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End-of-life investment decisions for windfarms: an opportunity for climate change and for energy community

Thesis presented by

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for the degree of

Doctor of Philosophy

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Abstract

A growing share of onshore wind farms is approaching the end of its originally permitted operational lifetime, creating an urgent need for robust decision-making frameworks to guide lifetime extension, repowering, and decommissioning. While early research primarily focused on deployment and cost reduction, end-of-life (EoL) decision making has emerged as a critical yet under-examined stage of the wind farm lifecycle. This thesis develops an integrated understanding of wind farm EoL decisions by examining the interaction between financial risk, investment flexibility, and community risk perception. The research adopts a mixed method approach and is structured around three complementary studies.

The first study quantifies the financial risks associated with turbine component failures over the operational lifetime of wind farms using stochastic modelling and tail-risk metrics. It shows how failure-driven losses generate substantial downside risk and erode economic viability. The second study applies real options analysis to evaluate the financial value of alternative EoL strategies under electricity price uncertainty revealing that repowering offers significant upside potential, while lifetime extension provides limited strategic value and decommissioning remains economically unattractive under most market conditions. The third study examines community investment behaviour using behavioural finance frameworks and survey data from developed and developing countries, showing how risk attitudes, experience, and institutional context shape investment decisions in wind energy.

By integrating these financial, operational, and social perspectives, the thesis conceptualises wind farm EoL as a strategic investment and governance problem embedded within complex socio-technical systems. The research delivers two complementary decision-support frameworks: one focused on commercial risk-based evaluation of EoL options, and the other on community investment and social feasibility. Together, these frameworks support more holistic, resilient, and socially legitimate EoL strategies, contributing to the long-term sustainability of wind energy infrastructure and the effective governance of ageing renewable assets in the energy transition.

Dhahania

Idadi kubwa ya mashamba ya upepo ya nchi kavu inakaribia kufikia mwisho wa muda wake wa uendeshaji ulioruhusiwa awali, hali inayosababisha hitaji la haraka la mifumo thabiti ya kufanya maamuzi ili kuongoza uwezekano wa kuongeza muda wa matumizi (lifetime extension), uboreshaji (repowering), na uondoaji (decommissioning). Ingawa tafiti za awali zilijikita zaidi katika utekelezaji na upunguzaji wa gharama, kufanya maamuzi katika hatua ya mwisho wa maisha wa mashamba haya kumeibuka kama hatua muhimu lakini ambayo haijachunguzwa kwa kina katika mzunguko wa maisha wa mashamba ya upepo. Tasnifu hii inaendeleza uelewa jumuishi wa kufanya maamuzi katika hatua ya mwisho wa maisha kwa kuchunguza mwingiliano kati ya hatari za kifedha, unyumbufu wa uwekezaji, na mtazamo wa jamii kuhusu hatari.

Utafiti unatumia mbinu mseto na umeundwa katika tafiti tatu zinazokamilishana. Utafiti wa kwanza unapima hatari za kifedha zinazohusishwa na hitilafu za vipengele vya mitambo ya upepo katika kipindi cha uendeshaji kwa kutumia uigaji wa kistokastiki na vipimo vya hatari za mkia (tail-risk metrics). Utafiti huu unaonyesha jinsi hasara zinazosababishwa na hitilafu zinavyozalisha hatari kubwa za kushuka kwa mapato na kudhoofisha uhalali wa kiuchumi. Utafiti wa pili unatumia uchambuzi wa chaguzi halisi (real options analysis) kutathmini thamani ya kifedha ya mikakati mbadala ya mwisho wa maisha ya mashamba ya upepo kwa kutokuwa na uhakika wa bei ya umeme, ukibaini kuwa uboreshaji una uwezo mkubwa wa faida, wakati kuongeza muda wa uendeshaji kuna thamani ndogo ya kimkakati, na uondoaji unabaki kuwa chaguo lisilovutia kiuchumi katika hali nyingi za soko. Utafiti wa tatu unachunguza tabia ya uwekezaji wa jamii kwa kutumia mifumo ya fedha kitabia na data za utafiti kutoka nchi zilizoendelea na zinazoendelea, ukionyesha jinsi mitazamo ya hatari, uzoefu, na muktadha wa taasisi vinavyoathiri maamuzi ya uwekezaji katika nishati ya upepo.

Kwa kuunganisha mitazamo ya kifedha, kiutendaji, na kijamii, tasnifu hii inaweka dhana ya hatua ya mwisho kwa maisha wa mashamba ya upepo kama tatizo la kimkakati la uwekezaji na utawala lililojikita katika mifumo changamano ya kijamii na kiteknolojia. Utafiti huu unatoa mifumo miwili inayokamilishana ya kusaidia maamuzi: mmoja unaolenga tathmini ya kibiashara inayotegemea hatari za chaguzi za

mwisho wamaisha yamashamba ya upepo, na mwingine unaolenga uwekezaji wa jamii na uwezekano wa kijamii. Kwa pamoja, mifumo hii inawezesha mikakati ya mwisho wamaisha yamashamba ya upepo iliyo jumuishi zaidi, imara, na yenye uhalali wa kijamii, hivyo kuchangia uendelevu wa muda mrefu wa miundombinu ya nishati ya upepo na utawala bora wa rasilimali za nishati jadidifu zinazozeeka katika mchakato wa mpito wa nishati.

Acknowledgement

I begin by expressing my deepest gratitude to God for granting me the strength, wisdom, grace, and perseverance to complete this doctoral journey.

My sincere thanks go to my supervisors, Dr. Peter Deeney, Dr. John O'Brien , and Dr. Paul Leahy for their guidance, motivation and enthusiasm through the past four years. I am especially grateful for their patience, availability, and commitment to rigorous scholarship, which challenged me to think critically and develop ideas with clarity and confidence. This work would not have been possible without their mentorship.

I would also like to acknowledge all individuals who participated in the study, wind energy stakeholders who provided data and insight and particularly the survey respondents and focus group participants in both Ireland and Tanzania. I would also like to thank the funders of this research, Taighde Éireann - Research Ireland and The National University of Ireland.

Finally, I would like to thank my family and friends for their unwavering support throughout this journey. Their patience, encouragement, and understanding sustained me through the many challenges of doctoral study. Special thanks need to be given to my mother (Veronica), my siblings (Miriam and Flora), my niece (Emelyn), and my friend (Jimmy) for always being there to listen to me and support me in every way possible.

Dedication

“This thesis is dedicated to the memory of my father, Allan Mikindani, who will always be my inspiration”.

Declaration

"This is to certify that the work I am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism and intellectual property."

I acknowledge the use of generative artificial intelligence (AI) tools during the preparation of this thesis. These tools were used solely to support language refinement, structural organisation, and proofreading. All intellectual content, analysis, interpretation, and conclusions presented in this work are my own. I accept full responsibility for the accuracy and integrity of the material contained herein.

Digital signature of the candidate: 

Chapter 1 . Introduction

1.1 Background

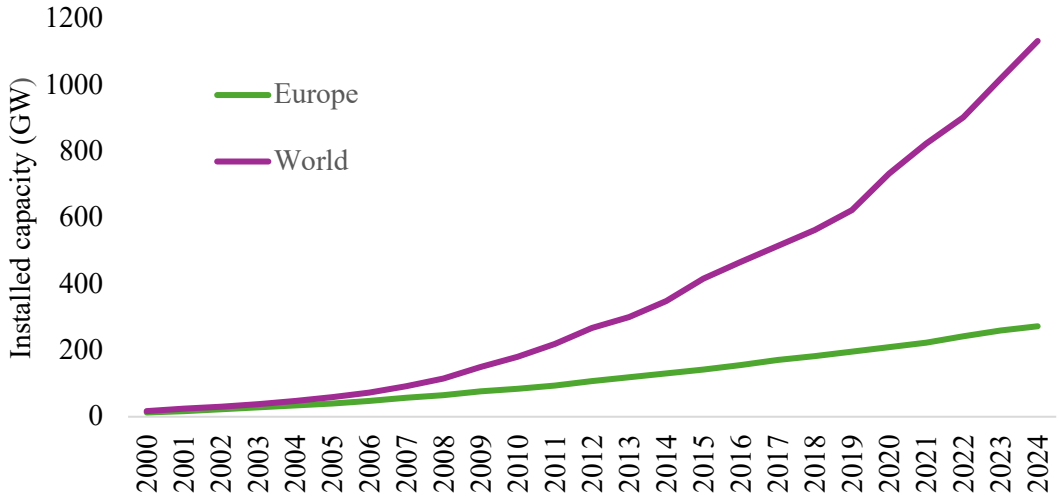
The substantial investment in wind farms over the past three decades has enabled significant reduction in greenhouse gas emissions and displaced fossil fuel based electricity generation (Barthelmie and Pryor, 2021). Wind energy now represents one of the most mature and widely deployed renewable technologies worldwide. Global installed capacity grew from 17 GW in 2000 to 1,133 GW in 2024 (IRENA, 2025). Alongside this the cost of wind-generated electricity has fallen sharply, strengthening wind's role not only as a decarbonisation technology but also as a cost competitive source of new power generation.

The global weighted average levelised cost of electricity for new onshore wind turbines reached USD 0.033/kWh in 2023, which was 67% lower than the weighted average cost of fossil fuel generated electricity in the same year (IRENA, 2024a). This declining cost trend has been enabled by turbine technology improvements (higher hub heights, larger rotors, better capacity factors), economies of scale in manufacturing and project development, and learning effects across supply chains. This cost competitiveness is evident in independent benchmarking. Lazard's latest LCOE analysis continues to place onshore wind among the lowest cost energy generation options, generally competitive with (and often below) the cost range for new conventional generation technologies, depending on regional financing and system assumptions (Lazard, 2025).

Wind turbines are typically designed for, and granted operational permits of twenty to twenty five years. This reflects assumptions about component reliability, structural fatigue, and economic viability at the time of installation (Leite et al., 2022; IEA, 2023). A growing proportion of the global wind fleet commissioned during the late 1990s and early 2000s particularly in Europe and North America is now reaching or exceeding this threshold (WindEurope, 2021a; IRENA, 2022). A substantial share of this capacity was commissioned in the early 2000s (Figure 1.1). As early generations of wind farms approach the end of their designed and permitted operational lifespan, attention is increasingly shifting from capacity deployment toward the long term sustainability and management of ageing wind energy infrastructure.

Figure 1.1: Cumulative installed wind energy capacity

This figure presents the cumulative installed wind energy capacity in Europe between 2000 and 2024.



Source: (IRENA, 2024c)

The ageing of this installed base marks a critical juncture for the wind energy sector, introducing complex questions regarding the most appropriate end-of-life (EoL) strategies for wind farms. Asset owners and policymakers must decide whether to extend the operational life of existing turbines through enhanced inspection regimes, component replacement, and revised maintenance strategies; repower existing sites with modern, higher-capacity technology; or decommission turbines and restore sites (González and Lacal-Arántegui, 2016; De Laurentis and Windemer, 2024). These investment pathways represent distinct strategic responses to ageing infrastructure in the context of evolving market conditions.

