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Assessment of Operational Losses as a Mean for Decision Making and Risk Assessment in Wind Energy Assets

Supervisor: Athanasios Kolios

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

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ABSTRACT

In recent years, the wind energy industry has rapidly advanced and is now considered a mature technology. Nevertheless, some researchers and critics doubt its capacity to survive without governmental incentives and subsidies, particularly in the medium- and long-term period, given the increase in costs and operational losses. This thesis aims to explore the challenges of wind energy deployments, focusing on operational losses and costs trends that threaten projects viability. To achieve this goal, first an extended review on operational losses were performed, and an adaptation of the tool Overall Equipment Effectiveness (OEE) was proposed, considering the entire process and losses elements namely availability, performance, and quality. Then, three operational loss trends, increase in failure rate, ageing, and curtailment were identified. Finally, economic analyses, which incorporated traditional metrics such as Levelized Cost of Energy (LCoE) and Net Present Value (NPV), were conducted to establish the impact of cost and losses trends on project viability over their anticipated lifespan. The results suggest that the economic failure of wind systems is mainly due to the underestimation or neglection of part of these losses. Moreover, the newly proposed metric, adapted from OEE, is shown to be an effective tool for highlighting hidden losses and revealing the impact of certain decisions on the entire system. Several case studies and economic analyses were performed to demonstrate the advantages of the proposed framework, including a Multivariate Monte Carlo Simulation (MMCS), which provided a more comprehensive understanding of loss trends rates impact and the benefits of the implementation of solutions such as Condition Monitoring System (CMS) and overplanting to reduce operational losses. Overall, this study provided practical tools that can be easily adapted and tailored to different deployments. The findings have significant implications for researchers, investors, and industry professionals, helping them make better-informed decisions over wind energy projects.

Keywords: Economic appraisal, Operational Losses, Overall Equipment Effectiveness, Availability, Performance, Quality, Ageing, Curtailment, Levelized

cost of energy, Net Present Value, Monte Carlo Simulation, Condition Monitoring System, Overplanting.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to everyone who supported me, both directly and indirectly, throughout the completion of this thesis. First and foremost, I am deeply thankful for the guidance, encouragement, and unwavering support provided by my PhD supervisor, Athanasios Kolios. His expertise, insightful feedback, and commitment have been crucial in shaping the direction and scope of this project.

I would also like to acknowledge the financial and administrative support provided by Petrobras and CNPq, which enabled me to effectively carry out this research.

I would like to thank all my colleagues and employers from the University of Strathclyde, especially Susan Pawson, who assisted me in resolving administrative issues even before I moved to the UK. Additionally, I extend my appreciation to several employers and contacts from various wind energy companies who provided me with essential information and some data, and to Meteodyn for providing me with their software license and technical assistance.

I want to give a special thanks to my friends who were always there to offer support and keep me grounded amidst the stress of this project.

Most importantly, I dedicate this work to my beloved family. To my wife, Abgail, for her unconditional backing and sacrifices throughout the entire process. To my parents, sister, and niece, for their encouragement, callings, and support. I love you all.

Lastly, I offer my gratitude to God, who gave me the strength and encouragement to persevere through the challenging moments of completing this thesis. I am truly thankful for His unconditional love, mercy, and grace.

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LIST OF EQUATIONS

LIST OF ABBREVIATIONS

A	Availability
A_{MM}	Availability Maintenance Metrics Methods
A_{TB}	Availability Time-based Method
B	Performance
BS EN	British Standard European Norm
C	Quality
CAPEX	Capital Expenditure
CF	Capacity Factor
CFD	Computational Fluid Dynamic
CMS	Condition Monitoring System
CT	Coefficient of Thrust
DECEX	Decommissioning Expenditure
DTR	Decision Tree Regression
ESS	Energy Storage System
ETM	Extreme Turbulence Model
IEC	International Electrotechnical Commission
LCC	Life Cycle Cost
LCOE	Levelized Cost of Energy
LNR	Linear Regression
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCS	Monte Carlo Simulation
MMCS	Multivariate Monte Carlo Simulation
MTBF	Mean Time Between Failure
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
NPV	Net Present Value
O&M	Operational and Maintenance
OEE	Overall Equipment Effectiveness
OPEX	Operational Expenditure
PC	Power Coefficient
R^2	R-Squared

RAM	Reliability, Availability, and Maintainability
RFR	Random Forest Regression
RMSE	Root Mean Square Error
SVR	Support Vector Regression
TI	Turbulence Intensity
TSR	Tip Speed Ratio
β	Pitch Angle
λ	Failure Rate
μ	Mean
σ	Standard Deviation

1 INTRODUCTION

Wind energy has rapidly developed in recent years and has emerged as a leading renewable alternative to reduce dependence on fossil fuels. However, some authors have questioned the long-term viability of wind systems, particularly due to increasing operational losses. In response, this study focuses on developing a metric to effectively measure operational losses, identify loss trends over the lifespan of wind systems, and investigate critical factors that could impact their viability. This chapter provides an overview of the research, starting with the background of the problem (Section 1.1), followed by the aims and objectives of this work (Section 1.2), and its justification (Section 1.3). In Section 1.4, the thesis structure is outlined, and Section 1.5 highlights the papers produced and submitted during the PhD.

1.1 Background

With significant political and financial incentives in recent years, wind power has experienced a sustainable increase in its contribution to the national energy mix. In fact, it covered 15% of European electricity demand in 2019 [1], and there is a target to achieve approximately 30% by 2030 [2]. This growth is reflected in the cumulative wind energy capacity worldwide, surpassing 900GW (including both onshore and offshore projects) as shown in Figure 1-1, aligning with the trends observed in Europe. Although the annual growth rate has slightly declined in recent years, it is projected to exceed 15% in the next five years, from 2022 to 2026 [3]. While these figures are highly positive, for wind energy to become more independent of incentives and attract greater investment, there are still challenges to overcome. These include reducing the cost of energy and enhancing performance to maximize profitability throughout the service life of wind projects.

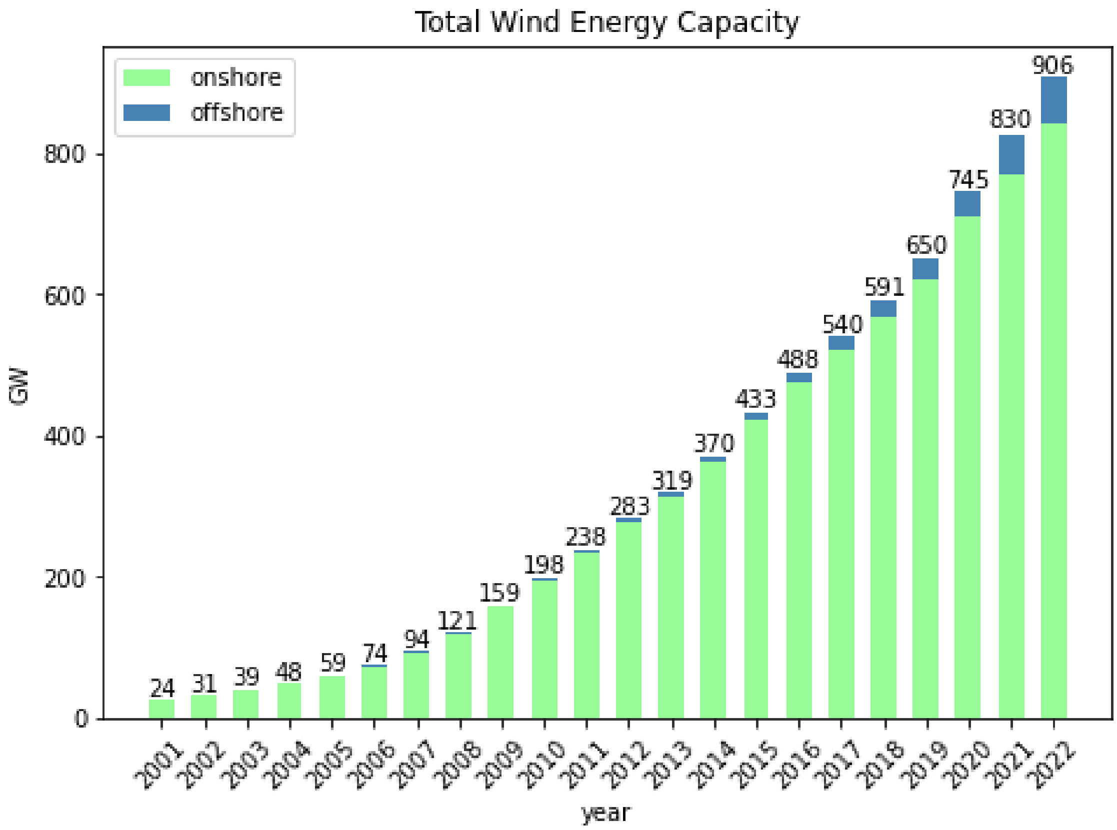

Figure 1-1 Cumulative wind energy capacity in the world, adapted from [3].

A very common metric to calculate the cost of energy is through LCOE (Levelized Cost of Energy). LCOE should be thought as the ratio between the total production and total costs during its lifespan, considering financial costs, time value of the money, and some profits to investors. The total cost of implementation is known as Capital Expenditure (CAPEX), while during the operational lifetime, there are O&M and management costs, also known as Operational Expenditure (OPEX) [4]. At the same time, it is during this period that the benefits are achieved through the electricity produced and sold. Finally, after the nominal service life period and a potential service life extension, Decommissioning Expenditure (DECEX) will take place and relevant costs should be considered. Figure 1-2 summarizes all these costs and benefits. It is important to mention that some return might come from the disposal of materials and equipment after decommissioning, and, for that reason, the disposal is represented in blue and has a question mark. Studies show that recycling can cover up to 20% of offshore decommissioning costs [5].

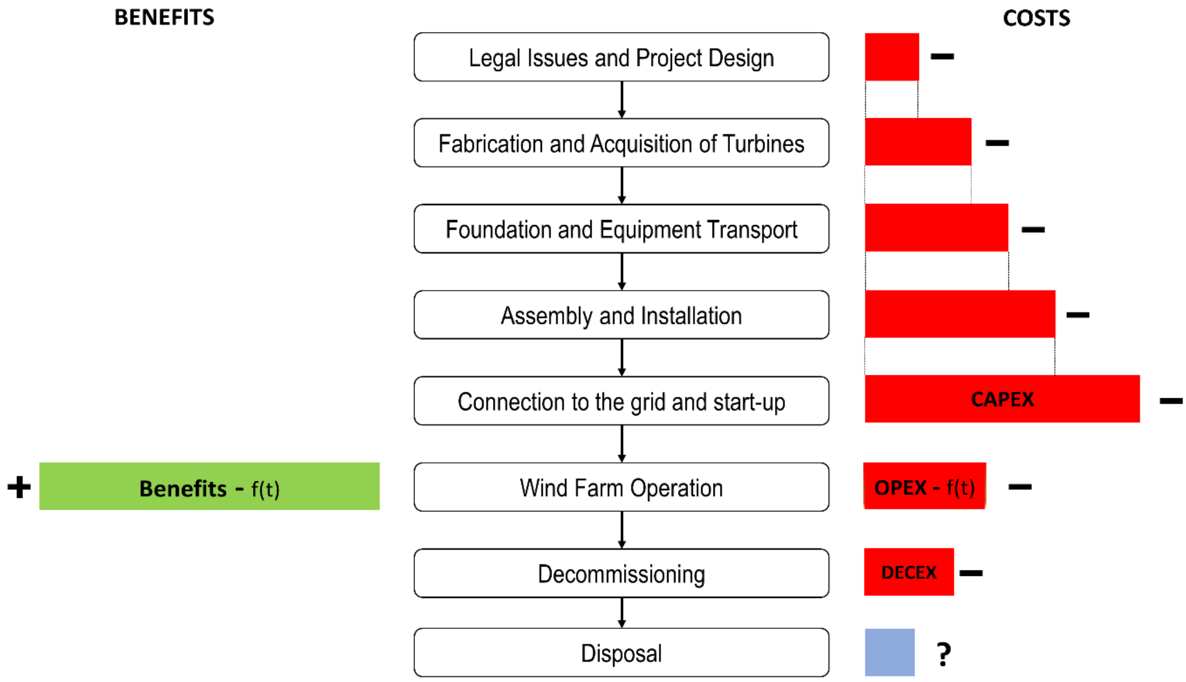

Figure 1-2 Costs of wind turbine lifespan – adapted from (Sathler 2013).

Even though one might consider that reducing the CAPEX value might be an adequate approach to reduce the total life cycle cost of a wind power project, it can be a rather simplistic solution. As shown in the first scenario of Figure 1-3, a poor implementation choice can affect the whole operational performance, increasing the total cost. Thus, it is important to strike a balance between all costs during the project design phase, as prioritizing the reduction of implementation costs alone may negatively impact future operational costs and result in higher overall costs, as illustrated in the second scenario of Figure 1-3, where higher implementation costs result in lower overall costs.

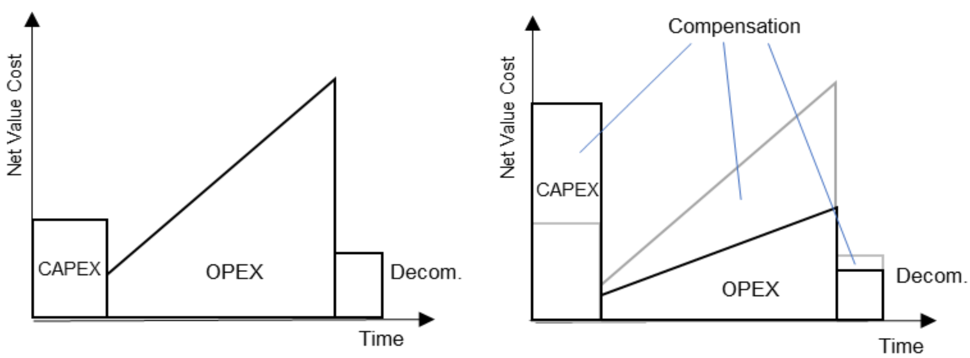

Figure 1-3 Comparison of two Life Cycle Cost scenarios – Adapted from [7].

Towards reducing LCOE, there are mainly two approaches to be followed: increasing production or reducing the total costs. Traditionally, after installation, connection to the grid and commissioning, wind farm operators focus on maximize production and availability, while reducing its costs. However, in modern wind farms, operators consider more sophisticated KPIs, such as the maximization of profitability. This is because there comes a point where producing additional electricity may incur additional costs that outweigh the benefits. This situation is more prevalent when projects are not operating under fixed prices or when costs become elevated [8]. In such cases, operators may choose to curtail the energy production to avoid incurring excessive costs. This strategic decision can help optimize the overall profitability of the wind farm.

Either way, the operational period plays a critical role in determining the success of the entire project and subsequently the potential of an extended service life can be anticipated or postponed. This decision is made based on the decrease of profitability, reliability and performance [9]. Some studies have found that the operational costs of wind turbines could jump from two to four times throughout their service life [10]–[15]. While others identified the impact of the degradation of the system with time, or ageing, which could reduce the relativity production capacity from 5 to 20% in 20 years [16]–[18]. Some countries have already registered yearly curtailment levels (which includes energy rejections and lack of demand) from 5 to 17% [19]–[21]. Therefore, investigate the impact of these losses along project`s lifespan and develop an efficient metric to measure real productivity of a wind farm can be crucial to reduce risks and support decisions and a continuous improvement culture.

1.2 Aims and Objectives

The first aim of this work is to investigate the operational losses in wind energy assets and gather them as a unique and solid metric. This metric is an adaptation of the well-known in manufacturing industry, OEE (Overall Equipment Effectiveness). Additionally, the second aim of this work, the impact of operational loss trends in wind energy viability through economic models will be investigated and performed. Thus, the specific objectives of the work are summarized below:

1. Review of operational losses throughout the entire process, including wind penetration into the grid, and classify them into groups following OEE concepts to help operators to identify specific areas for improvements.
2. Apply OEE to wind energy following framework previously developed and perform quantitative analysis according to literature figures and real cases to evaluate wind energy effectiveness.
3. Conduct data analysis to develop different models and procedures to monitor and estimate OEE.
4. Investigate in literature how some operational losses increase along the lifespan of wind energy assets and evaluate its impacts on costs and viability.
5. Perform stochastic analysis to check viability, costs, and risk of economic failure of wind energy assets along its lifespan in different scenarios, combining different losses trends and some proposed solutions to reduce operational losses identified in literature.

1.3 Justification

Operational losses can vary depending not only on project particularities, but also on how they are accounted. Wind energy assets are surrounded by uncertainties and affected by external factors, which contributes for the complexity of the activity of measuring and monitoring them. Therefore, a simple and reliable metric that accounts for all possible losses is important for both academia and industry to effectively compare and assess assets deployed in different settings, and to investigate proposed solutions thoroughly. This is particularly vital, as improvements in one specific area may negatively affect other parts of the system. Additionally, some studies have shown the increase of losses and the decrease of productivity of wind assets along its lifespan. Thus, identifying and monitoring these operational losses trends beforehand can be critical for a more accurate financial model and for reducing risks.

1.4 Thesis Structure

This thesis has been organized as follows:

Chapter 1 provides a comprehensive summary of the motivations, aims, justification, and presents the overall framework of the present work.

Chapter 2 presents briefly OEE concepts and a critical literature review of main operational losses in wind energy assets. In this chapter, it was defined a classification criteria following the concepts of the tool.

Chapter 3 estimates the average OEE of onshore and offshore deployments, considering some figures found on the literature. Additionally, a real case is presented to compare results.

Chapter 4 investigates how to monitor and evaluate wind farms through traditional machine learning techniques and SCADA data analysis.

Chapter 5 identify losses trends in the literature and two economic analyses are performed. First, considering average offshore costs to understand the impacts of each scenario. Second, a simulated case compares the adoption of different turbine classes.

Chapter 6 introduce to some common solutions and briefly discuss its impacts on the costs. Additionally, a multivariate Monte Carlo is developed.

Finally, Chapter 7 presents a discussion of the main findings of the thesis while the chapter 8 concludes the thesis, by summarizing each chapter, stating the limitations, and suggesting future work.

Figure 1.4 gives an overview of the thesis structure and content.

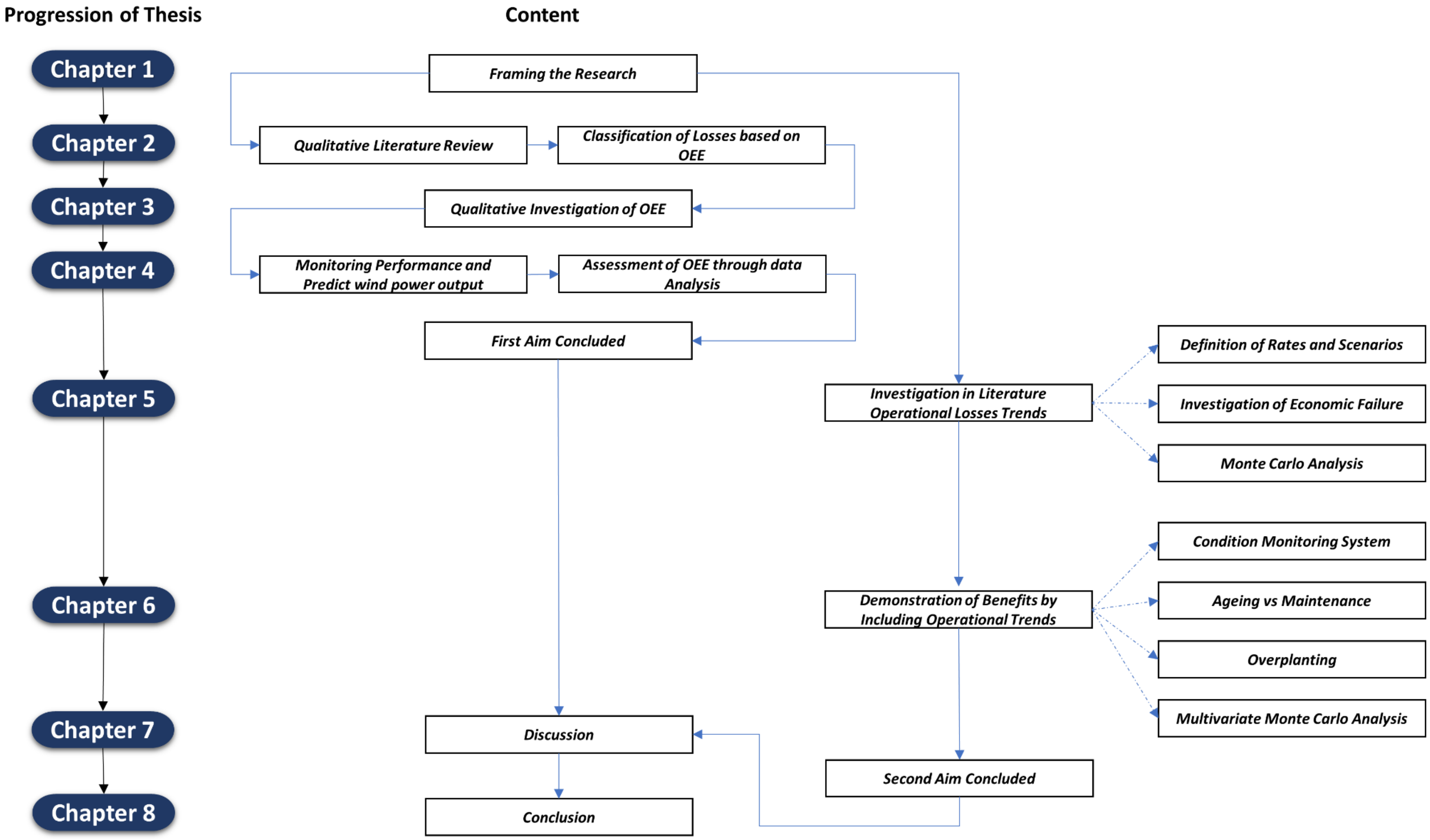

Figure 1-4 Thesis Structure.

1.5 Related Publications

The following papers were developed along the PhD and was already published or under review at the moment this thesis was written. Parts of this work are extracts of them.

K. P. B. Sathler, A. Kolios, S. Al-Sanad, and J. Parol, "Application of the Overall Equipment Effectiveness Concept in Wind Energy Assets," 2020, doi: 10.3850/978-981-14-8593-0.

K. P. B. Sathler and A. Kolios, "The Use of Machine Learning and Performance Concept to Monitor and Predict Wind Power Output," *Int. Conf. Electr. Comput. Energy Technol. ICECET 2022*, no. June, pp. 20–22, 2022, doi: 10.1109/ICECET55527.2022.9873076.

K. P. B. Sathler, K. Salonitis, and A. Kolios, "Overall Equipment Effectiveness as a Metric for Assessing Operational Losses in Wind Farms: A Critical Review of Literature," *Int. J. Sustain. Energy*, 2023, doi: 10.1080/14786451.2023.2189490.

K. P. B. Sathler, B. Yeter, and A. Kolios, "Impact of operational losses on the levelized costs of energy and in the economic viability of offshore wind power projects," [Manuscript submitted for publication] 2023.

K. P. B. Sathler, A. Kolios, and B. Yeter, "Effect of Energy Losses on Onshore Wind Turbines Techno-economic," [Manuscript submitted for publication] 2023.

2 OEE & OPERATIONAL LOSSES IN WIND TURBINES[1]

There are mainly three sources of loss that can be expected from a wind energy converter: Aerodynamics-related, electromechanical, and operational. Whilst the first two are related to manufacturing and design, which can be reasonably estimated, the same argument can hardly be made for the operational losses. Wind turbines are surrounded by uncertainties, including factors such as the wind features inputs, grid integration challenges, and degradation of the system, which makes operational losses assessment a hard task. Other industry has dealt with similar problems and developed different tools to help operators and managers to identify weak points and the main causes of losses. One of these tools is OEE, widely used in manufacturing systems to enhance equipment efficiency by reducing operational losses. Therefore, Section 2.1 will briefly present the metric. In section 2.2, the classification criteria and the literature review are presented, and the finds are discussed in Section 2.3.

2.1 What is OEE?

In the early 1970s, the Japan Union of Scientists and Engineers (JUSE) has developed a maintenance strategy called TPM (Total Productive Maintenance), where the goal was to achieve maximum performance in its production considering all phases related to the production. In order to check its efficiency, a metric called OEE (Overall Equipment Effectiveness) was introduced, where all possible causes of losses and the main six losses are identified and classified in three main elements, named availability (A), performance (B) and quality (C), as shown in Figure 2.1.

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[1] This chapter is based on publication by Sathler, Salonitis and Kolios [288]

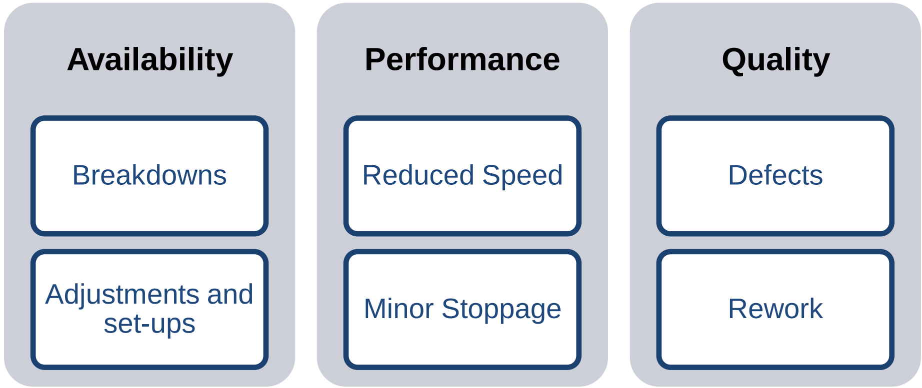

Figure 2-1 Six Main Losses.

Any change in the process can affect one or more elements. For that reason, OEE became an important productivity tool, since it considers the overall result and efficiency, helping to identify where losses are more frequent, and hence targeting improvement interventions. The OEE index is obtained through the multiplication of the three elements, and it represents the overall performance of the equipment. This index is considered an important metric to help managers and operators to make decisions, increasing the productivity of the equipment or process.

$$\mathrm{OEE} = \mathrm{Availability}\ (\mathrm{A})\ x\ Performance\ (B)\ x\ Quality\ (C) \qquad \textbf{(2-1)}$$

2.1.1 Availability (A)

Availability is calculated considering the planned operating time discounted by the period that the equipment is not available to operate, known as downtime [22]. There are two main types of losses in the availability category which can cause downtime, as shown in Figure 2.1. The first accounts for breakdowns, which is generally related with maintenance or failures and the time spent to fix the interruption cause. The second type accounts for adjustments and set-ups, where we refer to pauses in production which are not related with breakdowns. Relevant examples include planned maintenance interventions and adjustments of the equipment for new products. Even though some losses are expected, it is important to quantify them and understand their influence to key output indicators, in order to identify areas of improvements of the process. The basic formula to calculate operational availability is:

$$\mathrm{A} = \frac{Planned\ Operating\ Time - Downtime}{Planed\ Operating\ Time} \quad \textbf{(2-2)}$$

It should be noted that in practice different formulas are adopted for different types of availability, such as inherent, time-based, revenue-based etc, so it is important to ensure that the right metric is adopted.

2.1.2 Performance (B)

Losses related to performance can be the most challenging ones to identify since they are considered through instances where the equipment is performing outside the specification limits set. This type of losses can be related to reduced speed, meaning that for any reason a part of the equipment is running with lower performance, which can be caused by a damage, a not-well-lubricated bearing or lack of alignment, for instance. Another reason for performance losses is minor stoppages, where faults cannot be measured, but production performance is affected. An example is when in a cycle for any reason a motor is taking one second more to start due to a mechanical or electric fault, which is not easy to be recognized by operators. However, it can become a significant loss when accumulated throughout every operational cycle. A performance rate control can warn operators when something is wrong and needs to be investigated. Performance is calculated over planned operating time minus downtime, so the availability loss is not considered twice:

$$B = \frac{Standard\ Production\ Rate\ x\ Parts\ Produced}{Planned\ Operating\ Time - Downtime} \quad \textbf{(2-3)}$$

2.1.3 Quality (C)

Finally, quality is related to the final product as a result of a process or operation of equipment. Any producing process should ensure that the final product meets the end users' requirements or the client. The first type of losses in this factor accounts for defects, i.e., when the product is out of specification, and it should be discarded. The second element is rework, when minor defects are identified, and extra work is required in order to recover the product. According to the OEE concept, this is also considered as a loss because the time and the resources spent to fix it could be used to produce a new product or they can reduce the operational life of the process. The formula to calculate quality only considers products that were produced on the period assessed:

$$C = \frac{Units\ Produced - Defective\ Units}{Units\ Produced} \tag{2-4}$$

While OEE is widely utilized in the manufacturing industry and incorporates major losses in an intuitive manner, it is important to acknowledge its drawbacks and limitations. Firstly, this metric lacks detailed insights into the causes of operational losses, requiring additional effort to accurately identify and correlate each measured loss with its root cause. Additionally, OEE does not encompass critical aspects such as costs and potential investments. Moreover, the tool can potentially lead to misguided actions if the operational team fails to measure the elements accurately or compares results across different deployments without considering project-specific factors. However, these limitations can be largely overcome through the implementation of automation or a systematic approach to calculate OEE, coupled with proper training of the operational team. It is also important to recognize that OEE functions as a complementary metric and should be used in conjunction with other performance metrics such as reliability, maintainability, Failure Tree Analysis, FMEA (Failure Mode and Effects Analysis).

2.2 Operational Losses in Wind Turbines

2.2.1 Classification Criteria

As demonstrated in Section 2.1, the OEE focus is to identify, classify, and quantify operational losses. To adapt it to wind farms projects, some considerations need to be done. The flowchart shown in Figure 2.2 illustrates the assumptions considered in this work to classify the losses found in literature and what the authors believe would be a suitable approach to adapt the tool in wind energy assets. It is important to notice that the decision element in the flowchart started with the preposition “from” because each index is considered from the result of the previous one, avoiding losses being accounted twice during the process analysis.

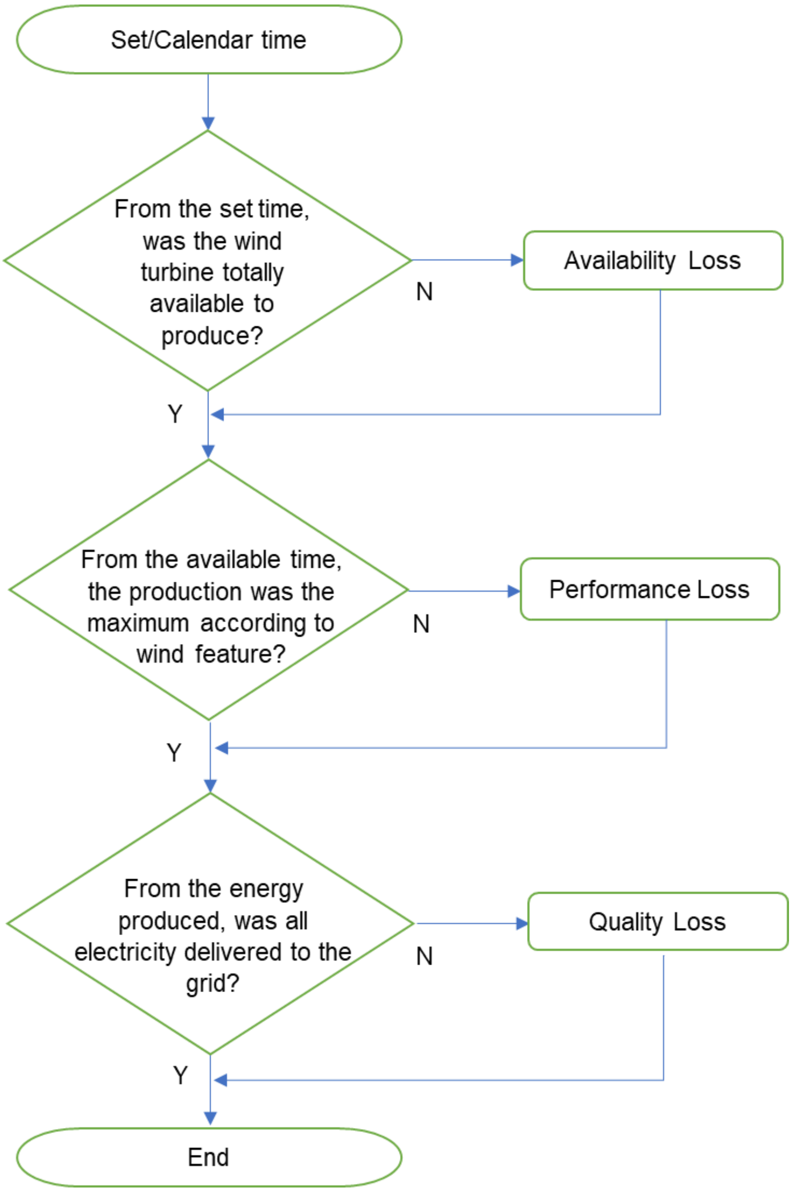

Figure 2-2 Flow Chart Losses in Wind Power according OEE tool.

Another important observation in the flowchart is related to the final result. Although the decision question was included in the flowchart, it is very unlikely that no losses is registered in an industry. This could be achieved in a short-term period, but considering long term periods, losses are expected and considered in all projects. For instance, an OEE of 85% is considered world class benchmark [23], representing that, even in reliable projects, there are losses. The following subsections detail the losses and how the scientific community has been aiming to minimize them, especially in the operational perspective. Also, it is important to mention that OEE results cannot be fully compared between deployments. Even turbines from the same company may not have the same OEE, as the equipment productivity relies not only in operational system, but also on the management commitment, involvement of the O&M team, maintenance efficiency, wind farm location, deployment environment and other particularities that any project has.

To identify the operational losses, before categorizing them, an extended literature review was performed. The focus was on papers published from 2010 to nowadays that had key words or expressions such as “operational losses”, “quality losses”, “production losses”, and “performance losses”, together with “wind energy” or “wind power”, in their titles and/or abstract. Then, a carefully reading was performed to check if important information could be retrieved and if the paper was really related to wind power and operational losses. To a better illustration of the sort of solutions or discussion was provided in the studies, assessed, five categories was also defined. “Investigation” refers to papers that assess the operational losses and discusses it, through reviews, numerical models, trends, or data analysis. “Decision Support” refers to when a framework or a new methodology is created or adapted, which resolves in important information that could help operators to minimize losses. “Controllers” refers to the development of a controller to reduce losses, find optimal point, or change the premises and settings of traditional controllers. “Machine Learning” refers to papers which use any machine learning technique to perform predictions or find correlations among inputs and outputs. And, finally, “Others” refers to solutions that are not listed before, including technical changes or addition of components or gadgets in the system.

