Besides a strong dependence on CapEx, the financial viability of offshore wind operations is also influenced by fluctuations in electricity market prices. This raises the following question: How robust is the centralised coordinated dispatch strategy when faced with extreme changes in day-ahead electricity prices? To examine this, a sensitivity analysis is conducted by doubling and halving the day-ahead electricity prices (λ_t^{DA}). The following hypotheses will be tested:

- **Hypothesis 1:** A doubling of λ_t^{DA} will lead to an increased profitability, as higher market revenues will directly boost the financial performance of stakeholders.
- **Hypothesis 2:** Halving λ_t^{DA} will cause profitability to decline, as lower market prices reduce revenue potential while the expenses on component costs stay the same.
- **Hypothesis 3:** Since revenue is highly dependent on electricity prices, the dispatcher will experience the most significant changes.

In this experiment, price variations are applied to the day-ahead market prices while all other parameters remain constant. Two distinct scenarios are tested: one with λ_t^{DA} being doubled and another with λ_t^{DA} being halved.

Table 8.6 shows the percentage change of economic performance metrics under each scenario. The colour coding is varied compared to the previous coding as the input parameters are more strongly varied.

Table 8.6: Percentage change in economic performance metrics under electricity price variations. Red indicates a percentage difference greater than 100%, while green indicates a difference below 50%.

Category	Metric	λ_t^{DA} doubled [%]	λ_t^{DA} halved [%]
Dispatcher	Revenue	105.75 %	-52.57 %
	Costs	0.45 %	0.00 %
	Profit	286.11 %	-142.22 %
Maintenance	Revenue	10.86 %	-8.14 %
	Total costs	11.07 %	-8.15 %
	Blade costs	25.26 %	-15.38 %
	Gearbox costs	-0.31 %	3.74 %
	Profit	9.81 %	-8.11 %
Owner	Revenue	0.45 %	0.00 %
	Total costs	7.55 %	-5.97 %
	Support structure costs	0.00 %	-1.03 %
	Profit	-6.02 %	5.44 %
Global	Investment costs	7.25 %	-5.69 %
	Netto profit	240.11 %	-116.50 %

The results confirm a strong correlation between electricity price variations and the profit of the dispatcher and system-wide profitability. When day-ahead prices double, global profitability increases by 240.11%. Conversely, when prices are halved, global profits decline by -116.50%, confirming that market prices are the primary parameter influencing economic performance, supporting Hypotheses 1 and 2. The dispatcher is the most affected stakeholder, aligning with Hypothesis 3. A doubling of electricity prices increases dispatcher revenue by 105.75%, while halving prices results in a -52.57% drop in revenue.

For the wind farm owner, the changes in electricity prices primarily affect profitability rather than costs. When electricity prices are halved, total costs decrease slightly (-5.97%), but this reduction is insufficient to offset revenue losses, leading to a -6.02% profit reduction. When prices double, the owner's profit does not increase significantly (-6.02%), indicating that higher revenues primarily benefit the dispatcher.

At the global level, investment costs are slightly impacted (+7.25% when prices double, -5.69% when prices halve), but the primary driver of economic shifts is profitability. The extreme profit fluctuations observed in the dispatcher and global system confirm that the value of an offshore wind farm is highly sensitive to electricity market prices.

8.4. Concluding remarks

This chapter has analysed verification, validations, and sensitivity analysis of the developed optimisation model, aiming to ensure its robustness and reliability to guide decision-making in offshore wind dispatch strategies. The verification process confirmed that the model correctly enforces constraints and produces consistent outputs, while the validation confirmed the accuracy of the input data and demonstrated that the degradation functions behave as expected.

The sensitivity analysis showed the dependency of profitability on electricity prices, with significant variations in dispatcher and system-wide profits when market conditions change. While component costs factor into decision-making, market fluctuations have a more dominant impact on overall profitability. The remaining uncertainties will be addressed in the next chapter, which details the discussion and recommendations.

9

Discussion and recommendations

This research has provided valuable insights into the value of coordination within dispatch strategies for offshore wind turbines in volatile electricity markets. This chapter first interprets the main research findings. Next, Section 9.2 explores practical price incentives designed to encourage dispatch strategies to integrate asset health considerations. The uncertainties and limitations of this study are identified in Section 9.3, which, in turn, shape the areas for future research, as discussed in Section 9.4.

9.1. Interpretation of results

The findings of this study show that the current dispatch strategy is sub-optimal from a system-wide perspective as investment costs are substantial compared to profits, as seen in Figure 7.1. In the current situation, the dispatcher determines when curtailment should take place based on short-term market dynamics, such as negative prices, without taking asset health into account. This represents a negative externality, where the long-term degradation costs fall on the other stakeholders. This particularly affects the economic viability of the wind farm owner, who bears significant reinforcement and replacement costs due to premature degradation of both replaceable and non-replaceable components.

The value of coordination in dispatch strategies

One of the main findings of this research is that a coordinated dispatch framework improves the economic viability of offshore wind farms by extending the lifespan of components, thereby reducing reinforcement and replacement costs. This is particularly relevant in electricity markets with volatile price formation, driven by a high share of vRES. As large-scale energy storage and demand response mechanisms are not yet fully developed, these fluctuations are expected to persist, reinforcing the need for dispatch strategies integrating both financial profits and asset degradation. As verified in Section 8.1, the benefits of coordination appear to be most significant in markets with volatile market prices, while the value diminishes in a market where price volatility is lower and negative prices do not occur.

The value of coordination arises from integrating asset health into the currently short-term market-based dispatch strategy. By incorporating the long-term impact of dispatch decisions on component degradation, degradation can be reduced, thereby extending the operational lifetime of critical components. This ultimately results in lower overall costs and improves the financial viability of offshore wind farms.

Centralised compared to decentralised coordination

While the theoretical potential of a centrally coordinated dispatch strategy is evident, its practical implementation depends heavily on the contractual structure of offshore wind farms. Some projects operate under an integrated model, where a single entity owns the wind farm, acts as the dispatcher, and manages maintenance. In such cases, the adoption of a centralised coordinated dispatch strategy could work, as all financial benefits remain within the same organisation. Furthermore, the sharing of sensitive data and company trade secrets or know-how is possible without the risk of losing a competitive advantage.

However, many offshore wind projects involve multiple stakeholders, including several shareholders of the wind farm, third-party dispatchers, and separate maintenance parties. In these cases, trust issues and sensitive data-sharing concerns may arise, preventing the implementation of centralised coordination. Stakeholders may be reluctant to disclose sensitive operational data, as it could backfire via contractual disputes. This lack of transparency can hinder the implementation of a centrally coordinated dispatch strategy. Therefore, this study explored the use of a decentralised framework. The results in Section 7.2 indicate that, for the dataset used in this study, a decentralised coordination strategy can achieve similarly promising outcomes compared to the centralised framework.

If the contractual structure does not allow for centralised optimisation, an iterative negotiation process could serve as a practical way to implement the decentralised coordination. In this approach, the dispatcher, maintenance party and wind farm owner engage in a multi-stage iterative negotiation to reach a mutually agreed-upon dispatch strategy (detailed in Section 7.2.3).

A possible disadvantage of the coordination strategy is the uneven distribution of financial benefits among stakeholders. As a result, practical mechanisms are necessary to align incentives and ensure fair cost-sharing. The next section explores potential pricing mechanisms to achieve this.

9.2. Practical application

To bridge the gap between theoretical findings and real-world implementation, financial mechanisms should be introduced to incentivise dispatchers to integrate asset health into curtailment strategies. Three options are explored below.

Adjusting the PPA price

This research shows that wind farm owners benefit significantly from curtailment strategies that prioritise component longevity. One way to incentivise dispatchers to adopt such strategies is through PPA price adjustments. A lower PPA price could be offered in exchange for a more asset-health friendly curtailment strategy, ensuring that the dispatcher is compensated for shifting from a purely market-driven strategy to one that integrates long-term asset health.

Another approach is to set a higher PPA price, reflecting the inclusion of additional upfront steel reinforcements in the turbine design to better withstand the long-term effects of curtailment. This ensures that curtailment remains feasible when needed, while protecting the structural integrity and lifespan of the turbine. In economic terms, this mechanism functions as a form of Pigouvian tax, traditionally imposed by governments to internalise negative externalities, yet in this case, the stakeholders themselves embed the externality cost into the contract [126, 127]. By adjusting the PPA price to account for anticipated degradation, the financial burden of curtailment is transferred to the dispatcher, who is thus incentivised to consider asset health in their operational decisions. However, this approach depends on an accurate pre-estimation of the number of negative price hours over the contract duration. Since future electricity price trends and curtailment frequencies are uncertain, there is a risk of over- or under-compensating for degradation. While this solution offers a predictable cost structure and maintains operational flexibility, it relies heavily on reliable market forecasting to appropriately calibrate the PPA adjustment.