Each EoL pathway carries different financial, environmental, technical, regulatory, and social implications. Lifetime extension offers a low capital option but exposes operators to heightened operational and financial risks due to increasing failure rates, uncertain remaining useful life, and rising operation and maintenance costs (Carroll et al., 2016; Izquierdo et al., 2020). Repowering can substantially increase energy output and improve efficiency, but often requires new capital investment, updated grid connections, and renewed planning consent, which may face regulatory and community resistance (WindEurope, 2021; Windemer, 2023). Decommissioning require significant costs related to dismantling, waste management, and site

restoration, while raising concerns about material recycling and long term environmental responsibility (IRENA, 2022). These challenges highlight that wind farm EoL decisions are no longer purely technical determinations, but strategic, risky investment choices embedded within broader social, economic, and technical systems.

1.2 Problem statement

End-of-life (EoL) decision making represents a pivotal yet historically under-examined stage of the wind farm lifecycle. Early policy frameworks and academic research largely prioritised project feasibility, performance optimisation, and environmental impacts during the operational phase, reflecting the sector's focus on rapid deployment and cost reduction (Wiser et al., 2021). EoL considerations were treated as distant or secondary concerns and many early wind farm developments entered their later years without clear, standardised plans for lifetime extension, repowering, or decommissioning (IRENA, 2022). As large cohorts of wind farms now approach or exceed their originally granted operational lifetime, this institutional and analytical neglect has become increasingly consequential.

Recent literature shows that EoL decisions are inherently multidimensional and characterised by multifaceted uncertainty. From a technical perspective, ageing turbines exhibit increasing failure rates, declining reliability, and growing uncertainty regarding remaining useful life, particularly for critical components such as gearboxes, generators, and blades (Carroll et al., 2016; Olabi et al., 2021). Financially, operators must balance rising operation and maintenance costs against uncertain future revenues in electricity markets that are increasingly volatile due to higher renewable penetration, fluctuating demand, and evolving market design (Kanamura et al., 2021; Kitzing et al., 2017). Regulatory environments further complicate these decisions, as permitting requirements, subsidy eligibility, environmental compliance, and grid access rules for lifetime extension or repowering vary widely across jurisdictions and are frequently subject to policy change (González and Lacal-Arántegui, 2016; IEA, 2023).

Social acceptance has also emerged as a key factor in shaping EoL outcomes. Community perceptions, trust, and wind projects experience influence planning approval processes, investment risk, and the long-term legitimacy of wind energy

projects (Aitken, 2010; Windemer, 2023). Yet social factors are commonly treated as external constraints rather than as integral elements of EoL decision making, even though community opposition, dissatisfaction with benefit distribution, or declining trust can delay projects, increase costs, or render technically and financially viable options infeasible.

Existing research and regulatory practice continue to address wind farm EoL strategies in a fragmented manner. Many studies focus narrowly on individual pathways such as lifetime extension feasibility, repowering performance gains, or decommissioning costs without providing integrated decision-making frameworks that allow systematic comparison across alternative EoL options under uncertainty (Leite et al., 2022; Agra Neto et al., 2024). In parallel, regulatory guidance in many jurisdictions remains reactive and incomplete, often concentrating on decommissioning obligations while offering limited or ambiguous direction on repowering and lifetime extension. This lack of standardisation and clarity creates significant uncertainty for operators, investors, policymakers, and host communities at precisely the point when long-term financial exposure, environmental responsibility, and social legitimacy are most at stake.

EoL decision making is further undermined by the dominance of deterministic or static financial appraisal methods. Such models typically fail to capture downside risk, tail events, and the value of managerial flexibility under uncertainty, despite the high exposure of late-life wind assets to component failure, escalating maintenance costs, electricity price volatility, and the expiry of long-term support schemes. As a result, operators may underestimate financial risk, misjudge optimal timing, or commit to irreversible decisions based on incomplete and misleading assessments.

Taken together, these technical, financial, regulatory, and social deficiencies mean that wind farm EoL decisions are frequently made using incomplete, fragmented, or overly simplified information. This increases the likelihood of suboptimal outcomes, including financially risky lifetime extension strategies, repowering projects that encounter significant social resistance, or premature decommissioning of economically and environmentally valuable assets. There is a clear and pressing need for integrated decision-support approaches that explicitly incorporate financial risk,

investment flexibility, and community perspectives in order to guide sustainable EoL strategies for wind energy infrastructure.

1.3 Aim and objectives

The aim of this thesis is to develop an integrated understanding of wind farm EoL decision making by examining the interaction between financial risk, investment flexibility, and community risk perception. The study treats end-of-life not as a purely technical or regulatory event, but as a strategic investment problem embedded within uncertain markets and socio-institutional contexts. This thesis pursues four interrelated objectives to achieve this aim.

First, it quantifies the financial risks associated with turbine lifetime failures and to examine how these risks affect realised profits and operational viability across wind farms of different sizes.

Second, the thesis develops and applies a real-options-based framework to evaluate the financial value of alternative end-of-life strategies (lifetime extension, repowering, and decommissioning) under electricity price uncertainty and evolving market conditions. This objective focuses on capturing the value of managerial flexibility and timing in end-of-life investment decisions, which is typically ignored in conventional appraisal approaches.

Third, the study assesses community perceptions of risk and investment in onshore wind energy, and to examine how experience with wind farms and socio-demographic characteristics influence project acceptance and willingness to engage in end-of-life co-investment models. This objective explicitly incorporates the social dimension of end-of-life decision making, recognising that financial and technical viability alone is insufficient to ensure successful outcomes.

Finally, the thesis integrates financial, operational, and social insights in order to inform more holistic and resilient end-of-life decision-making frameworks for ageing wind energy infrastructure. By linking commercial risk analysis with community investment behaviour, the research aims to support end-of-life strategies that are not only economically robust but also socially legitimate and aligned with long-term sustainability goals.

Together, these objectives address the limitations identified in the existing literature and regulatory practice by providing two complementary decision-support perspectives: one focused on the commercial and risk-based evaluation of end-of-life options, and the other focused on community engagement and co-investment potential.

1.4 Thesis structure

This thesis is presented in eight further chapters. The next chapter reviews the literature on wind farm end-of-life challenges to identifying key research gaps. Chapter three presents theoretical foundations of the financial techniques used in the analysis. Chapter four presents the methodology, outlining the mixed-method research design. Chapter five, six, and seven consist of the three research papers that form the basis of this thesis. Chapter eight integrates and discusses the three papers findings forming decision support frameworks, and chapter nine concludes with implications for policy, practice, and future research.

The content three papers in chapters five, six and seven corresponds exactly to the published or latest submitted versions. However, some layout and reference changes were made to keep the document consistent. All separate bibliographies were removed and replaced with one shared bibliography. The numbering of sections, tables, and figures was updated so they can be referred to consistently throughout the thesis. Some tables and figures were also reformatted to fit the layout of this document.

A multi-attribute review of end-of-life decisions in wind farms: financial, technical, and social perspectives: The current academic evidence on end-of-life decisions for wind farms is assessed. The literature review synthesises research on how wind farm end-of-life (EoL) decisions are currently understood and where key limitations remain. The chapter reviews four core themes: lifecycle dynamics, financial and investment risk, community engagement, and the policy and regulatory frameworks that shape EoL choices. Together, these strands provide the basis for understanding why EoL decision making has become an increasingly important and contested issue in wind energy and how research gaps influence this thesis objectives.

Financial theories, risk and investment under uncertainty in wind energy infrastructure: This chapter develops the theoretical framework underpinning the

study's design and analytical approach. Each theoretical component is explicitly connected to a corresponding empirical inquiry, thereby integrating the conceptual basis with the three studies presented in Chapters five, six, and seven.

Methodology: Chapter four describes the methodological framework of the thesis. It outlines the mixed-methods research design, underpinning the quantitative and qualitative components, and the data sources, modelling approaches, and analytical techniques used across the three empirical studies. The chapter discusses a risk-based investment decision framework that conceptualises wind farm end-of-life (EoL) choices as strategic decisions made under conditions of uncertainty rather than as purely technical or operational determinations.

The financial risks from wind turbine failures: a value at risk approach: This chapter quantifies the financial risk arising from turbine failure costs over the operational lifetime of a wind farm and examines how such failures drive variability in realised project profitability. A stochastic model of the failure-generation process is developed and parameterised using industry data. This is used to estimate project-level financial risk using the Value at Risk (VaR) and Conditional Value at Risk (CVaR) metrics. By applying the model to wind farms of different sizes, the analysis also reveals how exposure to failure risk scales with asset portfolios.

Real options valuation for end-of-life investment decisions in wind farms: This chapter evaluates wind farm end-of-life investment decisions by applying real options analysis (ROA) with Monte Carlo simulation to compare the option value of lifetime extension, repowering, and decommissioning under electricity price and financing uncertainty. By explicitly valuing managerial flexibility and uncertainty, the study demonstrates how ROA provides a more appropriate basis than conventional discounted cash-flow analysis for determining when continued operation ceases to be optimal and capital should be redeployed through repowering or exit. In doing so, the paper establishes a rigorous financial framework for timing and selecting end-of-life strategies in ageing wind farms.

Perceptions of risk and investment in wind energy in rural communities: This chapter examines investment appetite of energy communities in onshore wind energy, with direct relevance to end-of-life strategies that rely on local co-ownership,

repowering, or asset renewal. Using behavioural finance frameworks and survey data, the study applies regression models to analyse how risk attitudes, prior experience, and socio-demographic characteristics shape investment decisions. Risk is identified as a driver of investment decision in mature wind markets such as Ireland whilst for developing countries like Tanzania, institutional context, awareness, and trust play a more dominant role than individual risk preferences. By identifying when and where community capital can credibly support repowering or lifetime extension at the end of a wind farm's life, the paper provides a social and behavioural counterpart to the financial models developed in the other studies, enabling end-of-life strategies that are both economically viable and socially legitimate.

Decision support frameworks: Chapter Seven integrates the findings of the three studies and synthesises them into a coherent decision-support perspectives. It discusses how financial risk, investment flexibility, and community dynamics interact to shape end-of-life outcomes and presents the combined implications for operators, policymakers, and host communities.

Conclusion: The final chapter concludes the thesis by summarising the main contributions of the research and outlining their implications for policy, industry practice, and future research on the long-term sustainability of wind energy infrastructure. The thesis is followed by a complete list of references and supporting appendices.

1.5 Key contributions

This thesis makes several substantive contributions to the field of wind energy and infrastructure decision making.

Firstly, it advances renewable energy finance by developing two complementary Monte Carlo-based modelling frameworks for late-life wind assets. One model quantifies downside financial risk arising from turbine failures, while the other uses real options analysis to estimate the value of flexibility across alternative end-of-life investment pathways. Together, these approaches provide a rigorous basis for evaluating financial exposure and strategic timing under uncertainty and are transferable to other markets and renewable technologies.

Secondly, the thesis contributes new empirical evidence on community investment behaviour in wind energy, particularly in under-researched developing-country contexts. The original survey of Tanzanian communities provides one of the first systematic datasets on attitudes toward wind farm investment in an immature market, allowing the analysis to move beyond high-income countries and informing the design of community participation models for similar institutional and market environments.

Thirdly, it integrates financial risk modelling**,** real options analysis, and behavioural perspectives on risk perception within a single, coherent analytical framework. In doing so, it responds to long-standing calls for more holistic approaches to renewable energy research that move beyond siloed technical, economic, or social analyses and instead recognise energy infrastructure as a socio-technical system shaped by uncertainty, institutional context, and stakeholder behaviour (Wolsink, 2007; Sovacool et al., 2020; De Laurentis and Windemer, 2024).