2.2.2 Availability Losses

The first aspect to be considered is the set time contemplated in the OEE calculations. In the wind energy industry, turbines are designed to operate all year long, so considering the entire calendar period as a set time base is realistic. The first source of downtime mentioned in OEE is breakdowns. This item is related to any time that the turbine is not available to produce due to unexpected downtimes, such as failures and corrective maintenance. To address availability losses, increase turbine reliability, and extend their lifespan, important tools such as Reliability Centred Maintenance (RCM) [24] and Reliability, Availability, and Maintainability (RAM) can be utilized. Within the framework of RCM, tools like Fault Tree Analysis (FTA) [25] and Failure Mode Effect Analysis (FMEA) [9][26][27], and specific studies on failure rates [28][29] and others reliability-based methods [30] can assist operators in identifying critical failure pathways and evaluating potential impacts on system performance. These methods exemplify useful approaches for informing decision-making, optimizing maintenance strategies and increase general reliability of the turbine and its components.

The second downtime factor mentioned in OEE refers to adjustment and set-ups. Differently from the traditional manufacture industry, wind turbines do not need to change worn out tools or adjust their process for new products. Therefore, the only “expected downtime” for wind turbines is preventive maintenance. Many papers that cover availability discuss both downtime cases, corrective and preventive maintenance, which makes hard to separate them efficiently. However, some paper focus on suggesting strategies to improve preventive maintenance schedule [31]–[33], including the use of machine learning to better predict wind conditions [34], which could be used to affect less the wind energy output [35]. It is worth noting that in some cases, this may result in increased costs due to vessel availability constraints, as many wind farms will likely operate within the same time frame.

Offshore deployments have a particular approach. While onshore wind farms can achieve around 98% of availability [36], offshore wind farms present a lower pattern achieving around 92% [37][10]. Besides the distance to the shore and the need of vessels, also considering safety constraints, accessing the turbine is only possible in appropriate climate conditions. Therefore, the cost may be increased affected by this dependency, since some maintenance or changing of components needs to be done in advance, in the appropriated time, instead of the best and more effective time, wasting some of the components remaining lifetime [38]. A logistic maintenance review for offshore operations is presented in [39] and maintenance cost reduction review for offshore farms in [40].

Table 2.1 presents the main causes of losses by availability in wind turbine. The second column gives some examples of the losses cause, and the third column includes studies in which losses were assessed or quantified, suggested solutions, or compared different approaches. The category of the papers, as mentioned in Section 2.2, is also pointed in Table 2-1.

Table 2-1 Main Cause of Losses by Availability in Wind Power.

Losses	Example	Related Papers	Investigation	Decision Support	Controllers	Machine Learning	Others
Breakdowns	Failures Corrective Maintenance	FMEA - [9], [26], [27], [41]	X	X		X	
		Reliability and Failure Rate Analysis - [24], [28]–[30], [42], [43]	X	X			
		Fault Tree Analysis on floating offshore turbine - [25]	X				
		Fault Predictions/Detection - [44]–[51]		X		X	
		Uncertainties in O&M models - [52], [53]	X				
		Human Impact on maintenance - [54]	X				
		Fatigue and Failures related to weather - [55]–[61]	X	X		X	X
Preventive Maintenance	Preventive Maintenance Inspections	Maintenance Cost Review for Offshore [40], [62]	X				
		Method for better maintenance scheduling - [31]–[33], [35], [39], [63]–[67]		X			
		CBM - [27], [68]	X	X		X	
		Reliability Monitoring - [34], [46], [47], [49], [69]		X		X	

2.2.3 Performance Losses

Differently from the traditional manufacturing industry, wind turbines have different performance rates to be assessed, since the production output depends directly on the wind features, especially wind speed and density. Therefore, before discussing about the losses, the standard rate needs to be commented. The most usual way to assess wind production is through the wind power curve, which defines the production according to the wind speed, normally tested in a lab and later confirmed in a Power Curve Test, according to IEC 61400-12 standard and some local regulations [70]. Some researchers have proposed more accurate power curve considerations, including other factors such as wind direction [71]–[73], turbulence [74] or air density [75] and controllers [73].

Even though these approaches are good for a better production prediction, according to OEE, this can hide some opportunities for improvement. To illustrate this, one common problem related to wind direction is the wake effect. Although wake effect losses are expected, some researchers have proposed solutions to minimize them during the operational phase, such as intentional misalignment of yaw controller [76][77] or changing individual controllers to farm controller [78][79]. In other words, although some wind features cannot be controlled, considering it in the best performance rate can mislead the results and do not incentivize operators to find ways to minimize them in case of a high impact.

Some additional observations regarding the standard rate, as discussed in section 2.1.2, merit further discussion. While there is no rigid rule, and operators can adapt these concepts to their specific needs, it is important for the standard rate to be as simple as possible to minimize human errors and misinterpretations. Unlike other performance metrics, OEE aims to closely align with the best possible performance. Therefore, instead of using manufacturing curves that typically consider average production within a given wind speed bin, the standard rate in OEE should consider the best achievable rate. The goal for operators then becomes minimizing the gap between the best performance and the actual production. As a general guideline, if the actual performance frequently exceeds 100%, it suggests that the standard rate is underestimated. On the other hand, if the actual performance is far from reaching the standard rate, or if it has never reached the standard rate even for a short period, it indicates that the standard rate is overestimated.

With respect to performance losses, two main causes were pointed: reduced speed and minor stoppages. As mentioned in Section 2.1.2, performance index considers losses that cannot be measured as easily as availability, so comparing production output at the same conditions could be the best way to identify reduced speed and minor stoppages, including faults and failures in the system that does not send alerts to operators. Since wind turbines are complex equipment and exposed to hard and uncontrolled environments, the performance losses can be caused by several factors. Some of these are related to the equipment itself, while others are related to the environment.

Even though climate features are not controlled by the operator, they need to be considered in order to better understand the performance behaviour. Some papers relate differences in performance due to seasonal conditions or periods of the day [80], humidity [81], turbulence [82], and other papers are looking for a way to minimize losses due to rain [83] and icing [84]–[86], even using machine learning [45]. For offshore wind farms some additional issues can be considered in this category, such as wave impact due misalignment of the turbine [56][57] and platform motion that can affect the performance of other controllers [87]–[91].

The ones related to the system can be influenced by the condition of other components. Usually, the increase of temperature, vibration, or abnormal effort can affect productivity. Thus, these can be considered examples of reduced speed caused by damaged bearing [92], lack of lubrication, wear outs in components or even ageing [16]. For instance, [58] indicates a performance decrease before failures. Another important loss that is usually neglected is the time spent to start the generation of energy. Every time the turbine is shut down, due to safety reasons, maintenance, or lack of wind, the equipment spends time to gain inertia, start rotation and generate electricity. Thus, a more efficient “starting up” time can directly affect the production rates throughout the year. In some situations, the time needed to achieve the operational rotation can be affected by wind speed, as demonstrated in [93], which tested this in small scale wind turbines. However, some innovative solutions have been proposed to deal with this problem, such as engaging a motor to increase production range and reduce loss due to starting up [94].

Finally, another cause of losses that were not mentioned before are controllers' systems (which includes sensors and actuators). They could be related to reduced speed or minor stoppages due to malfunctioning or faults. However, in this paper, controllers were considered separately because some researchers focused on improving production by changing controller`s models, settings and/or premises. Besides reducing wake effects, as mentioned in the second paragraph of this section, yaw systems can be used to increase production [95]–[99]. The same stands true for other controllers, such as pitch control [100][101], stall [102], and other PI controllers [103]. Artificial Neural Networks, Machine Learning and new algorithms to control or find optimum sensor placement are studied as well [76][104]–[106].

To summarize, it is important to keep OEE calculation as simple as possible, so using maximum performance in a certain range of wind speed can be appropriate as a start. Obviously, this does not indicate to the operator the reason of the loss, but it shows that something is not functioning well and, depending on the level of the loss, the operator can decide if some action needs to be prioritized. Table 2-2 gathers the main losses identified and papers related. Some of losses can be classified in different criteria, but the most important is to have a reliable and simple index that does not account the same loss twice.

Table 2-2 Main Cause of Losses by Performance in Wind Power (*Not fully responsibility of operators **Only offshore deployments)

Losses	Example	Related Papers	Investigation	Decision Support	Controllers	Machine Learning	Others
Climate Conditions*	Wind Features: Turbulence Direction Air Density Rain Humidity Season High Temperature Period of the day Waves**	Power curve models (important to define Standard Rate) and Output Prediction - [71], [74], [75], [107]–[112]	X	X		X	
		Investigation of the impact of climate and wind conditions:					
		Turbulence - [82]	X				
		Air Density - [73]				X	
		Rain - [83]	X				
		Humidity - [81]	X				
		Period of the day - [80]	X				
		Seasons - [113]	X	X			
		Direction - [114]	X	X		X	
		Waves - [57], [88], [89]	X				
Reduced Speed	Ageing Blades Factures/Erosion Icing Dust Wake Effects Low Speed of components Start-up	Losses due ageing - [16], [18], [115], [116]	X				
		Losses due fractures/erosion - [117], [118]	X				
		Icing losses detection and estimation - [45], [84]–[86], [119], [120]	X		X	X	
		Investigation on wake effects - [79][121][122][114][123][124]	X	X			
		Reduce wake effects - [76]–[78], [105], [106], [125]–[128]		X	X		
		Losses due impact of wave loads - [56], [87], [89]		X	X		X
		Improving performance - [129]–[131]	X		X		
		Balance between load and output - [132]			X		
		Reduce cut in and minimize losses - [94]					X
Minor Stoppage	Small Failures (don`t stop production) Defects	Identifying malfunctioning - [92], [107], [129], [132], [133]	X	X		X	
		Fault tolerant identification - [134]		X			

Losses	Example	Related Papers	Investigation	Decision Support	Controllers	Machine Learning	Others
Controllers	Misinterpretation of signals	Yaw Controller - [95]–[99], [105]	X		X	X	
		Stall Controller [102]			X		
	Faults Controller`s setting	Pitch Controller - [91], [100], [101], [104], [106]	X		X		
		PI Controller - [103]			X		

2.2.4 Quality Losses

Quality assessment in wind energy production poses significant challenges due to the complexity of calculating and classifying all losses that occur after the electricity is produced by the generator. To address this challenge while ensuring simplicity and effectiveness, this study defines quality losses as any losses occurring between the generator and the grid. Unlike traditional manufacturing industry, where the outcome is a physical product that can be reworked, wind energy production cannot "fix" electricity once it is generated. It is important to note that some quality losses in wind energy systems are directly influenced by turbine operational conditions and operator decisions, highlighting a partial connection between quality and other elements. This will be presented and discussed along this section.

As mentioned in Section 2.1.3, defects refer to when the outcome does not achieve the client’s requirements. In the wind industry, the client can be considered the grid, so quality in this study refers to grid requirements. Due to the intermittent and uncontrolled input, wind power suffers from several variance and fluctuations. Some of the problems related are flickers, harmonic variance, impedance, resonance, and frequency fluctuation. It is out of scope of this study to discuss each of these problems, but it is important to mention that they can vary according to each grid’s characteristics or country regulations. Further grid problems related to quality, including local issues in different countries, are discussed in relevant literature[107][135]–[137].

Some of the quality problems are related to efficiency of intermediate equipment or design solutions [138]–[141] Since some of the energy output can be partly controlled, some researchers are studying ways to minimize them, such as control frequency [142] or harmonics [101] through pitch angle, and flickers and voltage fluctuation through yaw and stall control [102].

Another problem related to the grid which could affect the quality index is the grid availability. As mentioned before, the input in wind energy cannot be controlled, so if the grid cannot receive the electricity, the generation is disconnected, and this becomes an important loss. This can happen due to safety reasons, which include ramps, unstable electricity, grid faults or by lack of demand. Some operational measurements can reduce these losses as well. To minimize ramps, a paper suggests new controller approaches [143], while other works identify safety problems and relates them to other variables [144][145][100], which could be strategic for operators knowing when instability is more likely to occur. Curtailment issues have become a widely discussed topic [19][146], with some proposed solutions related to better production predictions [147][148], expand grid capacity [149] or strategically increase demand during high production [150].

Finally, the last problem related to quality element is due to transmission. This includes basically cabling and intermediary equipment. The transmission system is designed in the project phase and some technical losses are assumed, but it can be difficult to modify it after implementation. However, monitoring transmission losses can indicate when abnormal behaviour or wear outs occur in cables [151]–[153], or when intermediary equipment lose their effectiveness throughout the time. Also, the quality of the electricity produced can cause losses during transmission, as pointed in [154]. This information can guide some decisions made by operators, since the increase in the losses could justify some more extreme interventions. Table 2.3 outlines the main quality losses identified in wind turbine.

Table 2-3 Main Causes of Losses by Quality in Wind Power (*Not fully responsibility of operators).

Losses	Example	Related Papers	Investigation	Decision Support	Controllers	Machine Learning	Others
Out of Requirements	Frequency Voltage Harmonics Flickers Converters` fault	Fluctuations in output - [141], [155]–[157]	X				
		Loses due frequency - [142], [158], [159]			X		X
		Flickers - [102], [155]	X				
		Losses in quality due to wave misalignments - [89], [90]	X				
		Harmonics - [101], [154]	X		X		
		Voltage fluctuation - [102], [138], [160], [161]	X		X		
		Losses due power flow controller and converter`s fault - [162]–[164]			X		
Grid Availability*	Curtailment Inertia Security Grid Faults Ramps	Estimation and investigation of curtailment in different countries - [19], [146], [149], [150]	X				X
		Proposed method to reduce curtailment - [147], [148], [165]–[167]	X		X		X
		Reducing/Monitoring ramps - [168], [169], [143]	X				
		Hybrid system to reduce curtailment and instability - [170]–[172]	X				
		Instability in grid, reduce inertia - [100], [113], [135]–[137], [144], [145], [173]–[177]	X	X	X	X	
Transmission	Cabling Impedance Controllers Equipment Intermediaries	Lifespan and efficiency of cables - [154][152][153][151]	X	X			
		Reducing transmission losses - [178][139][179][180][181][182]		X	X		X
		Losses in grid due wind penetration - [183][184][185]	X	X			
		Impact of impedance and harmonic resonance - [140][144]	X				

2.3 Discussion

Quantifying losses has proven to be an efficient method to identify clear gaps and lead improvement priority decisions in equipment and systems. Even though wind power has many aspects that are not in control of operators, researchers present interesting and promising approaches towards minimizing the losses and improve the production and performance during operational periods. This shows that wind power has still many opportunities for improvements.

In order to ensure a simple and reliable adaptation and implementation of OEE in wind energy, certain assumptions were made. Firstly, unlike many manufacturing applications, wind power is characterized by uncontrolled inputs. As a result, climate features were considered an additional factor contributing to performance losses. In addition, controllers were assessed separately due to the number of factors that they can influence. Finally, about quality, all losses between generator and grid were included, from grid requirements to distribution. For that reason, the six main losses of an equipment can be extended to nine in wind energy assets, as shown in Figure 2-3. It is important to mention that some losses could be classified in different items, but, for efficiency of the tool, the main attention needed is to not consider the same loss twice, following a linear reasoning.

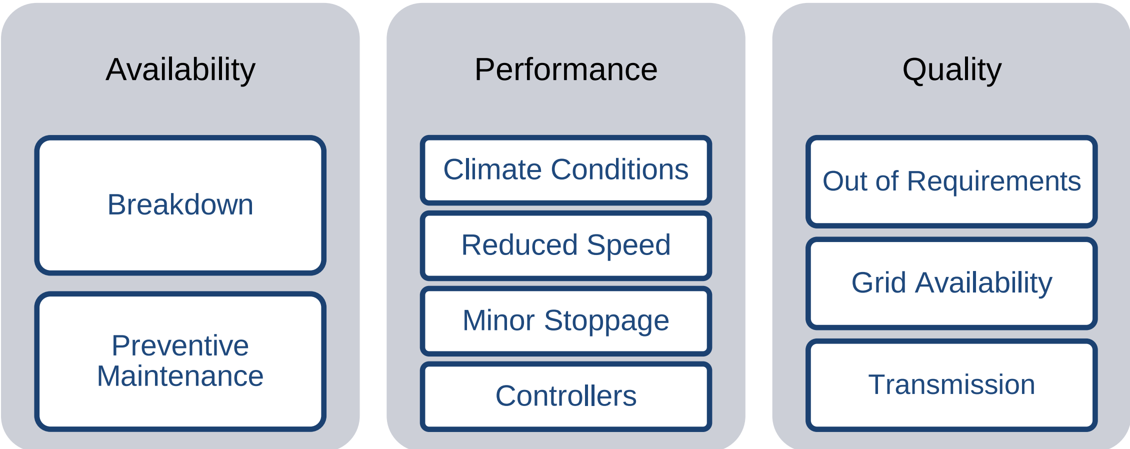

Figure 2-3 Main Operational Losses in Wind Power

While some papers focus on investigating and assessing the losses, some of them propose solutions focusing on minimizing or identifying failures and losses. Typical possible solutions discussed in the papers found by the review activity, could be summarized as follows:

- Understanding lifespan, failure rates, and behaviour of the turbine and its components,

- Machine Learning to identify causalities,
- Increasing performance and minimizing losses through controllers' settings (considering the whole farm instead of individual turbines to reduce wake effects),
- More accurate wind regime prediction, especially short-term, for decision making, including maintenance scheduling and avoidance of curtailment,
- Controllers' settings and the use of energy storage to minimize losses due to fluctuations that can also affect transmission system and grid availability.

From the solutions proposed, most could be implemented during the operational phase, which indicates that regardless of the project design or if the wind farm has already started its operation, developers and operators could still improve their productivity. In addition, some other manufacturing tools could be used to reduce losses. As an example, according to [52], when a failure occurs in an offshore turbine, on average 22% of time is spent for the actual repair activity, while the rest is due to organization, waiting for suitable weather and spare parts management. The papers mentioned in the review investigated how to reduce logistic time and scheduling; however, they are not suggesting solutions to reduce the repair time itself. So, tools such as the Single-Minute Exchange to Die (SMED), in which changeover during maintenance could be reduced drastically, could also be very beneficial to wind power installations. To identify the need of further tools, OEE is pivotal to quantify and identify these gaps, according to a TPM strategy.

As mentioned before, OEE can be used in many situations, such as for comparing before and after changings in the process [186], simulating which scenario has potential for achieving better results [187] or encouraging the continuous improvement culture [188]. The main advantages of using OEE are first, its simplicity and, secondly, the overall analysis, with all possible operational losses included in one single index. To exemplify this last advantage, back in Section 3.2, one of the solutions found to reduce wake losses is through yaw control system. Nonetheless, some researchers used the same yaw system to increase quality performance by reducing ramps. These are two different outcomes to be managed by the same actuator, where one can affect another. There is a study which suggests an optimum point on these two losses [77], however, it is not clear if these interventions can also affect availability. With that in mind, OEE seems to be a great solution to find overall improvements.

Another important observation about the decision making through OEE is that it can, and should, be related to the financial perspective. Even though it is out of scope of this study, any improvement suggested should find a balance between increased production and extra costs, since the final objective is to reduce LCOE, keeping equipment reliability and power quality high. Some papers, indeed, have proposed new equipment, gadgets, or more intrusive solutions, however, most of those presented in this review focused on changing control principles or using algorithms such as machine learning to find a better performance scenario, which probably does not require significant investments. Due to computational developments, improved processors, and the large amount of reliable data, machine learning has brought numerous possibilities to improve wind sector. In relation to OEE categories, machine learning can enhance availability and consequently profitability by improving wind predictions. It aids performance optimization through more reliable monitoring and effectively detecting abnormalities. And finally, for quality, machine learning algorithms can analyse sensor parameters and find patterns to improve power quality. Moreover, some studies present mixed algorithms, statistics and machine learning with OEE simulation [189].

To sum up, another three possible advantages of using OEE can be identified as follows. First, finding the actual OEE and tracking when the best rate was achieved can help operators and researchers to better understand the equipment. Second, the OEE tool considers that any equipment is unique, which means that the tool is conceptually tailored for each turbine particularities and wind farm location. Finally, some components reduce their performance before breakdown [58], so monitoring OEE has a potential preventive behaviour, by detecting problems that could potentially affect performance, but do not trigger any fault signs, warning operators for upcoming failures.

2.4 Chapter Summary

In this chapter, the concept of OEE was briefly explained together with its basic equations. A literature review was performed to identify main losses in wind energy assets. Then, these losses were classified in three different elements: availability, performance, and quality, following OEE concepts. Differently from manufacturing, wind energy can have more causes of losses, therefore, an extension of main losses causes was proposed as showed in Figure 2-3, following the assumptions contained in the flowchart in Figure 2-2. In addition, some of benefits of using OEE was discussed in Section 2.3.

3 QUANTITATIVE ANALYSIS OF OEE IN WIND ENERGY

Estimating the operational losses in wind energy assets can be a challenging task, due to the number of uncertainties and particularities that each project carries. The model and size of the turbine, generator type, external environment the turbine was installed, resources available for O&M, experience of the O&M team, type of contract and benefits, regulation of the country, and the capacity and resilience of grid are examples of aspects that can affect its overall productivity. In this chapter, each element of OEE will be discussed and some figures found in the literature will be presented. Later, in the section 3.4, the rates investigated in previous sections will be summarized. Section 3.5 will present a real case scenario and its OEE rate will be investigated.

3.1 Availability Analysis

Although availability losses in wind energy are widely discussed in both industry and academia, there is no consensus on how to account for or treat them. Various methods have been proposed in the literature to calculate this rate, with the production-based and time-based methods being the most common. Other methods that are not still widely disseminated, such as the monetary based method proposed by [190], will not be discussed here. Also, in accordance with the OEE concept, production-based is closely related to the performance element, which will be discussed in the section 3.2. Therefore, this work will focus on time-based method to estimate availability.

As mentioned in the section 2.2.2, the basic formula to calculate availability index needs the planned time for operation and the downtime. This is similar to the time-based method, perhaps the most popular way to calculate availability in any industry. A version of this method is presented and suggested in the standard BS EN IEC 61400-26-1:2019 for wind deployments. The equation (3-1) illustrates this Availability Time Based (A_{TB}), where the uptime means the equipment is available, or operating, and downtime, the equipment is unavailable.

$$A_{TB} = 1 - \frac{Downtime}{Uptime + Downtime} \tag{3-1}$$

Another alternative to calculate availability, also derived from time-based method and quite presented in the literature, is considering the popular maintenance metrics: MTTR (Mean Time to Repair), MTBF (Mean Time Between Failure), and MTTF (Mean Time to Failure). Figure 3-1 illustrates how these metrics can be connected to uptime and downtime concepts. This method is useful especially for the number of studies that investigates failure rates (which is the inverse of MTBF) and MTTR from main important components in wind turbine in different situations. The formula to calculate the availability considering maintenance metrics (A_{MM}) is shown in Equation (3-2).

$$A_{MM} = 1 - \frac{MTTR}{MTTF + MTTR} \tag{3-2}$$

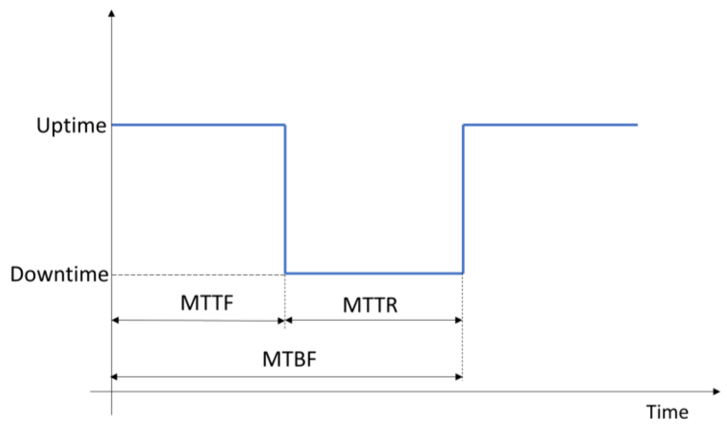

Figure 3-1 MTTR, MTBF, and MTTF

The two versions of time-based method are simple to be used, however, they can mislead decisions due to different assumptions. First, considering Equation (3-1), the definition of downtime needs to be clarified. According to the same standard, downtime should include not only maintenance activities, but also forced outage or shutdowns due to external factors. This would include, to name a few, high wind stops, extreme low or high temperature, and grid stops [191]. However, some studies do not account them, one possible reason for this is that, as these problems are not always operators' responsibility, including them would not measure the real efficiency of the O&M team.

Similar problem is found in the second version of the method. It is clear by the Equation (3-2) that only corrective maintenance is directly accounted. This could be justified by two reasons. First, since preventive maintenance can be planned, operators try to work in periods where is less likely to wind, so this would not affect productivity, although the costs can increase due to high demand of vessels. Second, an effective preventive maintenance and failures monitoring could increase MTTF and reduce MTTR, improving availability rate indirectly. Another problem is what is considered in the MTTR, while some authors consider all period where the equipment was not operating, including waiting for spare parts, logistic, weather condition and team availability, others consider only the repair activity itself. In their review, [192] found these incongruency in some data base, especially for offshore projects. This can affect viability analysis and losses estimation in wind energy projects. To exemplify this, the A_{MM} was estimated to be around 97%, considering only the MTTR and failure rates provided [10]. However, the authors included 250 hours logistic time to certain activities and included an estimated calendar-based maintenance. This made the index plummet to about 92%, the value they used in their economic simulation. According to [52], 22.2% of the downtime for offshore is actually spent on repair activity itself, while for [192], the rates are 40% and 20% for onshore and offshore projects, respectively. Therefore, it is important to always consider the entire period the equipment is not available to work.

As mentioned in the introduction of this chapter, the particularities of each project can directly affect the availability. To demonstrate this, Table 3-1 presents a summary of downtime distribution by component of onshore wind energy studies in three different countries, Turkey, Japan, and China. For the situation where more than six components were presented, only the first five were included and the rest was put together as “others”. The Japanese study shown considerable low availability when compared to the others. The authors have investigated and compared with several popular databases and found that although their failure rate was similar, their downtime was three times higher. This was due to the high dependency of the importation of spare parts and, in some cases, due to

Agricultural Land Act in Japan, which can delay activities by nearly one month, in case they need to use cranes.

Table 3-1 Summary of downtime investigation for onshore projects.

[193] - Turkey		[194] - Japan		[195] - China	
Categories	**Values**	**Categories**	**Values**	**Categories**	**Values**
Electric System	29%	Electrical System	38%	690V Cable	29%
Pitch System	20%	Blade	25%	Pitch System	15%
Structure	15%	Generator	18%	Control System	14%
Yaw System	12%	Pitch System	4%	Converter	8%
Controllers	10%	Gearbox	4%	Generator	7%
Others	14%	Others	11%	Others	27%
Availability	96.8%	**Availability**	87.4%	**Availability**	98.8%

The Turkey study has presented the results of the analysis of the first two operational years from a real onshore wind farm. Considering that the average of onshore projects is close to 98% [28], the availability of this project is a bit lower. This could be due to early life of the project. As shown in Figure 3.2, the failure rate behaviour along a lifetime of an equipment is similar to a bathtub shape, which is usually higher at the beginning of the operation, due to “infant mortality”. After this period, the equipment gets constant failure rate most of its life. Conversely, some studies have shown that wind turbine failure rate increases slightly during this period [196], but this will be discussed in chapter 5. Finally, due to wear out and age, the failure rate grows in an accelerate rate, indicating its end of life. Another important aspect to notice is that key components as generator and gearbox have not presented any failure or malfunctioning during this period.

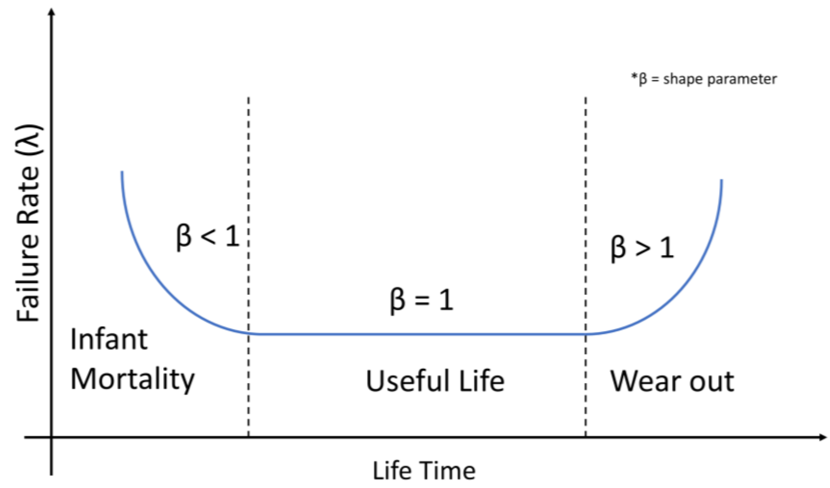

Figure 3-2 Bathtub curve

The main reason for downtime in the Chinese case, presented in Table 3-1, was "690V cable", which is not a common situation for wind energy projects. Nonetheless, this exemplifies how unusual problems could affect availability. The authors estimated that 87% of cable downtime was caused by third part, especially theft attempts of the neutral conductors. Another important aspect is that the study analysed only 6 months data, this could be one of the reasons why this loss got very evident and why the availability was near to 99%. Also, no preventive maintenance was recorded in the period. However, for availability estimation is important to always consider reasons the equipment was forced to shut down.

Although it has been shown that availability rates can vary significantly depending on the method selected, how the losses are accounted, particularities of each the project, resources accessibility and expertise of the team, large databases indicate similar availability rate. Obviously, for onshore and offshore projects, these figures are different. It is important to keep in mind that what is called offshore projects, includes fixed based and floating structures. While the first is closer to the shore, which reduces its weather dependency and consequently its costs and losses, the latter is farther from the coast and dependent on weather condition, which increases costs and losses. This been said, according to [191], considering the age the average losses vary from 1 to 6%, and the average availability is 97%. [197] investigated several databases and the average found was 96%, however, recent deployments in Germany are performing on average above 98.5%. Conversely, offshore deployments are considerably lower. [198] and [199] considered 90% availability rate, while [37], [10], and [200], a fair estimation would be 91.2%, 92.2% and 94.5%, respectively. A study developed by [201] demonstrated solutions to improve offshore availability, achieving 96% in their model. However, [202] shown that, considering the entire life and the size of the farm, offshore availability can be as low as 82.5%.

3.2 Performance Analysis

In the context of OEE, the performance of an equipment should be the real performance over its theoretical or maximum one, as demonstrated in the equation 2.3. This can be compared to the production-based availability index, suggested by the standard BS EN IEC 61400-26-1:2019, where the rate would be the actual production, frequently called as net production, divided by the potential production, known as gross production. Nonetheless, gross and net production can vary depending on the reference, what makes the values fluctuate considerably. A mix of the several rates will be discussed in this section, however, since one of the goals of OEE is measure production stability, alternative methods will be discussed in the section 4.2 and 4.3.

The climate condition, first main cause of performance losses discussed in the section 2.2.2, can be controversial. While some researchers do not consider them by not being fully responsibility of operators, others consider as a way to compare performance and indicate opportunities to improve performance. The author of this work believes that the latter would be the best. To exemplify this, by comparing the performance of a real farm, [133] discovered a reduction in performance when ambient temperature was above 35 degrees, as the equipment reduces performance for system protection. Rather than accepting this issue, they conducted an investigation into how to improve nacelle conditions, leading to the changing on the specification of some filters that allowed for an increase in temperature protection settings. As a result, yearly production improved by 1.2%.

Considering all aspects that affects performance is important not only to increase the production, but also to identify them. Icing, blades erosion, dust, and insects' contamination can decrease lifetime of components, due to imbalanced operation, and reduce power output [191]. [133] found a reduction in production of up to 1.45% in the wind farm assessed due to excess of dust in the nacelles and soiling in the turbine blades. [203] found a reduction in the maximum lift coefficient up to 35% due to insect contamination. [85] proposed a method to reduce losses from icing accretion through changes in the TSR (Tip Speed Ratio) and achieved 7 to 23% reduction. Other climate conditions can also impact aerodynamic performance, leading to operational losses. For example, according to [83], rain can reduce performance by up to 5% in certain conditions. In more severe scenarios, depending on the rain and wind speed, this impact can increase to as much as 25%.

Wake effects, which is the turbulence or downwind speed reduction caused by operation of nearby turbines, is another controversial example of losses not directly related to operators. While some authors do not account these losses to performance, others measured and found interesting solutions to improve overall productivity. By considering the entire farm, instead of individual turbines, [76] developed a model causing intentional yaw misalignment to increase production by 2.73%. [121] presents a quantitative review on wake effects problems and available solutions in literature, where some studies achieved an improvement above 20% in losses reduction due to wake effects.

Besides the climate conditions, performance can be affected by other factors, as shown in the table 2.2. Some of these losses can be unseen by operators if the performance is not followed closely. Although previous paragraph has mentioned a technique considering yaw misalignment to improve production, [204] states that a misplaced vane by 5 millimetres, could cause 5% annual energy loss and misalignments can cause up to 2% losses. [105] shown that an optimization of yaw increased 7% of productivity. [76] points that production losses due yaw can be underestimated, because they are optimized using static wake models and in real life due to rapid fluctuations yaw correct position cannot be effectively tracked.

[130] investigated production losses in a real wind farm and found that 6% of losses was related to turbine errors, which include alerts or faults in the system. [94] included a motor in the system to reduce cut in speed (speed where turbines start producing energy), increasing total productivity by prolonging the working period and energy produced in early speed ranges. [205] uses fuzzy regulators to reduce torque fluctuations and increase productivity closely to 1.7%. Considering floating offshore wind turbines, [89] investigated several scenarios, and found extra losses close to 7% in power generation, due to wind-wave misalignment.

To define the performance efficiency, many aspects need to be accounted. As mentioned earlier, these losses can be accounted for in different ways, making comparison difficult. While some treats gross production as the maximum theoretical provided by the wind, others include several losses reducing the gap between gross production and net production. Nevertheless, as demonstrated in this section, there are several operational solutions capable to improve wind farm productivity. Thus, not considering this can hide possibilities for improvement in the performance. For this quantitative performance analysis, studies that account both assumptions will be considered, and the difference and possibilities of improvement will be presented as the range of uncertainty.