Expanding on this approach, one option is to split the PPA price into a fixed and variable component, where the variable portion depends on weather conditions. This would create an incentive for the dispatcher to avoid excessive curtailment during periods of strong wind and high waves, where the impact of curtailment on component degradation is the largest. The fixed component ensures a baseline revenue for the wind farm owner, while the variable component allows the dispatcher to optimise revenue while considering turbine longevity.

However, implementing this pricing structure introduces contractual complexity. Establishing a simple yet accurate marginal cost curve that reflects the impact of curtailment under specific weather conditions is crucial. The challenge is that the more precise these cost estimates need to be, the more complex they become to calculate and integrate into operational decision-making. An additional risk is the dependency on confidential operational data among stakeholders who may be unwilling or unable to share their data due to contractual limitations or competitive concerns. This complexity is even greater due to the fact that degradation rates vary significantly between turbines, even within the same wind farm. Factors such as turbine location, exposure to environmental forces, and the individual degradation of components influence overall wear and tear. Therefore, focusing on wind speeds and wave heights as important indicators is a logical first step in developing a variable pricing structure.

Implementing a penalty for deep curtailment

Another pricing mechanism to be included in a PPA agreement could be to introduce a penalty for deep curtailment. This is a practice that already exists in some agreements. Under this framework, dispatchers incur additional costs when they shut down turbines entirely instead of reducing power output to a minimum set point (for example, 20%). While this approach can help discourage unnecessary deep curtailment, determining the appropriate value for the penalty is challenging. Also, such a penalty does not directly account for weather conditions and the dynamic component degradation associated with this.

The penalty must reflect both the immediate degradation costs of reducing power output and the long-term revenue loss associated with shortening the turbine's operational lifespan. For instance, if deep curtailment occurs during high wind speeds and rough sea conditions, the impact on structural degradation will be significant. Over time, frequent deep curtailment could lead to a shorter operational lifespan for the wind farm or the loss of potential lifetime extension opportunities. However, quantifying these future losses and translating them into fair pricing mechanisms is complex.

Implementing a dynamic curtailment limit

A more flexible alternative is introducing a dynamic curtailment limit based on wind speed and wave height. This would allow the wind farm owner to protect critical components during periods of high loads while giving the dispatcher more flexibility to adjust power output when the structural impact is minimal.

Periods of strong winds combined with high waves pose a significant risk to turbine foundations if aerodynamic damping is reduced due to curtailment, accelerating structural degradation. In such conditions, a dynamic curtailment limit would restrict deep curtailment to ensure the turbine maintains a minimum power output to dampen the loads. Conversely, during periods of solar-driven negative price events, when wind conditions are mild and wave conditions less extreme, the impact of curtailment on the foundation is minimal. In these scenarios, the dispatcher could further reduce power output beyond the standard curtailment threshold without negatively affecting the health state of the turbine.

While these practical price incentives present viable alternatives to the centralised coordinated framework, their applicability depends on the different contract designs. The next section will explore the broader limitations of the proposed model.

9.3. Uncertainty within study

When interpreting the results of this study, it is important to consider the inherent uncertainties that arise from the necessary modelling simplifications. While the model gives a sufficient representation of OWT degradation and electricity market dynamics to be able to answer the research question, the model contains an inevitable degree of abstraction. To balance computational feasibility with real-world applicability, certain assumptions were made, which should be considered when evaluating the outcomes.

Even though the degradation functions are based on important relationships between environmental conditions and loads experienced by the components, they are simplified functions. The degradation functions used in this study represent a high-level approximation of real-world wear and tear, and while they are sufficient for comparative scenario analysis, they may not fully reflect the actual physical and operational conditions that turbines experience over their lifetime.

Another simplification relates to the use of economic data in the model. To ensure the research remains open-source and broadly applicable, no real-world financial data from stakeholders was included. Instead, generalised economic performance metrics are determined via the calculations in Section 5.4. These values provide meaningful insights in a relative comparison between different curtailment strategies but should not be interpreted as exact financial indicators of coordination value or PPA price reduction. Furthermore, this study assumes deterministic electricity prices. In reality, future prices are uncertain, but electricity price forecasting is outside the scope of this research. To evaluate the electricity price sensitivity of the model, three different pricing scenarios, representing a high, low and static price trend, were included in the analysis, as detailed in Section 8.3.2. Despite this variation, the model does not capture the unpredictable nature of stochastic electricity markets.

A similar degree of uncertainty exists in the modelling of environmental conditions. The model assumes wind speed, precipitation, and wave height will remain consistent with 2023 data for the entire operational period of the turbines. In reality, these variables will fluctuate every year and are influenced by climate change. Climate change introduces another layer of uncertainty, as the frequency and severity of extreme weather events, such as storms and conditions, are likely to increase over time [128]. These extreme conditions, occurring once in 50 to 100 years, are not accounted for in this study. These are rare events that have minimal financial impact over the lifespan of a project, although they do affect extreme load conditions. The greater uncertainty lies in structural shifts in weather patterns, such as the conditions experienced during last winter's Dunkelflaute. This typical winter weather phenomenon, characterised by calm winds and minimal solar radiation, led to energy shortages, high electricity imports, and elevated electricity prices [129, 130].

Besides parameter assumptions, the shape of this research is also shaped by practical computational limitations. Given the computational expansiveness of optimising offshore wind dispatch strategies for a 30-year operational lifetime, a reduced dataset was used to reduce run-time (reduction from multiple hours to minutes). While this dataset was carefully selected to ensure it includes a reasonable number of negative price hours and a representative range of electricity price variations and environmental conditions, a more extensive dataset incorporating long-term forecasting could have provided a more refined estimate of the economic and operational implications of curtailment. Similarly, the decentralised approach was tested using a smaller subset of data (11 time steps) due to the computational intensity of solving large-scale decentralised problems. While this was sufficient to assess whether decentralised coordination could theoretically converge to outcomes comparable to centralised strategies, further research involving a larger dataset would be required to evaluate the scalability of this approach in practice.

In addition to computational constraints, the model assumes that offshore wind is dispatched exclusively through the day-ahead electricity market. In reality, offshore wind assets participate in multiple revenue-generating markets, including the intraday and balancing markets [32, 44]. Since these markets are interconnected, excluding intraday and balancing mechanisms may lead to an underestimation of offshore wind's economic potential. A more comprehensive evaluation incorporating these additional market dynamics would provide a more holistic understanding of offshore wind's financial viability. The model's scalability to other markets is expected to remain relatively straightforward as power dispatch and curtailment follow similar operational processes across different market structures.

Finally, the study does not account for certain operational costs associated with the maintenance of components beyond component replacement costs. Only the CapEx for component replacements were included in the analysis, while OpEx costs, such as transportation to the site, labour costs and other logistical expenses, were excluded. However, these costs can be significant and, in some cases, may be comparable to or even exceed the direct costs of component replacement [101]. Therefore, the study underestimates the full economic impact of increased maintenance requirements due to curtailment. As this work involves a comparison of different scenarios, the exact financial values are not of primary importance, rather, the focus is on relative differences. Consequently, this assumption is justified within the context of this research, as including all associated costs would introduce unnecessary complexity and uncertainty in cost estimations.

These limitations introduce some degree of uncertainty, however, they do not undermine the validity of the study's findings. Rather, they propose opportunities for further research. Addressing these areas in future studies would improve curtailment optimisation strategies and provide a better understanding of the long-term trade-off between financial performance and asset longevity. The next section builds upon these limitations to offer recommendations for improving the integrated dispatch strategies within offshore wind.

9.4. Recommendations

Further research is needed to enhance the practical applicability, scalability, and long-term economic feasibility of these strategies. This section outlines recommendations for future research, focusing on improving optimisation models, refining degradation of components, extending investment and replacement costs, and analysing market-wide implications.

Scaling and implementing decentralised dispatch strategies

The study has demonstrated, for the first time, the feasibility of using ADMM for decentralised optimisation on dispatch strategies involving multiple stakeholders, including the dispatcher, maintenance party and wind farm owner. However, further research should explore whether the model can be scaled to larger datasets, spanning electricity prices and environmental conditions over extended periods of time. Scaling the decentralised framework would allow for a more robust conclusion regarding the applicability of decentralised optimisation. Furthermore, scaling has the potential to produce exact results more accurately.

While the model demonstrates a promising theoretical foundation for applying decentralised optimisation to dispatch strategies for an example set, its practical implementation is outside the scope of this study. Further research should explore how decentralised optimisation could function in real-world operations by conducting case studies. These studies could examine whether decentralised coordination indeed fosters better collaboration between stakeholders, resulting in more economically viable dispatch strategies that internalise turbine longevity while maximising revenue in the day-ahead market.