Fourthly, the thesis develops decision-support frameworks that can assist wind farm operators, investors, and policymakers in navigating the complex and uncertain conditions that characterise the end-of-life stage of wind energy assets. By explicitly incorporating downside financial risk, market volatility, and investment flexibility, alongside insights into community risk perceptions and acceptance, the research supports more robust and resilient decision making than traditional deterministic or static evaluation methods (Kitzing et al., 2017; Trigeorgis and Reuer, 2017). These tools are intended to inform real-world decisions regarding asset management, investment timing, and stakeholder engagement, reducing the likelihood of financially risky lifetime extension strategies, socially contested repowering projects, or premature decommissioning.

Finally, from a policy perspective, the thesis provides evidence in support of clearer, lifecycle-oriented policy frameworks that provide consistent guidance on lifetime extension and repowering, while also recognising the importance of community engagement and social legitimacy in shaping long-term project outcomes (González and Lacal-Arántegui, 2016; Windemer, 2023).

1.6 Scope of the study

This research focuses primarily on onshore wind farms, reflecting both their technological maturity and their dominant share of global installed wind capacity, as well as the growing prevalence of EoL challenges within this segment. Offshore wind farms, while increasingly important to future energy systems, are excluded from detailed analysis due to their differing cost structures, regulatory regimes, operational risk profiles, and decommissioning requirements, which would require a distinct methodological treatment beyond the scope of this study. However, an additional economic analysis of repowering technologies for offshore wind turbines is presented in Appendix H.

Financial and operational modelling is conducted primarily within a European market context, with Ireland serving as a key empirical reference point. Ireland is characterised by high wind energy penetration, a liberalised electricity market, and an evolving policy and regulatory landscape, making it a suitable and policy-relevant case for examining end-of-life investment decisions. Electricity price dynamics, operational cost assumptions, and regulatory considerations are therefore grounded in European and Irish market conditions. While these contextual assumptions may limit the direct generalisability of specific numerical results, the underlying modelling frameworks and decision-support frameworks developed in this research are designed to be adaptable to other jurisdictions with appropriate parameterisation.

The social dimension of the research examines community perceptions of risk and investment through comparative case studies in Ireland and Tanzania, enabling analysis across contrasting socio-energy contexts. Ireland represents a mature wind energy system where communities have long-standing exposure to wind infrastructure and, in some cases, experience with community investment schemes. Tanzania, by contrast, provides insight into contexts where wind energy remains less familiar and where energy access challenges and socio-economic conditions differ substantially. This comparative approach is intended to capture how risk perception, prior experience, and contextual factors shape community responses to wind energy investment opportunities at the end-of-life stage, rather than to offer statistically representative findings for either country.

The study examines three primary end-of-life pathways, lifetime extension, repowering, and decommissioning as distinct but competing strategic options available to wind farm owners. The research does not seek to prescribe a universally optimal solution, recognising that end-of-life decisions are highly context-specific and shaped by market conditions, regulatory environments, technical performance, and social acceptance. Instead, the analysis evaluates the conditions under which each pathway becomes financially viable, operationally feasible, and socially acceptable, with particular emphasis on uncertainty and risk.

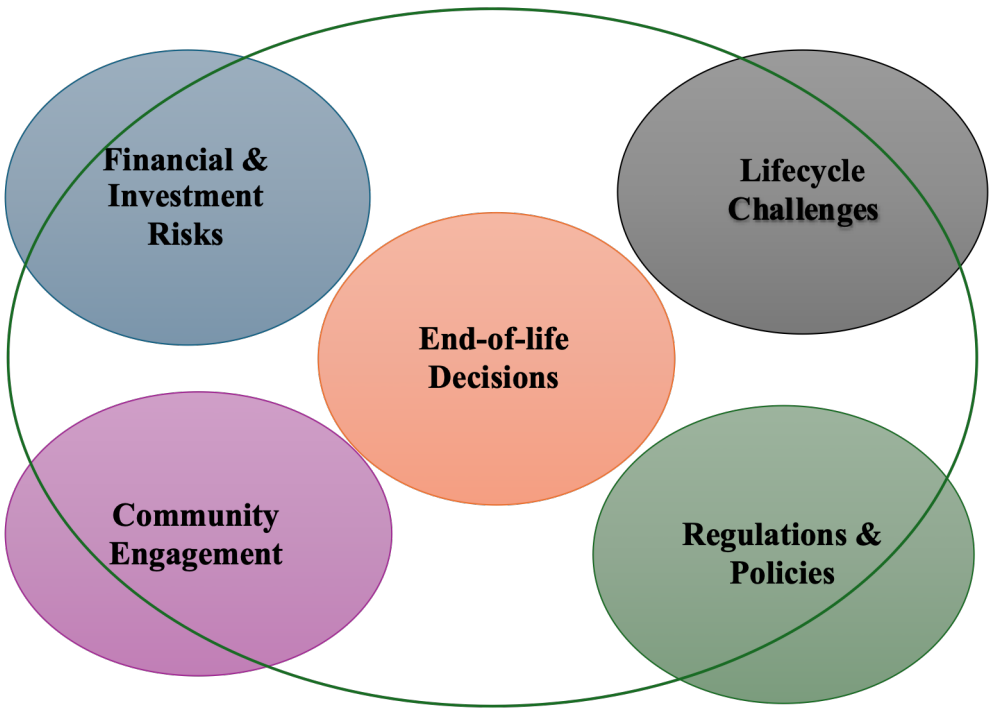
Environmental considerations are acknowledged as an important dimension of end-of-life decision making; however, the research does not undertake a full life cycle assessment (LCA) of environmental impacts. Instead, environmental implications such as material waste, land restoration, and sustainability concerns are considered conceptually and through engagement with existing literature. This delimitation allows the research to maintain analytical focus on financial risk, investment flexibility, and community perspectives, which form the core contributions of the study.

Chapter 2 . A multi-attribute review of end-of-life decisions in wind farms: financial, technical, and social perspectives

This chapter brings together diverse bodies of literature to examine how EoL decisions for wind farms are currently understood and to identify where key limitations in existing approaches remain.

EoL decision making has attracted growing attention across multiple academic disciplines, as this late-life phase becomes more prominent. Researchers in engineering, economics, finance, and the social sciences have explored different dimensions of how aging wind assets are assessed, managed, and governed. These studies vary considerably in their assumptions, methods, and analytical focus, reflecting the range of actors and priorities involved in EoL decisions. To capture this diversity, the chapter reviews literature across four interrelated themes: (i) wind farm lifecycle dynamics and EoL challenges, (ii) financial and investment risks associated with late-life assets, (iii) community involvement and risk perception in EoL projects, and (iv) the policy and regulatory frameworks that shape available choices. Together, these strands of literature provide the foundation for understanding how EoL decisions are currently approached and why they have become increasingly consequential (Figure 2.1).

Figure 2.1: The converging academic domains underpinning this thesis



This chapter brings these literatures into dialogue to identify where current knowledge falls short and to motivate the empirical contributions of this thesis. Specifically, it highlights three interrelated gaps: (i) the limited treatment of financial risk and failure uncertainty in late life wind assets; (ii) the absence of financial valuation frameworks that reflect the flexibility embedded in EoL decisions; and (iii) the lack of empirical insight into how communities perceive and engage with risk and investment at the EoL stage. By synthesising research on wind farm lifecycles, financial risk modelling, community energy, and policy frameworks, this review establishes the foundation for the three studies that follow. Together, these studies reconceptualise end-of-life decisions not as a terminal phase, but as a strategic opportunity to align climate objectives with financial resilience and community participation.

This review focuses on literature published from 2010 onward to ensure relevance to current practices, technologies, and policy landscapes in the wind energy sector. Since 2010, significant developments have occurred in turbine design (Agbayani and Vega, 2012; Gupta, 2015; Kaldellis and Zafirakis, 2011; Serrano-González and Lacal-Arántegui, 2016), decommissioning strategies (Beauson et al., 2022; Delaney et al., 2023), financial modeling (Judge et al., 2019; Lai et al., 2025), and stakeholder engagement (Solman et al., 2021), making older studies less applicable to present-day EoL decision making. Restricting the scope to this period also reflects the growing academic and industry focus on sustainable lifecycle management, circular economy principles, and community involvement, which were less prominent in earlier literature. Foundational or highly cited pre-2010 works are included where necessary to provide context or establish key theoretical underpinnings.

2.1 Wind farm lifecycle and end-of-life challenges

This section explores the lifecycle of wind turbines focusing on the challenges that accompany them. The life cycle of a wind turbine can be broken down into five main stages, each involving specific processes, materials, and environmental considerations (Alsaleh and Sattler, 2019). The first stage is raw material extraction, where materials like steel, copper, aluminium, , and rare earth elements (for magnets in some turbines) are mined. Second stage is manufacturing and component production such as turbine blades , tower , and nacelle which contains gearbox, generator, and electronics. Third is transportation and installation involving, transporting components to the site, site

preparation (including road building and foundation laying), and assembling the turbine using cranes, here the project is commissioned. Fourth is operation and maintenance (lubrication, inspections, part replacements). Last is decommissioning and EoL practices (turbine disassembly, recycling of metals , disposal or recycling of blades).

Each stage is accompanied by some environmental impacts, The extraction and manufacturing stage result in energy intensive processes, emissions from steel and composite fabrication, and potential waste (Morozovska et al., 2024; Shamoon et al., 2022). In transportation and installation there is fuel use, emissions, land disturbance, and noise (Farina and Anctil, 2022; Katinas et al., 2016). In the last stage (decommissioning and EoL) material recovery helps offset earlier impacts, but blade disposal remains an issue, some are landfilled or incinerated (Heng et al., 2021; Liu et al., 2019).

The key purpose of renewable energy sources such as wind is to generate clean, sustainable electricity without emitting greenhouse gases or depleting natural resources (Klepacka, 2019). However, the concept of sustainability is put to question by scholars as the EoL practices may offset the whole idea of sustainability (Delaney et al., 2023). At the end of their service life, turbines are dismantled. Metals like steel and copper are often recycled, but blades, made from composite materials, present recycling challenges and are sometimes landfilled or incinerated (Mishnaevsky, 2022). The sustainability of wind turbine use largely relies on the effective recycling of their blades. In the USA, turbine blades are often disposed of in landfills (Kim, 2024; Sneve, 2019), while in Europe they are frequently incinerated (Beauson et al., 2022; Fonte and Xydis, 2021). However, according to the waste hierarchy for sustainable blade waste management, it is advised to reuse first, then repurpose, recycle, recover, and last disposal (Leahy, 2019; Potestio, 2021).

Research on reusing EoL wind turbine blades has caught attention of scholars. Various methods for recycling wind turbine blades are under investigation with more attention given to reuse of EoL blades (Mishnaevsky Jr, 2021). Reuse offers the benefit of retaining the blades' specialized engineered properties. Unlike recycling, which often involves breaking down blades into lower-value materials for uses like fillers or solid recovered fuel, this strategy can help minimize or postpone the entry of blade glass

waste into conventional disposal systems such as landfills or incinerators. However, the process is complicated by the wide range of materials used in their construction, such as composites, polymers, and wood.