To [37], 90% efficiency would include all losses by wake effects, transmissions, and other performance losses. To [199], the losses only due to performance would be 11.8%. [206] estimates the net and gross production from offshore projects and found that performance fluctuates from 95% to 98%. However, they also calculate scenarios including 10% uncertainty, which drop this rate significantly. [207] consider 3% performance loss for onshore projects. For [208], the average loss of offshore projects is 16.5% (from which half is due to performance losses) and 15% to onshore.

3.3 Quality Analysis

Different from manufacturing industry, energy is not a tangible integer product, what makes quality estimation a difficult task. When compared to other means to produce energy, renewables, which includes wind energy, has some particularities. First, wind energy is considered a non-dispatchable source, which means that operators cannot fully control the output to match electricity demands [209]. Another problem is related to the high and unpredictable fluctuations of its production, due to weather dependency. Since the grid operator tries to find balance between production and demand, unexpected energy fluctuations could cause undesirable disturbances in the grid. And finally, wind energy provides electricity through inverters, which do not offer inertia to the grid, and therefore, do not allow a time lag for grid adjustments.

It is important to understand that energy relies on the balance between production and grid demand. In order to keep the grid stable and reliable for consumers, there are some requirements that need to be followed. Otherwise, the energy produced can be rejected or, in some cases, the producer can be penalized financially by causing disturbances in the grid. For that reason, grid operators usually limit the power penetration from wind energy from 20 to 35% [210]–[212]. There are some situations where higher penetration levels were reported, especially in short-term, but to this be more reliable and frequent, changes in the operating practices is necessary, including demand response or storage systems [19]. Power Quality is the common term used to check the stability of the electricity in the grid. Wind turbine can usually exhibit the following power quality problems [213][214]:

- Steady-stage voltage level fluctuations
- Voltage variations and flickers
- Transients
- Harmonics
- Power frequency variation
- Grid protections

It is out of scope of this work to describe all items cited before. Nonetheless, to simplify, each grid network has its tolerance level to allow wind energy penetration. Some grid network requirements in Europe can be seen in [215]. It is important to mention that before the construction of a wind farm, the project designer needs to consider the capacity and how weak or strong is the grid. According to [155], although 10% fluctuation in wind energy voltage is considered a usual limit, 0.3% variation can bring nuisance in weak grids. Also, the study developed by [213] calculates some of operational losses in a wind park located in the southern of Crete Island. They estimated a loss due to grid rejection equals to 4.6%. However, by simulating the same network and doubling the total wind parks, the rejection would be 27%.

Besides the problem of particularities in each project, to find a reliable quality losses index has other adversities. As mentioned before, power quality is related to the balance of production and demand in the grid. Therefore, most of studies that try to identify losses, compares power quality in the grid before and after wind energy penetration. [157] has developed a power quality index and simulated power grid and wind penetration in different situations, while [216] and [217] used ETAP (a digital twin software able to simulates a grid and its disturbance) to assess the impact of different wind turbines generators.

Another challenge in dealing with these losses is how they are treated. For quality losses in wind energy, the available energy can be either rejected or curtailed. Curtailment occurs when operators are forced to disconnect turbines or reduce production due to either lack of demand or grid availability. Many studies in the literature use the term 'curtailment' for both cases, but there are exceptions, as demonstrated in [21]. According to this report, out of the total 12.1% losses registered in 2020, 51.2% were due to curtailment, while the rest were due to wind energy rejection caused by issues such as poor quality or grid safety.

According to [20], China achieved an average of 13% curtailment during the period from 2010 to 2017, where its peak was in 2016, achieving 17%. In 2020, Ireland had 11.4% of its energy from wind deployments curtailed, while North Ireland, had 14.8% [21]. Other countries faced better this problem, in 2018, Germany, UK, and Italy got around 4% curtailment, while in Spain, this value was close to 1% [218]. It is important to note that comparing the curtailment percentage across countries may be unfair, as they depend on the level of renewable energy integration in the system and how aggressive were the investments in renewable energy.

Transmission is another common reason for losses in energy industry. These losses are estimated in the designing phase, where a percentage of losses from cables, which usually represents the bigger part of losses [219], and intermediary equipment, are already included in the project. The voltage level of the network, type of conductors, or current transformation, and distance need to be considered as well. [151] and [153] are examples of studies that investigate the best layout considering the minimization of losses and costs in offshore projects. According to [213] transportation losses varies between 3 to 5%, however, when connection network is greater than 100km, this could be higher.

Nonetheless, considering the operational period, which is the focus of this work, these losses can be higher than expected. According to [154], deviations in power factor, voltage, and harmonic distortions could not only reduce the operational life of cable and intermediaries' equipment, but also lead to additional losses. In their study they simulated several scenarios considering different levels of disturbances, and in the worst-case scenarios, the losses tripled, when compared to base scenarios. [180] investigated the efficiency of transmission cables from far offshore wind farm, and showed 9% losses reduction, only by adjusting voltage levels.

In addition to the expected losses from transmission, power quality issues can also increase transmission losses. This is mainly due to impedance in the line, which is directly affected by harmonic levels [140]. Furthermore, high capacitive impedance can lead to a high quantity of reactive power and cable losses, according to [220]. The difficulty in correlating losses with their causes arises because power quality can be affected by external aspects, such as turbulence [221], or abnormalities in the turbine, as shown in [222], where power quality was compared with CMS (Condition Monitoring System) signals.

3.4 OEE Analysis

In this section, the average OEE expected for onshore and offshore deployments, according to the losses and values discussed in the previously sections, will be summarized and presented. Obviously, these values work as reference, since the real OEE will depend on the particularities of each project. Some extreme scenarios as the Japanese availability of 87% or the 17% curtailment loss in China will be treated as outliers, therefore, they will not be included.

Figure 3.3 shows the expected rates of OEE and each element, considering the most frequent value as the average and the range is a summary of what was discussed in previous sections. For availability, 98% is a reasonable value for most onshore deployments, however, in some scenarios this can reduce to 95%. Although in the literature authors includes different loss in their assumptions, 93% for performance seems a fair rate. The range was defined by more optimistic values, which generally ignores the wake effects, and the improvements estimated in alternatives proposals to increase productivity. Quality is the most difficult to find reliable information, however, 95% seems a reasonable rate, considering wind energy rejection, and further electrical and transmission losses. The limits were defined by removing part of wind rejection for the best scenario, while the worst included 3% curtailment. Therefore, the average OEE for onshore is around 87%, which is higher than average world benchmark, 85%, discussed in section 2.2.1.

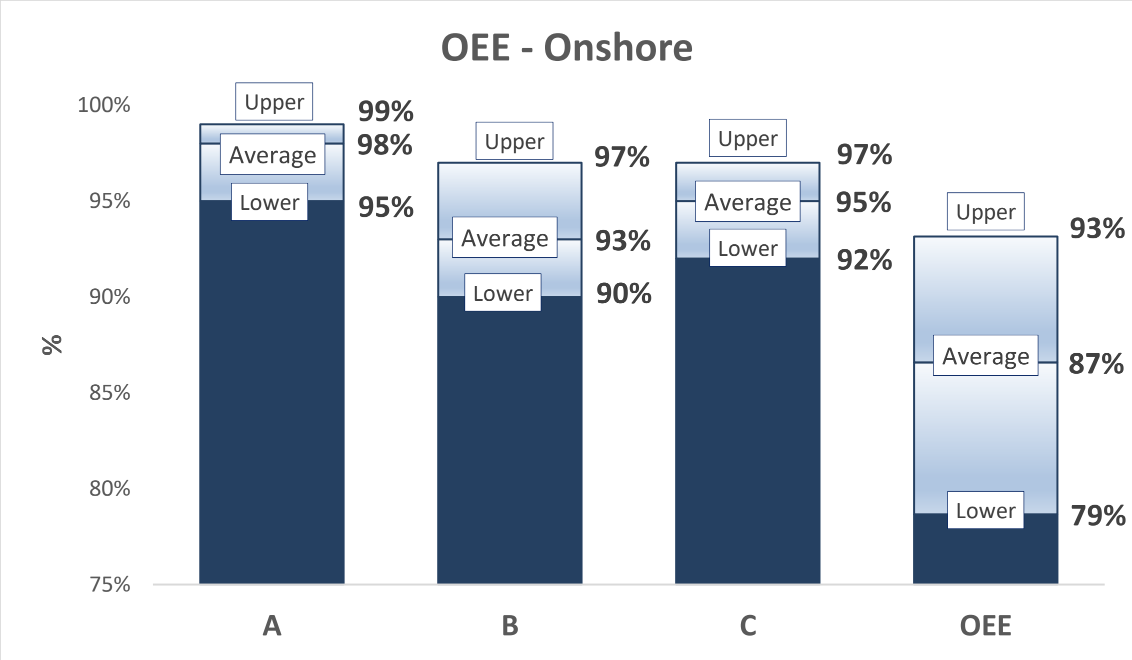

Figure 3-3 Analysis of OEE for onshore and its elements according to literature.

As expected, OEE for offshore is lower than from onshore. As shown in Figure 3.4, the average availability for offshore is 92%. As demonstrated before, some studies proposed ways to improve it to 96%. Although some studies show rates below 90%, they are not very frequent in the literature especially for new deployments, so 89% was set as the likely worst scenario. About the performance, it is expected that the losses level is higher, due to the harsher environment. As demonstrated by [29], the wet and more corrosive environment contributes to higher failure and misinterpretation of sensors, and the wind-wave misalignments can reduce the performance [89]. All this will have impact not only on performance, but also in the quality. The higher level of instability, vibration, and loads can affect Power Quality, as discussed in section 3.3. Another possible reason for higher losses level in quality is the longer transmission lines, so in total, the lower level considered was 88%.

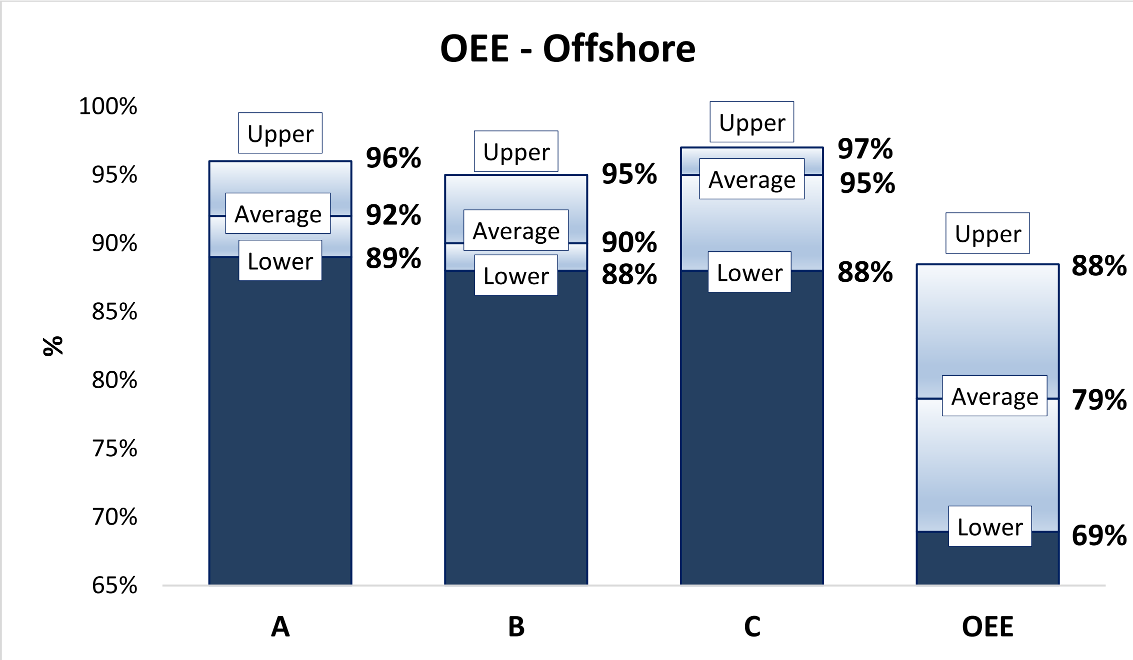

Figure 3-4 Analysis of OEE for offshore and its elements according to literature.

3.5 Case Study

In this section, the OEE of a real onshore farm will be assessed. For confidentiality agreement, the identification and technical details cannot be disclosed. The farm has 17 wind turbines and two different datasets already filtered from one entire year were provided, that were already pre-processed and ready to be used. First, a weekly summary of gross production, net production, and average wind speed in each wind turbine is presented. The second spreadsheet is the list of faults and downtimes, which contains date and time the failure occurred, the category, description, if causes downtime in the turbine or if it was only an alert, and finally what sort of intervention was needed. Table 3.2 summarizes the content of both datasets provided.

Table 3-2 Summary of Dataset

Dataset	**Spreadsheet 1**	**Spreadsheet 2**
Type	Average per Week	Per Fault or Event
Content	• Week Number • Turbine • Average Wind Speed • Gross Production • Net Production	• Date & Time • Wind Turbine • Event Category (Ambient, Grid, Turbine, or User) • Log Number & Fault Description • Type of Intervention (Follow, Error, In Service) • Sum of Alert Time • Sum of Downtime

To assess the availability the "sum of downtime" was used, considering the A_{TB} (Equation 3.1). For this analysis, the "Grid Events" was considered as quality losses, since it is not clear what really happens when the production in generations stops due to grid. In the case of the turbine is only disconnected from the grid and keeps running, consuming its components operational life, this cannot be considered as availability loss. Therefore, Figure 3.5 presents the total downtime (close to 2120 hours) in the first year considering typing of intervention. To make easier to understand, all operation that was not due to failure was called as scheduled Service. The Ambient category includes high wind speed, safety stop activated without failures related and untwist of cables. Figure 3.6 presents only the downtime caused by failures breakdown. The second chart presents the number of alerts activated that did not interrupt the production, which was around 5500 hours. Although, this would not affect the availability itself, it is important to follow them, since this could explain some losses performances.

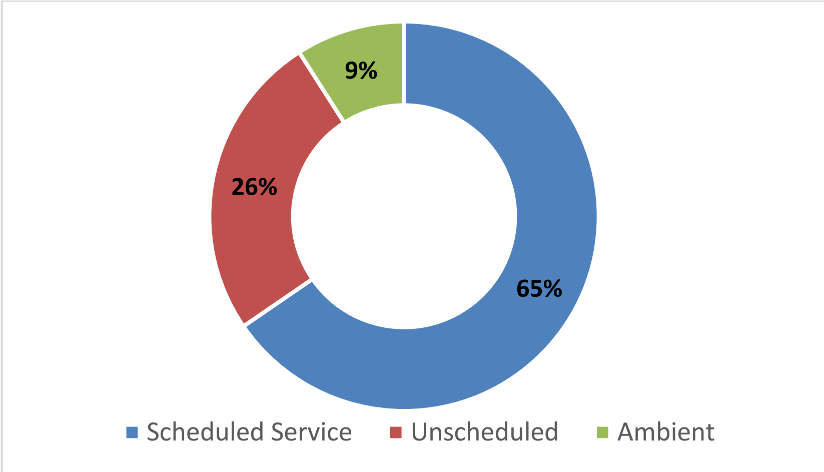

Figure 3-5 Downtime Breakdown.

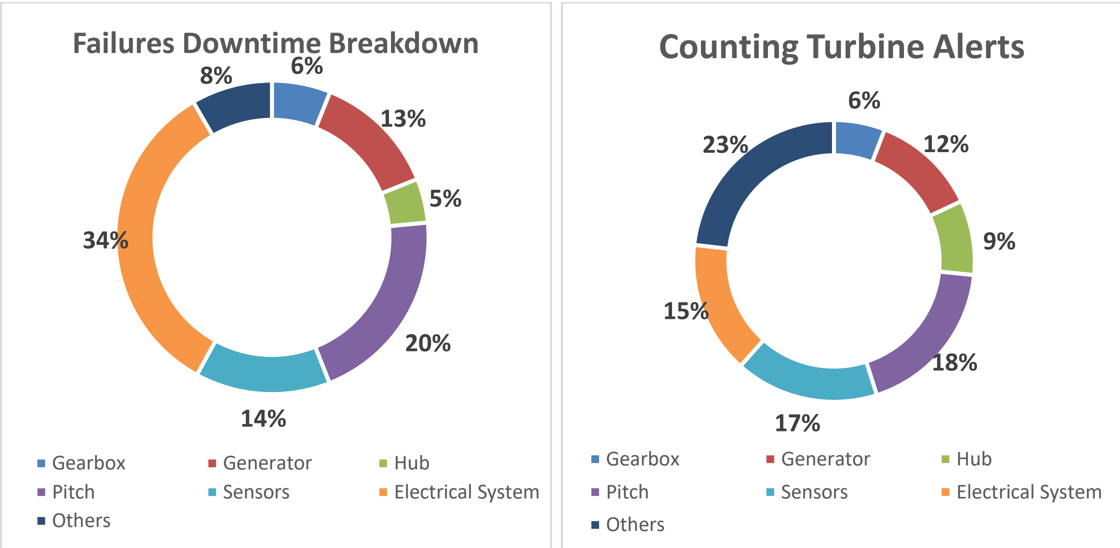

Figure 3-6 Fault Alerts and Failures Downtime Breakdown

Since the production data provided was collected on a weekly basis, there is a risk of bias in the estimation of the system's performance. As mentioned earlier, an accurate performance calculation should consider the maximum production achieved under identical conditions. However, the provided dataset lacks certain elements necessary for a more reliable analysis. Nevertheless, this method was still employed to maintain consistency throughout the analysis. A more comprehensive discussion on performance calculation methods and their limitations will be presented in Chapter 4.

In Figure 3-7, the manufacturer power curve is presented, along with real data and maximum performance. The performance index was calculated by comparing the real production to the maximum production, while accounting for availability on a weekly basis to correct for any discrepancies. Additionally, the difference between gross production and net production, as provided in spreadsheet 1, was taken into account during the calculations. An outlier that could potentially impact the analysis was identified and subsequently removed. It is important to emphasize that the weekly data provided is far from ideal and may significantly affect the analysis and the shape of the maximum curve. Nonetheless, this example can serve as a valuable reference for future studies.

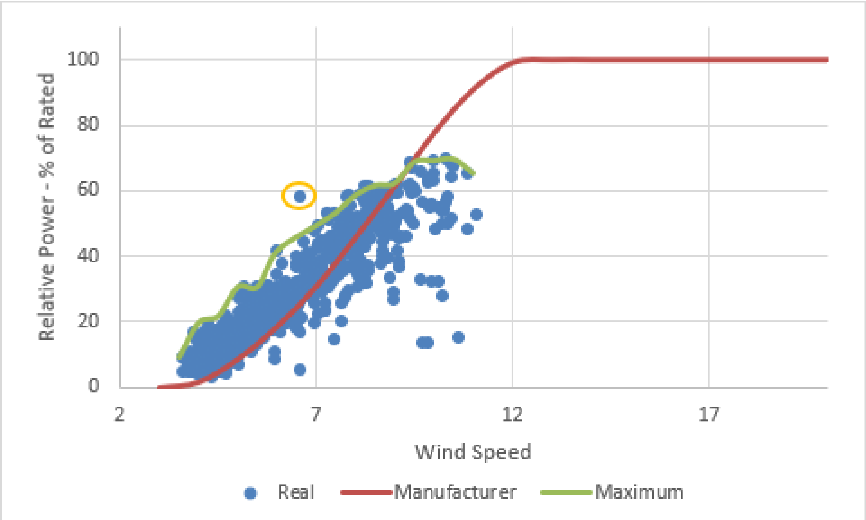

Figure 3-7 Production Real Data - Outlier highlighted.

As explained before, since it is more likely that the turbine keeps running during grid events, this was considered as quality losses. The first chart in Figure 3-8 illustrates the total downtime caused by grid events and its breakdown by reason. The second chart shows the fault list, which summed five times more hours than the downtime itself. It was not provided any information about wind energy rejection or curtailments, so further analysis was ignored. Moreover, the project estimates 2.5% transmission loss, and this was included considering the energy after all losses calculated.

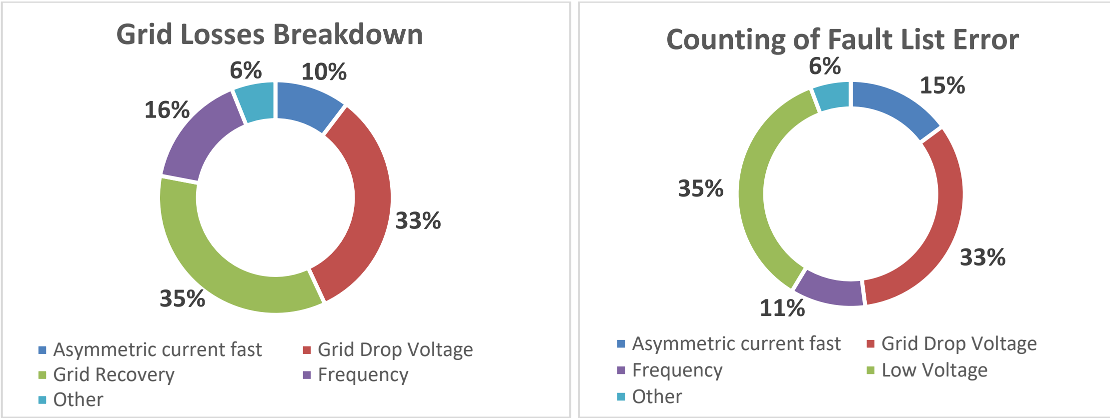

Figure 3-8 Grid Losses Downtime Breakdown and Fault List.

Figure 3-9 shows the OEE results for this case scenario, which were in line with the values discussed and presented in the section 3.4. The availability rate reached a high level of 98.6%, indicating that the equipment was operating effectively and with minimal downtime. The performance rate, subject to some limitations in calculation, scored 94.6%, still above the literature average of 93% (Figure 3-3). Finally, Quality was slightly above the literature upper limit of 97%, but only included grid faults and transmission. Further losses such as curtailment or wind rejection could bring the value to the estimated range for onshore projects. The final OEE measurement for the assessed year was 90.7%, indicating high productivity and efficiency.

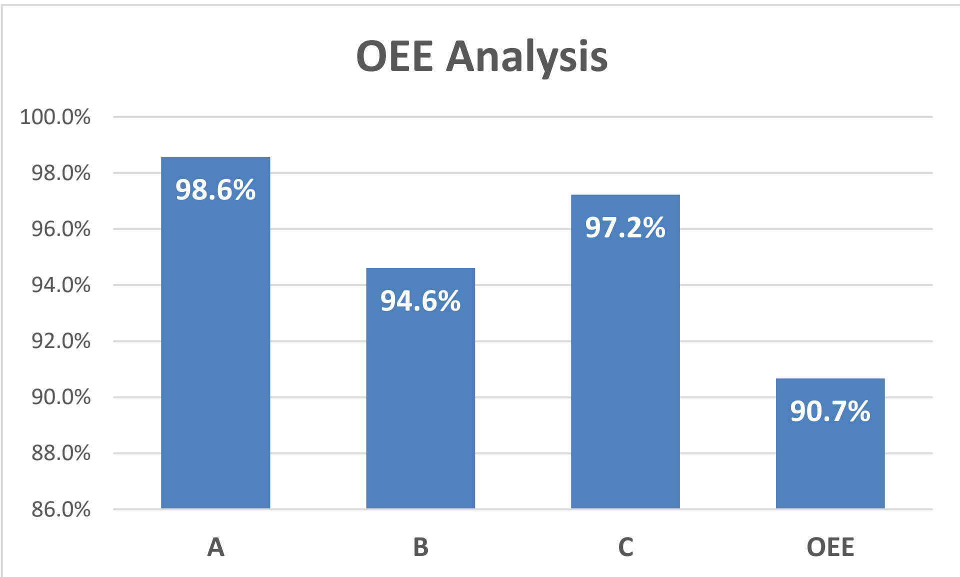

Figure 3-9 OEE Analysis of Wind Farm Case Study.

3.6 Chapter Summary

In this chapter, a quantitative analysis of wind energy of each element of OEE was discussed. The usual formulas and losses rates were presented. This activity showed how hard estimate and monitor losses can be. Different projects and studies calculate their rates considering different equations and assumptions. Nonetheless, an attempt of putting all figures together was presented in section 3.4. Figure 3-3 presented the range of each element and the total OEE expected for onshore deployments, while Figure 3-4 for offshore. Section 3.5 presented a OEE analysis of a real farm in its early age. The result was coherent with what was found in the literature, despite of the lack of detail in part of the data provided.

4 MONITORING and EVALUATING WIND FARMS

It is important to monitor and evaluate wind farms effectiveness as frequent as possible. This could help to identify abnormalities and also to understand better the equipment. As mentioned before, the estimation of losses can vary between different projects, and this is not different for monitoring. One of the main objectives of OEE is to measure the stability of the system. So basically, best performance in same operational condition should be used for this activity and this is what will be proposed in this chapter. In section 4.1, a simple performance index will be defined, and traditional machine learning algorithms are applied to predict and monitor performance and power output through MET MAST DATA. In section 4.2, a data analysis considering the SCADA DATA provided and its OEE analysis will be performed. For this, some assumptions to calculate OEE elements had to be done, including a proposed method to estimate wind rejection by the grid. Finally, section 4.3 will present alternatives ways to monitor the performance.

4.1 Predict and Monitoring Performance through Machine Learning[2]

The most common way to monitor and predict wind power output is through the power curve, which in most cases is provided by the manufacturer. As defined by BS IEC 61400-12-1-2017, the power curve is based on the average power produced in a predetermined wind speed bin [109]. Although very useful, these curves do not usually consider the external features and some of the possible operational losses. Therefore, during the design phase a rate is considered in order to calculate the net production. According to Ioannou et al. [37] 90% is a reasonable estimation to be used in the design phase. However, in the operational phase, this approximation does not help operators to understand and identify what is causing the operational losses and fluctuations in production.

[2] This section is based on publication by Sathler and Kolios [112].

Wind energy output is mainly calculated through the amount of Kinect energy flux from the wind taken by the rotor, considering the density of the air, wind speed, rotor area and the power coefficient. The power coefficient is what determines how much energy can actually be captured from the wind and it is related to some wind features and rotor features, which include the tip speed ratio and blade pitch angle [223]. According to Betz's law, the theoretical maximum possible performance is equal to 16/27, i.e., 59.3% of the kinetic energy in wind.

External factors such as climate, wind conditions and topography can clearly affect the outcome and could be the reason for high fluctuation. Recent studies have been trying to create alternative curves to increase accuracy in prediction and comprehension of production. In the literature there are studies creating curves adding more inputs, such as air density [75], humidity [81], wind direction [71], turbulence [74], and periods of the day [80]. Also, machine learning has been largely used to predict wind power output, as shown in [224], [73], [158], [225] and also to create a model of day-ahead prediction [35], very important for market biding. Even though these models are very useful and beneficial for operators, the great number of curves can make decision making more complex, thus, they do not seem to offer a totally tailored approach.

A solution given by Sathler et al. [110] is the creation of a new way to monitor performance and track fluctuations, where the variance of production is calculated by dividing each value by the maximum registered on the related bin. As a result, the index itself has proved to have similar efficiency in predicting production and, when used together with wind speed, the results were higher than 96% when considering the entire farm. The results also showed that some periods with similar wind can have drastically different production when relying on the index created. Even though these are promising results, the study does not bring solutions for calculating performance in an effective way.

As mentioned before some of possible reasons for fluctuation in production are due to external factors. To monitor the external factors, farms have a separate tower with sensors to measure wind and climate features. Therefore, the goal of this study is to check if the information provided by this tower, also known as

Meteorological Mast Data (Met Mast Data), can be used to predict the performance index of the turbines and check if they provide a reliable power output prediction to assist operators in monitoring their turbines. To execute all the steps outlined in the algorithm, including pre-processing, method selection, hyperparameter optimization, and final model creation, Python 3.8 was utilized along with the open-sources libraries: NumPy, pandas, and scikit-learn. Figure 4-1 summarizes the process proposed in this work and the following sections will explain each step of the pipeline in details.

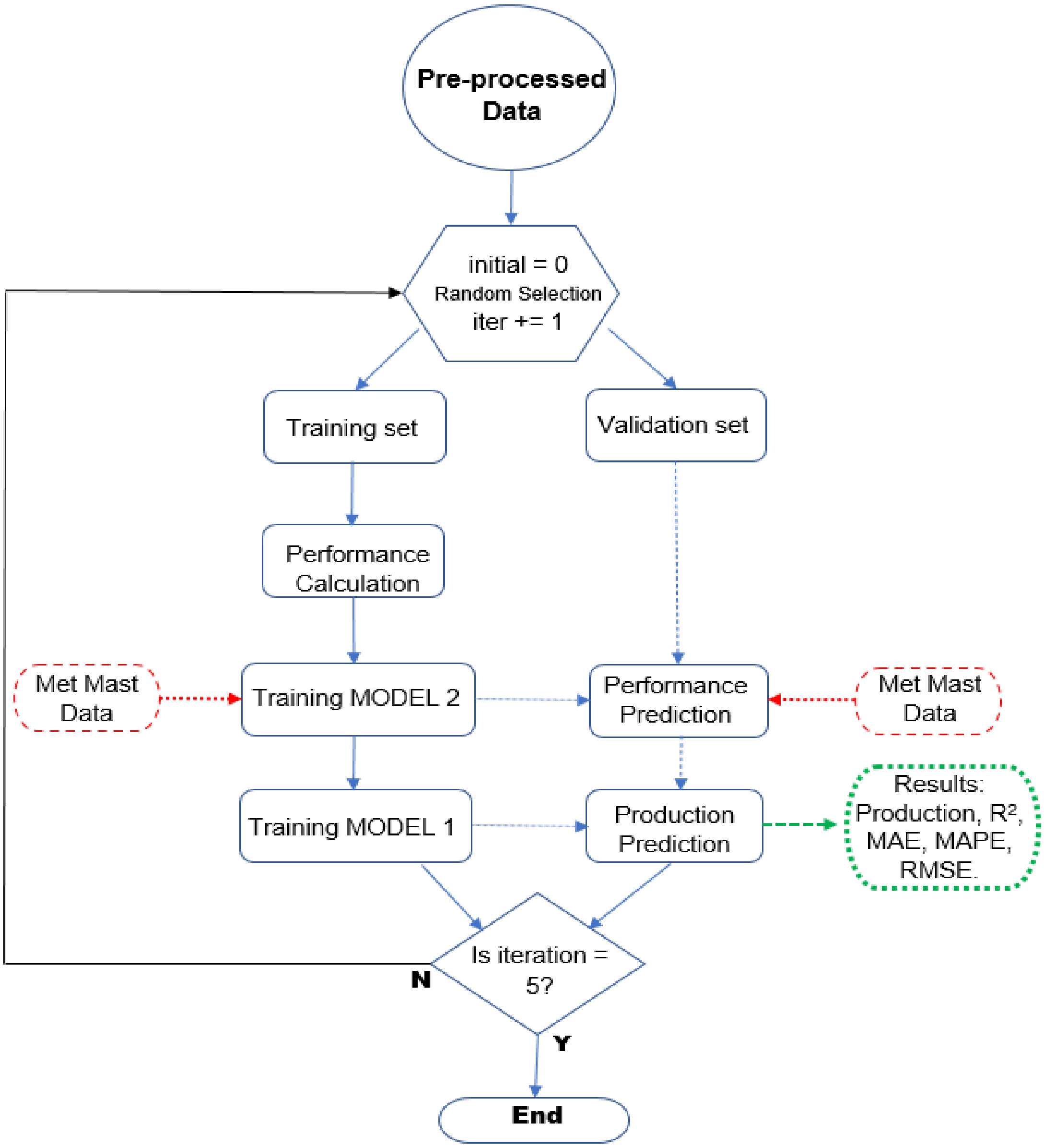

Figure 4-1 Flowchart of the model proposed.

4.1.1 Methods

Machine learning has become very popular in recent years; this is due mainly to the advances in technology, especially those related to storage systems and faster processing of data. There are many types of algorithms and methods inside machine learning, which can help to find patterns in their outcomes, connecting inputs to outputs to make predictions with lower errors. In this study, regression-supervised models will be used. They are classified as supervised because the algorithm is trained based on historical data previously available, and as regression since production and performance are considered quantitative continuous values.

It is considered a good practice to start with simpler methods before testing more sophisticated ones to avoid waste of computational resources. According to [226], decision trees, support vector machines and naive bayes are the traditional methods for supervised learning. Therefore, to design both models proposed, production output and performance prediction, four traditional methods were chosen: Linear Regression (LNR), Decision Tree Regression (DTR), Support Vector Regression (SVR) and Random Forest Regression (RFR). Table 4-1 gives a short explanation on each method with references for further interest.

Table 4-1 Description of Machine Learning Methos Selected.

Model	Description	Reference
Linear Regression (LNR)	Linear Prediction method. Look for best fit with lower errors, considering straight linear equation.	
Decision Tree Regression (DTR)	It is a nonlinear supervised prediction method, which creates conditional statements.	[227]
Support Vector Regression (SVR)	Based on Support Vector Machines, it uses, hyperparameters with a tolerance to minimize errors.	[228]
Random Forest Regression (RFR)	Construction of multiple decision trees. A probabilistic analysis is made among those decision tree to select the best prediction.	[229]

The goal behind of the selection of these methods is to keep the models as simple as possible, avoiding the need of high computational resources, as mentioned before. However, each of them has its own set of pros and cons. LNR is a simple and interpretable method that provides insight into the relationships between variables, but it may struggle to capture complex nonlinear patterns. DTR, on the other hand, is capable of modelling intricate relationships and handling both numerical and categorical features, yet it can easily overfit the data and lacks interpretability for larger trees. SVR excels at handling high-dimensional data and can effectively handle outliers, but it can be very challenging and time consuming with regards to finding the right hyperparameter combination. Finally, RFR combines multiple decision trees to mitigate overfitting, provides feature importance rankings, and handles a wide range of data types, but it may be more challenging to interpret compared to individual decision trees.

The selection of a specific technique depends on the specific problem at hand, the available data, and the desired balance between interpretability and predictive performance. Although other traditional methods as Gaussian Process has proved to be a good alternative for wind energy assets [230], due to the amount of data and inputs used here this method was discarded. Gaussian Process involves inverting matrix which makes it computationally expensive as the dataset grows larger. Also, as demonstrated in the section 4.1.2.2, the methods selected provided accurate predictions, which makes the use of more advanced methods unnecessary for the aim of this activity.