Refining degradation values

The model constructed in this work integrates the most important relationships between environmental conditions and component degradation, serving as a foundation for analysing the potential of incorporating degradation into dispatch strategies. However, more exact methods exist for determining the degradation of components under various curtailment strategies. The model can be expanded using empirical data from operational offshore wind farms. As modern turbines are equipped with measuring instruments to monitor actual load cases on the foundation, this data can be utilised to enhance the accuracy of degradation predictions [92]. One promising approach is the use of structural health monitoring (SHM) data or Supervisory Control And Data Acquisition (SCADA) data, both of which are widely adopted for monitoring wind turbine conditions [58, 131]. These datasets could provide more detailed insights into how different environmental conditions affect component longevity.

This research assumes a 20% curtailment threshold, but this is a fixed value which may not be optimal across all environmental conditions. Future research should examine how advanced aerodynamic and hydrodynamic models can refine the determination of an optimal minimum set point for power dispatch. While a 20% curtailment limit is commonly applied, further research could introduce more differentiations based on varying environmental conditions. This distinction could improve the use of curtailment to extend the lifetime of components. It is assumed that operating below 20% of the theoretical power output introduces additional stress on the foundation. However, curtailing power above this threshold may be beneficial for components that degrade due to high production, as observed in this study for the gearbox and blades.

Additionally, the loss of aerodynamic damping is particularly harmful when wave periods coincide with the turbine's natural frequency, as this results in resonance effects amplifying the structural loads. This issue is relevant for monopile turbines in the range of 10-20 MW, where resonance effects pose a significant challenge [92]. For smaller turbines or alternative foundation types, the impact may be different. Therefore, in addition to environmental factors, future research could also consider the influence of turbine size and foundation technology when refining degradation models.

Extending component costs calculations

This work considers investment and replacement costs, giving an economic value to the degradation of components. It is recommended to include additional costs related to dispatch strategies in future research. For example, by integrating transport, labour, and other operational costs, which are required to replace the components or reinforce them. This could increase the accuracy of determining the value of integrating asset health into the dispatch strategy.

The study successfully integrates component health considerations with market-driven revenue optimisation, demonstrating that integrating asset health into dispatch strategies can enhance the profitability of offshore wind farms by extending the lifespan of critical components. Another dimension to consider is the trade-off between short-term financial gains and long-term costs. This includes weighing higher upfront investment against the potential for an extended operational lifespan. Since capital investments depreciate over time, strengthening wind turbine foundations to accommodate more frequent curtailment could become more financially viable if it extends the operational years of the wind farm. Future studies should quantify this trade-off to provide clearer guidance on long-term investment decisions, especially when balancing definite costs against uncertain benefits.

Analysing market-wide implications

Currently, the model focuses on optimising the dispatch strategy of a single turbine. However, its principles could be extended to assess the collective impact of adjusting dispatch strategies across an entire electricity market. While the bid strategy of a single 1 GW wind farm may not significantly influence electricity market prices in the Benelux region, incorporating marginal wear-and-tear costs into bidding strategies across multiple wind farms could affect market dynamics. Such an approach would provide deeper insights into how the widespread adoption of cost-reflective bidding could shape the financial viability of offshore wind farms. Future research should integrate findings from this study into long-term electricity price forecasting models to examine the broader economic implications of the proposed decision framework.

9.5. A realistic path to implementation

While fully optimised solutions offer the greatest theoretical benefit, practical implementation does not require full adoption at once.

A pragmatic first step is the integration of a simplified assessment of the marginal cost of curtailment into the existing bidding strategy. This allows dispatchers to incorporate asset health considerations and compensates owners for additional fatigue or resulting OpEx. The responsibility for calculating and negotiating how the costs and benefits of an integrated curtailment strategy should be distributed lies primarily with the wind farm owner.

Since the wind farm owner is already responsible for contractual agreements and asset management, it is a practical and logical choice for them to take the lead in curtailment negotiations. This aligns with economic theory, which predicts that optimal solutions are more likely when the entity that legally owns the asset also bears the residual financial risks and rewards [132]. The findings in this study show that the benefits of integrating asset health into the curtailment strategy primarily go to the wind farm owner, as outlined in Chapter 7. Therefore, it is the owner's responsibility to incentivise other stakeholders, such as dispatchers and maintenance teams, to adopt strategies that support long-term turbine health. As this study shows, the owner has a budget to activate that responsibility. In this case, the wind farm owner, who ultimately benefits from an extended turbine lifespan, should be the key stakeholder in structuring financial incentives that align curtailment decisions with long-term asset sustainability.

Additionally, wind farm developers play an important role in ensuring market-driven curtailment is accounted for in turbine design. Rather than prioritising short-term reductions during the development phase, developers must consider the expected curtailment trends over the turbine's lifetime and adjust the design specifications accordingly. This could be reflected in adjusted terms in the PPA. A combination of these practical price incentives to integrate asset health in curtailment strategies has the potential to enhance the long-term value of offshore wind power.

10 Conclusion

The objective of this research is to identify how curtailment strategies could be improved to increase the value of offshore wind power. This requires a coordinated curtailment strategy that internalises turbine longevity while maximising revenue in the day-ahead market. To achieve this, an optimisation model was developed. Chapter 4 introduced the complexity of quantifying degradation due to market-driven curtailment for offshore wind turbines (OWTs). OWTs are subject to a combination of aerodynamic and hydrodynamic loads, as detailed in Section 4.2, both of which impact the support structure (foundation and tower). In addition to assessing the degradation of the support structure, in Section 4.3, two other critical components were selected: the gearbox and the blades, which are the replaceable components. Based on the relation between parameters influencing the components, combined with expert interviews, degradation functions were established. These have proven to sufficiently represent the relation between environmental factors and component degradation in Section 8.2.2. If dispatchers, wind farm owners or maintenance parties would want to improve the accuracy of the degradation, more extensive simulation models can be used as discussed in Section 9.4. Together with the stakeholder perspectives, of which the foundation lies in Section 5, a centralised coordination framework is developed, which is formulated mathematically in Section 6.4.1.

As the health of the critical components has not been formulated before in an optimisation model, three different strategies are formulated in Section 6.3. The first strategy consists of a linear optimisation method, which assumes linear degradation of the state of health factor, representing the remaining useful life of the component, over time until it reaches the failure threshold. In practice, the component should be replaced if the state of the health factor is below the failure threshold. Unfortunately, the linear model does not allow for replacement. Therefore, a second strategy is investigated by formulating a mixed integer optimisation, which includes a binary replacement variable. As this increases, the computational complexity and the ability to calculate shadow prices are lost, which can be helpful in the sensitivity analysis. Therefore, a third optimisation method is formulated. This is a non-linear penalty formulation in which continuous replacement variables are introduced, which effectively behave as binary variables due to a penalty function. The linear optimisation method is selected due to its scalability and computational efficiency, which are essential when developing an optimisation framework which handles long-term decision-making and large-scale problems. This linear formulation, together with the baseline formulation in Section 6.2, forms the basis of the centralised coordinated strategy.

The centralised coordination strategy could yield significant value in certain contract structures, for instance, when a single organisation is responsible for the dispatching, maintenance, development, and ownership of the wind farm. However, this might not be beneficial under other contract structures, as the centralised coordination strategy benefits the owner and maintenance party but disadvantages the dispatcher. Collaborating parties would be hesitant to share sensitive data and company trade secrets or know-how, fearing it could backfire via contractual obligations. Therefore, a decentralised optimisation framework is formulated, which is specified in Section 6.4.2. The research aimed to provide insights into the value of integrating asset health into curtailment strategies. This chapter presents conclusions on the comparison of the baseline situation, the centralised coordinated framework and the potential of using decentralised coordination. The comparison is done based on the impact on component longevity, economic performance of the stakeholders and system-wide profitability. First, 10.1 presents conclusions on the sub research question. Second, the conclusions are combined to answer the main research question in 10.2.

10.1. Sub-conclusions

1. *What effect does curtailment have on the degradation of critical offshore wind turbine (OWT) components?*

   Curtailment directly influences the wear and tear of OWTs by altering the aerodynamic and hydrodynamic loads they endure. Section 4.2 details the highly interconnected and complex relation between wind and wave-induced loads. The study identifies three critical components affected by curtailment: the gearbox, the blades, and the support structure, as explained in Section 4.3.

   The support structure, composed of the tower and foundation, is particularly sensitive to aerodynamic damping effects. During operation, rotor-induced aerodynamic damping stabilises the structure against oscillations caused by wind and waves. However, curtailment can reduce this damping effect, accelerating structural fatigue. As a non-replaceable component, the support structure constrains the turbine's lifespan, limiting opportunities for lifetime extension. Furthermore, wind farm developers often prioritise minimising steel costs to reduce the Levelised Cost of Energy (LCOE), which can result in a design that is less capable of withstanding significant loads, especially during curtailment. Consequently, the support structure is more prone to long-term degradation, particularly when wave frequencies align with its natural resonance.