Within the wind energy lifecycle literature, EoL practices are typically framed around three options: lifetime extension, repowering, or decommissioning. Lifecycle assessment studies analyse EoL pathways primarily through technical feasibility, cost-benefit analysis, or energy yield improvements (Jadali et al., 2021; Leite et al., 2022). While this body of work provides valuable insights, it often assumes deterministic operating conditions and underplays uncertainty related to turbine failure, maintenance escalation, and market volatility. As a result, decisions making process is simplified living out other areas of considerations.

2.1.1 Lifetime extension challenges

Wind turbine lifetime extension refers to operating turbines beyond their original design and permitted life, through structural assessments, component upgrades, and maintenance improvements. Lifetime extension is increasingly considered a cost-effective alternative to repowering or decommissioning. However, extending turbine life is not without challenges. This section explores current research on the technical, environmental, economic, and regulatory issues surrounding lifetime extension strategies.

The primary technical barrier is structural fatigue and aging of components. Over time, materials degrade due to environmental exposure, load cycles, and wear. According to Astolfi et al., (2017), Faulstich et al., (2016), and Ozturk et al., (2018) key components such as gearboxes, blades, and control systems are particularly vulnerable, and failure rates increase significantly after twenty years. Uncertainties in load assumptions and operational history further complicate structural assessments. Turbines often operate under conditions that deviate from their design assumptions, especially in complex terrains or turbulent wind regimes. Pfaffel et al., (2017) highlights the lack of detailed historical operational data as a major obstacle to accurate lifetime prediction models. Another technical challenge is the lack of standardized lifetime extension methodologies. While various diagnostic tools such as vibration analysis, SCADA data mining, and drone inspections are available, no

unified framework exists for evaluating remaining useful life leading to inconsistent decisions across the industry.

Lifetime extension strategies may delay environmental impacts associated with decommissioning and waste disposal, but they also prolong the operation of outdated technology. Older turbines may have lower efficiency and higher noise and wildlife impacts compared to modern designs. Additionally, continued operation increases the risk of environmental incidents, such as lubricant leaks or structural failures. According to Ziegler et al., (2018), aging components may pose increased safety and environmental risks if not regularly upgraded.

Lifetime extension is less capital-intensive than repowering, but its cost effectiveness is uncertain. The decision hinges on balancing inspection and maintenance costs against the value of additional energy generation. Failures, operations and maintenance costs create significant financial concerns in wind projects (Costa et al., 2021). Older turbines may also suffer from limited access to spare parts, especially if manufacturers have exited the market. Custom or retrofitted components can drive up maintenance costs, making lifetime extension economically unattractive in some cases (Zhang et al., 2019). Furthermore, capacity limitations of legacy turbines mean lifetime extension does not benefit from economies of scale seen in newer models. This can limit profitability, particularly in markets with declining subsidies or feed-in tariffs.

From a regulatory perspective, lifetime extension may fall into a grey area. Some jurisdictions require new environmental assessments, permitting, or public consultations when operational life is extended significantly. According to Windemer, (2019) inconsistent regulatory frameworks for lifetime extension complicate long-term investment and planning. Moreover, grid codes and safety standards may have evolved since the original commissioning of older turbines. Bringing legacy turbines into compliance with modern standards can be costly or technically infeasible, presenting a regulatory barrier to lifetime extension.

Reliable lifetime extension decisions depend heavily on access to accurate operational and failure data. However, data ownership is often divided between turbine manufacturers, operators, and service companies. Lack of open data sharing limits the

development of predictive models and industry benchmarks. Researchers such as Carroll et al., (2017) emphasize the need for digital twin technologies and long-term condition monitoring systems to support evidence-based extension decisions. Without these tools, operators risk making either overly conservative or overly optimistic decisions about turbine longevity.

Recent innovations aim to address lifetime extension challenges: Prognostics and Health Management systems combine machine learning and sensor data to predict component failures more accurately (Ochella, 2021). Modular upgrades (e.g., replacing control systems or blades with newer versions) are being explored as intermediate strategies between basic maintenance and full repowering. Some countries are developing lifetime extension-specific regulations to provide clarity on compliance and permitting pathways. In parallel, academic efforts are focusing on standardizing lifetime assessment methodologies, such as IEC 61400 extensions (Villena-Ruiz et al., 2022), to harmonize lifetime extension practices across jurisdictions.

Wind turbine lifetime extension offers a potentially low-cost, low-disruption option for prolonging the utility of existing infrastructure. However, it is accompanied by considerable technical, economic, and regulatory uncertainties. Improved diagnostics, predictive modeling, and regulatory clarity are essential for making informed lifetime extension decisions that align with broader sustainability goals.

2.1.2 Repowering challenges

Repowering which is replacing or upgrading aging wind turbines with newer, more efficient technology, has emerged as a strategic approach to maximize energy output and extend the life of existing wind farms. Repowering offers a more sustainable alternative to full decommissioning. However, while technically promising, repowering also presents significant challenges across multiple domains. This literature review synthesizes current research on the technical, environmental, economic, and regulatory barriers to wind turbine repowering.

The heterogeneity of legacy infrastructure is a core technical obstacle. Older wind farms often have smaller turbines with incompatible foundations, grid connections,

and layouts compared to modern, larger capacity turbines. According to Ahmed et al., (2024) and Gil-García et al., (2021) partial repowering or replacing only certain components such as nacelles or blades is limited by structural and technological constraints. Another challenge lies in site optimization. Repowering can cause layout inefficiencies due to wake effects, spacing issues, and land use limitations. Recent studies (e.g., Hasen and Rather, 2025) show that unless the entire wind farm is redesigned, the benefits of repowering may be suboptimal. Additionally, grid infrastructure and interconnection limits may not support increased capacity from repowered turbines. Aging substations and power lines must often be upgraded, increasing costs and technical complexity (IRENA, 2019).

While repowering is often framed as a sustainable option, it still presents environmental trade-offs. The dismantling of old turbines generates similar waste streams to full decommissioning, particularly regarding composite blade materials. Beauson et al. (2022) highlight the need for improved recycling systems even in repowering contexts. There are also ecological and landscape impacts. Repowered turbines are usually taller and more powerful, which can alter bird and bat mortality patterns (Arnett and May, 2016) and affect local communities' visual perceptions of the landscape. Environmental impact assessments may need to be revised, especially for sites originally permitted decades ago under different criteria.

From a financial standpoint, repowering is capital intensive. Although it avoids some of the costs associated with greenfield development, such as land acquisition, it still requires major investment in equipment, labour, and potential grid upgrades. Hasen and Rather, (2025) and López García, (2024) note that the cost-benefit balance of repowering is highly sensitive to local conditions, including wind resources, regulatory incentives, and electricity market prices. A key challenge is the uncertainty around financial returns. Repowering projects often face difficulties securing financing, particularly in markets where feed-in tariffs or tax incentives for repowered sites are unclear or less favourable compared to new installations (Rövekamp et al., 2021).

Regulatory uncertainty is consistently highlighted as a major impediment to repowering. Many original wind farm permits do not include provisions for repowering, leading to permitting bottlenecks. In some jurisdictions, repowering is

treated as a new project, triggering full environmental assessments, land use negotiations, and public consultations (Windemer, 2019). Moreover, there is often limited policy differentiation between repowering and greenfield development. Countries such as Germany and Denmark have introduced repowering-friendly regulations (Meyer, 2025), but global practices remain inconsistent. This lack of standardized frameworks makes planning timelines and investment strategies more complex.

Public acceptance is another significant barrier. Communities accustomed to smaller turbines may resist the introduction of larger, noisier, or more visually intrusive models. Rand and Hoen, (2017) suggest that transparent stakeholder engagement and community benefit-sharing are critical to repowering success. Furthermore, land lease renegotiations can be contentious. Original land use agreements may not account for repowered turbines' changed dimensions or energy outputs, leading to disputes between developers and landowners.

Recent research and industry practice suggest several strategies to overcome repowering challenges: Hybrid repowering models, combining old and new turbines strategically within a site, are being explored to optimize both output and land use (Gil-García et al., 2021; Hou et al., 2017). Modular design principles for future turbines can enable easier retrofitting and replacement, reducing long-term repowering costs (Christoffel et al., 2025). Policymakers are increasingly considering repowering-specific incentives and streamlined permitting pathways, recognizing its role in decarbonization targets. While repowering holds strong potential for extending the lifespan and improving the efficiency of wind energy infrastructure, it is accompanied by complex challenges. These range from technical integration and environmental considerations to financial uncertainty and regulatory ambiguity. As the global wind fleet continues to age, addressing these challenges through coordinated research, policy reform, and stakeholder engagement will be essential for unlocking the full benefits of repowering.

2.1.3 Decommissioning challenges

The decommissioning process involves dismantling turbines, managing waste, and restoring land, all of which present technical, environmental, economic, and regulatory

challenges. This discussion examines the key issues surrounding wind turbine decommissioning, drawing from academic studies, industry reports, and policy analyses.

First, one of the most discussed technical challenges in wind turbine decommissioning is the dismantling of large and complex structures. According to Bošnjaković et al., (2022), turbine size has increased significantly over the years, complicating the logistics of removal. Heavy lift cranes, access roads, and specialized labour are often required, increasing the risk and cost. The transport and recycling of components also pose technical difficulties (McKenna et al., 2016). While most turbine parts, like steel towers and copper wiring, are recyclable, composite materials, particularly fiberglass blades, are not easily processed. Liu and Barlow, (2017) note that the lack of scalable recycling technologies for blades leads to widespread landfilling or incineration, both environmentally unsustainable.

Second, the environmental impacts are significant, especially concerning waste management and land restoration. The European Environment Agency (EEA, 2019) warns that without effective policies, decommissioned blades may add to growing landfill pressures. Research by Beauson et al., (2021) emphasizes the need for circular economy strategies to reduce the lifecycle environmental footprint of wind energy. Another concern is site restoration. Decommissioning plans are expected to restore sites to their original or agreed-upon conditions, but this is often only partially achieved. Soil contamination from hydraulic fluids or concrete foundations remaining in the ground can have long-term effects on ecosystems (Welstead et al., 2013; Szumilas-Kowalczyk et al., 2020).

Third, wind turbine decommissioning involves considerable costs, often underestimated during initial project planning. Decommissioning expenditure is valued by decommissioning bonds or reclamation bonds. These are financial assurances provided by the insurance companies to renewable energy developers (Integrity Surety, n.d). Unclear financial liabilities and insufficient decommissioning bonds exacerbate the risk of "orphaned" infrastructure, especially in deregulated markets. Moreover, the lack of a secondary market for aging turbines (Tyurkay et al., 2024) limits the potential for reuse or repowering. This situation contrasts with other infrastructure sectors, where components are often salvaged or refurbished.

Lastly, policies governing decommissioning vary widely between jurisdictions, leading to uncertainty and non-standardized practices. The U.S. and several EU countries require decommissioning plans as part of permitting processes, yet enforcement remains inconsistent. Invernizzi et al., (2020) highlight the need to develop explicit policies that can be used to determine 'if' and 'when' to decommission energy infrastructures. Moreover, there is often limited oversight of end-of-life responsibilities. In many cases, operators transfer ownership to smaller companies at the end of a turbine's life cycle, creating difficulties in tracking and enforcing decommissioning obligations.