A normal problem in machine learning is the selection of the data, which can affect results positively or negatively. So, to avoid any misleading in the conclusions or any bias due to data selection, k-fold Cross Validation (CV) will be used. In this method, the data are split into “k” equal parts, where each of these parts is used as a test set, while the rest of data is used as a training set, so the model runs k-times. This process provides “k” different outcomes, so further statistical analysis will lead to evaluating each regression model, and the one that fits best for the purpose of this study will be selected.

Finally, to assess the accuracy of the method proposed, four different metrics were selected. These metrics were not only the most popular ones for evaluating regression accuracy but also offer unique perspectives when used together. First, the coefficient of determination, also known as R-squared (R^2). It measures the extent to which the dependent variable explains the independent variable. R^2 is calculated by considering the squared sums of the differences between predicted and observed values and the total sum of squares, as shown in formula 4-1. The results vary from 0 to 1, where 1 means perfect correlation, in other words, the dependent variables explain 100% of the variance in the independent variable. Conversely, a result equal to zero means there is no correlation.

$$R^2 = 1 - \frac{SSR}{SST} \quad \textbf{(4-1)}$$

where SSR is the sum of squared residuals and SST total sum of squares.

The other metrics are Mean Absolute Error (MAE), Mean Percentage Absolute Error (MAPE), and Root Mean Squared Error (RMSE). As suggested by its name, MAE calculates the average absolute difference between predictions and actual values (formula 4-2). It is less sensitive to outliers compared to other metrics. Similarly, MAPE (formula 4-3) considers absolute values, but also divides the error by the actual value, providing a ratio that reflects its accuracy. On the other hand, RMSE (formula 4-4) penalizes poor predictions by squaring the errors, offering valuable insights into the accuracy of the model. In equations 4-2 to 4-4, y_i is the tested value and $\hat{y}$ is the predicted one.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} 1 - \frac{SSR}{SST} \quad \textbf{(4-2)}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad \textbf{(4-3)}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad \textbf{(4-4)}$$

4.1.2 Data Analysis

To test the model proposed, SCADA (Supervisory Control and Data Acquisition) data from five onshore wind turbines of 2MW and Met Mast Data from the farm tower were used. For confidentiality reasons the location of the farm and model of turbines cannot be disclosed. It was provided information from 172 days with 10 minutes range, totalling 24,768 records per turbine. From the SCADA data was retrieved production and wind speed. The Met Mast Data, on the other hand, includes wind speed measured at five different heights, direction of the wind at four different points, humidity and temperature, both from two distinct points, and finally ambient pressure.

4.1.2.1 Pre-processing

From these data some abnormalities, such as negative outputs, incomplete data, and periods where wind speed was out of the production range were removed. Even though the cut-in speed of this turbine is 3.5 m/s, recordings below 5 m/s were not considered, because of the high fluctuations caused by the starting-up of the turbine. Production below 100kW was eliminated as well for the same reason. Hence, these values are more likely to be an error and could mislead the model. The goal of this work is to create a model to predict production and performance. Therefore, outliers can minimize the accuracy of the model. Considering that, an interval of confidence of 99% was calculated and the values out of this range were considered to be outliers.

As mentioned in the introduction, the performance index was calculated by the division of each validated data to the maximum production recorded in the same bin. The wind speed range of 0.5 m/s was selected for this study, following the recommendation from BS IEC 61400-12-1-2017. From now on, all the processes will be presented only considering the first wind turbine generator (WTG01) in order not to be repetitive. But the process explained here is the same applied to all turbines and in the same farm. As a result, from the original 24,768 recordings provided, 15,141 were used to assess the methodology proposed after pre-processing in WTG01.

Figure 4-2 illustrates the pre-processing evolution in three different stages. The first graph represents the total amount of data provided; it can be seen that the production fluctuates significantly during the period assessed. In the second graph, the first criteria for data reduction, wind speed below 5 m/s and production below 100kW, was undertaken and the interval of confidence of 99% was calculated. In this graph it is clear how outliers, especially those above the upper limit, can affect results. Since the performance is a rate between each value and its maximum, the outliers would affect all values in that bin, creating distortions in the model. It is important to note that this outlier was occasional, since there are no other points around it in the range, which justifies its removal. Finally, the last graph includes a colour map with the performance index calculated. The black line is the power curve provided by the manufacturer.

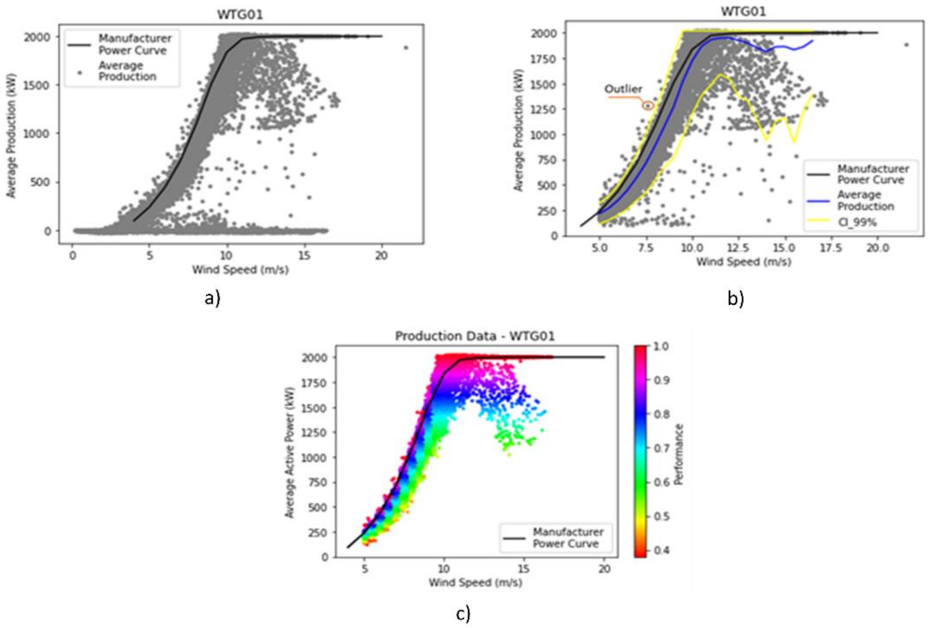

Figure 4-2 Pre-processing steps in WTG01: a) Complete Data; b) Initial excluding and Interval of Confidence; c) Data Pre-processed + Performance.

4.1.2.2 Model Selection

In the model selection activity, basic procedures and parameters were used. Nonetheless, a deep investigation of parameters was developed to run the methodology proposed and it is presented in the subsection 4.1.2.3. Hence, in few words, to find the best LNR model, Ordinary Least Square method was used.

To train the RFR, one hundred trees was used, and the kernel selected to the SVR was the “Radial Basis Function”. In all methods square error was used as a metric to the loss function and the input features were scaled through Standardization.

To avoid bias, a cross-validation was conducted to select the optimal regression method. In this analysis, k = 10 was considered, and the metric used was R^2. This study is divided into two different models: one to calculate the power output considering wind speed and performance (MODEL 1), and the other to predict the performance of production using Met Mast Data (MODEL 2). To provide a visual comparison of the results, a box plot from each method will be presented, illustrating the interquartile range, whiskers denoting the minimum and maximum values (excluding outliers), and individual data points. Additionally, a separate box within the graphs displays the mean value and standard deviation for each method, providing a summary of their performance. This concise representation facilitates a swift evaluation of prediction accuracy and variability across the different machine learning methods. Before defining the models, a similar procedure was done considering only wind speed to assess the advantages of including performance as an input, as illustrated in Figure 4-3.

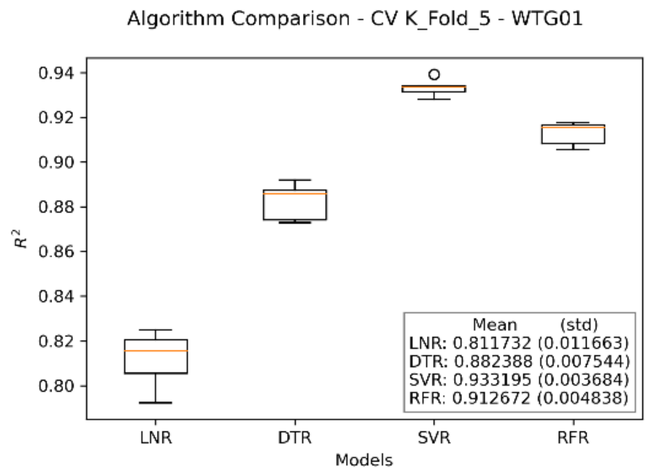

Figure 4-3 Box Plot of CV of Power Output Prediction with only Wind Speed

Figure 4-4 presents the results of the models to calculate production considering wind speed and performance. Even though considering only wind speed has some good values (Figure 4-3), the addition of performance significantly improved the accuracy in all methods. The high result is not a surprise since the performance index identifies the fluctuation of production in a certain bin, in other words, where exactly the production output will be. Although the visible curvature, LNR, obtained a high result, around 0.94, which illustrates and reaffirms the importance of the performance index as an input. DTR and RFR, which are nonlinear regression conditional models, achieved an exceptional correlation, with RFR demonstrating a slightly higher result (0.99988) compared to DTR (0.99980). This marginal difference suggests that the two models performed similarly, indicating a strong and nearly indistinguishable correlation.

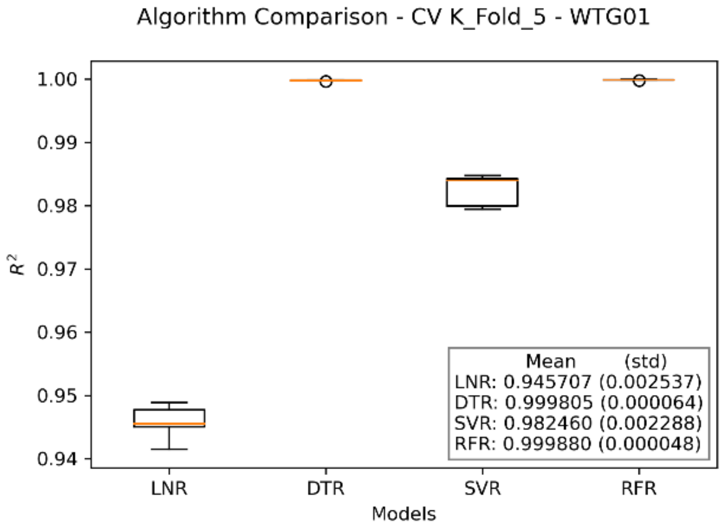

Figure 4-4 Box Plot of CV of Power Output Prediction with Performance and Wind Speed (MODEL 1)

The biggest challenge of the model proposed is the prediction of the performance index. Figure 4-5 shows the results of MODEL 2, where the performance was predicted using Met Mast Data as input. In this scenario SVR and RFR had the best results, achieving an average R^2 of 0.866 and 0.892 respectively. Considering the best outcome, RFR, the result is very consistent since the standard deviation was lower, around 0.0049, which means that around 89% of wind turbine performance can be explained by the Met Mast Data or external interferences.

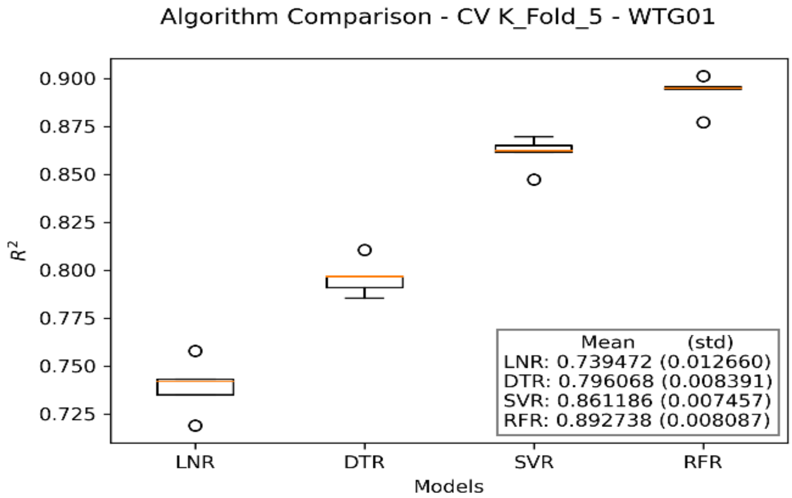

Figure 4-5 Box Plot of CV Performance Prediction through Met Mast Data Prediction Model. (MODEL 2)

4.1.2.3 Power Output Model

Based on the model selection analysis, RFR demonstrated superior performance compared to other methods in both proposed models, leading to its selection for predicting the performance index (MODEL 2) and calculating the power output (MODEL 1). RFR, with its versatile architecture and numerous parameter options, offers extensive possibilities for optimization. In this study, six widely adopted parameters used in optimizations were investigated. 'Bootstrap' enhances model robustness, while 'max depth', 'max features per leaf', and 'min samples per leaf' control tree complexity to prevent overfitting. 'Min samples split' captures meaningful patterns by determining the minimum number of samples required to split a node. The 'number of estimators' impacts overall performance and stability by determining the ensemble's tree count. These parameters are the most common and have the potential to enhance the accuracy and effectiveness of the wind energy prediction model. Further details on the parameters can be found in [231].

To tune the best set of parameters, two routines were created. Firstly, a range of commonly used parameter values was explored through random selection. Then, based on the best results obtained, a more focused range was retested, considering all possibilities. Each iteration used a fivefold cross-validation approach. Table 4-2 shows the parameters and criteria assessed at each stage, along with the selected parameters. Figure 4-6 shows the box plot of MODEL 2 after the parameters redefinition, resulting in 0.65% improvement in average R^2. As MODEL 1 achieved R^2 equals to 0.999, no further analysis was conducted on its basic structure.

Table 4-2 RFR Optimization parameters – WTG01

	Random	Single	Selected
Bootstrap	[‘True’, ‘False’]	[‘False’]	[‘False’]
Max. Depth	None & linspace (20,110,4)	[‘None’, 20, 80]	[‘None’]
Max. Feature per Leaf	[1, 2, 5, 10, 14]	[1, 2, 5]	[1]
Min. Samples per Leaf	[1, 2, 4]	[1, 2]	[1]
Min. Samples Split	[2, 4, 10]	[2, 10]	[2]
Number of Estimators	linspace(10, 1010, 11)	[110, 210, 410]	[210]
Total Possible Combinations	4950	108	-
Total Tested	1000	108	-

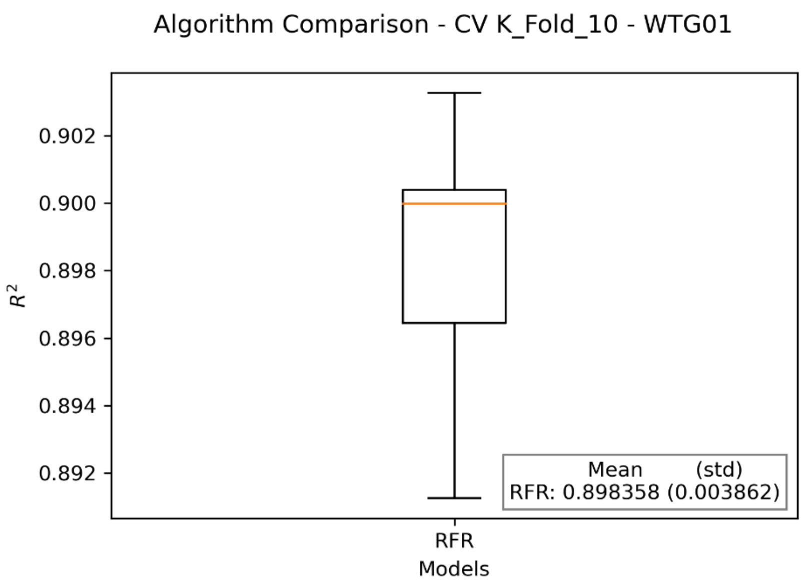

Figure 4-6 Boxplot of MODEL 2 after RFR tuning.

Finally, from the total data provided, 30% was set aside to validate the model, while 70% was used to train the models. To increase reliability on the models proposed, increment results and reduce the risk of bias, the selection of the validation group was random, and the procedure were run five times. It is important to mention that the validation data were separated before the performance calculation. The goal behind this strategy is to emulate a real scenario, where the performance index is calculated only with provided data and the performance index predicted is unknown. It is important to mention that to calculate the complete farm, the whole process was redone adding a new input variable to identify each one of the five turbines. In other words, "All Farm" scenario is not the average analysis of the five turbines individually, but it is a new simulation.

4.1.3 Results and Discussion

The proposed approach proved to be efficient to predict the wind power output. Table 4-3 presents the results from the five iterations considering turbine WTG01, where the predictions achieved an average of 0.24% error when compared to the real production. Regarding the metrics, the results were also very consistent, independently of the iterations. The R^2 was close to 100% and the average RMSE was around 77.9kW; since this is a 2MW turbine, this error is acceptable considering the benefit the model can bring. Gross production, i.e., the one considering the manufacturer power curve, was presented as a reference as well as the net production, considering 90.0% performance.

Table 4-3 Results from WTG1 with 15,141 data points (RP = Real Production, MP = Model Prediction, GP = Gross Production, NP = Net Production).

Iteration		RP (kWh)	MP (kWh)	GP (kWh)	NP (kWh)	R^2	MAE	MAPE	RMSE
1	Values	883,364.64	885,941.83	972,915.38	875,623.84	0.9852	52.6931	6.00%	78.1422
	Δ	-	0.29%	10.14%	-0.88%				
2	Values	884,423.00	886,833.65	976,478.52	878,830.67	0.9848	53.4556	5.97%	78.6284
	Δ	-	0.27%	10.41%	-0.63%				
3	Values	888,095.65	890,885.79	978,283.22	880,454.90	0.9851	52.9711	5.94%	78.3595
	Δ	-	0.31%	10.16%	-0.86%				
4	Values	881,308.79	882,689.29	971,379.26	874,241.33	0.9854	52.2486	5.85%	77.2820
	Δ	-	0.16%	10.22%	-0.80%				
5	Values	889,771.90	891,025.18	977,694.58	879,925.12	0.9857	51.4527	5.77%	77.1723
	Δ	-	0.14%	9.88%	-1.11%				

It is important to note that the net production has achieved a good result as well; however. this value is more appropriate for the design phase. By using a fixed rate, this value does not help the operators to understand the production behaviour, during the operational phase. As mentioned before, there are many factors that affect the turbine performance, many of which are related directly to the external factors and climate features. Therefore, the use of Met Mast Data to monitor performance and estimate production can be considered reliable. Some of the known operational losses are due to turbulence, air density, or wake effects, for example, and they can be linked to the differences in wind speed in different points, temperature, and wind direction, respectively, and all this information is provided by the Met Mast Data.

Another advantage of the model is that it gives extra information to operators about possible losses in the equipment’s efficiency. Components of the turbine tend to reduce its performance before breakdowns [58], but considering the high fluctuation in production, it is hard to identify if and when this possible loss is due to wind features or an equipment issue. Monitoring the expected performance through Met Mast Data could work as a reference to operators to check if the fluctuation is normal, considering the environment characteristics, or if this could be a mechanical or electrical problem.

While the model seems very useful to monitor production and performance in real time, future predictions were not evaluated until here. Knowing that it is very unlikely to have accurate forecasts within a 10-minute range, as calculated so far, an additional simulation of performance prediction considering daily average results was done and the results are shown in Figure 4-7. From the 172 days of data provided, the month of January, i.e., 31 days, was separated out as a test set, and the other 141 days as training. In this simulation the R^2 of the performance prediction was 0.89 and RMSE was 0.04, which means the model can provide a good accuracy even considering larger ranges. This can be useful, especially in order to plan maintenance in advance, since in some periods the total production can be lower, even though the wind speed is the same.

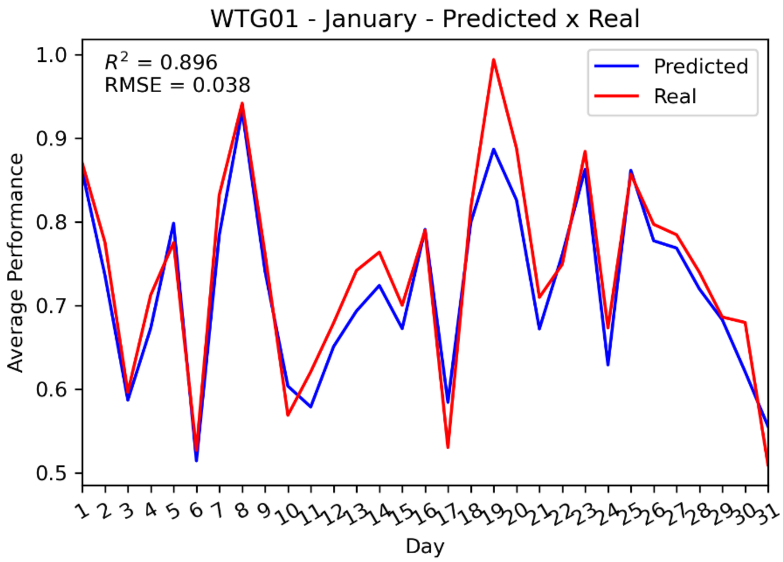

Figure 4-7 Performance Prediction X Real Performance – WTG01 – January

Although it is possible to find in the literature similar results in terms of accuracy, the model presented in this study has the advantage of use less computational resources when compared to more advanced techniques, such Artificial Neural Network or Gaussian Process as mentioned before. For real-time monitoring this can become an important advantage. Also, since the model here proposed uses data from diverse sources, this can avoid redundancies and provides a new independent input to operators. Nonetheless, it is expected an improvement in the performance prediction with more data, a deeper analysis and elimination of abnormalities (fault alarm data were not provided by the operators in this study), and a feature analysis and reduction.

Table 4-4 presents the average results achieved in each turbine and when the entire farm is assessed together. Considering all simulations, the average error between the real production and from the model was 0.16%. The MAPE and the RMSE was respectively, 5.68% and 72.83kW. The entire farm obtained a slight better result, with an average RMSE of 64kW, which could be due to the amount of data or by the identification of the turbine as input. It is expected that the difference in individual performance can be better tracked when they are assessed together, especially considering the wake effect loss.

Table 4-4 Average Results from Simulations

Param.	WTG1	WTG2	WTG3	WTG4	WTG5	All
Error	0.24%	0.07%	0.16%	0.08%	0.18%	0.21%
R^2	0.9852	0.9871	0.9863	0.9860	0.9858	0.9905
MAE	52.5642	49.4654	49.5505	51.1040	50.8078	41.4567
MAPE	5.90%	5.54%	5.71%	5.83%	5.93%	5.00%
RMSE	77.9169	71.1578	73.7286	74.6535	75.4473	61.5918

To sum up, the use of Met Mast Data to predict performance can be very beneficial: First because they contain most of the external information that directly affects wind power production, so it could reduce the use of several curves, which assess these inputs individually, to only one model. Second, for the authors, the turbine behaviour is unique, which means that although known, the influence of each factor on production losses can vary from farm to farm due to the topography, wind conditions and climate. So, the use of the Met Mast Data related to real performance provides an increasingly tailored model. In addition, a daily average model was created and proved to be as effective as using a 10-minute range, which means the model can be used for short- or medium-term predictions, depending on the accuracy of climate and wind feature forecasts or a historical database. To end up, the model proposed proved to be very effective in helping operators with decision making as a tool to monitor performance and predict production in real time or for future predictions.

4.2 OEE Analysis through SCADA[3]

Different from previous section, where MET MAST data was used to monitor the performance, in this section this element will be assessed considering only SCADA data. The goal behind this is activity is not to predict performance, but measure in a reliable and coherent way the real performance and productivity of the wind farm. Additionally, each of the OEE element will be discussed and measured. Due to limitation of the dataset, some assumptions needed to be considered. To not be repetitive, only the first wind turbine will be demonstrated

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[3] This section contains extracts from the publication by Sathler et al [110].

in following subsections, however, in the subsection 4.2.5, a summary considering the entire farm will be presented.

4.2.1 Availability

The data provided did not show when abnormalities and failures occur, neither if the turbine was shut down by the operator or in test/maintenance mode. Although this affects availability analysis, all missing data will be considered as downtime as well as when the wind speed was higher than 5m/s and the production was below 50kW. These abnormalities can be seen in Figure 4-1a. To calculate availability, the time-based method (A_{TB}) was selected, according to the equation 3-1.

4.2.2 Performance

The power output from wind turbine is directly related to the wind features as discussed before. The equation to calculate the power output is:

$$Power\ Output = \frac{1}{2}\,\rho A C_p(\lambda, \beta) V^3 \tag{4-5}$$

where,

ρ is the air density [kg/m^3].
A is the rotor area [m^2].
C_p is a performance constant, and it is related to the tip speed ratio (λ) and pitch angle (β).
V is the wind speed [m/s]

As shown in Equation 4-5, the power output is directly related to the air density. Three weather features can influence the air density, the local pressure, humidity, and temperature. These values are connected to each other, what makes the estimation of production through a simple power curve less effective. To correct this, a normalization of the measured values is recommended in the standard BS EN IEC 61400-12-1:2022. In this method, air density normalization is applied to the SCADA data provided before the calculation of performance. This method is briefly described below. First, the relative air density is calculated, through the Equation 4-6:

$$\rho_{10min} = \frac{1}{T_{10min}} \left(\frac{B_{10min}}{R_0} - \phi P_w \left(\frac{1}{R_0} - \frac{1}{R_w}\right)\right) \tag{4-6}$$

where,

ρ_{10min} is the derived 10 min averaged air density.

T_{10min} is the measured absolute air temperature average over 10 min [K];

B_{10min} is the air pressure corrected to hub height [Pa];

R_0 is the gas constant of dry air, 287.05 [J/kgK];

Φ is the relative humidity [%]

R_w is the gas constant of water vapour, 461.5 [J/kgK];

P_w is the vapour pressure equal to $2.05 \times 10^{-5} \exp(0.0631846\, T_{10min})$ [Pa].

Then, the wind speed measured is normalized according to the Equation 4-6:

$$V_n = V_{10min} \left(\frac{\rho_{10min}}{\rho_0}\right)^{\frac{1}{3}} \tag{4-7}$$

where,

V_n is the normalized wind;

V_{10min} is the averaged wind speed measured;

ρ_0 is the reference air density, here was assumed 1.225kg/m^2.

Additionally, the V_n is corrected with nacelle position:

$$V_m = V_n \cos(\varphi) \tag{4-8}$$

where φ is the misalignment angle between the nacelle and the average wind speed and V_m is the equivalent wind speed.

To calculate the performance analysis, the maximum production in each wind speed bin (0.5m/s) was identified and a rate of real value over maximum was considered its actual performance. However, in this activity, two extra components were added to straight the gap and makes the maximum performance assessment more realist. Besides the wind speed bin, the wind direction (WD30) and the wind turbulence intensity (TI) was considered. The first was grouped as 30º bin, while the later was calculated following Equation 4-8, according to BS IEC 61400-1:2019:

$$TI = \frac{\sigma_{10min}}{V_{10min}} \tag{4-9}$$

Where σ_{10min} is the standard deviation and V_{10min} is the mean wind speed calculated within 10 minutes. Some tests were performed before the classes was defined, following the impact in results and similar amount of sample to avoid bias in the analysis. Therefore, the three classes considered was:

- Class 1 - TI < 5%
- Class 2 - 5% ≤ TI ≤ 10%
- Class 3 - TI > 10%

4.2.3 Quality Estimation

As discussed in subsection 2.2.4, there are various causes of quality losses in wind energy deployments, ranging from the power quality of generated energy to transmission loss levels. Unlike in the manufacturing industry, which produces tangible goods, energy involves some subjectivity, making loss estimations a more challenging task. Unfortunately, to this analysis only SCADA data was provided, which limits the scope. However, some of quality losses can be calculated by considering the difference in the production output.

One of the main problems of wind energy is its high level of fluctuation. As wind energy is weather dependent, operators have limited control over its output. Grid operators must maintain a stable frequency by balancing active power in the system, and extreme energy variations can pose a problem. This effect, also known as ramp rate, is widely discussed, and some countries have included requirements in their national grid codes to better address this issue [232]. High increases (ramp-up) and high decreases (ramp-down) are both problematic, but while in the first, operators can minimize the fluctuation by reducing power output through the pitch angles, the same cannot be said for ramp-down. Either way, in both cases, wind farms can suffer financial losses due to curtailment or rejection of energy production or penalties, depending on the contract. Therefore, to estimate some possible quality losses, a ramp rate analysis will be conducted.

There are different ways to define the ramp rates, which could be by variation, duration, and/or change rate [168]. A rate considering the difference of power output in a defined period of time is the most common. Some grid codes define the acceptable rate of variance, usually 5, 7.5, or 10% [233], which allows an estimation of energy curtailed. Here, the grid limits were not provided, but to simulate some of these losses the ramp rate will be calculated considering the 10 minutes data available, and a deduction from the energy produced will be accounted as wind energy rejection. The following equation and rules summarize how the energy loss (EL) was calculated in the present simulation; the rated power considered was 5%:

$$\begin{cases} if\ |P_t - P_{t+10}| \leq 0.05\ x\ RP \quad \longrightarrow \quad P_{t+10} \\ if\ |P_t - P_{t+10}| > 0.05\ x\ RP\ \longrightarrow EL = \ P_{t+10}\ x\ (1 - \frac{|P_{t+10} - P_t - 0.05*RP|}{RP}) \end{cases} \tag{4-10}$$

where *RP* is the Rated Power, P_t is the Active Power, and P_{t+10} is the Active Power measured 10 minutes later.

4.2.4 Partial Results and Discussion of WTG01

To simplify the analysis, Table 4-5 presents the summary of results per week. The number of the week is the official one, according to the calendar and it was sort in chronological order. The average OEE was 70%, which for an onshore turbine can be considered a low value, as discussed in section 3.4. However, as mentioned before, it was not provided further information about faults or mechanical problems. This information could explain the reason behind low availability from the weeks 27 to 34. Ignoring this period, the availability would be 98%, close to the average found in the literature.

Table 4-5 Summary of the results of WTG01

Week	Average of Availability (A)	Average of Performance (B)	Average of Quality (C)	Average of OEE
26	1.000	0.641	0.966	0.619
27	0.706	0.755	0.928	0.495
28	0.522	0.816	0.946	0.403
29	0.307	0.862	0.939	0.248
30	0.612	0.895	0.963	0.527
31	0.704	0.802	0.965	0.545
32	0.870	0.768	0.952	0.636
33	0.906	0.765	0.960	0.665
34	0.486	0.732	0.977	0.348
35	1.000	0.757	0.959	0.725
48	1.000	0.915	0.975	0.892
49	1.000	0.876	0.985	0.863
50	0.982	0.868	0.976	0.833
51	1.000	0.790	0.987	0.779
52	1.000	0.868	0.969	0.842
53	1.000	0.771	0.989	0.763
1	1.000	0.850	0.969	0.823
2	1.000	0.852	0.983	0.837
3	0.897	0.849	0.974	0.741
4	0.923	0.853	0.964	0.759
5	0.921	0.834	0.976	0.750
6	0.979	0.808	0.969	0.767
7	0.996	0.874	0.965	0.840
8	0.999	0.833	0.960	0.799
9	1.000	0.763	0.962	0.734
10	0.922	0.803	0.963	0.713
11	0.998	0.882	0.955	0.841
12	1.000	0.812	0.967	0.786
Total	**0.867**	**0.830**	**0.967**	**0.699**

Table 4-5 shows an average performance rate of 83%, which is below the average reported in the literature. However, unlike availability, performance did not fluctuate significantly over the assessment period. With the exception of weeks 32 to 35, where the performance was approximately 75%, the rate varied from 80% to 90% for most of the period. To illustrate one advantage of the proposed analysis, assuming that the low availability recorded in weeks 28 to 31 was due to maintenance and the performance below 80% was seasonal, the overall productivity of the farm would be higher if the maintenance was done in this period, without any substantial changing in the project. In terms of quality, the values were consistent with the literature, although other losses such as transmission were not considered. While further testing is necessary to validate the criteria and rules used, the results are promising.

Other analyses can be conducted using the proposed OEE assessment. An investigation of performance variance revealed significant differences in situations with similar wind features. Table 4.6 exemplifies this observation, demonstrating that even with similar wind speed bin (WS), wind direction bin (WD30), TI class (TI_Class), and season (both were during summer and night-time), the performance varied by approximately 23%. The average performance during the first period was nearly 100%, while in the second period, it dropped to 77%. It is important to mention that OEE helps to identify abnormalities in the system, but further investigation is necessary to understand the root cause of this performance difference. This information is crucial for identifying possible solutions to minimize such variations and optimize wind energy productivity, ensuring efficient and cost-effective operation. The data provided does not allow further investigation, which could include even production reduction due to curtailment. However, it is important to consider this potential loss in the OEE assessment to ensure the metric captures the overall performance accurately and accounts for any operational limitations or curtailment effects.

Table 4-6 Comparison of two different periods with different performance

Month	Day	Time	WS	WD30	TI_Class	Average of Performance (B)
July	30	02:00	12.5	330	1	0.992836
July	30	02:10	13	330	1	0.999962
July	30	02:20	13	330	1	0.99995
July	30	02:30	13.5	330	1	0.994367
July	30	02:40	13.5	330	1	0.994346
July	30	02:50	13.5	330	1	0.994366
Month	**Day**	**Time**	**WS**	**WD30**	**TI_Class**	**Average of Performance (B)**
August	20	21:00	13	330	1	0.748819
August	20	21:10	13	330	1	0.75835
August	20	21:20	13	330	1	0.764873
August	20	21:30	13	330	1	0.772976
August	20	21:40	13	330	1	0.785902
August	20	21:50	13	330	1	0.793626

Other patterns can be found when the elements are grouped according to different criteria. Table 4-7, 4-8, 4-9, 4-10, and 4-11 summarizes the results grouped by temperature range, month, TI class, wind speed bin, and wind direction bin, respectively. About the temperature criteria presented in Table 4-7, the results are clearer correlated, but when the temperature is above 35º C, the performance decay is more evident. According to the manufacturer`s manual, above 35ºC, the production is reduced for equipment`s safety. This could also explain the performance variance when assessed per month (Table 4-8). As expected, higher turbulence caused lower performance and lower quality (Table 4-9), and the performance is higher when wind turbine works in its rated power (Table 4-10). Regarding wind direction presented in Table 4-11, only the angle bins 240 and 270 had a significant difference in the result, probably by the increased wake losses. It is worth mentioning that the rate considers the maximum in the same bin, so the reason for lower stability needs to be better investigated. Although the availability has varied among the tables, no conclusion can be done, due to the limited and size of the sample, as already shown in Table 4-5.