   The gearbox undergoes variable loading conditions due to fluctuations in rotor speed and power output. As a replaceable component, it is designed with the expectation to be replaced once over the turbine's lifetime. However, because gearbox failures often result in significant downtime, extending its operational lifespan is desirable. While abrupt load variations can accelerate wear, moderate curtailment above 20% of rated power may help mitigate this by reducing torque fluctuations. Conversely, extensive curtailment at very low power outputs can introduce unstable loading patterns, increasing stress on the component and potentially accelerating degradation.

   Blades degrade due to aerodynamic load and environmental exposure. Leading-edge erosion (LEE) can potentially accelerate by high tip speeds during periods of rain. Curtailment could mitigate this degradation by lowering the blade tip speed, thereby reducing the impact velocity of rain droplets. This suggests an erosion safe operating mode which could extend blade lifespan. Blade replacement is a calculated decision, as during the design, blade replacement is not necessarily accounted for, but it is possible.

   To estimate the impact of curtailment on component wear, simplified degradation functions are developed based on the relation of degradation with thrust, environmental conditions, and an efficiency factor as outlined in Section 4.5.

2. *What are the objectives of different stakeholders (dispatchers, maintenance party, and wind farm owners) regarding curtailment strategies?*

   The objectives of dispatchers, maintenance parties and wind farm owners are shaped by operational, financial, and regulatory considerations. Their differing priorities often lead to conflicting interests regarding decision-making in curtailment strategies.

   Firstly, dispatchers prioritise short-term market optimisation, aiming to maximise profit in the day-ahead electricity market. Decision-making is constrained by PPAs, strike prices and subsidy conditions, which vary across assets, as detailed in Section 5.1. While reducing output during negative price events is financially attractive, dispatchers must often adhere to contractual minimum power output requirements. These minimum power output requirements are proposed by turbine manufacturers and/or foundation designers, depending on the design of the turbine, and do not take into account occurring environmental conditions.

Secondly, manufacturers are often responsible for the maintenance during the service contract period, typically 15 years, of the wind farm. The maintenance parties focus on asset availability and cost-efficient operations. They are responsible for ensuring the turbine remains functional within the availability guarantees, often requiring uptime of at least 95%. From their perspective, curtailment strategies must consider the impact on replaceable components, such as the gearbox and blades, to prevent excessive wear and associated maintenance costs.

Thirdly, wind farm owners take a long-term financial perspective, as they are responsible for the overall profitability and lifecycle costs of the asset, which spans 25-35 years for upcoming wind farms. Their primary objective is to maximise turbine longevity. Unlike dispatchers, who focus on immediate market gains, owners must consider long-term degradation costs for non-replaceable components like the support structure and replaceable components such as the gearbox and blades.

The economic performance of each stakeholder is analysed in Section 5.4. The current curtailment strategy remains fragmented, as dispatchers make decisions purely based on market signals, while maintenance teams and wind farm owners focus on physical longevity. This misalignment leads to inefficiencies: dispatchers incur financial losses due to curtailment limits, while owners bear increased costs for reinforcement and component replacements.

To optimise curtailment strategies, improved coordination between stakeholders is essential. Integrating economic incentives with asset health considerations could mitigate financial risks, reduce unnecessary wear on components, and improve the overall efficiency and profitability of offshore wind farms.

3. *How can the degradation of asset health be formulated in an optimisation problem?*

   To enable the integration of asset health into curtailment decision-making, this work introduced a state of health variable. This represents the remaining useful lifetime (RUL) of critical OWT components. The state of the health variable degrades based on the previously defined degradation functions, as detailed in Section 4.5. This variable allows for the formulation of a coordinated centralised framework, which internalises turbine longevity by formulating asset health constraints, while simultaneously optimising revenue in the day-ahead market within the objective function.

   Three optimisation methods are presented and compared based on a trade-off between computational efficiency and model accuracy, namely, a linear programming problem (LP) without replacement, a mixed-integer programming (MILP) problem with replacement, and a non-linear programming (NLP) problem with a penalty function which resembles replacement. .

   The LP formulation introduces a continuous state of health variables to track component degradation over time but does not explicitly model replacement decisions. While computationally efficient, this approach simplifies asset health as it does not allow for replacement, limiting its practical applicability in long-term operational planning. However, it enables the calculations of shadow prices, which provide insights into the sensitivity of constraints, making it useful for understanding degradation cost implications.

   A MILP problem is formulated which extends the LP model by introducing binary replacement variables, enabling explicit replacement decisions. This improves the accuracy of the model by allowing the model to restore the state of health when a failure threshold is reached. However, this approach significantly increases computational complexity which makes it less scalable for large-scale optimisation.

   To balance computational efficiency and accuracy a NLP formulation was introduced using a penalty function to approximate binary replacement decisions. This method avoids the full computational burden of MILP while still capturing replacement behaviour. However, tuning the penalty too small may allow intermediate replacement values (which are not physically meaningful), while a too large penalty may distort optimisation results.

   Given the trade-off between computational feasibility and accuracy, the LP formulation including a continuous state of health variable was selected. This approach maintains computational efficiency while incorporating asset health considerations for the first time in curtailment strategies.

4. *Can a global consensus framework, such as ADMM, be utilised to achieve coordination decision-making in a decentralised curtailment strategy?*

   The results of this research set out both the potential and the limitations of using a global consensus framework, specifically the Alternating Direction Method of Multipliers (ADMM), to coordinate decision-making in a decentralised curtailment strategy [3]. The general underlying framework proposed by Boyd [3] is explained in Section 3.3.3.

   It can be concluded that a fully centralised coordination framework can offer theoretically improved outcomes by integrating all stakeholder objectives into a unified curtailment strategy. However, its implementation faces several practical constraints. This centralised coordination could yield significant value in contract structures where one organisation is responsible for the dispatching, maintenance, development, and ownership of the wind farm. The main challenge is its implementation within the often complex contractual structures of offshore wind projects, involving multiple independent stakeholders with differing financial and operational incentives. The reluctance to share sensitive data, such as trading strategies and asset degradation reports, creates barriers to full transparency. Additionally, the centralised approach leads to an uneven distribution of financial benefits, where dispatchers face profit reductions while wind farm owners benefit from prolonged asset health, as shown in Section 7.1. Without appropriate incentive structures, centralised coordination may not be feasible in real-world applications.

   This research presents the first application of ADMM to optimise curtailment strategies that internalise long-term asset health while maximising the financial performance of wind power. Unlike a centralised framework, decentralisation enables each stakeholder to optimise their objectives independently while iteratively refining their decisions based on shared information. The results in Section 7.2 show that, with a reduced dataset of 11 time steps, the decentralised framework successfully converged to an outcome closely approximating the benefits of the centralised strategy. The power dispatch profiles, degradation functions, and financial performance of the decentralised approach are closely aligned with those of the centralised framework, demonstrating that decentralised coordination can deliver comparable system-wide benefits without requiring full transparency.

   However, decentralised optimisation introduces computational challenges, particularly due to intertemporal constrains, as discussed in Section 9.3. The scalability of the approach is a critical concern, as the computational complexity of solving interconnected time steps grows exponentially with larger datasets. While this study offers a theoretical proof of concept, further research is needed to validate the framework's scalability and applicability in real-world projects. This includes testing ADMM with long-term market data, varied environmental inputs, and assessing its potential to enhance stakeholder collaboration in practice.

   In conclusion, although centralised coordination remains the ideal benchmark, decentralised frameworks such as ADMM present a promising alternative for optimising curtailment strategies in offshore wind power. This research has demonstrated that, under specific conditions, decentralised decision-making can approximate the benefits of centralised optimisation while maintaining stakeholder autonomy. However, further refinement is necessary to enhance its practical applicability.

10.2. Main conclusion

The study was guided by the following central research question:

To what extent can integrating asset health improve the value of offshore wind power generation through coordinated curtailment strategies?

The findings in this work indicate that the current curtailment approach is suboptimal, as reinforcement costs for non-replaceable components and replacement costs for replaceable components are disproportionately high relative to system-wide profits. This demonstrates that the existing curtailment strategy is not financially viable in the long term, considering expected market developments with increasing offshore wind energy capacity and trends in frequency and magnitude of negative price hours. By incorporating asset health considerations into curtailment decision-making and aligning the perspectives of dispatchers, maintenance teams, and wind farm owners, the value of wind power can be significantly enhanced. The results show a 57% reduction in investment costs, and a 439% increase in system-wide profit, reflecting a notable increase from 0.38 M€ to 2.06 M€. The return on investment (ROI) also increases sharply from 5.82% in the base case to 73.31% in the centralised scenario, representing a gain of 67.49 percentage points, clearly demonstrating the considerable added value of coordination. Strategic curtailment has the potential to extend component lifespans, possibly delaying expensive replacements and lowering maintenance costs.