Recent studies suggest several pathways to address these challenges: Blade recycling innovations (e.g., pyrolysis, solvolysis, or mechanical grinding) show promise but require significant upscaling (Hu et al., 2024). Circular economy models advocate for design for disassembly, component reuse, and lifetime extension through repowering (Rios, 2018; Woo and Whale, 2022). Policy frameworks that mandate financial assurance mechanisms (e.g., decommissioning bonds) are increasingly recommended in the literature (Lopes da Costa, 2020; Mackie and Besco, 2020; Deeney et al.,2025). Decommissioning wind turbines presents multi-dimensional challenges involving technical, environmental, economic, and regulatory aspects. As the installed base of turbines ages, these challenges will become more pressing. Comprehensive planning, cross-sector collaboration, technological innovation, and robust policy frameworks are essential to ensure that wind energy remains a truly sustainable power source throughout its entire lifecycle.

2.1.4 Research gaps and future work on lifecycle EoL challenges

Despite growing interest in end-of-life (EoL) management for wind farms, significant research gaps persist across technical, environmental, economic, and regulatory domains. Much of the existing literature tends to examine decommissioning, repowering, and lifetime extension as separate strategies, often in isolation as in (Beauson et al., 2022; Delaney et al., 2023) for EoL of turbine blades. However, integrated comparative assessments that evaluate trade-offs between these options under varying site-specific, regulatory, and market conditions are lacking. For instance, there is limited research offering robust decision-support models that factor

in multi-criteria variables such as turbine age, failure probabilities, grid compatibility, and community preferences to guide optimal EoL pathways.

Data availability and transparency are another critical limitation (Delaney et al., 2023; Leahy et al., 2019). Many lifetime extension and repowering assessments rely on assumptions rather than empirical operational data due to restricted access to turbine performance and maintenance records. Proprietary data held by original equipment manufacturers and service providers inhibit the development of industry wide benchmarks and predictive failure models. Future research should advocate for open-access data protocols and support the deployment of digital twin and condition monitoring systems to enable evidence-based EoL decision making. Recent studies have highlighted the potential of digital twins, advanced condition monitoring systems, and data-sharing initiatives to support evidence-based EoL decision making, though their application remains uneven across the sector (Kabashkin, 2024; Schröder, 2020).

From an economic perspective, more work is needed to quantify long-term cost-benefit ratios of EoL strategies under real-world market conditions. For example, lifetime extension appears cost-effective upfront but may incur increasing O&M costs over time, particularly in unsubsidized markets. Conversely, repowering has high capital requirements but potential long-term revenue benefits. Uncertainty around electricity price volatility, access to subsidies, carbon pricing, and secondary turbine markets further complicates investment decisions. This calls for dynamic techno-economic models that incorporate these uncertainties and assess risk-adjusted returns for investors and developers.

Environmental research has focused extensively on blade waste and recycling technologies management (Liu and Barlow, 2017; Leahy, 2019; Heng et al., 2021; Deeney et al.,2021; Beauson et al., 2022; Delaney et al., 2023), but less attention has been given to the life-cycle environmental implications of choosing one EoL strategy over another. Holistic Life Cycle Assessment (LCA) frameworks that compare the environmental footprint of decommissioning, repowering, and lifetime extension including emissions, material use, and land disturbance are essential. Additionally, reuse and remanufacturing options for components other than blades (e.g., nacelles and foundations) remain underexplored in circular economy contexts.

Finally, social and community dimensions are underrepresented in lifecycle EoL literature. Technical studies rarely engage with social acceptance; financial models often abstract from community dynamics; and policy analyses typically assume rational investment behaviour without considering how risk is perceived by different actors. As a result, EoL decision making is insufficiently understood as a multidimensional process shaped by interacting financial, technological, social, and regulatory forces.

Future work should prioritize the following directions.

- Develop integrated decision-support tools that evaluate the technical, environmental, financial, and social trade-offs of decommissioning, repowering, and lifetime extension.
- Conduct comparative cross-country regulatory analysis to identify policy best practices and harmonization pathways.
- Improve access to high-quality operational and maintenance data to support predictive modelling for turbine lifetime extension and failure risk.
- Expand research on circular economy solutions beyond blades, including reuse of towers, foundations, and electrical infrastructure.
- Explore community engagement frameworks tailored to EoL transitions and investigate their influence on risk perception and project feasibility.

2.2 Financial and investment risk in end-of-life decisions

End-of-life decisions for wind farms whether to decommission, repower, or extend operational life are inherently shaped by a complex landscape of financial risks. These risks stem from volatile electricity markets, fluctuating capital and operational expenditures (CAPEX and OPEX), regulatory uncertainty, and the technical degradation of aging assets. This section draws upon the existing body of scholarly literature to critically examine how financial risk factors influence strategic EoL choices in the wind energy sector. We explore three key dimensions of financial risk. First, cost uncertainty, particularly arising from operational challenges such as turbine failures, impacts maintenance planning and lifetime extension feasibility. Second, market risk, driven by electricity price volatility and the effects of variable renewable energy (VRE) penetration, revenue projections and investor confidence. Third,

investment risk, captured through frameworks such as real options analysis, helps quantify the value of managerial flexibility under uncertainty. By synthesizing insights across these dimensions, this review aims to highlight how financial considerations are central to optimising end-of-life strategies, and how integrated risk assessment tools can support more informed and resilient decision making.

2.2.1 Financial risks from wind turbine failures

Wind turbines have evolved over time with innovations such as larger rotor diameters and an increase in tower height to enhance efficiency (Elkelawy et al., 2024). However, bigger and powerful turbine results in more complex operational risks. As wind turbines age, they become increasingly vulnerable to component failures, leading to a significant rise in operation and maintenance (O&M) costs. O&M expenditures can account for approximately 20-25% of the total lifecycle costs of a wind turbine (Costa et al., 2021). For comprehensive reviews of operational challenges in wind farms, see Costa et al. (2021) and Ren et al. (2021).

The standard design of wind turbines assumes a fatigue life of twenty to twenty five years, after which they are generally deemed unsuitable for continued operation without major intervention (Nielsen and Sørensen, 2021). Even if the reliability of the structure design is proven sufficient, a decision between a trade-off between costs from increased repair or continued revenue is to be made. Technology upgrades and maintenance strategies for ageing turbines can diverge sharply. However, unlike initial project phases that may benefit from feed-in tariffs or power purchase agreements, extended operations are often exposed to the uncertainties of the spot market, leading to diminished revenue potential (Bezrukovs and Sauhats, 2017).

Froger et al. (2018) observe that repair and maintenance of wind turbines in investor owned wind farms are often outsourced to third-party service providers, typically the original equipment manufacturers. This arrangement can create operational tensions, as investors prioritize cost minimisation following the initial capital deployment, while service providers may advocate for higher maintenance expenditures to protect the performance and reputation of their equipment. To mitigate these misaligned incentives, Froger et al. (2018) recommend the adoption of condition-based maintenance strategies, which can optimize repair decisions based on real-time

performance data. In contrast, Tazi et al. (2016) emphasize that improving turbine reliability should begin at the design stage, incorporating careful consideration of environmental conditions**,** manufacturing quality, economic constraints, and the system's global warming potential. Their approach advocates for a more holistic, lifecycle-oriented perspective on wind turbine reliability.

The financial risks from turbine failures has previously been explored by scholars both onshore and offshore. Blain et al., (2021) developed a novel approach for planning replacement projects for turbines and generators to maximise economic gains and minimise risks from operational faults. They found that, accounting for unexpected breakdowns enhances the effectiveness of risk-informed planning and mitigation. The paper suggested adjusting maintenance by varying stress induced conditions to preserve certain units while maximizing usage and wear on others and delay the replacement of equipment that presents minimal risk of failure for as long as possible. Therefore, decisions on generator or turbine investments should take account of these risks. Mentes and Turan (2019) also support the concept of risk based maintenance to manage risks from turbine failures.

The uncertainty from turbine failure and unscheduled repair is the biggest driver of financial risk from turbine failures (Kim et al., 2011). Jaimes et al., (2020) and Ozturk and Fthenakis, (2020) suggested machine learning techniques and prediction of failure frequency and associated cost as a way to analyse and manage risk from failures. Differently, Altuntas, Berry-Stölzle, and Cummins (2021) argue that farm size paradigm and economies of scale concept can be utilised to balance the risks, with proper risk management practices showing increased benefits obtained. By following the Morden portfolio theory, risk can be effectively reduced by diversifying investments across assets with low or no correlation, thereby minimising exposure to systemic fluctuations (Mangram, 2013). This is similar to wind farms as having multiple turbines in one farm ensures operation continuity in case some turbines fail (Mikindani et al., 2024). Wind turbines function autonomously, so the failure of one unit whether due to a lightning strike or component malfunction such as in the generator, blades, or gearbox does not impact the operation of others. Research has identified economies of scale across a wide range of industries, including power generation (Bejan, Almerbati, and Lorente, 2017; Triebs et al., 2016). As firms

increase the scale of their operations, they often reduce average production costs by leveraging bulk purchasing, specialization, and more efficient resource utilization. Nevertheless, these cost advantages may be accompanied by heightened risks associated with operating at larger scales.

Elsahhar et al., (2025) studied turbine components failure focusing on aging wind farms. Their results identified hydraulic system, sensors, and electrical system to be the most failure prone subassemblies, whilst, the gearbox, the generator, and the hydraulic system are found to bear the highest economic risk at EoL. The study recommended a careful consideration of failures and maintenance records for decision making at the EoL of wind farms. A recent literature review on factors influencing decision making at the end-of-life of wind farms, list economic/financial and operational issues as the internal factors influencing the decision making process (Agra Neto et al., 2024). Critically, overlooking failure risk in EoL strategies can result in underestimating costs, overestimating asset value, and making suboptimal investment decisions. Therefore, integrating turbine failure risk into techno-economic assessments not only enhances decision accuracy but also supports the development of more resilient, financially sound EoL strategies.

2.2.2 Investment risk driven by electricity price volatility

Financial risk arising from electricity price volatility is a pivotal consideration in end-of-life (EoL) decisions for wind farms. As operators evaluate whether to decommission, repower, or extend turbine lifespans, the unpredictability of wholesale electricity prices can critically affect projected revenues and investment thresholds.

The interaction between electricity markets and wind energy investment has been widely studied, particularly in relation to electricity price dynamics e.g. (Kyritsis et al., 2017; Rintamäki et al., 2017; Tao et al., 2012) and regulatory instruments such as renewable energy subsidies e.g., (Chaurasiya et al., 2019; González and Lacal-Arántegui, 2016). However, relatively few studies have examined how these market dynamics influence EoL investment decisions for wind farms e.g., (Abadie and Goicoechea, 2021; Chinmoy et al., 2019; Pandit and Kolios, 2020).