Table 4-7 Results of WTG01 grouped per Temperature Range.

Temp (ºC)	Average of Availability (A)	Average of Performance (B)	Average of Quality (C)
5-15	0.963	0.898	0.973
15-25	0.978	0.839	0.972
25-35	0.977	0.847	0.966
35-45	0.739	0.808	0.964
>45	0.614	0.752	0.945
Total	0.867	0.830	0.967

Table 4-8 Results of WTG01 grouped per month.

Month	Average of Availability (A)	Average of Performance (B)	Average of Quality (C)
January	0.944	0.844	0.972
February	0.991	0.843	0.965
March	0.972	0.823	0.962
July	0.571	0.835	0.952
August	0.777	0.759	0.961
December	0.996	0.858	0.979
Total	0.867	0.830	0.967

Table 4-9 Results of WTG01 grouped per TI Classes.

TI_Class	Average of Availability (A)	Average of Performance (B)	Average of Quality (C)
1	0.919	0.834	0.977
2	0.906	0.844	0.962
3	0.762	0.784	0.938
Total	0.867	0.830	0.967

Table 4-10 Results of WTG01 grouped per Wind Speed Bin.

WS_5	Average of Availability (A)	Average of Performance (B)	Average of Quality (C)
5	0.939	0.735	0.981
5.5	0.884	0.768	0.977
6	0.911	0.751	0.975
6.5	0.900	0.771	0.970
7	0.883	0.783	0.962
7.5	0.905	0.784	0.958
8	0.888	0.787	0.947
8.5	0.877	0.790	0.946
9	0.885	0.775	0.939
9.5	0.901	0.794	0.945
10	0.919	0.863	0.966
10.5	0.865	0.930	0.978
11	0.839	0.960	0.985
11.5	0.831	0.969	0.990
12	0.796	0.972	0.995
12.5	0.806	0.967	0.994
13	0.785	0.961	0.996
13.5	0.798	0.943	0.989
14	0.816	0.925	0.979
14.5	0.798	0.948	0.987
15	0.745	0.954	0.994
15.5	0.667	0.960	0.976
16	0.649	0.948	1.000
16.5	0.833	0.996	0.999
17	1.000	0.974	0.992
17.5	1.000	1.000	1.000
18	1.000	1.000	1.000
18.5	1.000	1.000	0.996
19	1.000	1.000	1.000
21.5	1.000	1.000	0.896
Total	0.867	0.830	0.967

Table 4-11 Results of WTG01 grouped per Wind Direction Bin.

WD30	Average of Availability (A)	Average of Performance (B)	Average of Quality (C)
0	0.872	0.931	0.938
30	0.908	0.812	0.968
60	0.928	0.847	0.956
90	0.770	0.846	0.948
120	0.830	0.853	0.961
150	0.926	0.845	0.969
180	0.933	0.827	0.972
210	0.943	0.824	0.965
240	0.924	0.730	0.949
270	0.915	0.747	0.957
300	0.875	0.846	0.970
330	0.816	0.833	0.973
360	0.790	0.842	0.962
Total	0.867	0.830	0.967

4.2.5 Results of the Wind Farm

Table 4-12 summarizes the results considering the entire farm. The first aspect to notice is that on average all elements performed slightly better when the entire farm is assessed. The total OEE of the period assessed was 73%. The availability only improved 3%, however, the low value was achieved in the same period, which means some abnormality or event might have occurred in the entire farm.

Table 4-12 Results considering all wind farm.

Week	Average of Availability (A)	Average of Performance (B)	Average of Quality (C)	Average of OEE
26	0.705	0.714	0.986	0.496
27	0.685	0.773	0.970	0.516
28	0.696	0.760	0.977	0.522
29	0.664	0.772	0.980	0.510
30	0.677	0.813	0.981	0.547
31	0.732	0.812	0.981	0.587
32	0.793	0.785	0.974	0.608
33	0.846	0.781	0.971	0.641
34	0.804	0.785	0.980	0.617
35	0.907	0.769	0.968	0.674
48	1.000	0.923	0.980	0.906
49	0.974	0.887	0.988	0.855
50	0.977	0.875	0.979	0.838
51	0.990	0.807	0.988	0.789
52	0.973	0.879	0.972	0.834
53	1.000	0.781	0.991	0.774
1	0.980	0.858	0.972	0.819
2	0.962	0.863	0.985	0.815
3	0.890	0.872	0.976	0.753
4	0.984	0.862	0.969	0.822
5	0.987	0.841	0.978	0.813
6	0.998	0.814	0.969	0.788
7	0.952	0.873	0.967	0.801
8	0.951	0.830	0.963	0.756
9	0.930	0.818	0.967	0.733
10	0.990	0.852	0.967	0.816
11	0.960	0.880	0.960	0.813
12	1.000	0.818	0.976	0.797
Total	**0.891**	**0.832**	**0.975**	**0.727**

4.3 Alternative of Performance Analysis

The performance analysis discussed in the subsection 4.2.2 considered only external factors, as turbulence and some weather features. However, it is also possible to evaluate performance by considering internal factors such as the generator rotational speed or the pitch angle. In this section, some alternative methods to measure performance will be presented.

4.3.1 Wind Speed x Generator Speed

Similar procedure as shown in subsection 4.2.2 was adopted for this analysis. However, instead of the wind direction and the turbulence, the best performance in each wind speed was found considering the generator rotational speed. The generator speed was grouped in bins of 50 rpm. To facilitate comparison and visualization, the average results are presented on a weekly basis in Table 4-13.

Table 4-13 Summary of Performance Analysis - Wind Speed x Generator Speed

Week	Average of Performance (B)	Week	Average of Performance (B)
26	0.757	1	0.898
27	0.832	2	0.925
28	0.881	3	0.903
29	0.899	4	0.919
30	0.902	5	0.926
31	0.836	6	0.900
32	0.816	5	0.926
33	0.791	6	0.900
34	0.760	7	0.905
35	0.810	8	0.904
48	0.921	9	0.878
49	0.927	10	0.890
50	0.935	11	0.906
51	0.870	12	0.898
52	0.905		
53	0.887	**Total**	**0.888**

The result of this method was 0.888, 0.058 higher than the previous method, which considers only weather features. By adding the generator speed the performance was more stable, however, the value is still lower than the average performance found in the literature. As mentioned before the techniques used to measure performance can vary a lot, which makes comparisons less precise. Unfortunately, there is not enough information to interpret these results properly, but machine learning techniques have provided a couple of solutions to explain black box models that can give some tips on what might be happening.

There are several methods for interpretability of machine learning models, including feature importance, partial dependence plots, permutation importance, LIME (Local Interpretable Model-agnostic Explanations), SHAP (SHapley Additive exPlanations), and integrated gradients. After careful evaluation, SHAP values were chosen as the preferred method for interpretability in this model.

SHAP is a comprehensive and unified method that provides detailed explanations of feature impacts on individual predictions. It utilizes Shapley Values, a game theory concept, to distribute predictions fairly among features. In this study, the open source SHAP library [234], available for Python users, was employed. Given the high accuracy achieved by RFR in the performance analysis of wind turbines, presented in section 4.1, the 'tree explainer' method recommended in the SHAP documentation was selected for this analysis. The assessment metric for the model was R^2.

The R^2 achieved in this activity was 0.85, indicating a strong correlation. The bee swarm graph in Figure 4-8 provides a summary of the SHAP analysis. Each point represents an instance, positioned vertically based on feature importance. The swarm's centre represents the central tendency, indicating the impact on the prediction (positive or negative). The colour signifies the feature's value, indicating its correlation with the final accuracy. The width of the swarm represents the uncertainty or spread associated with the SHAP values. From the analysis of the Figure 4-8, it is evident that Stator Active Power had the highest contribution to the performance, followed by Rotor Speed, Generator Speed, Ambient Temperature, and Pitch Angle.

Given that this is a DFIG (Double-Fed Induction Generator), the significant impact of Stator Active Power on performance can be attributed to its direct connection to the grid, aiding in reducing disturbances. As previously discussed, ambient temperature plays a crucial role in performance, particularly when temperatures exceed 35ºC. Some studies have proposed solutions to increase productivity in such scenarios without compromising equipment safety, as mentioned in [133]. In this study, modifications to existing dust filters and enhancements in nacelle ventilation allowed for an increase in the start protection temperature from 35 to 40ºC. The operational temperature of several components had a marginal impact on the performance, but should be investigated, since this could indicate some abnormality in the equipment.

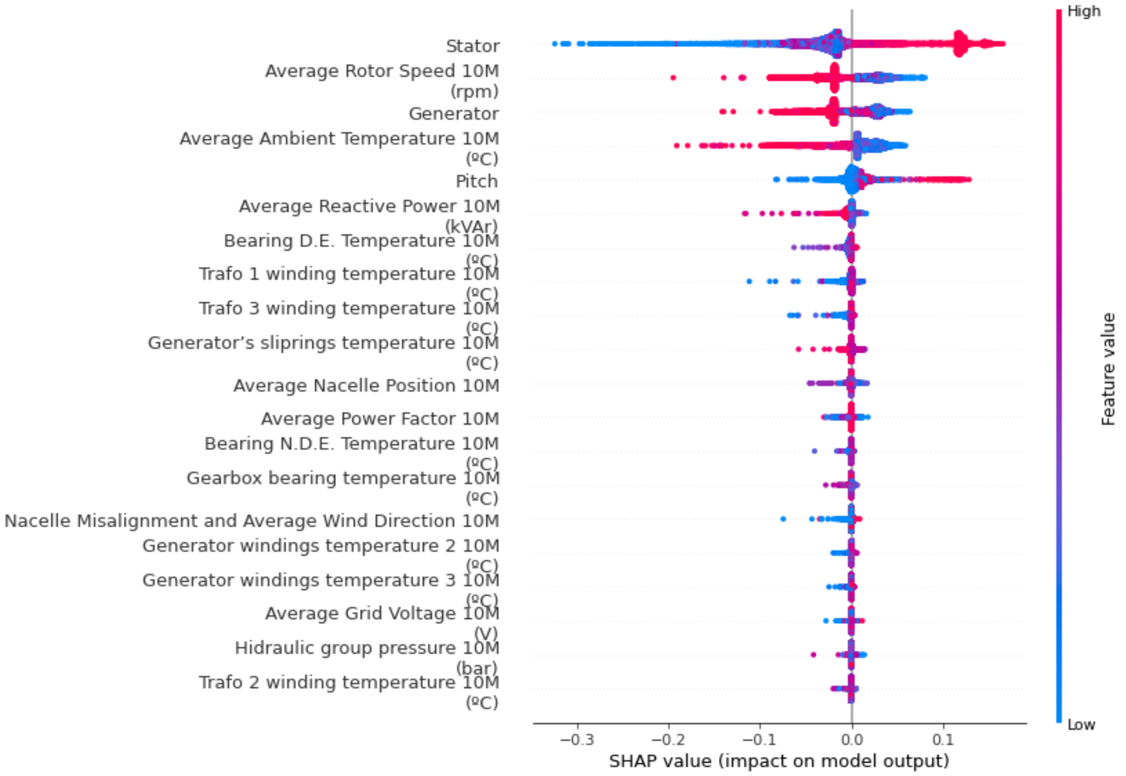


Figure 4-8 SHAP results of the performance.

4.3.2 Power Coefficient (PC)

As demonstrated in Equation 4-5, the power coefficient (PC) is directly related to the power output, and it is function of the tip speed ratio (TSR) and the pitch angle (β). Both values can be retrieved from the data provided. The tip speed ratio is the rotor speed divided by the wind speed, so this could be calculated following by taking the rotor speed measured by SCADA and converting the speed, as follows:

$$TSR = \frac{Rotor\ Tip\ Speed}{Wind\ Speed} = \frac{Rotor\ Speed\ x\ \pi D}{60.V_{10min}} \qquad \textbf{(4-11)}$$

D is the rotor diameter.

To assess the best performance, the tip speed bin and pitch angle bin was rounded as integers numbers. Table 4-14 presents the results of this analysis, where the average value was 75.4%. By considering the pitch angle and the rotor speed it was expected a better efficiency of the equipment, but the result was lower than the previous methods selected.

Table 4-14 Summary of Performance Analysis – CP.

Week	Average of B	Week	Average of B
26	0.669	1	0.751
27	0.776	2	0.759
28	0.763	3	0.759
29	0.821	4	0.749
30	0.836	5	0.743
31	0.801	6	0.729
32	0.754	5	0.768
33	0.719	6	0.736
34	0.715	7	0.708
35	0.725	8	0.736
48	0.823	9	0.782
49	0.767	10	0.740
50	0.752	11	0.751
51	0.696	12	0.759
52	0.767		
53	0.683	**Total**	**0.754**

4.3.3 Discussion

Regardless of the method selected, the most important thing is to not narrow too much the criteria for assessing performance. For the author, considering only external factors would be the best way to identify the equipment and operational losses, as demonstrated in subsection 4.2.2. Since, conceptually, if the wind conditions and weather features are the same, the equipment should provide same power output in normal situations. The problem behind narrowing the criteria too much is that this would mislead operators and managers about possibilities to improve the equipment productivity. In chapters 2 and 3, some simple solutions to improve the performance of the equipment, found in the literature, were briefly presented. However, according to OEE concept, this means that the equipment was not extracting power output at its maximum capacity.

4.4 Chapter Summary

This chapter was divided in two main parts. The first, section 4.1, a model was proposed to monitor and predict wind power output through traditional machine learning techniques. MET MAST Data was used as input and provided a high accuracy, even in daily average forecasts. The second part, sections 4.2 and 4.3, presented a data analysis of the same farm considering only SCADA data. The assumptions to calculate availability was discussed in subsection 4.2.1 and a method to estimate wind energy rejection was proposed in subsection 4.2.3. How to monitor and measure the performance was first presented in subsection 4.2.2, where only wind features was considered. Alternatives methods using internal information, such as generator speed and/or rotor speed, was presented and discussed in section 4.3. Finally, OEE was estimated, and its rate was grouped considering different categories for a better understanding of productivity and losses behaviour. This was presented in subsection 4.2.4 and 4.2.5.

5 LOSSES TRENDS & COST IMPACTS[4]

It was found in the literature three main reasons for projects to not achieve financial return along its entire operational life. They are the increase in OPEX more than expected in medium and long term, the decline of wind turbine performance due to the ageing of components, and finally, the curtailment and its tendency to be higher in the future. Therefore, the first section will introduce each of these problems with more details. Later, in section 5.2, an economic analysis is performed, considering the losses discussed previously. Finally, section 5.3 will present a cost analysis of a hypothetical onshore farm. Besides the loss trends discussion, this simulation will also check and compare the impact of different wind turbine classes in same location and layout.

5.1 Losses Trends

5.1.1 Failure Rate

As demonstrated in the Figure 3.2, the life cycle of an equipment can be represented by the bathtub curve, which represents the three main phases of an equipment life. First, the equipment starts with a high failure rate, also known as infant mortality, then, during the operational life, its failure rate stabilizes, and finally, failure rate starts increasing again, until running the equipment is not considerable viable anymore. Nonetheless, for some authors, the parameter shaper of the operational life period of wind turbines can be slightly higher than one [15], which indicates a slow constant increase in failure rates.

Some studies have shown this behaviour. According to [13], maintenance is far from being uniform across projects. As demonstrated by [235], annual failure rates of wind turbines rated above 1MW tends to increase significantly with time. In worser scenarios, the average annual failure rate starts close to 0.25, but it overpasses 2 failures per year in seven years. [236] and [237] have shown similar trends and [238] shown an increase in downtime during the operational life of wind turbines. Since the increase of failure rates directly affects the OPEX and

[4] This chapter was based on the publication by Sathler, Yeter and Kolios [289].

the availability of an equipment, investigating these aspects can help to confirm if this is a consistent trend.

According to [239], the leading cause of the increase of costs are the more frequent failures with age. [14] found that operational costs of onshore farms can quadruple during its lifespan, similar scenario was pointed by [15]. Although offshore wind projects are newer and relies on more robust technology and engineering, the behaviour is comparable. In 2012, [12] affirmed the costs are likely to be 3.6 times higher after 20 years. [239] estimates the costs are likely to double in 10 years, without considering transmission costs. Regarding the availability index, [28] estimates a decay in the availability close to 95% after the 11th operational year for onshore projects. [240] investigated several databases, and found old projects, with 30 years, can have availability close to 80%.

It is worth mentioning that some of database investigated in the literature are old and can bring some bias in the analyses. However, although the technology has improved during the last years, it is difficult to confirm if this trend has been minimized, since most of companies, do not provide this information in detail. According to [13] which has followed the costs of some farms, the overall costs have indeed reduced, however, they still seem to increase with the age. In their study, newer or older projects have almost doubled its costs in five years, though the sample size of their investigation was limited.

5.1.2 Ageing

Any engineering system is at the risk of degradation during its lifetime. For system such as wind turbine this scenario can be worse, due to uncontrolled environment in which they are located. Besides the wear out of components, problems such as corrosion or blades erosion are examples of reasons why the performance of a wind system can deteriorate with the age and replace them can be costly and time consuming. According to [191], the increase in failures and downtime cannot explain the decreasing trend in capacity factor and expects that at least two thirds of the performance reduction is due to worsened efficiency, particularly resulting from the loss of aerodynamic efficiency caused by worn-out blades. In other words, an older turbine tends to produce less than expected in the same wind regime, when compared to its early operational years.

In a study conducted by [16], for oldest turbines the yearly relative loss was on average 0.53% during the first 10 years, then this rate increased to 1.23%. The study concluded that this was due to the end of subsidies from the government, hence, companies tend to compensate for costs by reducing maintenance activities to keep the profit margin at the same level. For newer projects, they had the data from only the first 10 years, and the relative degradation level was 0.17% per year. These results illustrate the importance of a good maintenance routine and how newer turbines are more prepared to resist degradation.

Other studies have also investigated the theme. [115] assessed the performance of one farm through SCADA for one year and found no significant loss, but they found an impact on the temperature and vibration of the system. [17] investigated performance losses in wind farms in Germany from 2000 to 2014 and found that yearly ageing losses are, on average, 0.63%. [191] calculated an early decrease rate of 0.15%, which would account a total of 6% reduction in performance until the end of the turbine`s life. A worser rate was identified by [18], where farms from UK were investigated from 2002 to 2012, and the average relative ageing loss found was 1.6%. Although this study was well conducted, it is more likely that this rate is an outlier, when compared to other studies investigated.

5.1.3 Curtailment Trend

Curtailment is when the production needs to be interrupted or reduced, regardless of the wind regime and the availability of the turbine. This could be by operational problems, when production is out of requirements and could put the system in risk, or by external factors, such as bird migrations, shadow flickers, or lack of demand. The last one is particularly a big problem, since they are unexpected and in case of the project assumes these losses, this could affect the viability and the final price of the energy. As discussed in section 3.3, while some countries experience curtailment rates below 5%, others have reported energy dispatch curtailment of more than 15%. This issue has raised concern among several countries.

According to [149], who investigated curtailment in Nordic countries, although there are no big concerns nowadays, this can become a problem in the future if new transmission lines are not constructed. [19] had similar conclusion, where in their simulation 15.5% of the wind energy produced in USA in 2050 could be curtailed without expansion of transmission lines. [241] simulated various scenarios to assess the impact of increasing renewable energy penetration, and their findings showed that curtailment loss in Great Britain could reach 17%. However, they also examined how power grid limitations could mitigate these losses.

Given the global push to increase renewable energy sources rapidly, there is a genuine risk of increased curtailment levels. As noted in [220], the installation time for wind farms is usually shorter than that of transmission networks. Although there are some solutions (discussed in 6.3) to reduce curtailment and increase wind power penetration, it might not be feasible to use or store all excess of energy generated [212]. With higher levels of wind energy penetration, the cost of grid strengthening may increase significantly.

5.2 Cost Impacts

5.2.1 Methods

There are several methods to assess a project viability, profitability, and its total costs. In this section, the three methods selected to develop this work will be presented. LCOE, to check the average cost expected to produce one unit of energy and NPV, to assess its viability. Additionally, a Monte Carlo Simulation and Sensitivity Analysis are included for a better analysis of results.

5.2.1.1 LCOE

The levelized cost of energy (LCOE) is one of the most commonly used metrics for estimating the cost of energy production, allowing for comparison of different energy sources or projects within the same energy source. In brief, the LCOE takes into account the present value of all costs and expenses over the lifespan of the project, from its conception to decommissioning, and divides it by the discounted sum of all energy delivered over the same period. The main formula and its adaptation to the wind power model being developed are shown below:

$$LCOE = \frac{Life\ Cycle\ Cost}{Total\ Energy\ Delivered} = \frac{\dfrac{CAPEX + DECEX + \sum_{i=1}^{t} OPEX}{(1+r)^t}}{\dfrac{\sum_{i=1}^{t} Anual\ Energy\ Output}{(1+r)^t}} \quad \textbf{(5-1)}$$

Where r is the discounted rate and t corresponds to the lifespan of the project.

5.2.1.2 NPV

The net present value (NPV) provides insight to confirm the viability, profitability, and value added by the project. Unlike LCOE, this metric considers the revenue value, comparing the cash flow expected throughout its lifespan. The projects that are worthwhile to invest in, need to have a positive value at the end of the project's lifespan, while the project with a negative value should be rejected. Figure 5.1 illustrates a diagram with the cash flow analysis. It is essential to check that even if the project has some negative years, as illustrated in year 4, the overall analysis of the project could still be positive in the end. When this method is used to compare different projects, the one with the highest value, where the expected return is higher, should be selected. The NPV formula is as follows:

$$\begin{aligned} NPV &= \sum_{i=1}^{t} \frac{Yearly\ Cash\ Flow}{(1+r)^t} - Investment\ Capital \\ &= \sum_{i=1}^{t} \frac{\{(Year\ Production\ x\ Revenue) - OPEX\}_i^t}{(1+r)^t} - CAPEX \end{aligned} \quad \textbf{(5-2)}$$

Where r is the discounted rate and t corresponds to the lifespan of the project.

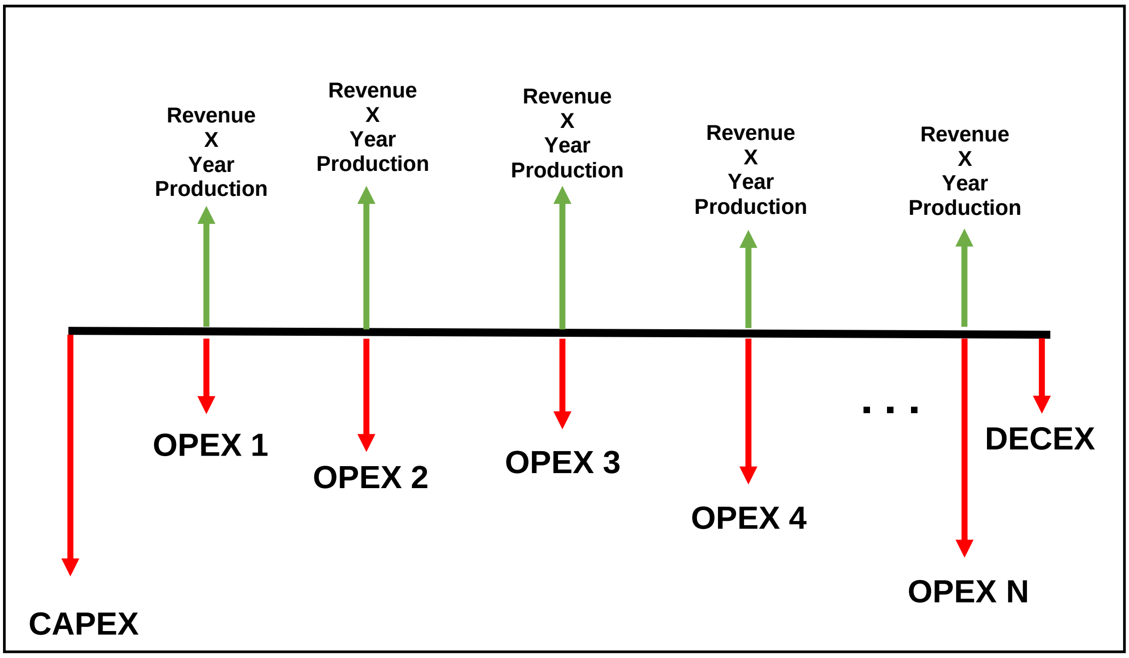


Figure 5-1 Diagram with cash flow analysis

5.2.1.3 Monte Carlo Simulation

It is very difficult, if not impossible, to develop a fully accurate model for any long-term project. During the design phase, some assumptions need to be made, which affect the results, in turn misleading investors' decisions. In order to address this issue, several methods are available to create a more reliable financial model, one of which is the Monte Carlo Simulation (MCS). In a Monte Carlo Simulation, the range of uncertain inputs is randomly selected, and the model is run a significant number of times, producing the range of all possible outcomes. Therefore, MCS helps investors to understand the variability of financial outcomes, providing a better insight into the risks associated with the viability of an offshore wind project.

5.2.2 Cost Assessment

This simulation will focus on offshore projects. Usually, the distribution of costs of an offshore deployment are on average 20 to 30% of costs from OPEX, 70 to 80% to CAPEX, and 1 to 3% from the DECEX. In the next subsections, the values found on literature related to these elements will be presented. Additionally, some other essential elements will be discussed, the strike price, capacity factor, and operational losses to determine the production and incomes of the project; and, finally, the discounted rate, a key component used in long-term economic analysis.

5.2.2.1 CAPEX

Going further away from the shore requires more complex engineering solutions, consequently, the cost of energy produced is expected to be higher and thus potentially unviable. However, even though offshore wind is more expensive than its onshore counterpart, operating in better wind regimes makes it a competitive energy source when considering cost per unit. According to [242], offshore projects can be cheaper than onshore wind or even compete with some gas plants in few years.

According to [243], the average CAPEX in 2019, considering projects delivered in the UK, Netherlands, France, and Norway was around 3.7m£/MW. Although more expensive, this value is not far from the models developed by [10], [244], [198], achieving respectively, 3.1m£/MW, 3.3m£/MW, and 2.8m£/MW. Two other important renewable energy agencies, NREL [245] and IRENA [246], registered respectively, 2.7m£/MW and 2.2m£/MW, while the UK government predicts that this cost could be around 1.6m£/MW in 2025 [247].

5.2.2.2 OPEX

The share of OPEX in the total costs of offshore projects, can be as high as five times, when compared to onshore [248]. Besides the harsher environment, which can cause more fatigue loads combined with degradation mechanisms, the bottleneck regarding supply vessels and the dependency on weather conditions for maintenance activities are the main reasons why operations can be quite costly. Storm conditions could make the journey to the turbine riskier. According to [52], in offshore only 22.2% of the mean time to repair are related to repair activity itself, and the rest is due to preparations and the waiting for appropriate conditions and spare parts. Moreover, according to [38], components might be changed before its ideal life cycle because of limited interventional opportunities, which could also affect the cost.

The values regarding OPEX found in literature vary significantly. Most agency reports have shown a lower cost, from 50 to 60k£/MW per annum, while in economic simulations, prices were shown to be higher than 100k£/MW. This could be explained by the fact that there are ambiguous assumptions about the distance. Furthermore, the cost associated with offshore wind would vary for each country due to salaries, taxes, bureaucracy, and infrastructure affecting all operational activities. Another problem is that most companies do not provide the actual costs, considering it confidential and strategical.

5.2.2.3 DECEX

Wind farm projects are designed with a specific operating period in mind, and after this period, it is expected that the investor will decommission the project and clean the area, leaving the environment as close to its original state as possible. Although projects can be extended, the DECEX needs to be taken into consideration when the project is no longer financially viable. [249] conducted a bottom-up analysis and found that the DECEX would fluctuate from 175 k£/MW to 480k£/MW. This range is close to what was found in another research, such as cost of 462k£/MW [10], 244k£/MW [244], and 135k£/MW [198]. As presented in Figure 1-1 it is likely that part of these costs will be covered by the recycling of residuals, but this was not considered in this analysis.

5.2.2.4 CF

The expected wind speed varies considerably throughout the year, and due to other inefficiencies in offshore wind operations, the actual energy output can differ from the theoretical maximum energy output from offshore wind assets. The difference between the actual energy output and the theoretical maximum output is represented by a ratio called the “Capacity Factor (CF)”, which provides a more realistic estimate of expected energy output from an offshore wind site and is used in energy resource and feasibility assessments. For accurate capacity factor estimations, it is crucial to know the wind regime, site characteristics, and technical information from wind turbines.

There is an optimistic expectation that technological advances, larger wind turbines, and offshore wind sites with higher wind potential will allow for much higher capacity factors. In this regard, some agency reports forecast capacity factors surpassing 60% in the next few decades [247]. However, the present study only considers the actual capacity factors available in the literature, rather than what is expected in the future. Thus, the capacity factors used in the analysis vary from 42.5% to 53.5%.

5.2.2.5 Strike Price

The revenue estimate is a vital part of the economic viability analysis. This value corresponds to the strike price of the energy delivered and depends on the contract details of each project. Most wind farm projects have an agreement about their prices and do not compete directly in the market, which has been an effective way to incentivize offshore wind development. Nonetheless, the strike prices have been reducing drastically, as shown by The Low Carbon Contracts Company (LCCC) and the Electricity Settlements Company (ESC) projects. At this moment, they manage 40 offshore projects through contract for difference (CfD), where the current strike prices to offshore projects fluctuate from £45.73 to £176.57 [250].

A similar difference is described by [242] where they state that between 2017 and 2020, the average value from offshore dropped from £167 to £112 per MWh, and the average future values expected is £59.25/MWh. Other researchers estimated to their simulation £140/MWh [10], £74/MWh [198], and £87.60/MWh [251].

5.2.2.6 Discounted Rate

To perform a long-term economic analysis, the time value of money must be considered. As money can depreciate over time and future expenses can have a lower value in the present, investments made in different periods must be corrected to eliminate the effects of time. According to [252], the discount rate varies from 5 to 7% in most developed countries, while this value can be higher than 10% in other emerging countries. [239] reports that the discount rate in subsidized wind projects fell from 8% in 2009 to 4% in 2019. Other studies, such as [253], [247], and [10] which estimated 8.06%, 6.3%, and 6.15% respectively.

5.2.2.7 Summary

In light of the discussion above, estimating the costs and production of offshore installations can be challenging. The distance to the shore, structural basis, logistics, policies in each country, and the expertise and size of the company are the main reasons why costs fluctuate significantly.

Table 5-1 summarizes the values found in the literature, which will be the cost basis for this study. Regarding the assumption outside Table 5-1, the mean value shown in Figure 3.4 will be considered, So, the availability, performance, and quality rates used will be 92%, 90%, and 95%, respectively. The discounted rate assumed is 6%, according to values discussed in the subsection 4.2.2.6. The lifespan assumed is 20 years, since this is the technical life most wind turbines are certified for [254] [255].

Table 5-1 Costs from the literature review

CAPEX	OPEX	DECEX	CF	Strike Price	Reference
£3,079,650.00	£112,300.00	£243,770.00	0.425*	£140	[10]
£2,276,384.00	£66,122.24		0.44		[246]
£2,701,000.00					[256]
£3,305,526.24	£180,218.75	£461,655.81	0.535		[244]
£2,837,500.00	£53,250.00	£135,000.00	0.49	£74	[198]
		£327,500.00			[249]
	£100,018.86				[257]
£2,737,500.00	£54,750.00			£87.60	[251]
£3,784,000.00					[243]
£1,630,000.00	£54,170.40*		0.51		[247]
	£146,200.00				[258]
				£167 - £47	[242]
				£155 - £59	[250]

Conversion Rate (2021) £ = 0.73US$
£ = 0.86€
*Stipulated by the authors

5.2.3 Scenarios

As discussed in the section 5.1, there are three main risks to be considered during operational life. The rates for each scenario will be discussed in following sub-sections. After that, the economic model proposed will be briefly explained and a summary of the scenarios, parameters and costs considered in the simulations will be presented.

5.2.3.1 Scenario A - Failure Rate Increasing

OPEX includes all operational costs, from administrative to maintenance. As the increase in the costs are related to the increase of failures, only maintenance costs will be considered to rise in this simulation. The other costs are going to be considered as constant throughout the lifespan, as inflation are not incorporated in this work. In the model developed by [10], around 50% of the OPEX are due to maintenance. While to [251], [244], [259], the share is 58%, 45%, and 43% respectively. Considering the average of these values, this work will consider that 49% of OPEX costs are due to the maintenance.

Following the trends found and discussed in the section 4.1.1, the increase in the maintenance costs will be 3 times during its entire life, which means an increment of 6% per year. It is important to notice that more failures result in more production losses. In this study, it will be considered that half of availability losses, or downtime, are planned (preventive maintenance); while, the other half are considered unplanned, so failures and breakdowns. Thus, for each increase in cost, a further deduction in the production following the same rate will be added. Since it is difficult to determine when these failures will occur, these losses are multiplied by its CF, as an attempt to be closer to real life scenario.

5.2.3.2 Scenario B – Ageing

According to subsection 5.1.2, the yearly relative ageing rate fluctuates from 0.17 to 1.6%. Great part of the studies assessed focused on onshore deployments and in some cases older deployments. To convert this to offshore to aspects needs to be considered. First, offshore wind turbine can be considered a recent technology, especially the ones that go further to the shore. In that case, assuming a lower ageing rate could fit better to offshore farms. However, offshore are exposed to a harsher environment and face more loads in its operational periods. So, it is reasonable to consider the range presented, therefore a constant relative ageing rate of 0.5% will be considered.

5.2.3.3 Scenario C – Curtailment and Quality Losses Trends

It is difficult to determine how much energy will be curtailed in the future. The energy can be curtailed by several reasons, including lack of demand and power quality. As described in the section 2.2.4, this work will consider all losses after the turbine as a quality loss. It is expected that the losses in cable and the power quality reduces together with the degradation of the turbine. Therefore, in this scenario, the initial quality loss of 5% will triple during the entire life. Considering all risks involved and the curtailment rates discussed in the subsection 5.1.3, this assumption is not only consistent, but also a conservative, since this loss can occur by several reasons.