While a centralised coordination strategy can yield substantial benefits, its feasibility depends on contractual structures. In fragmented ownership models, concerns over data-sharing and operational autonomy may hinder full implementation. A decentralised coordination strategy, as explored in this study, offers a theoretically viable alternative, although further research is needed to assess its practical scalability.

It is important to acknowledge that implementing a fully optimised solution is not a requirement for realising operational improvements. A pragmatic approach, via integrating a simplified assessment of the marginal cost of curtailment into the existing bidding strategy, could already prove to be rewarding. Additionally, wind farm developers should account for market-driven curtailment when designing OWTs to prioritise long-term financial sustainability over short-term material cost reductions. This could be reflected in adjusted terms in the Power Purchase Agreement (PPA). A combination of these practical price incentives to integrate asset health in curtailment strategies has the potential to enhance the long-term value of offshore wind power.

Looking forward, centralised coordination shows the greatest benefit in electricity markets characterised by negative price hours and greater price volatility. As the share of variable renewable energy sources (vRES) continues to grow, these conditions are likely to become more common, strengthening the case for coordinated curtailment. Internalising asset health will become increasingly valuable in future energy systems.

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A
Interviews

This section provides an overview of the interviewees, including their function, the company they work for and their relevance to this research:

- **Interviewee 1 [44]**: Package Manager at Eneco, involved in curtailment decisions from a trading perspective and strike price determination.
- **Mariëlle Corsten [67]**: Relationship Manager Curtailment at Eneco, involved in curtailment agreements within PPAs.
- **Interviewee 2 [92]**: Package Manager Foundations, focusing on the structural implications of curtailment.
- **Lauren Rabaey [110]**: Senior WTG Asset Manager for Blauwwind, providing insights into curtailment impact on turbine components and replacement costs.
- **Interviewee 3 [111]**: Technical Director at Norther, with extensive knowledge of offshore wind farm construction, commissioning, and operation.
- **Interviewee 4 [116]**: O&M Package Manager Offshore Wind at Eneco, responsible for operational aspects of offshore wind farms.
- **Julian Visser [118]**: Fundamental Analyst at Eneco, specialising in long-term electricity price forecasting and merit order assumptions.
- **Interviewee 5 [133]**: Asset Analyst with experience in offshore wind projects, particularly in O&M strategies.
- **Interviewee 6 [134]**: Offshore Wind Engineer at 24Sea, specialising in Structural Health Monitoring (SHM) for offshore wind turbines.
- **Interviewee 7 [135]**: Onshore Wind Turbine Expert, working on curtailment strategies and their impact on turbine lifetime.
- **Interviewee 8 [136]**: Researcher and industry expert on wind energy integration in electricity markets.

Table A.1 provides an overview of the interviewees, the corresponding dates and discussed topics.

Table A.1: Interview topics

Name	Date	Specific Topics
Interviewee 1 [44]	09-2024	Curtailment strategies from the dispatcher perspective, strike price calculations, offshore wind as flexible asset
Mariëlle Corsten [67]	11-2024	Curtailment schedule, PPA, specific agreements on curtail-ment
Interviewee 2 [92]	12-2024	Impact of curtailment on the support structure
Lauren Rabaey [110]	11-2024	Curtailment impact on turbine wear, major failure mecha-nisms
Interviewee 3 [111]	01-2025	Curtailment effects on offshore foundations (for windfarm Norhter specifically), wind farm owner perspective
Interviewee 4 & 5 [116]	09-2024	O&M contracts (with a focus on curtailment agreements), curtailment impact on components, assumptions in design lifetime of components
Julian Visser [118]	09-2024	Long-term price forecasts, negative price trends, merit-order assumptions
Interviewee 6 [134]	01-2025	Structural Health Monitoring (SHM), fatigue loads, design adjustments for curtailment
Interviewee 7 [135]	09-2024	Onshore wind curtailment strategies, environmental and economic stops
Interviewee 8 [136]	10-2024	Market integration of wind energy, price trends, flexibility expansion

B

Data collection

This section provides detailed information on the data collection. First, it includes the final degradation parameters used within the simulations, explains how these parameters were adjusted to fit different simulation periods, and presents the test dataset.

B.1. Degradation parameters used in the simulation

The final values for degradation parameters are set at:

$$
\begin{aligned}
a_{\text{gbx}} &= 4.8 \times 10^{-6}, \\
a_{\text{ss}} &= 3.094 \times 10^{-7}, \\
c_{\text{damping}} &= 2.8125 \times 10^{-7}, \\
b_{\text{wave}} &= 3.094 \times 10^{-7}, \\
a_{\text{bld}} &= 4.8 \times 10^{-8}, \\
b_{\text{rain}} &= 4.8 \times 10^{-8}, \\
S_{\text{min}} &= 0.2.
\end{aligned}
$$

Where:

- S_{min} is the minimum permissible health factor for each component, below which replacement or reinforcement is required.

B.2. Degradation parameter adjustment

To incorporate long-term degradation rates accurately into the optimisation model, parameters were adjusted according to the simulation's timescale. The following scaling equation was applied:

$$
\text{parameter}_{T=8,640} = \left(\frac{8,640}{30 * 8,760} \right) \times \text{parameter}_{T=30*8,760} \tag{B.1}
$$

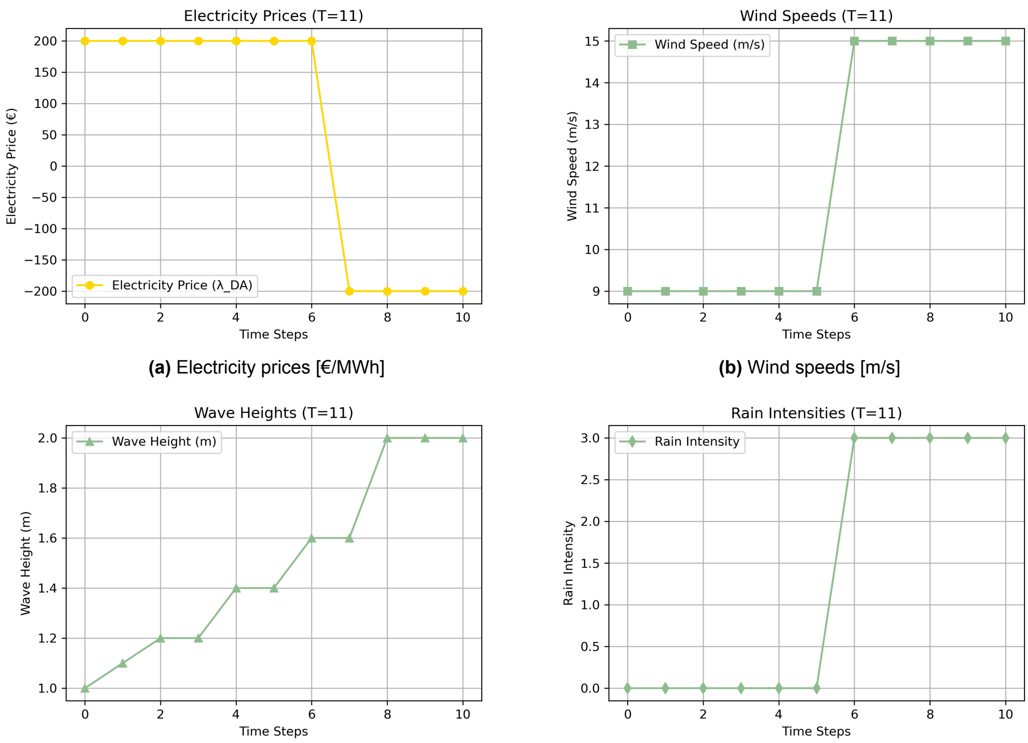
This conversion aligns the degradation parameters with a timescale of 8,640 hours (equivalent to one year of hourly resolution), making them suitable for use within the optimisation model. The same logic applies when adjusting the parameters to any other chosen timescale T.