Several studies have shown that increased wind penetration can suppress average electricity prices while simultaneously raising short-term price volatility. For example,

Martinez-Anido et al., (2016) and Benhmad and Percebois,(2016, 2018) highlight that higher wind shares lead to more volatile spot prices, particularly in markets like Germany. Paraschiv et al., (2014) further note that renewables lower wholesale prices by altering the merit-order curve, even though end-user costs may rise due to tariff schemes. Kök et al., (2018) emphasize how pricing structures flat versus peak can steer investment behaviour. In contrast, O'Flaherty et al., (2014) suggest that in Ireland, wind penetration has limited influence on long-term electricity pricing. Collectively, these findings underscore the importance of market conditions in shaping economics of wind farms.

In detail, when wind and solar generation coincide with low electricity demand it leads to sharp price depressions during peak renewable output (Hirth, 2013). During periods of high wind and solar generation, the increased electricity supply leads to a decline in market prices. As the installed capacity of variable renewable energy grows, this price reduction becomes more pronounced, resulting in a decreasing market value of at higher penetration levels. This topic of price cannibalisation was further studied by Reichenberg et al., (2023) where the results showed that high variable renewable energy penetration can reduce expected profits from around +33 % to between +13 % and -40 %, and raise investment thresholds by up to 67 %. Pavlík et al., (2025) used high frequency data on prices for European countries, variable renewable energy output, and residual load. The analysis reveals a marked rise in electricity price volatility post 2021, peaking during the 2022 energy crisis, especially in countries with high renewable shares and limited system flexibility. As systems approach critical levels of renewable penetration, empirical analysis reveals a 30% to 50 % increase in extreme price variability, especially in countries like Germany, Denmark, Spain, and Australia. In these contexts, electricity prices can even become negative during over supply periods further eroding project viability (Halbrügge et al., 2024). Such volatility disproportionately undermines late stage EoL projects, in which revenue margins are thin and sensitivity to price shocks is heightened.

The volatility in electricity prices have implications in investment timing and EoL strategies. When trying to estimate these risks, traditional Net Present Value (NPV) models inadequately capture the asymmetric risk embedded in volatile electricity markets (Watkiss et al., 2015). In contrast, Real Options Analysis (ROA) incorporates

price uncertainty and allows for managerial flexibility such as timing of lifetime extension or repowering decisions to better align with evolving market dynamics (Chen et al., 2024; Galay and Winter, 2025). Without incorporating price risk, EoL decisions may overestimate project value and misalign with optimal renewal timing.

To address revenue volatility, project developers increasingly rely on financial instruments such as Power Purchase Agreements (PPAs), forward contracts**,** weather derivatives**,** and index-based insurance. PPAs lock in fixed electricity prices for a defined volume and period, reducing exposure to spot market fluctuations (Mittler et al., 2025; Stanitsas and Kirytopoulos, 2023; Yang et al., 2024). Financial hedges, futures and swaps, are used to manage residual price exposure for energy not covered by PPAs (Giorgi, 2025). An example is AEP index insurance which hedges against wind-speed-driven production variability, offering income stability through payouts triggered by deviations from expected energy yield indices (Liao et al., 2021). Moreover, optimization of flexible assets such as storage and dispatchable generators can mitigate price volatility at the portfolio level. McKinsey, (2024) observes that incorporating flexible assets into a renewables heavy portfolio can dramatically smooth price swings and reduce downside exposure, a useful strategy for EoL income planning. Studies also show that optimally sited energy storage can significantly dampen extreme price events in some cases reducing volatility by up to 80% depending on system design (Bistline et al., 2020). In planning EoL strategies, assessing the extent of secured versus market exposed revenues is essential to understanding price risk exposure.

There are extreme price events such as sustained negative pricing which pose significant financial risk. In markets with high variable renewable energy penetration, extreme price spikes persist longer and propagate across regions, increasing the exposure to tail risk for wind operators (Reichenberg et al., 2023). To manage this, Profit at Risk (PaR) metrics are applied to capture downside probabilities in revenue distributions under-price uncertainty (Kath et al., 2020; Lemming, 2005). Such risk measurement tools are critical to evaluating whether extending operations, repowering, or decommissioning is financially viable under volatile price regimes.

The reviewed literature implies the following for End-of-Life decision making. First is repowering risk. Reduced revenues due to cannibalization may delay the financial

breakeven point for repowering, suggesting that timing decisions must account for peak price dynamics. Second, lifetime extension viability. Projects heavily reliant on spot markets are vulnerable; without long-term contracts or hedging, lifetime extension may expose operators to unacceptable income volatility. Last is decommissioning consideration. When price downside risk is high and financing terms favour certainty, early decommissioning or substitution may be economically justified.

2.2.3 Research gaps and future work on financial risk for end-of-life

A parallel stream of literature examines financial performance and investment risk in wind energy projects, including studies on cash-flow variability, price uncertainty, and policy dependence (Judge et al., 2019; Lai et al., 2025). Yet these analyses are rarely applied explicitly to late life assets, where failure risk, residual value, and downside exposure become dominant considerations. In particular, there is limited use of risk-sensitive metrics such as Value at Risk (VaR) and Conditional Value at Risk (CVaR) to capture the asymmetric nature of losses associated with turbine failures near the end of operational life. This creates a gap between how risk is modelled in finance and how EoL decisions are evaluated in practice.

The future direction of this research area requires more contribution on the following. Few EoL decision models explicitly integrate electricity price risk with lifecycle cost assumptions. Real options frameworks rarely incorporate hedging strategies such as PPAs or derivatives in evaluating end-of-life pathways. Tail-risk metrics and extreme price modelling remain underutilized in EoL strategy comparisons. Electricity price volatility introduces substantial market risk for wind farms at the end of their lifespan. This volatility intensified by renewable saturation and negative price events detrimentally affect project revenues and investment viability. Integrating price-risk modeling into EoL decision techniques, such as real options and probabilistic financial models, enables operators to make more resilient and informed choices. When combined with hedging strategies, flexible asset portfolios, and advanced risk metrics, these tools form the foundation of robust EoL financial decision making.

2.3 Regulations and policies

The transition of wind energy infrastructure from operation to end-of-life (EoL) poses significant regulatory challenges, especially as the first generation of commercial wind farms approaches or surpasses their designed twenty to twenty five year lifespan. While considerable policy focus has historically been placed on incentivizing new wind development through subsidies, feed-in tariffs, and streamlined permitting (Saidur et al., 2010), less attention has been directed toward regulatory frameworks governing EoL decisions namely decommissioning, repowering, or lifetime extension (Woo and Whale, 2022). The growing urgency to address aging assets highlights a pressing need for coherent policies that balance environmental, economic, and community concerns during this critical phase of the asset lifecycle.

2.3.1 Lifetime extension: regulatory ambiguity and technical standards

Lifetime extension of turbines beyond their certified design life has become an economically attractive alternative to decommissioning or repowering, especially for small or mid-sized project owners. Yet, regulatory guidance for safe and compliant lifetime extension remains limited, particularly regarding structural integrity assessments, warranty implications, and insurance requirements (Faber and Hansen, 2010; Schedat et al., 2016; Ziegler et al., 2018). In many countries, turbine certification bodies or original equipment manufacturers offer engineering assessments for lifetime extension, but these operate in a grey area with little formal oversight from national regulators.

Moreover, lifetime extension raises policy questions about subsidy eligibility (Rubert et al., 2016) and grid priority (Hasen and Rather, 2025; Piel et al., 2019). In several European countries, older wind farms exiting feed-in tariff schemes lose grid access guarantees or receive lower priority dispatch, thereby reducing profitability despite technical viability (Wind Europe, 2021). These regulatory disconnects can ultimately discourage operators from pursuing lifetime extension, even when it may be the most sustainable option.

2.3.2 Repowering and regulatory inertia

Repowering, the replacement of old turbines with newer more efficient models has gained momentum as a favoured EoL strategy due to its potential for increased output on existing sites (Leite et al., 2022). However, regulatory frameworks for repowering are often fragmented, treating these projects as either entirely new developments or simply extensions of existing permits. This ambiguity creates uncertainty for developers and may delay or disincentivize investment in repowering. For instance, in Germany and Denmark, repowering is encouraged through modified grid access priorities and premium tariffs for modernized sites, whereas in other countries such as the UK or Canada, repowering must often undergo a full planning approval process akin to greenfield projects leading to bureaucratic delays and added costs (IEA, 2020). Regulatory bottlenecks also arise around environmental impact assessments (EIAs), where newer technologies may trigger stricter scrutiny, despite the minimal footprint relative to original installations.

Madlener et al., (2019) investigate how shifts in Germany's policy framework specifically the renewable energy sources act (EEG) 2017 market premium scheme versus a free-market regime affect the optimal timing of repowering decisions. Key findings reveal that early repowering, well before a turbine reaches its operational lifespan, may be economically preferable under the EEG 2017 remuneration structure due to its guaranteed tariff inflows. Conversely, in interest rates or deployment under a purely market-driven regime, repowering often becomes profitable only after tariff guarantees expire and electricity spot prices rise highlighting how policy stability and incentive design directly influence investment timing for repowering.

2.3.3 Decommissioning regulations: clarity and enforcement gaps

In many jurisdictions, regulatory clarity around decommissioning remains insufficient (de Kruijf, n.d.; Majewski et al., 2022; Stripling, 2016; Topham et al., 2019). While most countries legally require wind farm operators to remove infrastructure and restore the land after decommissioning, the implementation and enforcement of these requirements vary considerably. For example, in the United States, decommissioning obligations are typically governed at the state or county level, resulting in inconsistent standards regarding timelines, financial guarantees, and site restoration (Musial et al.,

2023). In the European Union, although decommissioning clauses are often embedded in lease agreements or permits, compliance monitoring and the adequacy of financial securities such as bonds or escrow accounts are under scrutiny (Lantz and Tegen, 2009; Topham et al., 2019).

A recurring issue is the lack of clear guidance on decommissioning cost estimation and funding mechanisms, particularly in early-stage project approvals. Studies by (Beurskens and Hekkenberg, 2011) and (Gatzert and Kosub, 2016) show that the absence of enforceable financial guarantees poses risks of stranded infrastructure or "orphaned" turbines especially in cases where project owners dissolve or change hands before the end of the asset's life. The issue is more pronounced onshore than offshore since onshore windfarms assess environmental impact of decommissioning less than offshore (Hall et al., 2020).

2.3.4 Environmental and land use policy overlaps

EoL decisions are also deeply intertwined with environmental regulations and land use planning, particularly in sensitive or multi-use landscapes (Windemer, 2019). For example, decommissioning often involves soil disturbance, concrete removal, and replanting activities that may trigger compliance with biodiversity laws or land conservation measures (Mello et al., 2022). Repowering can also create conflicts with local zoning ordinances or height restrictions if new turbines exceed the dimensions of earlier models. Scholars argue for integrated land-energy planning that takes into account cumulative environmental impacts over the lifecycle of a wind farm, particularly as more sites reach the repowering stage (Ali, 2020; Nazir et al., 2020).

2.3.5 Policy gaps and emerging governance models

Despite increasing awareness of the EoL challenge, most national and subnational wind energy policies remain silent or underdeveloped in this domain. As Leite et al. (2022) point out, few energy transition strategies or regulatory roadmaps explicitly address decommissioning, lifetime extension, or end-of-life sustainability. Similarly, Chinmoy et al. (2019) highlight that uncertainty over future policy direction often leads to suboptimal investment decisions by operators at the EoL stage.