5.2.4 Economic Model Application

The proposed model is divided into two parts. The first part presents a projection of the real-time behaviour and extracts key financial metrics such as LCOE , NPV, critical year, and breakeven year. These metrics are calculated based on average values. The critical year helps determine when the costs will exceed the benefits, while the breakeven year represents the point at which the accumulated benefits surpass the total costs. The concept of the breakeven year is similar to that of the discounted payback year, which takes into account the time value of money.

It is important to note that the assessment of the critical year considers the fixed instalment payments of the CAPEX. Therefore, it is possible for a project to have a critical year before its end of life, while the investment breakeven can still occur during the operational life, as the analysis focuses on cumulative cash flows without considering investment obligations. This distinction will become clearer in the subsequent sections when discussing the results of the simulations. Figure 5-2 provides a visual representation of how the critical and breakeven years are determined, aiding in the understanding of these key concepts.

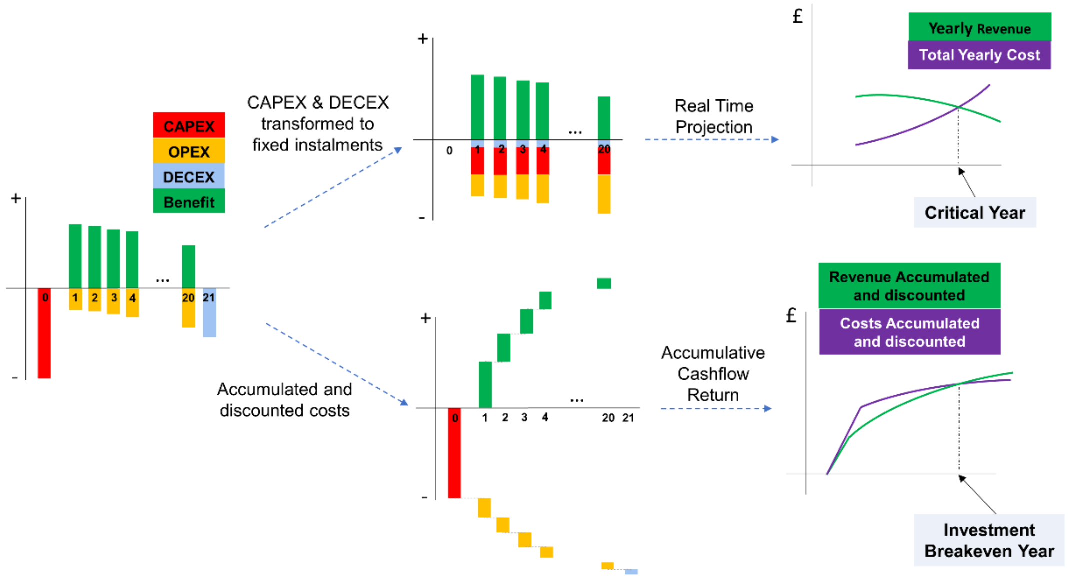


Figure 5-2 Diagram of Breakeven and Critical year analysis – Part I

The second part of the model proposed is the Monte Carlo Simulation (MCS). In addition to the scenarios presented before (Scenarios A, B, and C), a reference scenario is created in which no loss trends occur. This is more common to find in the literature, where costs and benefits are considered constant throughout the project life. Additionally, since it is more likely that the scenarios defined will occur at some level together, a mix of scenarios is investigated. To do this, all possible combinations are explored: Scenarios A+B, A+C, B+C, and A+B+C.

Figure 5-3 summarizes the economic model proposed and illustrates the MCS. For each simulated scenario, 100,000 iterations were randomly run, selecting the defined cost range, one positive and one negative standard deviation, and dividing them into 25 possible values with the same interval. There is no fixed rule or concept for determining the exact range size in Monte Carlo Analysis. However, a larger number of values generally enables a more comprehensive exploration of the variable space, creating a greater range of feasible scenarios. It is important to balance this with computational resources and time constraints. In this case, considering the standard deviation and average values, a range of 25 values was chosen, which was deemed sufficient to capture variability and provide robustness to the model.

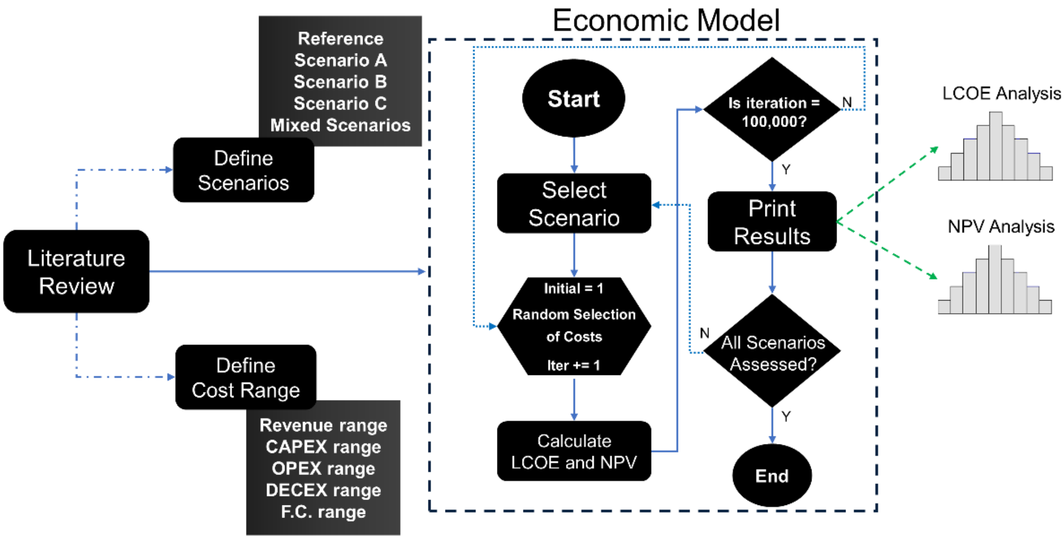


Figure 5-3. Flowchart of Economic Model and Monte Carlo Simulation – Part II

Table 5-2 presents the costs and all considered assumptions to run this model. The values correspond to the mean value, *μ,* found in the literature. The standard deviation, *σ,* was calculated assuming the values have a normal distribution. The assumptions regarding initial losses and performances, the operational period, and the discount rate are the same in all simulations. The parameters used in each scenario are presented in Table 5.3.

Table 5-2 Average Costs and Basic Assumptions to the model

	μ	σ
CAPEX	£2,793,945.03	£608,267.09
OPEX	£95,878.78	£44,813.62
DECEX	£291,983.95	£119,396.26
Revenue	£111.40	£37.43
CF	0.49	0.04
Availability	0.92	-
Performance	0.90	-
Energy Losses	0.05	-
Operational Period	20 years	-
Discount Rate	6%	-

Table 5-3 Scenarios investigated

Scenario	Parameters
Reference	-
Scenario A	OPEX Increase rate = 6% per year. 49% of OPEX is due to maintenance, or variable.
Scenario B	Year Ageing Loss = 0.5%.
Scenario C	Curtailment/Quality losses Increase rate = 6% per year.

5.2.5 Results and Discussion

The scenarios have been sorted from the most positive to the most negative. To avoid repetition, only scenario A is presented graphically. The results from the economic projection of all scenarios are presented in Table 5-4, which corresponds to Part I of the model discussed in subsection 5.2.4.

Table 5-4. Projected cost throughout lifespan considering average values.

	LCOE (£/MWh)	NPV (£/MW)	Critical Year	Investment Breakeven Year
Reference	£98.93	£501,609.17	-	15
Scenario C	£102.41	£349,487.39	-	15
Scenario B	£103.64	£298,076.55	20	16
Scenario B + C	£107.16	£157,326.81	12	17
Scenario A	£110.89	£19,773.91	10	18
Scenario A + C	£114.69	-£124,287.95	9	-
Scenario A + B	£116.34	-£183,758.72	8	-
Scenario A + B + C	£120.19	-£316,448.53	7	-

In Figure 5-4, a real-time and accumulated projection for scenario A is presented. The first aspect to notice is that, although the NPV of this Scenario was positive, the critical year was in the tenth year - half of the lifespan expected. This may be considered counterintuitive; however, this result is supported by some studies. According to [214], wind turbines require increased maintenance costs and significant refurbishment around the 11th year of operation. The breakeven year was in the 18th year, which is closer to the end of turbine's operational life. These results can be explained by the small margin projected, where the average LCOE (£110.89/MWh, 12% higher than the reference) was only £0.51 lower than the strike price assumed.

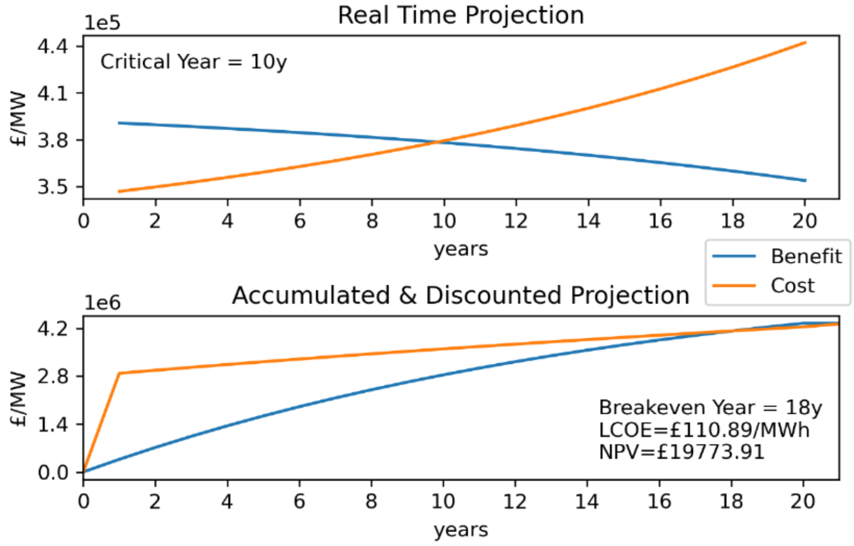


Figure 5-4 Results Scenario A

The impact on costs and viability is found to be lower in the other scenarios when assessed individually. While the increase in LCOE for Scenario C is around 3.5%, it is around 4.7% in Scenario B. This slight difference of 1.2% in Scenario B is enough to raise the breakeven year to the 16th year and bring the critical year to the last year of operation. Nonetheless, in both scenarios, NPV was higher than zero, meaning that the techno-economic analysis suggests it is worthwhile to invest in the project. In contrast, in the mixed scenarios, the results are not very positive. Apart from Scenario B+C, where the results are better than Scenario A alone, Scenarios A+C, A+B, and A+B+C appear to have negative net present values and do not achieve the investment breakeven year during the projected lifespan.

As discussed before, in addition to the impact on operational loss trends, Part II of the analysis aims to understand how assumed costs could affect the LCOE and the project's viability. Therefore, Table 5-5 summarizes the results from MCS, where the variation in LCOE is presented, considering a 95% confidence interval, together with the percentage of positive NPV values obtained in the simulation. Figure 5-5 presents the histogram with both analyses of Scenario A. The costs fluctuate from £81.64 to £140.65, and more than 50% of simulations considering Scenario A resulted in an NPV higher than zero. This means that despite the increased OPEX costs, there is still a considerable chance of the project being profitable for its investors.

Table 5-5. Results from Monte Carlo Simulations in all scenarios.

	LCOE (IC 95%)			**NPV > 0 (%)**
	Lower Limit	*Average*	*Upper Limit*	
Reference	£73.81	£99.08	£124.34	0.65986
Scenario C	£76.44	£102.62	£128.81	0.61316
Scenario B	£77.33	£103.79	£130.26	0.59954
Scenario B + C	£80.02	£107.43	£134.84	0.55164
Scenario A	£81.64	£111.14	£140.65	0.50332
Scenario A + C	£84.46	£115.04	£145.61	0.45415
Scenario A + B	£85.52	£116.63	£147.74	0.43399
Scenario A + B + C	£88.36	£120.49	£152.62	0.38728

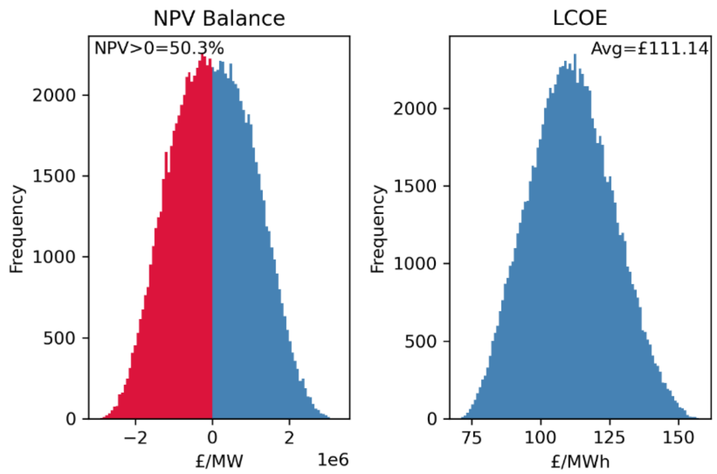


Figure 5-5 Results of Monte Carlo Simulation of Scenario A

Scenarios B, C, and B+C are also very positive for investors, achieving NPV higher than zero in more than 50% of the simulations. On the other hand, Scenarios A+B, A+C, and A+B+C are considered riskier to investors. Besides reassuring an elevated increase in costs, found in Part I, less than half of simulations are considered worthy of investing. The worst case is Scenario A+B+C, where the average LCOE is £120.49/MWh, 21.6% higher than the reference, and only 38.7% of simulations has got a positive NPV.

It is worth mentioning that these scenarios were investigated to understand how the operational loss trends would affect the projects financially. Nevertheless, operators and managers are expected to interfere in these projects before the situation becomes irreversible. Therefore, the proposed study not only provides an estimate of costs and risks but also serves as a guide for managers. Such guidance helps decision-makers monitor whether the project is going in the right direction and what the consequence would be if nothing is done to mitigate the risk.

Furthermore, conducting a sensitivity analysis is crucial for understanding the relationship between the defined rates and the output. This analysis helps identify which factors are more critical and sensitive to the overall outcomes. In this study, in addition to the three previously discussed scenarios, the discount rate was also investigated, as it is a key element in cost models. The range of values considered encompassed both more likely range and extreme scenarios, with the previously determined average value serving as the central value. The chosen step size for the investigation was 0.02, except for Scenario B, where a smaller step of 0.002 was used. This step size adequately covers the relevant assumptions, and further narrowing of the step is not necessary. Figure 5-6 presents the results for the levelized cost of energy (LCOE), while Figure 5-7 depicts the percentage of net present value (NPV) higher than zero. Both investigations utilized the same methodology as shown in Figure 3, but with 1000 iterations conducted instead.

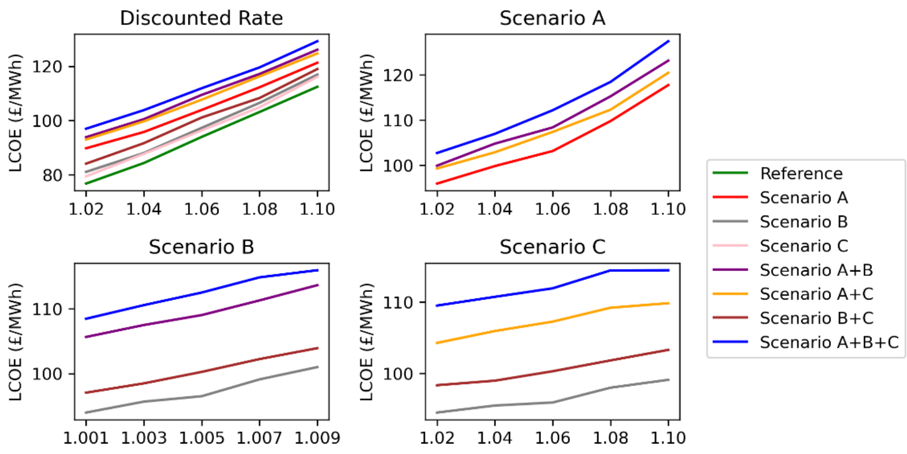


Figure 5-6 Results of the sensitivity analysis on LCOE.

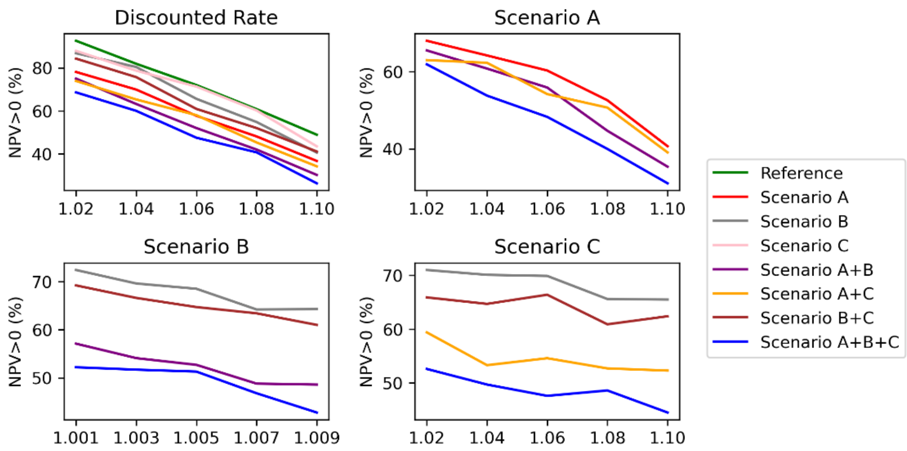


Figure 5-7 Results of the sensitivity analysis when NPV>0.

The first thing to notice is that the discount rate variation had the highest impact in the economic simulations, where the costs in the worst case, Scenario A+B+C, go from £97/MWh with a tax rate of 2% to £129/MWh with a tax rate of 10%. The result indicates that financial incentives are still important for the development of wind energy technology. OPEX rate variation was the second worst case. Although lower than the discount rate, it is evident by the graph that the impact due to the increase in OPEX has an exponential effect, so with higher rates is likely that OPEX becomes the most significant influence on LCOE costs. Variations of ageing and curtailment rates affected the costs less. In most cases, the percentage of positive NPV was higher than 50%, even considering worse rates.

To sum up, the model proposed showed that the inclusion of the scenarios discussed in Section 5.2.3 can explain why some projects are failing economically in the medium and long term. Nonetheless, this study does not consider any intervention by operators to reduce these losses, which is very unlikely to be true. For considering operators' interventions, analyses which include refurbishment and new maintenance costs, should be developed to compare the financial advantages of such interventions. Nevertheless, the results obtained in the present work confirm what was found in the literature. The increase in operational losses might be the main reason for wind energy projects to have a shorter financial lifespan. In appendix A, a summary considering return tax of 4% and 8% is presented.

5.3 Case Study[5]

The present study case is a hypothetical onshore wind farm model built in Meteodyn WT, a commercial CFD-based software which makes use of the turbulence flow method RaNS (Reynolds averaged Navier Stokes), transport equations, and thermal stability to model wind flow [260][261]. It is out of scope from this work to discuss how CFD works. Some inputs cannot be disclosed due to confidentiality concerns, such as the modelled wind farm's location, corresponding wind regime, and wind turbines' model. The provided wind regime covers an entire year averaged by 10 minutes of reading. The motivation behind this simulation is to compare the performance and costs of different classes of turbines in the same conditions and the impact of the trend losses discussed in the previous sections. Therefore, the layout was not optimized; however, a minimal distance between rotors is considered, following manual requirements. Figure 5-8 presents the average wind speed analysis calculated in the software and the farm's layout. This farm is located in a relatively open area, so there is no significant interference from the surroundings. In this case, ambient wind speed variation is stable within the farm.

[5] This section was based and contains extracts from the publication Sathler, Yeter and Kolios [290].

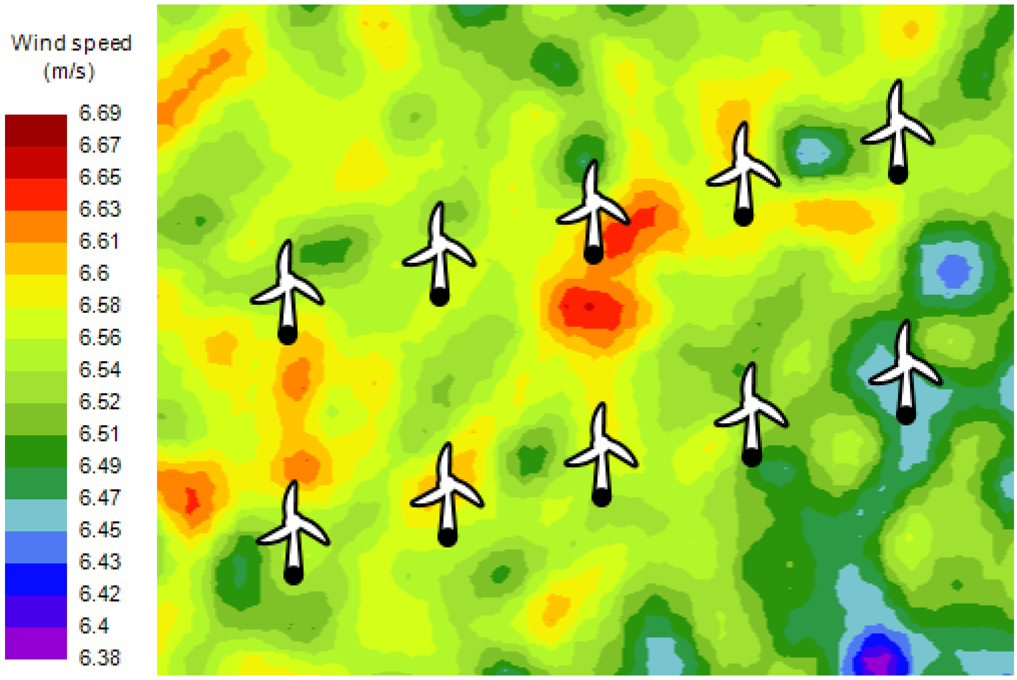


Figure 5-8 Mean Wind Speed analysis of the hypothetical farm in Meteodyn.

Figure 5-9 presents the power curve and the coefficient of thrust (CT) curve from each turbines assessed. which are 2 MW wind turbines. The classes tested were IA, IIA, IIIA, and IIB. Also, the hub height considered was the same for all turbines, 80 m. The CT is necessary for calculating the downwind speed reduction with higher precision. It is crucial to notice that the cut-out of the wind turbine IIB is 20 m/s, while the others are 25 m/s. Although in this case wind did not achieve higher value than 20m/s, by the distribution is very likely that this will eventually happen. For safety and durability of the turbine, the standard BS EN IEC 61400-1:2019 defines the basic parameters and criteria according to the environmental factors. There are three different wind classes, I, II, and III, and four different turbulence classes, A+, A, B, and C. Class S is defined by designer and do not follow the standard. Table 5-6 presents the criteria of each class according to the standard.

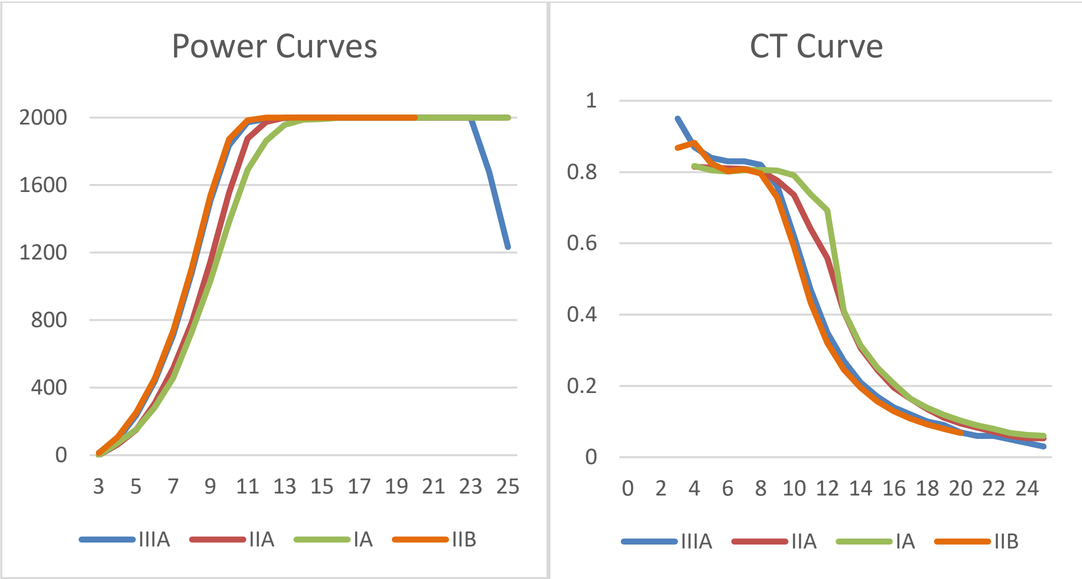


Figure 5-9 Power Curve and CT Curve from turbines assessed.

Table 5-6 Basic Parameters for wind turbines [IEC 61400-1:2019]

Wind turbine class		I	II	III	S
V_{ave}	(m/s)	10	8,5	7,5	Values specified by the designer
V_{ref}	(m/s)	50	42,5	37,5	
	Tropical (m/s) $V_{ref,T}$	57	57	57	
A+	I_{ref} (-)	0,18			
A	I_{ref} (-)	0,16			
B	I_{ref} (-)	0,14			
C	I_{ref} (-)	0,12			

The parameter values apply at hub height and

- V_{ave} is the annual average wind speed;
- V_{ref} is the reference wind speed average over 10 min;
- $V_{ref,T}$ is the reference wind speed average over 10 min applicable for areas subject to tropical cyclones;
- A+ designates the category for very high turbulence characteristics;
- A designates the category for higher turbulence characteristics;
- B designates the category for medium turbulence characteristics;
- C designates the category for lower turbulence characteristics; and
- I_{ref} is a reference value of the turbulence intensity (see 6.3.2.3).

It is possible to calculate the operational safety limits expected from each turbine using these basic parameters. Three aspects were assessed in this work. The Rayleigh distribution of the wind speed distribution, P_r, turbulence intensity model, TI_M, and the extreme turbulence model, TI_{ETM}. These parameters are estimated as follows:

$$P_r\,(V_{hub}) = 1 - \exp\left[-\pi\left(\frac{V_{hub}}{2V_{ave}}\right)^2\right] \tag{5-3}$$

$$TI_M = \frac{I_{ref}(0.75V_{hub} + b)}{V_{hub}}; b = 5.6m/s \tag{5-4}$$

$$\sigma_{ETM} = \mathrm{c}I_{ref}\left(0.072\left(\frac{V_{ave}}{c} + 3\right)\left(\frac{V_{hub}}{c} - 4\right) + 10\right); \mathrm{c} = 2\mathrm{m/s} \tag{5-5}$$

$$TI_{ETM} = \frac{\sigma_{ETM}}{V_{hub}} \tag{5-6}$$

V_{hub} is the real average wind speed at the hub height.

Figure 5-10 presents the average wind distribution in each turbine class. Figures 5-11 to 5-14 present the average result of turbulence intensity analysis and extreme turbulence model of the turbines IA, IIA, IIA, and IIB, respectively. The blue curve in the figures refers to the limit stablish by IEC standard, as mentioned before, while the red one is the one measured through Meteodyn software.

It is vital to notice in figure 5-10 that none of the wind distributions fits the wind classes perfectly, however, from the rated wind speed any of the curves were above the limit. Class III was the curve with closest shape, although the average wind speed in the hub height is more frequent. Also, it is worth noting that considering the rated speed of around 10 m/s, any of the curves are above the limit, which means less loading on the blades. Not meeting the standard means that the turbine is not working in the conditions in which the extraction of power output is maximized according to the turbine class.

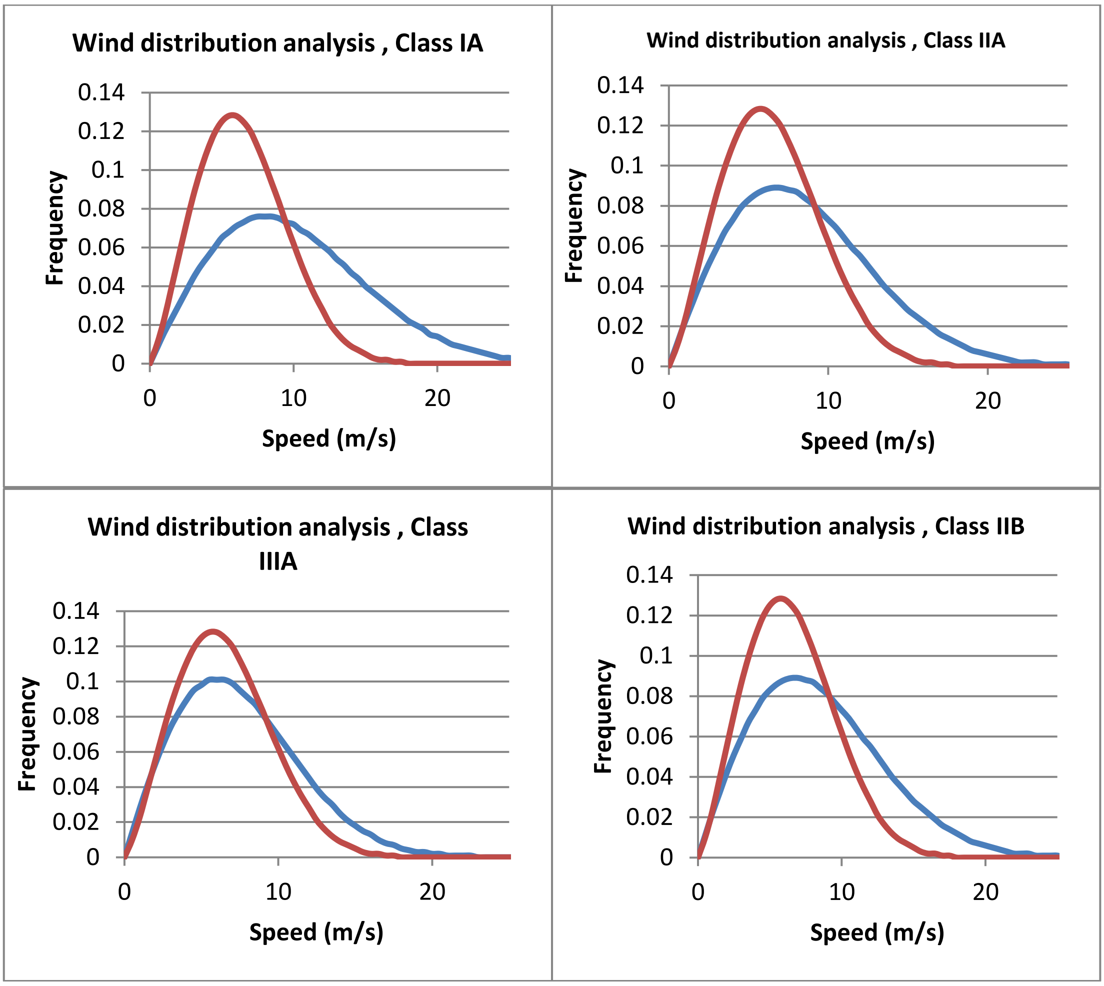


Figure 5-10 Wind Distribution of each class.

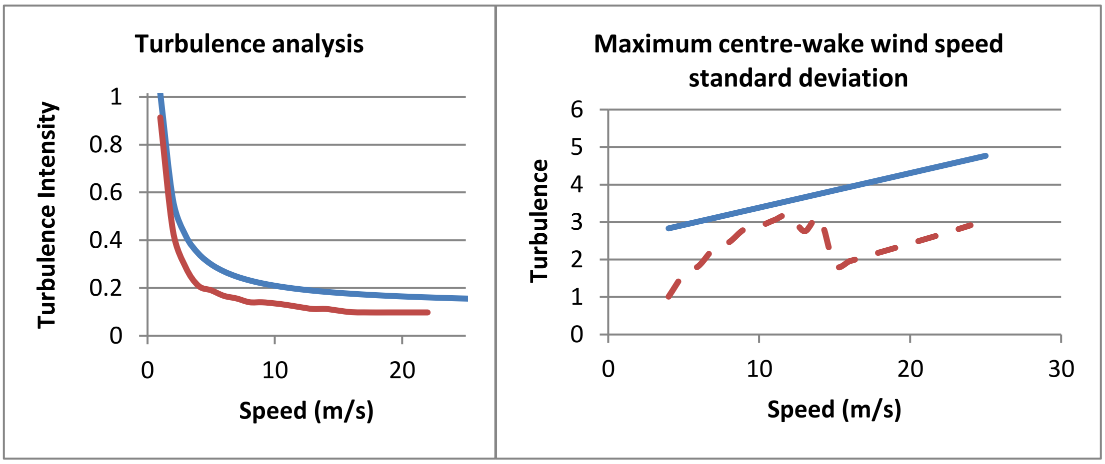


Figure 5-11 Turbulence Analysis of Wind Turbine IA.

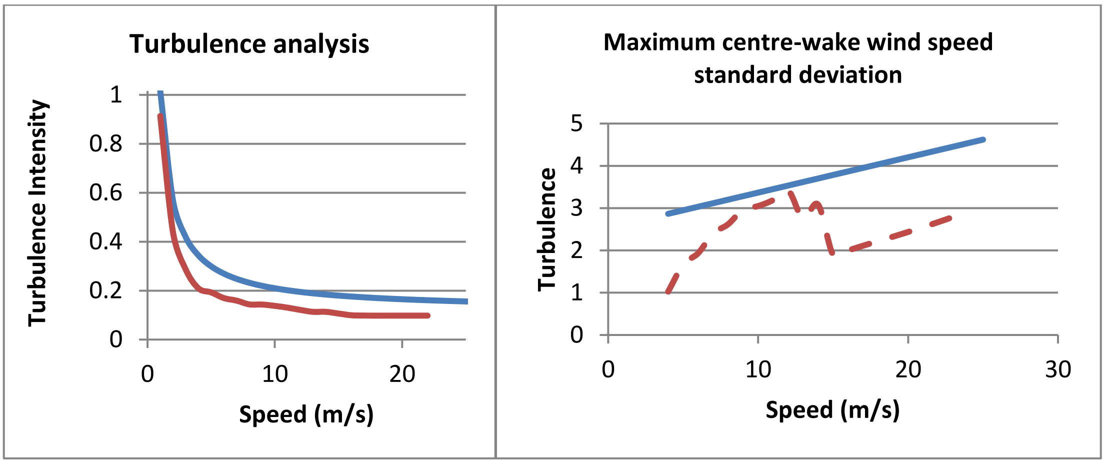


Figure 5-12 Turbulence Analysis of Wind Turbine IIA.