B.3. Test dataset: $T = 11$

To be able to compare the decentralised curtailment strategy with the centralised, a test data set is used. Therefore the degradation and cost parameters were adjusted using Equation B.1. The final parameter values are listed below.

$$\begin{aligned}
a_{\text{gbx}} &= 2.007 \times 10^{-2}, \\
a_{\text{ss}} &= 1.296 \times 10^{-3}, \\
c_{\text{damping}} &= 1.178 \times 10^{-3}, \\
b_{\text{wave}} &= 1.296 \times 10^{-3}, \\
a_{\text{bld}} &= 2.007 \times 10^{-5}, \\
b_{\text{rain}} &= 2.007 \times 10^{-5}, \\
S_{\text{min}} &= 0.2, \\
S_{\text{max}} &= 1.0, \\
C^{\text{gbx}} &= €2.000 \times 10^{3}, \\
C^{\text{ss}} &= €3.000 \times 10^{4}, \\
C^{\text{bld}} &= €2.000 \times 10^{3},
\end{aligned}$$

Figure B.1 illustrates the environmental and market conditions used as inputs for the test case with a time horizon of $T = 11$ time steps.



(a) Electricity prices [€/MWh]

(b) Wind speeds [m/s]

(c) Significant wave heights [m]

(d) Rain intensities [mm/h]

Figure B.1: Input parameters used in the example dataset: electricity prices (yellow) and environmental conditions (green).

C

Extended results

This section details any additional information supporting the results chapter. First the calculation of the system-wide financial metrics is given in Section C.1. Secondly an extensive overview of the financial metrics comparing the current situation with the centralised approach is presented in Section C.2.

C.1. Global economic performance calculations

The profit on the system level is calculated using the following equation:

$$\text{Netto profit} = \text{Revenue dispatcher} - \text{Total investment costs} \tag{C.1}$$

$$\text{Netto profit} = \sum_{t\in T} \left(\lambda_t^{\text{DA}} \cdot P_t^{\text{DA}}\right) - C^{\text{ss}} \cdot \left(1 - S_T^{\text{ss}}\right) - C^{\text{gbx}} \cdot \left(1 - S_T^{\text{gbx}}\right) - C^{\text{bld}} \cdot \left(1 - S_T^{\text{bld}}\right) \tag{C.2}$$

C.2. Comparison of the base case and centralised approach

Table C.1: Comparison of financial metrics between current situation and centralised coordination, values in million euros [M€]. red indicates a detrimental change, while green indicates a beneficial change.

		Base case scenario [M€]	**Centralised coordinated [M€]**
Dispatcher	Revenue	6.91	4.87 (-30%)
	Costs	6.67	6.67 (0%)
	Profit	0.25	-1.80 (-820%)
Maintenance Party	Revenue	6.53	2.21 (-66%)
	Blade costs	3.37	0.58 (-77%)
	Gearbox costs	2.07	1.07 (-48%)
	Total costs	5.44	1.84 (-66%)
	Profit	1.09	0.37 (-66%)
Owner	Revenue	6.67	6.67 (0%)
	Support structure costs	1.09	0.97 (-11%)
	Total costs	7.62	3.18 (-58%)
	Profit	-0.95	3.49 (467%)
Global	Investment costs	6.53	2.81 (-57%)
	Profit	0.38	2.06 (439%)
	ROI	**5.82 %**	**73.31 %**

D

Replacement decisions

This section provides a detailed overview of the replacement decision strategies available to a wind farm owner when critical components approach the end of their operational life. In Section D.1, the three strategies used in the study are presented. Section D.2 then explains the methodology used for discounting electricity prices over time and presents the financial performance metrics without discounting for reference.

Note: The figures included in this chapter are digitally edited illustrations intended to visually compare the expected evolution of component health under each scenario. They are not direct outputs from the optimisation model.

The following financial performance calculations will describe the revenue and cost calculations for each of the scenarios. In these equations, the following notation is used:

- T denotes the full time horizon.
- λ_t^{DA} is the day-ahead electricity price at time t.
- P_t^{DA} and P_t^{Th} are the power sold in the day-ahead market and the theoretical power, respectively.
- C^{m} is the total replacement (or reinforcement) cost for component m (gbx for gearbox, bld for blades, ss for support structure).
- $C^{\mathsf{m}}_{T^{\mathsf{m}}_{\mathsf{fail}}}$ is the one-time replacement cost incurred at the failure time $T^{\mathsf{m}}_{\mathsf{fail}}$ for component m.
- S_t^{m} is the state of health of component m at time t and $S_{\min}$ is the failure threshold.

D.1. Replacement scenarios

This section explores three replacement strategies, each representing a different approach to managing component degradation and failure. These scenarios illustrate the trade-off between extending operational life or minimising replacement costs:

1. **No replacement:** In this scenario, no component is replaced. The turbine is decommissioned as soon as the gearbox fails.
2. **Gearbox replacement:** Here, the gearbox is replaced upon failure to extend operation, however, if the blades reach their end-of-life, no replacement is performed, and the turbine is stopped.
3. **Selective replacement:** In this strategy, both the gearbox and the blades are replaced once at their initial failure events, but no further (second) replacements are carried out. This approach aims to extend the turbine's operational life.

Scenario 1: No replacement

Figure D.1: Health evolution for the no replacement scenario.

Figure D.1 illustrates the scenario where the turbine is decommissioned immediately upon gearbox failure. The curve shows that once the gearbox health reaches the failure threshold ($S_{\min}$), the operation stops. This results in the following computation of the financial performance of the scenario:

$$\text{Revenue dispatcher} = \sum_{t=0}^{T_{\text{stop}}} \lambda_t^{\text{DA}} P_t^{\text{DA}} \tag{D.1}$$

$$\text{Cost dispatcher} = \text{Revenue owner} \ = \sum_{t=0}^{T_{\text{stop}}} \lambda^{\text{PPA}} P_t^{\text{Th}} \tag{D.2}$$

$$\text{Cost gearbox} = C^{\text{gbx}} \cdot \left(1 - S_{T_{\text{stop}}}^{\text{gbx}}\right) \tag{D.3}$$

$$\text{Cost blades} = C^{\text{bld}} \cdot \left(1 - S_{T_{\text{stop}}}^{\text{bld}}\right) \tag{D.4}$$

$$\text{Cost support structure} = C^{\text{ss}} \cdot \left(1 - S_{T_{\text{stop}}}^{\text{ss}}\right) \tag{D.5}$$

Where:

$$T_{\text{stop}} = T_{\text{fail}}^{\text{gbx}} \tag{D.6}$$

Subsequent profit and system-level performance equations are then defined as in Section 5.4, with the operational period ending at $T_{\text{fail}}^{\text{gbx}}$.

Scenario 2: Gearbox replacement

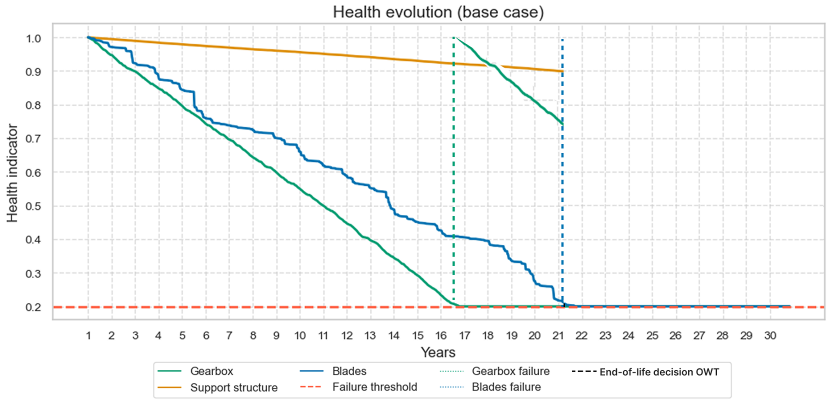


Figure D.2: Health evolution for the gearbox replacement scenario.

Figure D.2 shows the scenario where the gearbox is replaced upon failure, allowing the operation to continue. However, the turbine stops operating when the blades reach the failure threshold.

The financial performance is calculated over the period $t = 0, \ldots, T^{\text{bld}}_{\text{fail}}$:

$$\text{Revenue dispatcher} = \sum_{t=0}^{T_{\text{stop}}} \lambda_t^{\text{DA}} \, P_t^{\text{DA}} \tag{D.7}$$

$$\text{Cost dispatcher} = \text{Revenue owner } = \sum_{t=0}^{T_{\text{stop}}} \lambda^{\text{PPA}} \, P_t^{\text{Th}} \tag{D.8}$$

$$\text{Cost gearbox} = C^{\text{gbx}} + C^{\text{gbx}} \cdot \left(1 - S^{\text{gbx}}_{T_{\text{stop}}}\right) \tag{D.9}$$

$$\text{Cost blades} = C^{\text{bld}} \cdot \left(1 - S^{\text{bld}}_{T_{\text{stop}}}\right) \tag{D.10}$$

$$\text{Cost support structure} = C^{\text{ss}} \cdot \left(1 - S^{\text{ss}}_{T_{\text{stop}}}\right) \tag{D.11}$$

Where:

$$T_{\text{stop}} = T^{\text{bld}}_{\text{fail}} \tag{D.12}$$

Scenario 3: Selective replacement

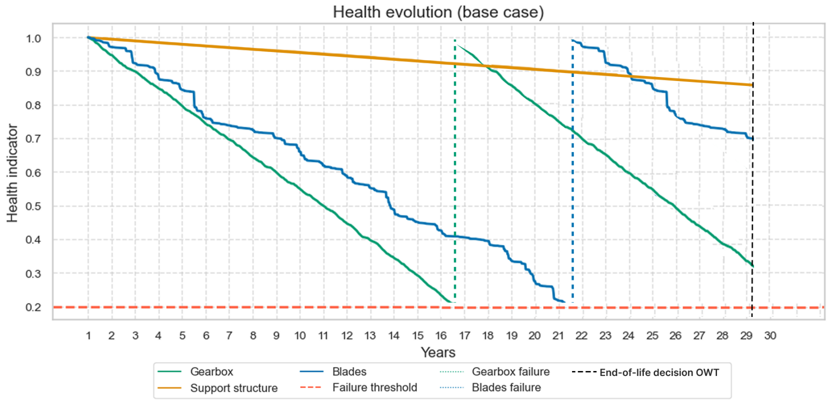


Figure D.3: Health evolution for the selective replacement scenario.