Some emerging frameworks, however, suggest promising directions. The Netherlands has implemented a centralized tracking system for turbine lifespans and decommissioning schedules (Nejad et al., 2022; van der Schans, 2025), while Spain is piloting circular economy guidelines for rotor blade recycling and material recovery (Diez-Cañamero and Mendoza, 2023; Ibarra and Fernandez Mendoza, 2024). These developments point to a shift toward life-cycle governance models, where policies not only incentivize clean energy deployment but also account for infrastructure aging, material reuse, and community input throughout the project lifecycle.

The literature reveals that while regulatory frameworks have matured around the deployment phase of wind farms, they remain fragmented, inconsistent, or underdeveloped when it comes to managing end-of-life decisions. Gaps in decommissioning enforcement, repowering approval processes, lifetime extension standards, and integrated land-use planning all contribute to regulatory uncertainty. To enable sustainable and socially acceptable EoL pathways, future policy efforts must address these shortcomings by fostering clearer, more integrated, and lifecycle-oriented regulations. This will be critical not only to ensure environmental compliance and grid reliability, but also to enhance investor confidence and community trust in the long-term sustainability of wind energy infrastructure.

2.4 Community engagement

Community acceptance or the lack thereof emerges as a pivotal dimension in EoL decision making. Scholars emphasize that procedural justice, trust, and institutionalized engagement mechanisms strongly influence social license outcomes. An expanding body of research emphasizes the importance of a social license to operate defined as a community's sustained approval and support for energy infrastructure as a critical factor in determining project viability (Gaynor and MIPI, 2018; Minadakis and Vega-Araújo, 2024). Investment in wind farms was positively linked to community acceptance in wind projects (Knauf and le Maitre, 2023). By recognising this need, project developers often offer co-investment opportunities not solely for financial reasons but as a tool to enhance community support and engagement (Knauf and Wüstenhagen, 2023).

2.4.1 What help with acceptance?

An expert assessment across six European countries found that procedural justice including transparent public involvement in siting and permitting and opportunities for both active and passive financial participation by local stakeholders significantly enhance social acceptance of wind energy projects. Conversely, the absence of meaningful engagement and equitable financial inclusion are consistently identified as critical barriers to community support (De Luca et al., 2020). Devine-Wright and Wiersma, (2020) place "technology fit" of how a wind project aligns symbolically and materially with local values and identity as fundamental to acceptance, especially during repowering phases in existing wind farms. Community engagement thus provides strategic insight into readiness, local risk sensitivities, and perceived fairness in EoL contexts.

Studies have further explored on understanding what help with effective community engagement in wind energy development. The Co-Wind project in Ireland found that early stage consultation, compensation for near neighbours, and the provision of local amenities are critical to fostering social acceptance (le Maitre, 2024). One of the most significant factors identified is proximity, residents living closest to wind farms tend to be more sensitive to both risks and benefits, often becoming the most vocal stakeholders, whether in support or opposition. To address these dynamics, community ownership and co-ownership models have emerged as promising mechanisms for increasing local buy in (Elkjær, 2022; Johansen and Emborg, 2018; Le Maitre, n.d.; San Martin et al., 2024). However, as Le Maitre (n.d.) cautions, co-ownership is not a universal remedy; its success depends on local preferences, trust in project developers, and the perceived fairness of benefit distribution. These findings align with results from Wind Energy Ireland's 2024 national survey, which reported that 80% of respondents support wind energy development, and 62% are open to wind farms in their local area. The main drivers of this support include the perceived contributions of wind energy to affordability**,** emissions reduction, and broader environmental benefits (WEI, 2024).

Mechanisms that enable community co-investment have proven effective in enhancing local engagement and reducing perceived risks associated with wind energy projects. Curtin et al., (2018) showed that financial incentives can serve as an effective

mechanism for promoting local ownership in onshore wind farms, thereby enhancing community acceptance. By allowing residents to share in ownership whether through cooperative models or joint ventures communities are more likely to endorse projects and contribute to their long-term sustainability (Knauf and Wüstenhagen, 2023). Such arrangements not only foster a sense of shared responsibility but also serve as important instruments for building trust, particularly when supported by transparent decision making processes and fair revenue allocation. Crucially, co-investment strategies align the economic interests of developers with the social priorities of local communities, thereby bridging the divide between institutional energy development and grassroots participation.

2.4.2 Risk perception, local identity, and procedural justice

Perceptions of fairness and trust shape local risk narratives at EoL. Residents often perceive EoL decisions as a continuation not resolution of perceived injustices related to original siting and ownership. In rural areas, grievances arise when benefits accrue only to turbine hosts or external investors, not the broader community (Lennon et al., 2019). Survey data from East China suggest that older, long-term residents are particularly sensitive to identity disruption (e.g. landscape, cultural continuity) and express higher opposition to site renewal without fair consultation or benefit-sharing (Guan and Zepp, 2020). Institutional trust and perceived inclusion in economic returns through shared funds or local investment options are key variables influencing community receptiveness to EoL pathways.

Although social acceptance is an essential component of successful wind energy projects, research shows that community investment decisions are shaped by a complex array of perceived risks that extend beyond general support for renewable energy. These perceptions are influenced by various interrelated factors, including demographic attributes such as age, education, and income (Witkowska-Dabrowska et al., 2021), as well as geographic elements like land use patterns and the visual impact of turbines (Hammami and Triki, 2016). Institutional credibility and the consistency of policy frameworks also play a significant role in shaping trust (Karakislak et al., 2023; Mey and Diesendorf, 2018), alongside environmental concerns related to ecosystem disruption and biodiversity loss (Delicado et al., 2016). Moreover, economic uncertainties particularly around financial returns and project

viability further influence community willingness to invest (Broughel and Hampl, 2018; Gatzert and Kosub, 2016). These diverse and intersecting factors highlight the limitations of narrow acceptance models, emphasizing the need for more holistic approaches that integrate trust-building, risk communication, and tailored incentives.

Community investment models such as shared ownership or local purchasing options can significantly alter perceptions of risk and support for EoL decisions. Sustainable Energy Authority of Ireland survey reported that over two-thirds of respondents would consider investing locally, and nearly half said investment opportunity would increase their acceptance of turbines near homes (SEAI, 2023). Locally managed revenues with clearly communicated social benefits like retrofit support or shared dividends are consistently rated as stronger drivers of acceptance than minimal outreach efforts. Demographic variables including proximity, tenure, education, and economic position substantially influence risk perception. Various studies show that close proximity often increases opposition, particularly when combined with low institutional trust or strong place attachment (Peterson et al., 2015). Machine learning analyses on public sentiment (Twitter) in Norway further reflect how opposition clusters temporally and nationally, not just locally highlighting the role of symbolic, cultural, and socio-political framing beyond mere technical risk assessments (Vågerö et al., 2024).

2.4.3 Engagement gaps & passive participation

Lack of meaningful civic engagement often compounds community conflict. Research indicates that a large portion of residents either remain unaware of consultation opportunities or choose not to participate, which exacerbates mistrust in decision making processes (Witkowska-Dabrowska et al., 2021). These dynamics are critical at EoL stages, where communities may feel their concerns about turbines' health, visual, or noise impacts are dismissed. This passive disconnection, often linked to socio-demographic factors like education and income, erodes opportunities for consent-based EoL strategies. Recent controversies provide real-world illustrations of EoL tensions. In New South Wales and other regions, lack of consultation and uneven benefit distribution sparked intense community opposition even when repowering or host-based projects were proposed (The Daily Telegraph, 2025). Communities expressed feeling sidelined by decision makers, leading to polarized rhetoric and

influence by external political activists. These cases emphasize the risk of community fracture in absence of transparent participation and equitable benefit sharing.

2.4.4 Implications for end-of-life strategy design

The literature suggests several strategic implications for integrating community risk considerations into EoL decision making. First, there is institutional participation where there should be embed consultation, zoning, and public deliberation early in repowering or decommissioning planning to ensure legitimacy and prevent opposition (De Luca et al., 2020). Second, enable benefit sharing by offering equitable returns through community funds, share offers, local dividends to align perceived risk and benefits (SEAI,2025). Third, map demographics and sentiment by using participatory methods and sentiment analysis tools to map local concerns, identify disenfranchised groups, and tailor outreach (Peterson et al., 2015). Last, frame projects for place compatibility through respect symbolic and identity-driven to place technology fit if repowering occurs in landscapes with strong community attachment (Devine-Wright and Wiersma, 2020).

Community risk perceptions are not peripheral but central to the viability of EoL decisions. Without structured engagement, locally relevant benefit structures, and sensitivity to identity and sentiment, efforts at repowering or lifetime extension may decline into adversarial outcomes. In contrast, financially shared, trust-centred, and contextually embedded strategies can transform EoL pathways into community-aligned climate-action opportunities.

2.4.5 Research gaps and future direction in community engagement

Despite a growing body of literature exploring community perceptions in wind energy development, several key research gaps persist in the specific context of end-of-life (EoL) decision making:

Most existing studies centre on the initial development or operational phase of wind energy projects, with far less attention given to how communities perceive or participate in repowering, lifetime extension, or decommissioning. EoL phases involve distinct technical, environmental, and emotional considerations such as fatigue with prior conflicts, expectations for improved technologies, or hopes for

landscape restoration that are rarely addressed in current models of community engagement. There is a need for engagement frameworks and empirical studies that focus specifically on community responses to wind farm EoL scenarios, including repowering and decommissioning. Most techno-economic and real options models for EoL decision making treat community acceptance as an exogenous constraint, if at all. However, community resistance can lead to permitting delays, legal challenges, or reputational risks affecting project timelines and cost structures. Future research is needed to incorporate community risk perception variables e.g., trust levels, historical conflict, benefit-sharing mechanisms into financial or risk-adjusted investment models for EoL decision analysis.

Studies often rely on surveys or public meetings that may exclude marginalized or less vocal community groups. As a result, risk perceptions of lower-income residents, non-host landowners, or indigenous communities are frequently underexplored, even though these groups may experience disproportionate impacts or have divergent views on project continuation. Inclusive participatory research methods (e.g., deliberative forums, ethnography, and focus group discussions) to surface diverse perspectives and integrate them into EoL governance strategies. Most research captures community sentiment at a single point, overlooking how attitudes shift across the lifecycle of a wind project. Understanding how perceptions evolve especially after years of operation can offer valuable insight into EoL readiness and acceptance. This can be improved by conducting longitudinal studies tracking communities from installation to EoL phases, identifying the social and psychological processes that influence repowering or decommissioning support.

Lastly, community responses to EoL scenarios vary by region, governance context, and cultural norms. Yet much of the literature remains Eurocentric, particularly focused on Northern and Western Europe. There is limited understanding of how EoL engagement unfolds in the Global South, where institutional capacities and ownership models differ. It is required to undertake comparative cross-country studies to explore how regional, cultural, and regulatory differences shape community risk perceptions and engagement in EoL transitions.

2.5 Research motivation

Despite a substantial and growing research base on wind energy systems, there is still no coherent framework for guiding EoL decision making under conditions of financial uncertainty, technological ageing, and social scrutiny. The literature reviewed in this chapter reveals that these dimensions are largely treated separately, obscuring how their interaction shapes EoL outcomes in practice. Addressing this fragmentation is essential for understanding why EoL decision making remains a persistent challenge in the wind energy sector.