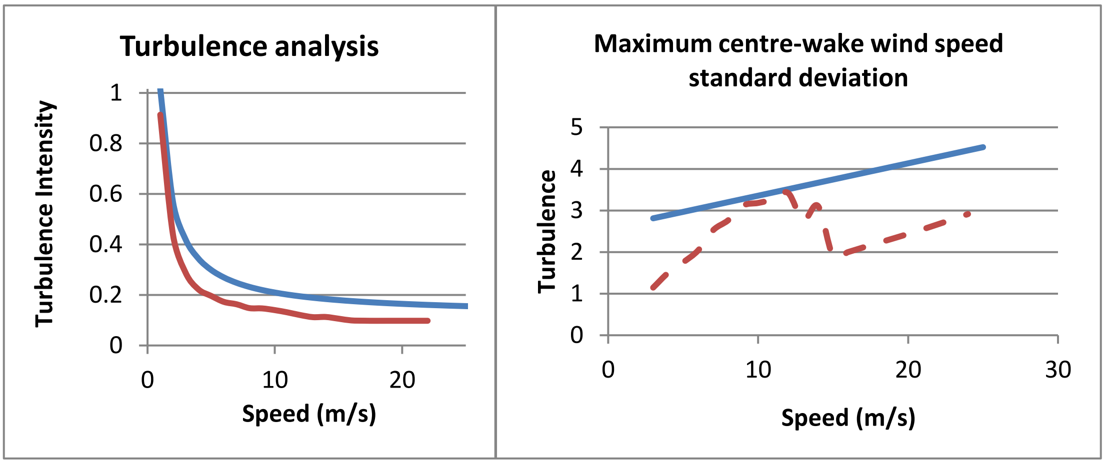


Figure 5-13 Turbulence Analysis of Wind Turbine IIIA.

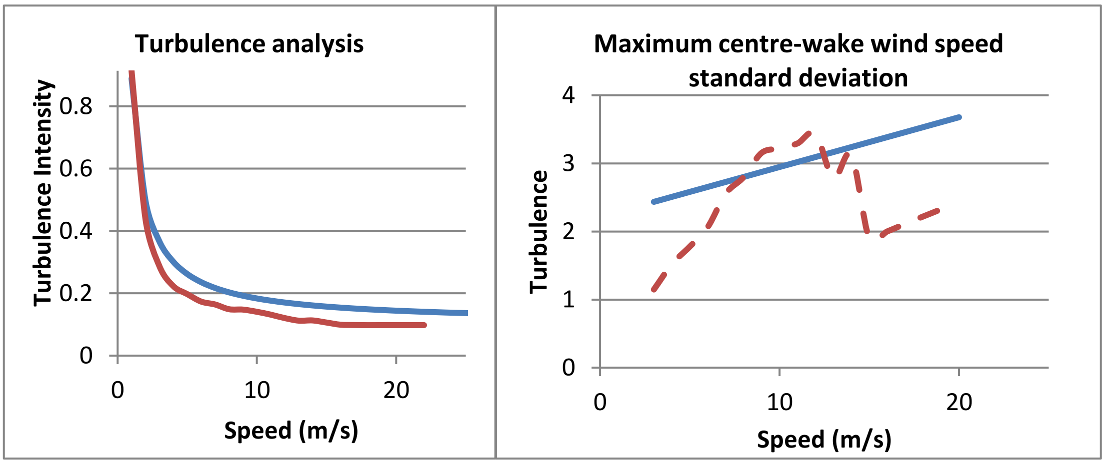


Figure 5-14 Turbulence Analysis of Wind Turbine IIB.

Regarding the turbulence intensity, the turbulence analyses are presented in Figures 5-11 to 5-14. The results suggested that only turbine IIB was out of standard limits. Since this behaviour is only in the Extreme Turbulence Model, reconfiguring the layout should reduce or solve this issue. The wind turbine manuals often note that if the turbulence intensity is high, the fatigue loads on the wind turbine are expected to increase; in turn, the expected turbine life decreases. Although the correct action would be to discard wind turbine IIB as an option, for educational purposes and comparison reasons, the complete analysis of the turbine IIB will be kept; however, a higher ageing and failure rate will be assumed, 0.7% and 8%, respectively.

Besides the estimation of the Annual Energy Production (AEP) and the wake losses, the software allows the creation of criteria for performance losses and curtailment losses through temporal analysis. In this context, two rules were created to curtailment. The first one is a power limit of 75% of the rated capacity during early mornings from 2:00 a.m. to 5:00 a.m. to simulate a lack of demand. During peak times (weekdays from 7:00 p.m. to 9:00 p.m.), 10% of the energy is curtailed, simulating grid operators' preferences during critical times and allowing some flexibility to deal with inertia. This consideration may eventually happen in real world, allowing operators to assist grid if more energy is needed. For the performance, two criteria were created. As mentioned in section 4.2.2, temperature higher than 35ºC and turbulence intensity higher than 15% can cause performance restrictions, so a further 10% reduction is considered. In this paper, high ambient turbulence intensity is above 15%. Finally, quality loss was simulated similarly to what was discussed in 4.2.3, but the limit was 10% and the interval investigated was 1 hour. Table 5-7 presents a summary of the output from the software for each turbine class.

Table 5-7 Summary of Turbines and Meteodyn Results.

Turbine	IA	IIA	IIIA	IIB
Diameter (m)	80	88	97	100
Rated (kW)	2000	2000	2000	2000
AEP (/$KW_{installed}$)	2551	2773	3462	3537
Wake Effect (%)	5.48%	5.98%	5.94%	5.89%
Ambient Performance (%)	2.08%	2.09%	2.11%	2.11%
Quality Losses - Ramp (%)	3.41%	4.16%	4.29%	4.50%
Curtailment (%)	1.44%	1.79%	2.14%	2.28%

For the economic analysis, the three main components of costs, CAPEX, OPEX, and DECEX, discussed in subsection 5.2.2, will be considered. For CAPEX, the costs will be divided into two main parts. The first part is the wind turbine, whose cost depends on its class, hub height, and rotor diameter. The wind turbine cost can be calculated through a tool called Wind-Plant Integrated System Design and Engineering Model (WISDEM) [262], tool developed by National Renewable Energy Laboratory (NREL). WISDEM correlates material mass and costs from several deployments, and through regression analysis generates easy-to-use equations to estimate wind turbine costs.

The second part is the Balance of Station Cost (BOS), which includes civil works, assembly, installation, engineering services, permits, electrical, and connections costs. The NREL repository is also used to calculate BOS following the design and scaling model developed by [263]. OPEX can be considered into three parts: Land lease, O&M, and replacement. These costs (in USD) can be calculated in USD using the expressions given in the following [263]:

$$\mathrm{O\&M\ costs\ in\ USD} = 0.007\mathrm{xAEP} \quad \textbf{(5-7)}$$

$$Land\ Lease\ Cost\ in\ USD = 0.00108xAEP \quad \textbf{(5-8)}$$

$$Replacement\ Cost\ in\ USD = 10.7xMachine\ Rating \quad \textbf{(5-9)}$$

DECEX, as discussed before, is still hard to estimate effectively due to a lack of experience [264]. DECEX depends on the age of the project, the availability of crane offers (second-hand market), and the price volatility of recyclable materials [265]. Although 5% of CAPEX was deemed as a reasonable estimate in [264], a recent study [266] estimated higher costs, ranging from 200,000 to 532,000 USD per turbine. The present work assumes that 10% of CAPEX covers the DECEX cost assumption, making it assumptions slightly less than 2% of the total costs, which is reasonable according to the literature. Additionally, the initial availability considered was 98% to all turbines, as demonstrated in section 3.4, while the economics elements assumptions, such as the discount rate and the operational life, are taken as 6% and 20 years, respectively (following subsection 5.2.2.7).

Table 5-8 summarizes the cost analysis of each element of costs considering all the turbines investigated. As expected, turbines with larger rotors result in higher costs. In this study, the O&M is considered as “variable OPEX”, while the Cost associated with land and replacements are considered to be “fixed OPEX”. Finally, the costs were converted to pounds following the rate of £0.73 = USD1.00.

Table 5-8 Summary of Cost Analysis of each Turbine Class.

Turbine	IA	IIA	IIIA	IIB
Foundation	£40,512.53	£43,753.20	£47,331.91	£48,510.37
Transportation	£62,692.40	£62,692.40	£62,692.40	£62,692.40
Civil Work	£71,861.20	£71,861.20	£71,861.20	£71,861.20
Assembly	£42,035.70	£47,010.70	£52,702.00	£54,620.02
Electrical	£116,011.60	£116,011.60	£116,011.60	£116,011.60
Permits	£32,555.08	£32,555.08	£32,555.08	£32,555.08
BOS - Total	£365,668.51	£373,884.18	£383,154.20	£386,250.66
Turbine/MW	£587,940.28	£618,864.86	£685,054.98	£708,994.32
CAPEX	£953,608.79	£992,749.04	£1,068,209.18	£1,095,244.98
DECEX	£95,360.88	£99,274.90	£106,820.92	£109,524.50
OPEX	£22,389.74	£23,345.56	£26,311.90	£26,632.44
O&M	£13,037.39	£14,171.72	£17,692.07	£18,072.47
Land Lease	£2,011.48	£2,186.49	£2,729.63	£2,788.32
Replacement Cost	£15,622.00	£15,622.00	£15,622.00	£15,622.00

Conversion Rate (2021) £ = 0.73US$

Table 5-9 summarizes the result of the economic analysis. the LCOE analysis of each turbine and each scenario. The turbine IIIA is found to be the best option in terms of cost-benefit, while the scenario “IA” is rated as the worst. This is explained by the fact that the smaller diameter wind turbines extract less power from the wind, which is not compensated by appropriated local wind regime.

Turbine IIB is estimated to be the second cheapest average LCOE despite higher loss trend rates. However, this can be considered riskier to investors since the uncertainty related to LCOE is the highest. The reference scenario shows that IIIA would still be the best turbine for this site, regardless of the slightly smaller diameter. The reason behind this is the higher losses estimated through Meteodyn (Table 5-7), which was higher for curtailment, performance, and quality. Another negative aspect to the wind turbine IIB, it is that its cut-out speed of 20m/s, which could limit the production during good wind conditions.

Table 5-9 Summary of Case Results.

Scenarios/Turbine	IA	IIA	IIIA	IIB
Reference	£52.37	£51.05	£44.77	£44.92
C	£54.15	£53.22	£46.84	£47.13
B	£54.71	£53.34	£46.78	£47.83
A	£57.15	£55.89	£49.59	£52.27
B+C	£56.51	£55.54	£48.88	£50.08
A+C	£58.08	£58.26	£51.88	£53.54
A+B	£59.71	£58.42	£51.83	£55.69
A+B+C	£61.67	£60.81	£54.15	£58.28
Avg. LCOE (£/MWh)	£56.79	£55.82	£49.34	£51.22
Std. LCOE (£/MWh)	£2.85	£3.03	£2.95	£4.26

To sum up, this case has shown how important is to create a scenario considering all losses. Although this did not directly affect the turbine selection, LCOE fluctuated considerably. The average LCOE was around 9.5% higher than the reference scenario for scenarios IA, IIA, and IIIA. For turbine IIB, this difference was 14%. This indicates that the costs can vary more than expected, which could explain why some projects fail to cover their costs in the medium and long term. The results indicated the importance of investigating different scenarios, turbine classes, and loss trends within the scope of economic analysis. Furthermore, while the technology is improved to overcome these trends, a better economic analysis is essential to identify the actual costs and de-risk in projects making them more attractive to investors. Although the results can be considered consistent, some assumptions were simplified. An increase in loss rates was considered to demonstrate higher wear of equipment. However, a load fatigue analysis should be performed together for a more precise cost estimation since the impact on costs could be higher than estimated here.

5.4 Chapter Summary

Some wind energy projects are failing to deliver what they were expected in medium and long term. This is mainly due to increase of operational losses and costs along its lifespan. In Section 5.1, the three main losses trends were identified along with relevant figures. In Section 5.2, it was investigated the impact of these trends on LCOE and NPV and the “Critical Year” and “Breakeven Year” were also identified. The cost estimation was based on average values from the literature for offshore deployments. Furthermore, a stochastic analysis using MCS was conducted, followed by a sensitivity analysis. In Section 5.3, a hypothetical onshore farm was modelled in a CFD software. The AEP, wake-effects, and other losses was estimated considering four different classes of turbines. Then, a cost-assessment was performed including the losses trends scenarios. The inclusion of the operational losses proved to be useful for decision makings and monitoring of project risks. It also has the potential to provide insights into the actual returns of proposed solutions aimed at reducing operational losses, as will be discussed in the next chapter.

6 SOLUTIONS TO REDUCE OPERATIONAL LOSSES

As discussed in previous chapters, operational losses have a big impact on the costs of wind energy, especially in medium- and long-term analysis. This means that there is space for improvements and opportunities to increase the asset value and attract more investments. The main reasons for operational losses are the increase of failure rates, ageing, and curtailment. In this chapter, some of the main solutions proposed to reduce them will be discussed. Additionally, a brief economic analysis of these solutions will be performed considering the economic model developed in the chapter 5.2. Thus, the costs and scenarios will be the same as the ones presented in Tables 5-2 and 5-3. In case of values with different currencies, they were converted into sterling pounds at the same rate presented in Table 5-1. Finally, in section 6-4 a multivariate MCS including a range of loss trends and the findings and figures from solutions discussed in previous sections is presented.

6.1 CMS

There are three main types of maintenance: reactive, preventive, and predictive. Reactive maintenance occurs when equipment is visibly not working correctly, or when a failure has already happened. Preventive and predictive maintenance aim to prevent equipment failure before it happens. Preventive maintenance is usually performed periodically, with technicians checking equipment health and performing scheduled maintenance routines such as oil and filter changes, general cleaning, tightening bolts, or replacing damaged seals and roller bearings. Predictive maintenance involves the use of gadgets, sensors, or transistors to monitor and identify abnormalities in the equipment that are difficult to be identified by technicians. Figure 6-1 shows a potential failure (PF) curve, illustrating the reduction in performance over time before a failure occurs. It is possible to identify early signals of abnormalities during this period, which may vary depending on the equipment or component. However, in some cases, the start of failure can be identified months or even more than a year in advance [267].

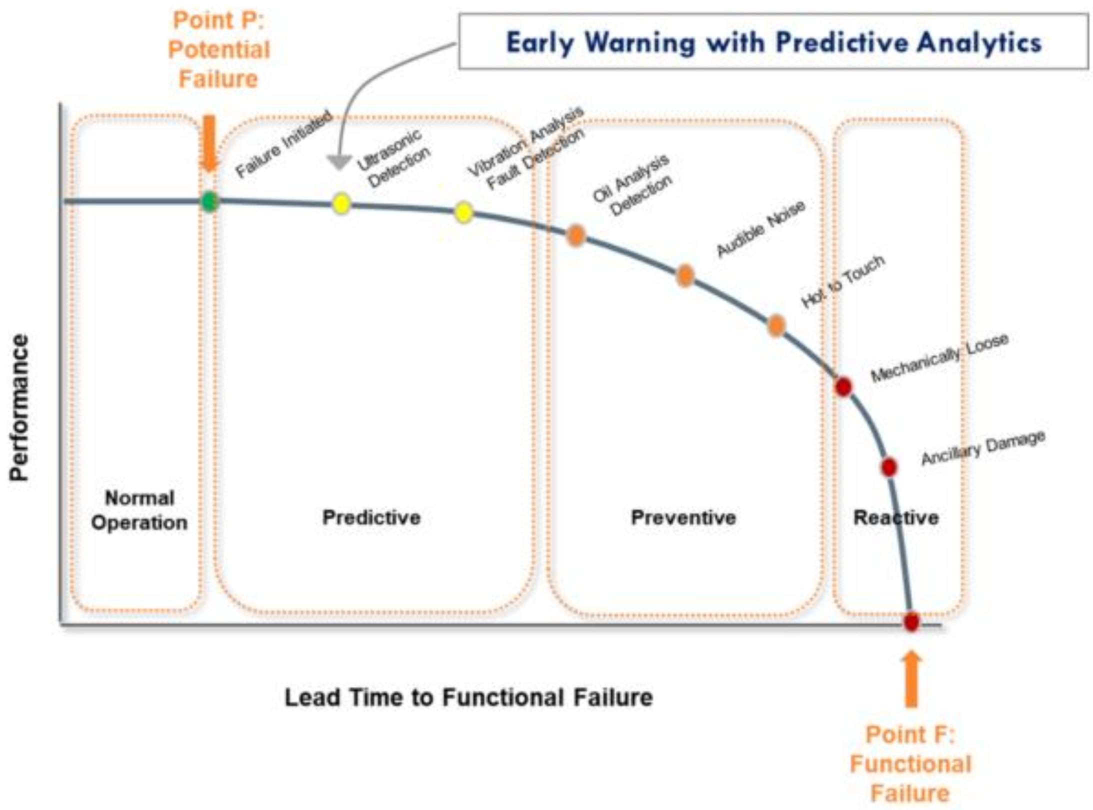


Figure 6-1 P-F Curve [268].

One common approach to monitor the safety and health of a machine is the CMS (Condition Monitoring System). This system is composed by a combination of sensors that can measure in real time different parameters, such as vibration and temperature of several components. Following these parameters could assist operational team to act before the failure happen or at least prepare beforehand to the intervention. As mentioned before, the time spent with repair itself is around 20 to 40% of the downtime, great part of this is due to logistics and availability of spare parts [52][192]. Thus, only by reducing the waiting time of downtime, the productivity could significantly increase. It is important to mention that to be effective, the CMS still relies on interpretability of the parameters and maturity of the team to act at the correct moment. For that, a further investment in training of operators and maintenance team, improvements in the process, or even the use of algorithms to assist in decision makings and develop a reliable historical data repository needs to be considered.

Accessing the real costs and benefits of CMS can be challenging, as they are dependent on each project, and manufacturers often do not share this information, considering it strategic and confidential. However, some studies tried to estimate them. [269] found an increase of almost 10% in the revenue and an increase of one point in the availability rate during the period simulated. [270] developed a Life Cycle Cost (LCC) analysis and estimated a benefit 36% higher than the scenario without CMS. [271] developed a method considering CMS and could reduce on average about 35% of maintenance costs. Nonetheless, the trade-off of CMS cost and possible return are not clear and needs to be carefully investigated.

To [38], it is unrealistic to install transistors to monitor all individual component, because of lack of space and high cost. According to [272], the payback of CMS investment could be from 5 to 7 years considering 45% downtime reduction, but 10 years if 35% is selected. Although [273] recognizes the benefit to the maintenance team of adopting CMS, in some of the scenarios investigated, the economic return is achieved only if 47% of reactive maintenance become preventive. [274] points the importance of integrating results with SCADA, to avoid false alarms or missed faults, and the real performance and cost-benefit is almost unknown. The interpretation complexity of faults report and the difficult to identify false alarms have discouraged operators to use CMS effectively, although most of wind turbines in Europe (with rated capacity above 1.5MW) are fitted with this system [275].

In this thesis, the impact of LCOE will be investigated before and after CMS implementation. To this end, the offshore economic model developed in section 5-2 is used. The investment cost by unit of power installed was £16,607.50/MW [276], £28,666.67/MW [270], and £63,266.34/MW [272]. The increase on O&M costs from the same references was £730.00, £2,580.00, and £2,075.00, respectively. Regarding the mitigation of losses, it was considered a reduction in downtime of 40% and 1%, 0.1% and 1% at the yearly rate from the scenarios A, B, and C, respectively. Finally, the CMS costs assumed were the average of values discussed in this paragraph.

Table 6-1 presents a comparison of the LCOE for the offshore scenarios investigated with and without the use of CMS. The low impact in the reference scenario suggests a low return on investment. However, by including the loss trends in the analysis, the economic benefits of CMS become more evident. With effective maintenance, the equipment is expected to perform at a high level of effectiveness over its lifespan, thereby reducing wear on components. Table 6-2 presents the financial return of this simulation, considering £/MW installed. By factoring in the likely increase in losses over the equipment's lifespan, CMS plays an important role in reducing costs, and the real return on investment could be higher than 5%. This highlights the importance of considering loss trends in any analysis of CMS efficacy.

Table 6-1. Comparison offshore case with and without CMS.

	LCOE (£/MWh)	LCOE + CMS (£/MWh)
Reference	£98.93	£98.51
Scenario C	£102.41	£101.20
Scenario B	£103.64	£102.13
Scenario B + C	£107.16	£104.86
Scenario A	£110.89	£106.76
Scenario A + C	£114.69	£109.65
Scenario A + B	£116.34	£110.75
Scenario A + B + C	£120.19	£113.67

Table 6-2 Results from financial return – With and without CMS.

	Without CMS				With CMS				Financial Return Comparison
	LCC	*Revenue*	*NPV*	*Return*	*LCC*	*Revenue*	*NPV*	*Return*	
Reference	£3,979,555.74	£4,481,164.91	£501,609.17	112.60%	£4,036,324.42	£4,564,435.83	£528,111.41	113.08%	0.43%
Scenario C	£3,979,555.74	£4,329,043.13	£349,487.39	108.78%	£4,036,324.42	£4,442,977.77	£406,653.35	110.07%	1.19%
Scenario B	£3,979,555.74	£4,277,632.29	£298,076.55	107.49%	£4,036,324.42	£4,402,488.20	£366,163.78	109.07%	1.47%
Scenario B + C	£3,979,555.74	£4,136,882.55	£157,326.81	103.95%	£4,036,324.42	£4,288,039.77	£251,715.35	106.24%	2.20%
Scenario A	£4,327,118.39	£4,346,892.30	£19,773.91	100.46%	£4,313,865.54	£4,501,285.24	£187,419.69	104.34%	3.87%
Scenario A + C	£4,327,118.39	£4,202,830.44	-£124,287.95	97.13%	£4,313,865.54	£4,382,722.81	£68,857.27	101.60%	4.60%*
Scenario A + B	£4,327,118.39	£4,143,359.67	-£183,758.72	95.75%	£4,313,865.54	£4,339,337.61	£25,472.06	100.59%	5.05%*
Scenario A + B + C	£4,327,118.39	£4,010,669.86	-£316,448.53	92.69%	£4,313,865.54	£4,227,784.81	-£86,080.74	98.00%	5.74%**

*This result ignored that first scenario had negative return.
**This result ignored that both scenarios had negative return.

6.2 Maintenance x Ageing

Good maintenance activities are beneficial not only to increase the availability but also in deaccelerating the ageing effects, extending its lifespan. In other words, it means the equipment can work for a longer period than expected with similar or acceptable performance levels at lower failures rates. [277] shown how an enhanced risk-based maintenance could increase the useful life of elevators from 25 to 35 years. [278] demonstrated how early decisions can influencing greatly the possibility of increase military equipment life. In this study, it was indicated the cost effectiveness should be assess for the decision about extension and how maintenance can contribute to that.

The same behaviour is expected to wind turbines. Although part of the ageing effect is caused by external factors, a bad maintenance can also directly influence on it. High temperature, high vibration level, excess of dust, and/or loose bolts, are example of factors that forces the turbine to operate unbalanced, which can wear components faster and reduce performance of the turbine with age. In this scenario, the productivity is reduced in three different ways. Increasing failure rates and downtimes, shortening equipment lifespan, and reducing performance during operational useful periods.

[16] has found that the decline in performance is also influenced by maintenance cost-benefit trade-offs. After the eligible period in which farms have access to Production Taxes Credits (PTC), the yearly performance ageing rate dropped from 0.53% to 1.27% per year. To [192], there is a strong relationship between operational maintenance expenditure and annual energy production. [16] also found an increase in curtailment during the period that the benefit is not paid, which indicates an attempt to maximize profitability from operators.

The extra credit will depend on the type and size of the project. The full credit value in 2022 was $26/MWh [279], but some projects could be eligible to $10/MWh [280]. In UK a similar benefit is the Feed-in Tariffs (FIT), which also is dependent on the project, and can vary from less than £5 to above 20£/MWh for wind projects [281].

To understand the impact of the maintenance and ageing trade-offs, three different scenarios was defined (Figure 7-2). The values assumed in this analysis were the same presented in Table 5-2. Considering the figures mentioned in previous paragraph, it was assumed a reduction of £10 after the 10th year. This year and the ageing rates were retrieved from the investigation performed by [16]. Therefore, Scenario I, after 10th year, the ageing rates dropped from 0.53% to 1.27% per year, and half of maintenance expenses is cut. Scenario II, the reduction is accepted, without changing the maintenance routine, so the ageing is kept equal to 0.53% the entire period. Scenario III is the intermediate scenario, in which the ageing rate is set at 0.9% and maintenance costs reduced by 25%. It is important to note that maintenance costs are only a part of the OPEX, which was previously discussed as accounting for 49% of the total OPEX.

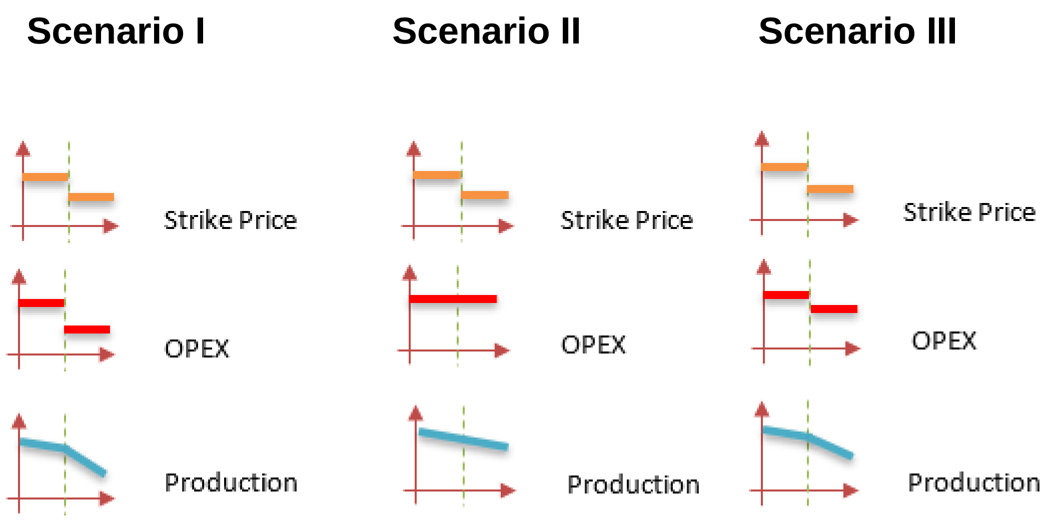


Figure 6-2 Scenarios Investigated – Trade-off Maintenance x Ageing.

Table 6-3 presents the results of the simulation. While the reduction in the strike price is significant, nearly 10%, keeping the maintenance activity would result in higher revenue for investors in the long term, as demonstrated in Scenario II. The NPV for Scenario II was above £200,000, which is 50% higher than Scenario I, where maintenance is reduced to compensate for the end of tax credit. Furthermore, the expected performance of the wind farm after 20 years of operation would be 0.894, indicating a decay of 10% compared to when the turbines were new. For Scenario I and III, this loss would be 27% and 18%, respectively. Thus, Scenario II presents a higher likelihood of having its life extended, making it both viable and profitable.

Table 6-3 Results from Trade-off Maintenance x Ageing Investigation.

	Scenario I	**Scenario II**	**Scenario III**
LCOE (£/MWh)	£104.84	£102.74	£103.71
NPV (£)	£126,188.59	£201,866.34	£166,185.73
Performance (After 20 years)	0.729	0.894	0.814

It is important to note that this analysis does not take into account certain factors that are crucial for investors, such as opportunity costs and investment returns. Additionally, the figures presented in this analysis reflect the entire 20-year lifespan of the project and do not consider the potential risks and reduced margins associated with delaying outcomes from an investor's perspective. However, this simplified simulation serves as a demonstration of the importance of monitoring the financial aspects of the project and exploring various scenarios before making decisions.

Figure 6-3 presents a sensitivity analysis of NPV, examining various combinations of maintenance cost reduction and ageing rates. The graph illustrates the results, with green values indicating increased returns compared to the base scenario (dark blue), and red values representing negative NPV. The ageing rates span from the reference rate (discussed earlier) in the middle, to extreme scenarios with no change on the left and double the estimated rate on the right. Five rates were considered in total, evenly spaced. Additionally, five levels of maintenance reduction were investigated, with a maximum assumed reduction of 50%. It is worth noting that this value represents an extreme scenario and is highly unlikely, particularly for projects with over 10 years of operational life. Overall, this range of values encompasses a wide spectrum of scenarios, covering the most probable situations in real-world settings. For reference, maintaining the tax credit throughout the entire period would result in an NPV of £335,506.18.

Sensitivity Analysis						
		Ageing After 10th Year				
		1.0053	1.009	1.0127	1.0164	1.021
Maint. Reduction	0%	£201,866.34	£117,915.10	£ 29,647.35	-£ 63,151.92	-£185,183.62
	10%	£221,174.59	£137,223.35	£ 48,955.60	-£ 43,843.67	-£165,875.38
	20%	£240,482.84	£156,531.60	£ 68,263.85	-£ 24,535.42	-£146,567.13
	30%	£259,791.09	£175,839.85	£ 87,572.09	-£ 5,227.17	-£127,258.88
	40%	£279,099.34	£195,148.10	£106,880.34	£ 14,081.08	-£107,950.63
	50%	£298,407.58	£214,456.35	£126,188.59	£ 33,389.32	-£ 88,642.38

Figure 6-3 Sensitivity Analysis of Maintenance Cost Reduction X Ageing rates.

6.3 Power Integration Solutions

As renewables increase its share in energy market, more concerns about level of curtailment are addressed. Energy relies on the balance of production and demand, therefore, as renewables are considered non-dispatchable source, grid operators limit its penetration to avoid stresses in the grid. This creates a clear conflict of interests between grid operators and renewable plant operators. While the first tries to guarantee supply, with required quality and safety in the most economical way, the second needs to enhance power output at maximum to minimize costs [220].

To become economic viable and competitive in energy market, especially offshore projects that are more costly, a high productivity is extremely important. If the energy is not purchased by the utility, the revenue is reduced [213], whether is curtailed or rejected (some exceptions can occur, depending on the commercial arrangement). Therefore, some solutions have been proposed to increase the wind energy penetration, which can vary according to the country and grid. Although in some situations, especially in short-term higher wind penetration might occur, generally, grid operators limit wind energy penetration at rates that varies from 20% to 35% [210]–[212].

The main problem of non-dispatchable energy is its uncontrollable nature and its high fluctuation. This suddenly change in production level can cause disturbances in the grid. One widely discussed solution nowadays to reduce curtailment losses is the Energy Storage System (ESS). In this system, the extra production, when there is a lack of demand, is stored to be used in periods where the production fluctuates significantly. Thus, the ESS keeps the output stable and become able to cover rapid ramp downs. There are different system types to store energy, as pumped hydro, compressed air, flywheel, electromechanical, super capacitors, and finally, through batteries [220][174]. None of them is capable of meeting both energy and power density simultaneously [174], however, battery is becoming popular due to its recent cost reduction [282].

Apart from ESS, there are other solutions to reduce wind energy curtailments, which includes: wind forecasting, demand-side management, electric cars, smart grids, super grids, and the adoption of electric water heating [283]. All these solutions are related at some level to increase the demand, bringing some benefits for consumers to use energy during predicted windy periods. Green Hydrogen is also getting popular, where hydrogen fuel is generated through renewables. According to [284], green hydrogen helps to overcome grid constraints of offshore deployments and it can be also cost-competitive with hydrocarbon fuel, if untaxed. Another common solution is overplanting, where to reduce curtailment, wind farms are built with higher capacity than the electrical infrastructure [165]. In this scenario, the individual turbine`s performance is reduced, so operators can regulate power output of the farm to increase overall productivity. This solution also minimizes losses related to availability.

As the reason behind overplanting is to reduce farm energy rejection and curtailment, there are a limit at which overplanting is viable. Obviously, this depends on each project and the grid capacity. According to [165] overplanting from 2 to 8% can reduce total LCOE, and the optimal scenario found in their MCS was 4%. Some countries have suggested overplanting from 5 to 20%, to prevent grid restriction [285]. Nonetheless, the average LCOE reduction was about 0.5% in both cases.

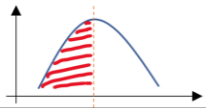
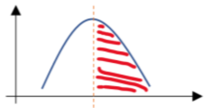
To [286], the level of sophistication and costs required to transform wind power into largely dispatchable are controversial. For that reason, it is important to perform reliable economic analysis. It is out of scope of this thesis to investigate all pros and cons from each solution proposed. However, to check some of the findings related to overplanting, a simplified economic analysis was simulated. For this, a reduction of 10% in availability and performance losses at the reference scenario was considered as well as 50% in quality losses. To achieve average 0.5% LCOE reduction, 3.7% of overplanting was needed. This result aligns to what was found in the literature.

6.4 Multivariate Monte Carlo Simulation Case

Wind energy is surrounded by a diverse cause of uncertainties, which includes ambient conditions, wind features, dispatchability to the grid, levels of wear out and its costs. Therefore, a stochastic analysis as MCS is more appropriated than deterministic models to assess its viability and risks. In subsection 5.2.4, an offshore model was developed considering different scenarios of operational losses trends. Although, those rates can be considered reliable, since they were based in strong evidence retrieved from the literature, they can vary according to the project. Another two important aspects that can affect economic viability assessment are: how some early decisions and the use of solutions, as described previously in this chapter, can impact cost models. To this end, a more elaborated MCS, called here as Multivariate MCS (MMCS) will be performed and discussed in this section.

Table 6-3 presents the range of operational losses trends that will be added to the model as well as some rules and assumptions created. Offshore figures can fluctuate considerably according to how far they are from the cost. More distant projects are only viable if the wind regime is higher, so it is reasonable that these projects contemplate higher capacity factor. Therefore, high CAPEX will randomly select a CF from upper limit and an additional rate was inserted to be more realistic. Another rule defined was about OPEX. To [263] a reasonable estimation is an annual OPEX equals to 2% of its CAPEX for offshore projects. However, more recent studies that also consider floating projects has considered higher values. In the literature review developed and presented in Table 5-1, this value is on average 3.2%. A higher investment in maintenance can be related to ageing levels, as demonstrated in section 6.2. Therefore, for relative OPEX costs above 3%, the ageing and failure rate trend will be selected randomly in its lower range.