Figure D.3 represents the scenario where both the gearbox and blades are replaced at their initial failure events. No further (second) replacement of the gearbox is performed, which eventually leads to decommissioning as degradation continues.

The financial calculations are as follows:

$$\text{Revenue dispatcher} = \sum_{t=0}^{T_{\text{stop}}} \lambda_t^{\text{DA}} P_t^{\text{DA}} \tag{D.13}$$

$$\text{Cost dispatcher} = \text{Revenue owner} \ = \sum_{t=0}^{T_{\text{stop}}} \lambda^{\text{PPA}} P_t^{\text{Th}} \tag{D.14}$$

$$\text{Cost gearbox} = C^{\text{gbx}} + C^{\text{gbx}} \cdot \left(1 - S_{T_{\text{stop}}}^{\text{gbx}}\right) \tag{D.15}$$

$$\text{Cost blades} = C^{\text{bld}} + C^{\text{bld}} \cdot \left(1 - S_{T_{\text{stop}}}^{\text{bld}}\right) \tag{D.16}$$

$$\text{Cost support structure} = C^{\text{ss}} + C^{\text{ss}} \cdot \left(1 - S_{T_{\text{stop}}}^{\text{ss}}\right) \tag{D.17}$$

Discussion

The figures above illustrate the following main takeaways:

- In the **no replacement** scenario, the turbine's operation is halted immediately when the gearbox fails. This approach minimises ongoing maintenance costs but results in an abrupt end to power generation.
- Under the **partial replacement** strategy, replacing the gearbox can extend the operational life. However, once the blades fail, the turbine will be decommissioned, which limits the overall operational period.
- The **selective replacement** scenario provides a compromise by allowing one-time replacements of both the gearbox and blades. This strategy extends the turbine's life more than the partial replacement strategy but avoids the recurring high costs associated with multiple replacements.

D.2. Discounting of electricity prices

This section describes the methodology used to discount electricity prices over time, thereby accounting for the time value of money. Discounting adjusts future cash flows to their present value.

Computation

To account for the time value of money, a 2% annual discount rate is applied to the electricity prices. The process is as follows:

1. The simulation period is divided into 288 time steps per year. Each time step is assigned a year index by performing an integer division of the time step number by 288.
2. For each time step, the discount factor is calculated as:

$$\text{discount factor} = \frac{1}{(1+0.02)^{\text{year\_index}}}$$

3. The original electricity price (in EUR/MWhe) is multiplied by the discount factor to obtain its present value.

Results without discounted electricity prices

The following table presents the financial performance of the replacement strategies when the electricity prices are not discounted. This serves as a basis for comparison with the discounted case.

Table D.1: Financial performance of replacement strategies without discounted electricity prices (in M€ and time steps).

Category	Metric	Scenario 1: No replacement [M€]	Scenario 2: Partial replacement [M€]	Scenario 3: Selective replacement [M€]
Dispatcher	Revenue	3.76	5.02	6.91
	Cost	3.59	4.75	6.67
	Profit	0.17	0.27	0.25
Maintenance party	Blade costs	1.98	1.98	4.46
	Gearbox costs	1.07	2.40	2.40
	Profit	0.61	0.88	1.37
Owner	Support structure costs	1.09	0.76	1.09
	Profit	-1.16	-1.26	-2.65
Global	Investment costs	4.14	5.14	7.95
	Netto profit	-0.38	-0.12	-1.04
Operational lifetime	T_{stop} [time steps]	4553 (T_{fail}^{gbx})	5955 (T_{fail}^{bld})	8592

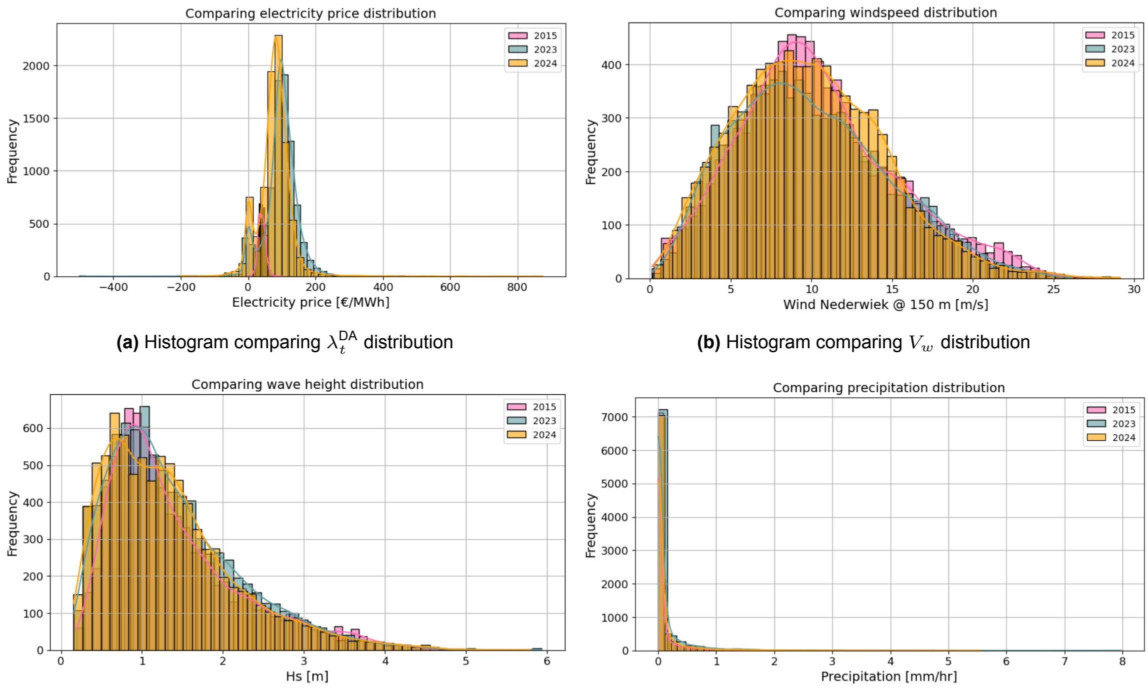
E

Verification

While the main report presents key findings for 2023, this section includes the full set of economic metrics and compares outcomes for the base years 2015, 2023, and 2024. First Section E.1 shows a visual comparison of the electricity prices and environmental data across the years 2015, 2023, and 2024. Next, Section E.2 outlines the methodology used to calculate percentage changes and ROI in the economic performance comparison. Finally, Section E.3 discusses the results of the sensitivity analysis, assessing the stability of the economic performance metrics across different base years.

E.1. Comparative distribution in electricity prices and environmental factors

A visual comparison of electricity prices and environmental data across the years 2015, 2023, and 2024 is shown in Figure E.1.



(a) Histogram comparing λ_t^{DA} distribution

(b) Histogram comparing V_w distribution

(c) Histogram comparing H_s distribution

(d) Histogram comparing I_{rain} distribution

Figure E.1: Comparison of data for different base years: 2015 (pink), 2023 (blue) and 2024 (orange) [87, 104]

- **2015**
  - Contains no negative electricity prices.
  - Exhibits lower peak prices, suggesting a less volatile market compared to 2023 and 2024.
  - Contains slightly more extreme wind gusts (>20 m/s).
- **2023**
  - Contains similar peak prices as 2024.
  - Exhibits greater volatility in the day-ahead market as there are more frequent price spikes > 200 €/MWh and a lower minimum price of -500 €/MWh.
- **2024**
  - Contains a higher occurrence of near-zero and negative prices, indicating a higher share of vRES.
  - A less negative minimum price compared to 2023, of -200 €/MWh and less frequent extreme price spikes compared to 2023.