Table 6-4 Operational Losses Trends and Rules for MMCS model.

Losses rates	**Range**
Failure increase rate	Linspace(1.02, 1.10, 9)
Ageing rate	Linspace(1.001, 1.009, 9)
Curtailment rate	Linspace(1.02, 1.10, 9)
Criteria	**Rule**
If OPEX/CAPEX > 3%	Ageing rate & Failure rate: 
If CAPEX > £3,000,000	F.C. range: + 0.02 

The adoption of overplanting and the use of CMS was also included in this simulation. For this, a random selection of ‘Yes’ and ‘No’ for each category was included in the algorithm. Table 6-4 presents the rules used as discussed in each of them. The overplanting calculated in Section 6.3 was 3.7%, however, this analysis only contemplated the reference scenario. Since overplanting makes sense only if some return is expected, this value was reduced to 3%, which makes less likely to have higher LCOE with overplanting in the model. The introduction of new wind farms in the future projects and/or expansion of transmission lines are not in control of operators, so a low curtailment rate was assumed, varying from 0 to 2% per year. The CMS followed the same assumptions discussed before.

Table 6-5 Overplanting and CMS Rules

Extra Implements	Rules
If overplanting == 'YES'	CAPEX, OPEX, DECEX = Increase of 3%. Availability Losses: 10% Reduction Performance Losses: 10% Reduction Quality Losses: 50% Reduction Curtailment Rate: linspace(1.00,1.02,3)
If CMS == 'YES'	CAPEX = CAPEX + £36,180.17 OPEX = OPEX + £1,795.00 Availability Losses: 40% Reduction Ageing Rate: -0.001 Failure Rate: -0.01

Figure 6-4 presents the NPV balance and the average LCOE results from 100,000 iterations. Considering all new criterions more than half of scenarios simulated brought economic benefits to investors. The average LCOE was £107.61, which is around 10% higher than the reference scenario presented in Table 5-5. However, it is important to notice that the fluctuation in cost range is still high. Considering an interval of confidence of 95%, the LCOE can vary from £82.35 to £133.87.

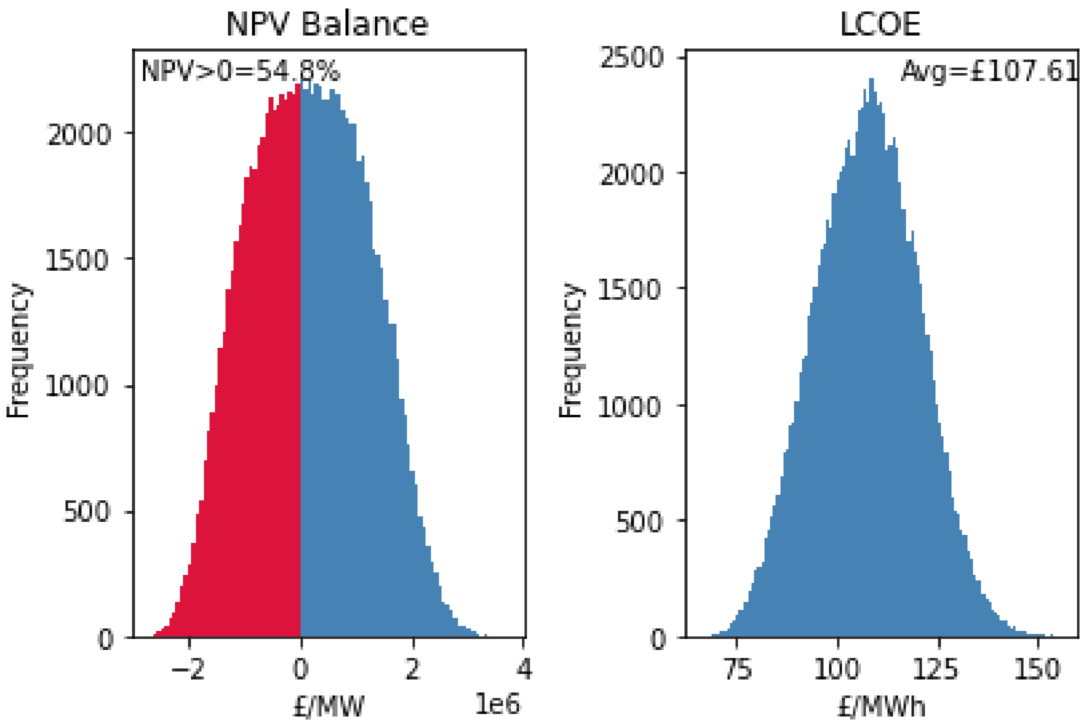


Figure 6-4 Result from Multivariate MMCSTable 6-6 summarizes the values into four categories: those without solutions, those with CMS, those with Overplanting, and those with both solutions. On average, the use of both solutions achieved the lowest average LCoE, £102.90. By using only one of the solutions, the return was similar to total average. For not using any solution, the result was £112.87, almost 5% higher than the average value.

Table 6-6 Summary of MMCS per solution type

	Sample Size	Average LCoE
Both	24970	£102.90
Overplanting	24868	£107.32
CMS	24880	£107.29
Without	25282	£112.87
Total	**100000**	**£107.61**

In conclusion, the model has demonstrated the significant impact of uncertainties on the economic lifespan of wind energy deployment over the medium to long term. It's crucial to investigate the loss trends to mitigate risks and anticipate future patterns before losses become irreversible, leading to premature project end-of-life. This study investigates two popular solutions - overplanting and CMS - to reduce operational losses and increase production, resulting in a reduced LCoE. Unlike other studies that overlook loss trends, the return on investment for these scenarios is higher than what is typically reported in literature. In other words, investing in efficient maintenance and loss reduction solutions may not yield immediate returns but can decelerate loss trends, reduce risks, and increase financial returns over the medium to long term. Appendix B presents the MMCS for return rates of 4% and 8%.

6.5 Chapter Summary

This chapter explores several solutions to reduce operational losses in wind energy deployment. Section 6.1 discusses the Condition Monitoring System (CMS), which can have a low return on investment due to its high investment and requirement for specialized expertise. However, in a long-term analysis that considers the reduction of loss trends, CMS has been shown to have a more significant impact on reducing LCoE. Section 6.2 investigates the relationship between ageing and maintenance activities, finding evidence of correlation between the two. Section 6.3 discusses solutions to increase power integration and reduce curtailment losses. While some of these solutions are gaining attention, they still need a reduction in investment costs to become more popular. All the solutions were analysed using the cost model presented in subsection 5.2.4, and the values align with other studies. To further investigation of the effectiveness of these solutions, a Monte Carlo simulation (MMCS) was performed in section 6.4. The simulation created a range of possible loss trends and included the use of some of the solutions in the model.

7 DISCUSSION

Wind energy is a promising solution to reduce fossil fuels dependency. However, it has been reported that some projects are forced to be shut or have significant refurbishments before completing its projected life, affecting investors return. The findings of this study indicate that the increase of failure rate along turbine`s life is the main reason for economic failure of wind energy assets. Although some studies have pointed to this problem, suggesting even a yearly increase in the OPEX on the economic models [255], they seem to be still underestimated. The increase of failure rate affects not only the OPEX costs, but also the availability of the turbine, consequently reducing its production, and this additional loss is not commonly added in economic analysis found in the literature.

The concept of “critical year” developed and presented in the section 5.2.4 tries to predict when the cost would overpass the benefit if operational loss rates remained constant. Although the critical year considering failure rate scenario (Scenario A) was close to the 11th year of operation, period where according to [214] wind turbines require significant refurbish due to increased maintenance costs, more studies are necessary to validate the rates assumed. Apart from the increase of failure rates, other two possible causes were identified, ageing and curtailment. It is likely that all three losses and trends will occur together at some level. In this scenario, the critical year was the 7th year, indicating that possibly some of the assumed rates can be considered high.

The inclusion of operational losses in economic models can be helpful not only to estimate investment risks, but also to understand the real return of some practical solutions. Referring to one of the solutions proposed in Chapter 6, [272] suggests that the investment in CMS could be paid back within 10-year period. Therefore, considering the projected operational life and the extra costs and risks involved to adopt CMS, this might not be very attractive for investors. However, none of the assessed studies reported on the potential reduction of degradation, which could mitigate ageing effects and slow down the growth of failure rates along turbine`s lifespan. Similar benefit is demonstrated in the sections 5.3, 6.1 and 6.2.

Throughout the thesis, several economic analyses were conducted. The main findings indicate that the LCOE is underestimated by 10% in the MMCS results in section 6.4 when compared to the reference scenario presented in subsection 5.2.5. Both scenarios used the same cost base. However, by implementing the two solutions discussed to mitigate operational losses and degradation, overplanting and CMS, this difference could be reduced to 5%. In today's highly competitive market, differences of this magnitude can be crucial for the wind energy industry.

Regarding the adaptation of the metric OEE to wind energy assets, the findings was unexpected positive. Despite the uncontrollable environment and uncertainties surrounding wind power, the first case study (presented in section 3.5) achieved an overall productivity rate of close to 91%. According to [23], an OEE higher than 85% is considered world class benchmark in manufacturing industry. This result indicates that the technology can be considered reliable enough to deliver what they are expected. Although the second case study (demonstrated in section 4.2) achieved 73% productivity, the short period assessed could explain its lower result. Also, it is clear that at first half of the data provided some abnormalities have occurred. By eliminating this period, the OEE would be close to 81%.

It's worth noting that both case studies were based on early-age wind projects, which suggests a likelihood of bias in the results. Also, in this thesis, the OEE analysis covered the entire energy production process, not just the turbine. This means that external factors such as curtailment, which may not always be the responsibility of operators, were also taken into account. Although there is no consensus on whether external losses should be included in OEE analysis, the energy industry is inherently interdependent, with production relying on a balance between production and grid demand. Thus, it is crucial to consider these external factors in the OEE analysis as well as in the economic models, particularly because depending on the contract, these losses can reduce revenue and consequently the viability of project. Although in some cases, the government may cover these losses financially, consumers would ultimately bear the costs through higher energy prices. Therefore, the strategy behind this was to avoid bias in the analysis by checking the real costs and productivity of the assets.

In conclusion, the successful accomplishment of these two main aims, which were to adept OEE to the wind energy context and investigate the underlying factors contributing to occasional economic failures in wind projects, reinforces the importance of carefully assessing operational losses in wind energy for informed decision-making and comprehensive risk assessments. The creation of a unique metric that encompasses all possible operational losses has the potential to provide a more comprehensive overview of the equipment's performance. The novelty lies especially in the inclusion of the quality element, usually neglected or assessed separately in other studies. Also, as discussed in Section 2.3, improving one specific part of the process can have negative impacts on other parts. Therefore, an overall analysis of the entire process, such as the adaptation of OEE, can be crucial in ensuring that the project reaches its full productivity capacity. It is important to mention that to be more effective, academia and the industry should try to use a unique procedure to calculate the OEE, so the results can be fairly compared. In any case, the scheme shown in Figure 2.2 has the potential to be kept as the basis of future analysis, since this would inevitably cover the entire process and consider all operational losses. Additionally, an attempt to estimate quality element was developed in subsection 4.2.3, while in subsection 4.2.2 and section 4.3, the performance element was investigated, where different options were presented. To the best of knowledge of the authors, this is the first practical attempt to adapted OEE in wind energy, which means that there is room for future improvements.

Regarding the economic analysis, as mentioned before, it was identified and investigated three main operational loss trends that could affect productivity along wind energy operational life: the increase of failure rate, ageing, and curtailment. The addition of these operational loss trends demonstrates when and why the project can fail before its projected life. It is very likely that if a project is failing economically, part of these rates has been neglected or underestimated. The study has revealed that ageing and curtailment have minor impacts on the overall costs, despite the latter being a widely discussed topic in recent papers. However, it is important to keep in mind that grid structures and transmission lines usually take longer to be construct [220] than the wind farms, so this could become a big problem in near future. The increase of failure rate has shown to be the most impactful loss trends, which means that OPEX and maintenance are still the main bottleneck to wind energy to become completely independent from subsidies, competing directly in the energy market. It is important to remind that the rates outlined here must be carefully reviewed and tailored to the specific technology and scenario at hand. Although, the economic analysis used on the stochastic analysis was based in figures found on the literature to only offshore deployments, the particularities, country, and type of technology were not considered. As demonstrated in reference [255], which investigates LCOE by country, the costs can vary significantly, with the most expensive option being twice as costly as the cheapest. Also, it is expected that the implementation and operational costs of floating offshore wind turbines (FOWT), for instance, might be higher than from bottom fixed structures, which are closer to the shore. This indicates that the larger cost ranges assumed could be narrowed for specific projects, providing a more precise result.

Beyond the results itself, the main contribution of this work was the development of a framework that can be easily adapted and tailored to different deployments. Additionally, it is expected that the methodology proposed would give a broader overview of possible causes of economic failure and also, considering the adaptation of OEE, a reliable metric to help operators to identify and eliminate wastes in the process, improving productivity and profitability. Although the focus of this thesis was on wind energy assets, the proposed methodology and framework are versatile enough to be applied to different technologies, particularly in the field of renewable energy, such as solar energy. Solar energy shares similar characteristics with wind energy and can thus easily adopt the principles and foundations developed here.

As implied throughout this chapter, there are certain limitations in this thesis that need to be acknowledged and addressed in future studies. The primary limitation is related to limited data due to confidentiality concerns. This is a common problem faced by researchers to develop an economic analysis in wind energy, which can reduce the confidence of results. As demonstrated by [287], the current strike prices from UK auctions are approximated half of the average LCOE predicted by different sources in the literature. This means that either the costs discussed in the literature will reduce drastically in coming years or the strike prices are underestimated, and those future projects might not be viable its entire life. Also, some generalizations had to be done to perform the economic analysis and should be revisited before assuming the rates stablished here. With regards to the estimation of OEE, the quality analysis was simplified by solely taking into account ramp rates and wind energy rejection, as demonstrated in subsection 4.2.3. However, it should be noted that by following only this proposed quality analysis, many identified quality losses discussed in subsection 2.2.4 were disregarded. Different from manufacturing industry, measuring quality of the energy produced involves some subjectiveness and for better use of the tool this should be better defined in future to be efficiently measured and related to operational performance of the turbines. Finally, it would be important to extend the OEE analysis to older projects to observe how the metric changes over time. Moreover, future work could explore other factors that might impact OEE, such as workforce training and equipment maintenance.

8 CONCLUSION

This chapter will conclude the research by summarizing and presenting the main findings related to its aims and objectives mentioned in the introduction chapter. Section 8.1 will present a summary of the chapters. Section 8.2 will discuss the thesis contributions. In section 8.3, the limitations are discussed, while in 8.4 a suggestion of future works.

8.1 Summary of Chapters

This thesis started with an introduction of the theme and the problem that would be investigated (Chapter 1). Some wind energy deployment is failing to deliver what they were expected in medium and long term and becoming economically inefficient before the end of its projected lifespan. Thus, the problem background and the scope of the thesis was defined together with its aim and specific objectives. Later, the structure followed along this work and the works and papers published and submitted are presented.

The goal of chapter 2 was to identify the main operational losses in wind energy assets. The manufacturing industry has developed a metric called OEE to gather all operational losses and assist operators and managers in decision making. Therefore, the first part of the chapter presented this metric. Then an adaptation of OEE to wind energy was defined and finally an extended literature review was performed. The losses identified were classified according OEE elements and the benefits of this metric were discussed.

While the previous chapter focused on the qualitative investigation, chapter 3 estimated and established the general rate losses of each element of OEE. It was clear that these rates are not accounted following a common rule, which can reduce the reliability and make comparisons a hard task. Nonetheless, all these aspects were considered and a general OEE with its likely range was summarized for onshore and offshore projects. In section 3.5, a real case scenario was investigated and presented.

Chapter 4, through real data, some alternatives proposals to monitor and evaluate wind farms performance and productivity were discussed. First, using MET MAST data information, a script using traditional methods of machine learning was presented and have shown higher accuracy, even considering daily average values. Then, the OEE of a wind farm from provided SCADA data was evaluated. Due to the limitations of the data, part of losses was estimated, as the quality rate in which a simple procedure considering ramps rates and wind energy rejection was developed. The values were aligned with what was found in the literature.

Chapter 5 identified possible reasons for the farms become inviable in medium and long term. The main aspects identified were the increase of failure rates, ageing and curtailment. The latter is getting much attention, because with more wind farms built, curtailment tends to be higher without changings in the grid and/or expansion of transmission lines. An economic analysis was performed considering the average of costs found in the literature and the losses trends investigated. In section 5.3, an onshore hypothetical farm was simulated in a CFD software, and its costs were calculated considering the losses and comparing the selection of different wind turbine classes.

Chapter 6 shown some important and popular solutions to reduce the operational losses discussed in the previously chapter. While the thesis presents several interesting proposals such as new controllers, gadgets, and machine learning models, this chapter focuses on discussing CMS, the trade-off between maintenance efficiency and ageing, and solutions to increase power integration. The offshore figures discussed in chapter 5 were used to investigate and demonstrated possible economic return by adopting the solutions. Finally, a multivariate MCS is performed integrating the solutions and different trends rates randomly.

Chapter 7 presents a discussion about the main findings, some of the impacts of this study and some limitations.

8.2 Thesis Contributions

Through different case studies and an extended literature review, this thesis found an indication of main problems that can reduce performance of wind energy assets along its lifespan. The impact of each loss trends was investigated stochastically considering different scenarios. Also, a metric was proposed to monitor and measure the operational losses and productivity stability of wind energy farms. The novelty, soundness, and value from each specific objectives presented in Section 1.2 are summarized in tables 8.1, 8.2, 8.3, 8.4, and 8.5. “Novelty” outlines what is new to academia and/or industry. Soundness sums up the methods used and how they were applied. Finally, the value explains why and to whom the outcomes can be significant.

Table 8-1 Summary of Objective 1

Objective 1: *Review of operational losses throughout the entire process, including wind penetration into the grid, and classify them into groups following OEE concepts to help operators to identify specific areas for improvements*.

Novelty	Soundness	Value
At best of knowledge of the authors no similar work has been developed so far. Most of reviews identified in the literature treat specific groups of operational losses. In this activity, they were all put together, including some third-party causes, giving a widely overview of the losses and risks of wind energy assets. The focus of this review was on publications starting from 2010.	This extended review used several key words as "operational losses", "quality losses", "performance losses", "availability", "grid losses", together with "wind energy" or "wind power". The losses were classified in three main elements, following basic concepts of the metric OEE. Apart from the classification, it was indicated what sort of discussion and solutions were presented.	This review might be for interests of not only researchers, but also for the industry. Although there are many papers discussing the operational losses, they are not treated together. This review summarizes all possible operational losses and also has presented a reasoning line to accommodate them in the elements of OEE. This criterion has the potential to become the basis of OEE adaptation to wind energy assets. Additionally, some solutions are presented, and they were grouped according to its proposal.

Table 8-2 Summary of Objective 2.

Objective 2: *Apply OEE to wind energy following framework previously developed and perform quantitative analysis according to literature figures and real cases to evaluate wind energy effectiveness.*

Novelty	Soundness	Value
OEE is a popular metric in manufacturing to measure equipment stability and productivity by assessing its operational losses. The advantage of this tool is that it puts all losses together, which contributes to find the best global solution. What outstands this metric from others is that it includes quality losses, often neglected in turbine performance analysis.	By following a linear reasoning strategy, developed in the review, the losses were grouped in the three elements of OEE. A further quantitative review was proposed to estimate the average rate of each OEE element for onshore and offshore projects. Two real case scenarios from early age projects were also performed to this end.	Any changing in a process can bring consequences in other stages of the process. This argument is also valid for wind energy assets. For the best of knowledge of the author, it was not found any metric where all possible losses are put together for wind energy, especially the ones related with quality. This metric is known as an important tool not only to measure equipment stability, but also to help to identify hidden losses to improve productivity and profitability.

Table 8-3 Summary of Objective 3.

Objective 3: *Conduct data analysis to develop different models and procedures to monitor and estimate OEE*.

Novelty	Soundness	Value
The adaptation of OEE proposed is a novelty itself, however, there is no procedures regarding the application and how the rates should be accounted. For that, some common metrics was investigated, and data analysis and machine learning methods used.	Availability is already a well-established concept in the literature. Although there are different options to calculate it, it was followed the time-based concept. Performance and quality, on the other hand, had to be developed. From a data analysis activity, the best performance registered in similar operational conditions was determined as reference. To the quality, by limited data, a script considering ramp rates losses and wind energy rejection was created. Therefore, OEE could be estimated in real scenarios. To monitor performance through MET MAST data, a model was developed considering RFR, achieving a high accuracy for wind power output prediction.	Estimate and monitor OEE can be beneficial to operators to identify hidden losses and understand better how the equipment is performing along its life. The main value of this tool is that it includes all elements in one metric, including quality. The ramp rate x wind rejection criteria developed provided coherent outcomes and could become a starting point for a more complete assessment. The cases have shown the potential of the tool, where in similar events the performance, for instance, could be half of expected.

Table 8-4 Summary of Objective 4.

Objective 4: *Investigate in literature how some operational losses increases along the lifespan of wind energy assets and evaluate its impacts on costs and viability.*

Novelty	Soundness	Value
A review of operational different causes of increase of operational loss were investigated and presented together. Here, common rates of operational losses trends were defined and its impacts on viability and costs were investigated. A diverse number of scenarios were drawn, considering them individually or together, to better understanding if they could be the reason of economic failures in the projects.	The main causes of losses of productivity along wind assets lifespan were investigated through literature review. Scenarios considering likely loss trends were created and added to economic analysis to check the impact in the LCOE and its viability. The critical and breakeven year of each scenario was also assessed. A hypothetical onshore farm was created to assess the impact in costs from different wind turbine classes with different scenarios.	Before deciding to participate in a project, investors want to have the risks drawn as clear as possible. By including the loss trends, a new range of possibles outcomes are created. It is not expected that operators will accept the losses without any action to minimize them. Therefore, the simulations are important to indicate how the costs could be in future and the consequences in case the trends keep growing at same rate. Some of externalities, such as curtailment by lack of demand was also investigated. Although this is not always responsibility of operators, depending on the contract their revenue can be affected, for that reason, they should be considered.

Table 8-5 Summary of Objective 5.

Objective 5: *Perform stochastic analysis to check viability, costs, and risk of economic failure of wind energy assets along its lifespan in different scenarios, combining different losses trends and some proposed solutions to reduce operational losses identified in literature*.

Novelty	Soundness	Value
Some solutions to reduce losses were investigated, including CMS to reduce breakdown, and overplanting to increase wind dispatchability. Also, the trade-off between maintenance and ageing was considered. Thus, a stochastic analysis assuming not only costs uncertainties, but also, the losses trends rates and some of solutions discussed were performed.	Due to the number of uncertainties in wind energy assets, stochastic analysis is the best approach to assess risk in wind assets. Two analyses were performed here. First, the impact of losses trends rates was investigated through MCS, considering only costs uncertainties. Later, a MMCS was run considering costs uncertainties, different losses trends rates, and finally, the implementation or not of some of solutions previously discussed.	As demonstrated in this thesis, besides uncertainties on wind regimes and operational costs, loss trends rates, curtailment risks, and the return of some solutions can also affect final cost of wind energy. Therefore, the MMCS proposed can give a broader view of the risks to investors. Although the range of costs can be considered higher, the model proposed is easily adapted to attend each specific scenario in real life models. Also, some of solutions found on the literature demonstrates low financial return; however, the reduced degradation level is usually not assessed, which can mislead decisions.

8.3 Limitations

Despite of prominent results achieved in this thesis; some simple assumptions were made due to data limitation. Real costs, productivity data, and level of operational losses, are considered key and confidential by the industry. Thus, the costs and values assumed were based in the literature and some international reports, which usually consider mean values from several deployments. In this case, it might be hard to avoid some sort of bias.

Another approach to deal with the data limitation was to expand the research including data from different types of deployments, turbines, countries, and ages. Although this generalization can be considered good to bring a wide overview, this hinders specific analysis. Wind energy is surrounded by uncertainties, so some subjectiveness and simplifications are acceptable for general analyses as the one proposed here.

The incomplete data also affected the attempt to measure OEE. In the data analysis activity, several assumptions had to be done, including that no abnormalities have happened during the period assessed. This could affect the rates of each element, since it was not informed for example, if the farm was in test or normal operation, if the losses in performance was due to grid restrictions, or if the farm was penalized by any disturbance created in the grid. Nonetheless, to best use of OEE, all losses, even the ones that could be justified, should be accounted.

It is worth to add that one of the main characteristics of OEE is its simplicity. The way OEE was adapted to wind energy in this work tried to be very clear and concise, keeping the fundamental characteristic of the tool. Nonetheless, the definition of the six main losses, which ended up becoming nine, did not consider how the operational losses interact to each other. Quality losses, for instance, can cause downtime, reduced speed, and/or increase wind energy rejection and transmission losses. Thus, considering it just at the end of the process might not be the best approach. Either way, regardless of the main losses' identification, the main purpose of OEE was achieved through the procedure suggested, which is to gather all losses in a solid metric, helping operators to identify hidden losses. In other words, by following the procedure suggested here, these losses would be included in OEE, despite of its element classification.

Finally, it is important to mentioned that this PhD has started in March of 2020, the same period of Covid outbreak. Part of the decisions and scope had to be changed and adapted, especially during the first two years, when companies, the university and the country had total or some level of restriction. Nonetheless, the overall structure and aims was kept as close as possible for the original goals and the results were satisfactory.

8.4 Future Works

This work has demonstrated the importance of including operational losses trends in economic analysis and the use of OEE for decision makings. However, some simplifications and generalizations had to be done due to the lack of complete data. Therefore, investigating if the considerations assumed here are coherent is an important sequence of this work. Also, as discussed along the thesis, OEE tries to find the best balance between all elements. Although the goal of the tool is to assist operators to find solutions to reduce all losses and not to decide the best configuration, this could still be used for this end.

Relating fatigue with operational behaviour could help to link performance with availability, for example. Also, the use of software that estimates power quality, could be related to performance. Here, only the ramp rate issue was used to estimate wind power rejection. Although the values found was coherent, further investigation is important. Creating a theoretical link between elements of OEE could facilitate comparisons between configurations and/or scenarios. Many studies presented here suggest solutions to solve or reduce losses in each element, but how this affects other parts of the process is rarely discussed. As demonstrated, an increase of performance at the cost of reducing its quality could make overall effectiveness worser than before.

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APPENDICES

Appendix A

Table_Apx A-1 Results of Economic Model - return rate = 4%

	LCOE (£/MWh)	NPV (£/MW)	Critical Year	Investment Breakeven Year
Reference	£88.65	£1,084,481.25	-	13
Scenario C	£92.07	£887,195.71	-	13
Scenario B	£93.22	£823,880.50	-	13
Scenario B + C	£96.71	£641,849.25	20	14
Scenario A	£101.43	£459,592.91	15	14
Scenario A + C	£105.25	£273,207.45	13	15
Scenario A + B	£106.85	£198,992.16	12	16
Scenario A + B + C	£110.74	27,861.00	11	17

Table_Apx A-2 Results of Economic Model - return rate = 8%

	LCOE (£/MWh)	NPV (£/MW)	Critical Year	Investment Breakeven Year
Reference	£110.16	£42,534.77	-	19
Scenario C	£113.69	-£76,267.28	4	20
Scenario B	£114.99	-£118,490.43	3	20
Scenario B + C	£118.55	-£228,721.84	2	20
Scenario A	£121.37	-£333,762.53	1	-
Scenario A + C	£125.15	-£446,541.55	-	-
Scenario A + B	£126.84	-£494,787.73	-	-
Scenario A + B + C	£130.65	-£598,996.11	-	-

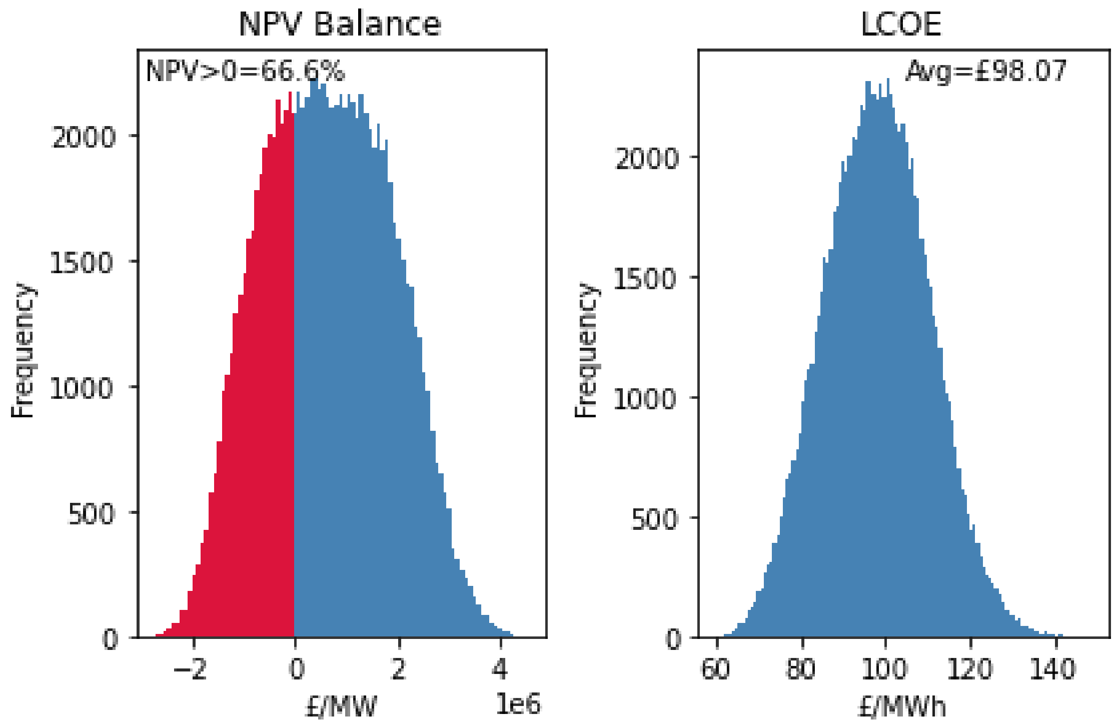
Table_Apx A-3 Result MCS – return rate = 4%.

	LCOE (IC 95%)			NPV > 0 (%)
	Lower Limit	*Average*	*Upper Limit*	
Reference	£65.75	£88.81	£111.88	0.7771
Scenario C	£68.26	£92.22	£116.18	0.7503
Scenario B	£68.77	£93.27	£117.77	0.7301
Scenario B + C	£71.45	£96.84	£122.23	0.6835
Scenario A	£73.55	£101.51	£129.47	0.6236
Scenario A + C	£76.52	£105.48	£134.44	0.5776
Scenario A + B	£77.45	£106.93	£136.41	0.5534
Scenario A + B + C	£80.53	£111.18	£141.84	0.5082

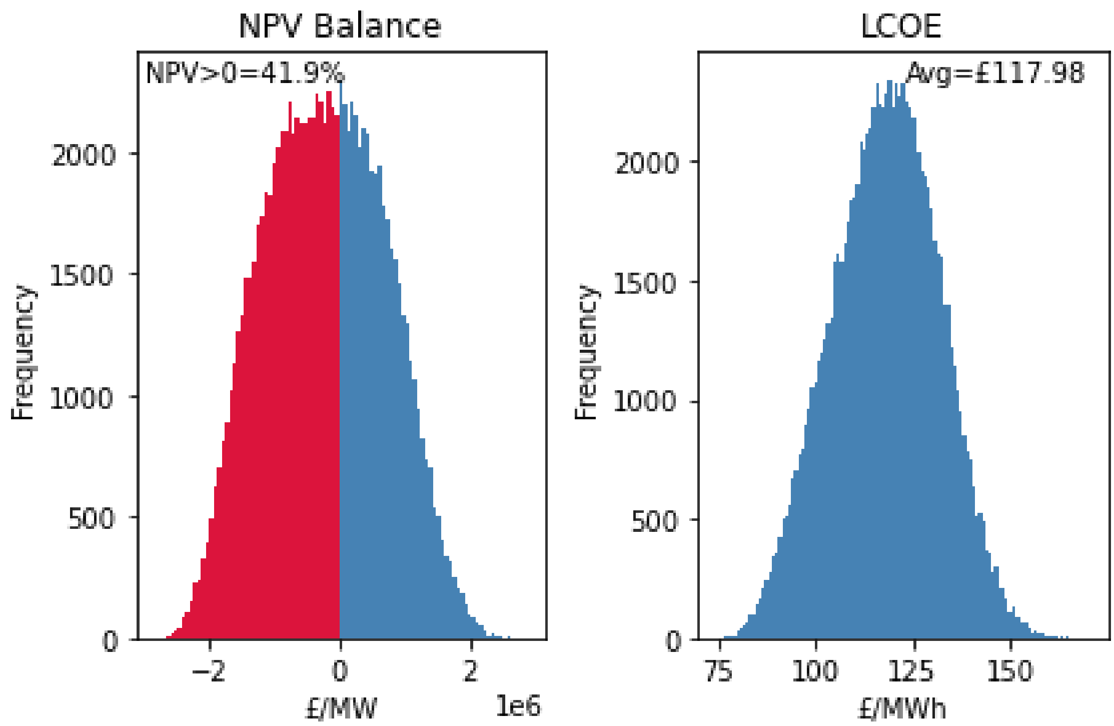
Table_Apx A-4 Result MCS – return rate = 8%.

	LCOE (IC 95%)			NPV > 0 (%)
	Lower Limit	*Average*	*Upper Limit*	
Reference	£82.60	£110.31	£138.02	0.5054
Scenario C	£85.01	£113.81	£142.62	0.4787
Scenario B	£86.21	£115.39	£144.57	0.4536
Scenario B + C	£89.21	£119.01	£148.80	0.4060
Scenario A	£90.22	£121.68	£153.14	0.3719
Scenario A + C	£92.68	£125.35	£158.03	0.3247
Scenario A + B	£94.02	£127.20	£160.38	0.3110
Scenario A + B + C	£96.31	£130.92	£165.52	0.2628

Appendix B



Figure_Apx B-1 MMCS results for returning tax = 4%.



Figure_Apx B-2 MMCS results for returning tax = 8%.