E.2. Economic performance comparison across base years

This section presents an extensive comparison of economic performance metrics across the baseline and centralised scenarios for the base years 2015, 2023, and 2024. The percentage difference between centralised and baseline scenarios is calculated as:

$$\text{Percentage change} = \left(\frac{\text{Centralised value} - \text{Baseline value}}{\text{Baseline value}} \right) \times 100\% \tag{E.1}$$

The Return on Investment (ROI) on the system level is computed as [137]:

$$\text{ROI} = \left(\frac{\text{Netto profit}}{\text{Investment costs}} \right) \times 100\% \tag{E.2}$$

Table E.1 provides absolute values (in million euros) for revenue, costs, profit, investment, and Return on Investment (ROI) across different base years (2015, 2023, and 2024).

Table E.1: Comparison of economic metrics: Baseline vs. centralised scenarios. Colour coding emphasises the performance: red indicates cost increases, profit decreases, or negative ROI; green indicates cost reductions, profit increases, or positive ROI.

Category	2015 [M€]		2023 [M€]		2024 [M€]	
	Baseline	Centralised	Baseline	Centralised	Baseline	Centralised
Dispatcher						
Revenue	3.24	1.81 (-44%)	6.91	4.87 (-30%)	5.57	3.91 (-30%)
Profit	-3.8	-5.23 (-38%)	0.25	-1.8 (-820%)	-1.18	-2.84 (-141%)
Maintenance Party						
Blade Costs	3.37	0.51 (-85%)	3.37	0.78 (-77%)	3.37	0.68 (-80%)
Gearbox Costs	2.07	0.88 (-57%)	2.07	1.07 (-48%)	2.07	1.07 (-48%)
Total Costs	5.44	1.39 (-74%)	5.44	1.84 (-66%)	5.44	1.75 (-68%)
Profit	1.01	0.28 (-72%)	1.09	0.37 (-66%)	1.09	2.69 (147%)
Owner						
Total Costs	7.66	2.61 (-66%)	7.62	3.18 (-58%)	7.59	3.04 (-60%)
Support Structure Costs	1.13	0.95 (-16%)	1.09	0.97 (-11%)	1.06	0.94 (-11%)
Profit	-0.62	4.43(815%)	-0.95	3.49 (467%)	-0.62	4.43 (144%)
Global						
Profit	-3.33	-0.53 (84%)	0.38	2.06 (439%)	-8.4	3.72 (231%)
Investment Costs	6.57	2.34 (-64%)	6.53	2.81 (-57%)	6.50	2.69 (-59%)
ROI	**-50.68%**	**-22.65%**	**5.82%**	**73.31%**	**-14.31%**	**45.14%**

E.3. Sensitivity analysis across base years

This section examines how economic outputs change when the base year shifts from 2023 to 2015 or 2024. Table E.2 presents the percentage differences for these metrics relative to 2023. Large deviations indicate that the model's performance is highly sensitive to the chosen base year, while smaller variations suggest greater stability in economic projections. The percentage change is computed as:

$$\text{Percentage change} = \left(\frac{\text{Metric value in 2015 or 2024} - \text{Metric value in 2023}}{\text{Metric value in 2023}} \right) \times 100\% \tag{E.3}$$

Table E.2: Economic performance metrics for 2015 and 2024 base years, using 2023 as the reference. Red (>10%) and dark (<10%).

Category	2023 [M€]		2015 [M€]		2024 [M€]	
	Baseline	**Centralised**	**Baseline**	**Centralised**	**Baseline**	**Centralised**
Dispatcher						
Revenue	6.91	4.87	3.24 (-53%)	1.81 (-63%)	5.57 (-19%)	3.91 (-20%)
Costs	6.67	6.67	7.04 (6%)	7.04 (6%)	6.75 (-1%)	6.75 (1%)
Profit	0.25	-1.8	-3.8 (-1620%)	-5.23 (-191%)	-1.18 (-572%)	-2.84 (-58%)
Maintenance Party						
Revenue	6.53	2.21	6.53 (0%)	1.66 (-25%)	6.53 (0%)	2.10 (-5%)
Total Costs	5.44	1.84	5.44 (0%)	1.39 (-24%)	5.44 (0%)	1.75 (-5%)
Blade Costs	3.37	0.78	3.37 (0%)	0.51 (-35%)	3.37 (0%)	0.68 (-12%)
Gearbox Costs	2.07	1.07	2.07 (0%)	0.88 (-18%)	2.07 (0%)	1.07 (0%)
Profit	1.09	0.37	1.01 (-7%)	0.28 (-24%)	1.09 (-6%)	0.35 (-24%)
Owner						
Revenue	6.67	6.67	7.04 (6%)	7.04 (6%)	6.75 (1%)	6.75 (1%)
Total Costs	7.62	3.18	7.66 (1%)	2.61 (-18%)	7.59 (-1%)	3.04 (-4%)
Support Structure Costs	1.09	0.97	1.13 (4%)	0.95 (-2%)	1.06 (3%)	0.94 (-3%)
Profit	-0.95	3.49	-0.62 (35%)	4.43 (27%)	-8.4 (-784%)	3.72 (7%)
Global						
Profit	0.38	2.06	-3.33 (-976%)	-0.53 (-126%)	-0.93 (-345%)	1.22 (-41%)
Investment Costs	6.53	2.81	6.57 (1%)	2.34 (-17%)	6.5 (0%)	2.69 (-4%)

The main findings are:

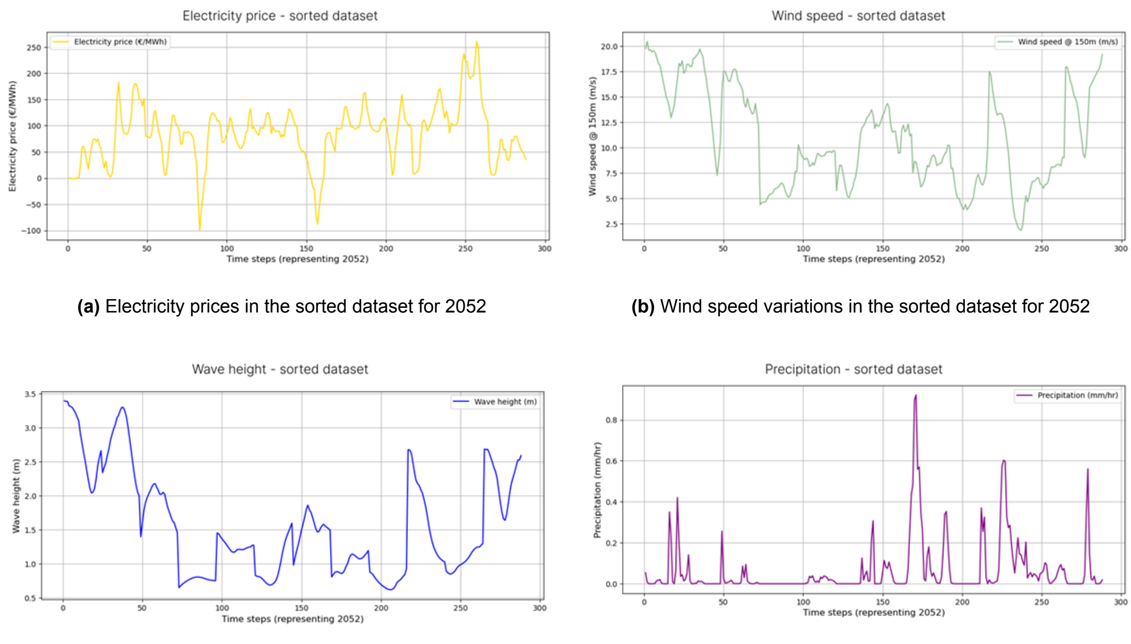
- Investment and maintenance costs stay relatively stable, suggesting they are less influenced by short-term market changes.
- Dispatcher and global profit fluctuate significantly. This indicates that these profits are highly sensitive to variations in electricity prices and environmental data dynamics.

F
Validation

This section presents validation outputs supporting the findings in the main report.

To validate whether these fluctuations are realistically represented, the input parameters, including electricity price, wind speed, wave height, and precipitation, are plotted over the final simulated year (2052). Figure F.1a shows price variations throughout the year, including both positive and negative price spikes.

Figure F.1b and Figure F.1c show similar variations, aligning with the assumption that most often if the wind speed increases, waves follow.



(a) Electricity prices in the sorted dataset for 2052

(b) Wind speed variations in the sorted dataset for 2052

(c) Wave heights in the sorted dataset for 2052

(d) Precipitation in the sorted dataset for 2052

Figure F.1: Overview of electricity prices, wind speed, wave height, and precipitation in the sorted dataset for 2052.