Existing literature recognises wind energy as a cornerstone of climate mitigation, with wind accounting for a substantial share of newly installed renewable capacity worldwide (Afridi et al., 2024; Hassan et al., 2024; IRENA, 2024). However, much of this work implicitly treats wind assets as static infrastructures whose contribution to climate goals ends with their initial operational lifetime. Less attention has been paid to how EoL decisions themselves can either reinforce or undermine long-term climate benefits, particularly when financial uncertainty, aging technology, and community expectations converge.

A growing body of social science research highlights the importance of community acceptance, participation, and perceived fairness in wind energy development (Solman et al., 2021; Knauf & le Maitre, 2023; Knauf & Wüstenhagen, 2023). Community ownership and co-investment models are increasingly promoted as mechanisms to enhance social legitimacy and distribute benefits more equitably. However, these studies tend to focus on early stage project development rather than late life decision points. Little is known about how communities perceive risk, uncertainty, and investment opportunities when wind farms are repowered or extended, despite these moments often reopening debates about local impacts and trust.

Chapter 3 . Financial theories: risk and investment under uncertainty in wind energy infrastructure

This chapter primarily sets out the financial theory that underpins the analysis in the following chapter. It frames wind farm end-of-life decision making as an investment problem characterised by uncertainty, irreversibility, and strategic flexibility, with risk as the central analytical construct. Secondly, it links these theoretical perspectives directly to the empirical analyses in Chapters Five, Six, and Seven, showing how each theoretical strand informs the structure and approach of the individual studies.

Section 3.1 outlines risk analysis and portfolio theory in investment decision-making. This section develops the concept of financial risk from a traditional investment perspective following modern portfolio theory, providing the theoretical basis for Chapter five, which models financial risks from wind turbine failures using discounted cash flow analysis and stochastic simulation to quantify volatility in projected returns.

Section 3.2 introduces real options theory to conceptualises repowering, life extension, and decommissioning as managerial options embedded within the asset lifecycle. This theoretical lens directly informs Chapter six, where real options valuation is applied to estimate the value of strategic flexibility under uncertainty.

Section 3.3 draws on behavioural finance and social theories of risk perception to examine how heuristics, affect, diffusion dynamics, and institutional trust shape community investment perceptions. This section underpins the survey design and empirical analysis presented in Chapter Seven.

Overall, the integration of these theoretical perspectives reflects a pragmatic epistemological position, in which multiple conceptual frameworks are employed to address different dimensions of a complex investment problem while maintaining analytical coherence.

3.1 Risk analysis and portfolio theory

3.1.1 The development of risk analysis

Risk occupies a foundational position in modern financial economics. Its formalisation is commonly traced to Modern Portfolio Theory (MPT), where Markowitz, (1952) defined risk as the variance of returns around an expected mean, thereby embedding uncertainty directly into optimisation models of asset allocation. This variance-based

conception became the analytical core of portfolio selection and subsequently informed the development of the Capital Asset Pricing Model (CAPM), which reframed risk in terms of systematic covariance with the market portfolio rather than total variability (Sharpe, 1964; Lintner, 1965). In this framework, risk was no longer merely dispersion, but exposure to non-diversifiable market factors.

By the 1970s, theoretical attention shifted toward state-contingent claims and intertemporal choice under uncertainty. Merton, (1973) extended risk analysis into a continuous-time, dynamic setting, linking portfolio choice to stochastic processes and consumption smoothing. Concurrently, option pricing theory (Black and Scholes, 1973) introduced a market-consistent valuation framework in which risk could be priced and hedged through arbitrage relations. These developments reoriented the concept of risk from descriptive variability toward equilibrium pricing and replication logic.

However, variance-based measures soon attracted criticism. Empirical return distributions were shown to exhibit skewness and fat tails inconsistent with normality assumptions (Fama, 1965). This led to the development of downside-risk measures and coherent risk metrics. Fishburn, (1984) argued that although risk is intuitively understood, its measurement requires normative clarity regarding loss evaluation. Later, Artzner et al., (1999) formalised the axioms of coherent risk measures, demonstrating that variance fails to satisfy properties such as subadditivity. Value-at-Risk (VaR) gained prominence in financial regulation and practice, but was itself criticised for not capturing tail severity, leading to the adoption of Conditional Value-at-Risk (CVaR) as a theoretically consistent alternative (Rockafellar and Uryasev, 2000).

Parallel to developments in financial economics, decision theory broadened the conceptualisation of risk beyond statistical dispersion. Expected Utility Theory (von Neumann and Morgenstern, 1944) provided the normative foundation for rational choice under uncertainty, but empirical anomalies most notably those documented in Prospect Theory (Kahneman and Tversky, 1979) and Psychometric Paradigm of Risk Perception (Slovic, 1987), demonstrated systematic deviations from expected utility maximisation.

Contemporary research therefore treats risk as a multi-dimensional construct. In asset pricing, it encompasses factor exposures and tail dependence (Fama and French, 1993; Harvey et al., 2016). In risk management, it includes coherent and spectral measures capable of capturing extreme events. In behavioural and institutional contexts, risk incorporates perception, trust, and framing effects. This historical trajectory demonstrates that risk in investment and decision-making has shifted from variance-based dispersion metrics toward a layered construct integrating probabilistic modelling, equilibrium pricing, downside exposure, behavioural perception, and systemic interaction. Any contemporary analysis of investment decisions under uncertainty must therefore engage with both the quantitative measurement of stochastic variability and the cognitive and institutional processes through which uncertainty is interpreted and acted upon.

In infrastructure finance, risk has evolved from short horizon asset volatility toward long horizon cash flow uncertainty driven by operational reliability, regulatory stability, and market dynamics. Renewable energy assets, and wind farms in particular, exhibit multi-dimensional risk structures: stochastic generation output, component degradation (Carroll et al., 2016; Olabi et al., 2021), electricity price volatility (Kanamura et al., 2021), and policy risk. These features challenge traditional equilibrium assumptions embedded in early portfolio theory, necessitating simulation-based and scenario-driven approaches. Within this thesis, risk is conceptualised as stochastic variability in expected financial returns, operational reliability, and socio-political feasibility. This definition integrates financial, technical, and social dimensions into a unified analytical construct.

Beyond technical and financial dimensions, regulatory and social risks play a growing role in shaping investment decisions in wind infrastructures. Policy uncertainty surrounding repowering permissions, grid access, and environmental compliance can alter the feasibility of lifetime extension or redevelopment (González and Lacal-Arántegui, 2016; Wiser et al., 2021). At the same time, social acceptance and community response increasingly influence whether repowering or continued operation is politically and practically viable, introducing a form of risk that is less easily quantified but nonetheless consequential (Aitken, 2010; Sovacool and Ratan, 2012).

3.1.2 Risk and portfolio theory

Financial risk theory provides the conceptual and analytical basis for modelling how uncertain outcomes translate into exposure, losses, and decision-relevant trade-offs. In investment analysis, "risk" is typically operationalised as uncertainty in returns (or cash flows) relative to expectations, and financial risk theory provides the tools to (i) characterise uncertainty probabilistically, (ii) quantify downside exposure, and (iii) evaluate how diversification and dependence structures shape aggregate risk (Markowitz, 1952; Sharpe, 1964; Lintner, 1965; Fama, 1965).

In its canonical form, financial risk theory treats asset outcomes as random variables. Let R_i denote the random return on asset i and w_i the portfolio weight. Expected portfolio return is linear weights:

$$\mathbb{E}R_p = \sum_{i=1}^{N} w_i R_i \qquad (3.1)$$

The central innovation of MPT is to quantify risk using the variance (or standard deviation) of portfolio returns and to show that portfolio risk depends not only on individual asset variances but also on covariances between assets (Markowitz, 1952). The portfolio variance is

$$Var(R_p) = \sum_{i=1}^{N}\sum_{i=1}^{N} w_i w_j . Cov(R_i, R_j) = W^{\intercal} \sum W \qquad (3.2)$$

Where $\sum$ is the variance-covariance matrix. When $Cov(R_i, R_j)$ is low or negative, diversification reduces portfolio variance even if individual assets are risky. This result-risk reduction through correlation is the "portfolio logic" that later underpinned mainstream asset pricing (Sharpe, 1964; Lintner, 1965) and factor-based interpretations of risk premia (Fama & French, 1993).

Financial risk theory distinguishes between systematic and unsystematic components of uncertainty, a distinction that is central to portfolio logic and asset pricing. Systematic risk refers to the portion of an asset's return variability that is correlated with broader market movements and therefore cannot be eliminated through diversification. Unsystematic risk, by contrast, is asset-specific and can in principle be diversified away in sufficiently large portfolios. Early formal treatments of this

decomposition were developed in the context of mean-variance equilibrium models. Beja (1972) demonstrated analytically how total variance can be partitioned into systematic and idiosyncratic components within a market model framework. In the standard single-index representation,

$$R_i = \alpha_i + \beta_i R_m + \varepsilon_i \qquad (3.3)$$

Where R_i is the return on asset i, R_m is the market return, β_i measures exposure to systematic risk, and ε_i captures idiosyncratic shocks with $\mathbb{E}[\varepsilon_i] = 0$ and $\mathrm{Cov}(R_m, \varepsilon_i) = 0$. The variance of returns then decomposes as

$$Var(R_i) = \beta_i{}^2 Var(R_m) + Var(\varepsilon_i) \qquad (3.4)$$

The first term represents systematic risk and the second unsystematic risk. Rubinstein (1973) integrated this decomposition into a broader mean-variance synthesis of corporate financial theory, linking firm-level financial structure to systematic risk exposure. Empirical investigations, such as Bowman (1979), further examined how accounting variables relate to systematic risk, reinforcing the idea that not all observed volatility is equally priced by markets.

Subsequent theoretical developments expanded this decomposition beyond equilibrium asset pricing. Bouchaud (1999, 2000) argued that financial risk cannot be fully understood through Gaussian assumptions and linear factor structures alone, highlighting the importance of collective dynamics, extreme events, and heavy-tailed distributions in shaping aggregate risk. These contributions underscored that systematic risk may emerge endogenously from market interactions rather than being purely exogenous. Together, this literature establishes that total financial risk comprises diversifiable (idiosyncratic) components and non-diversifiable (system-wide) components, and that understanding their relative magnitude is essential for risk aggregation, portfolio construction, and capital allocation decisions. In the context of wind farm assets, this distinction provides a useful analytical analogue: turbine-specific failures represent idiosyncratic risk that can be partially diversified across multiple units, whereas common-mode failures, shared exposure to electricity price volatility, regulatory shifts, or extreme weather events function as systematic risk factors that persist regardless of farm size.

3.1.2.1 Portfolio logic and its relevance to wind farms

A key strength of portfolio theory is that it is not limited to traded securities; it applies to any setting where outcomes are uncertain, can be aggregated, and exhibit dependence structures. Energy assets have long been analysed through portfolio lenses because they involve uncertain generation, uncertain prices, and large, sunk capital commitments (Awerbuch, 2000; Roques et al., 2008). In renewables, risk arises not only from market prices but also from operational performance and availability, which directly affect revenue distributions (Tavner, 2012; Carroll et al., 2016).

A wind farm can be conceptualised as a portfolio of turbines where each turbine contributes stochastic cash flows (driven by production and downtime) and where dependence across turbines matters. If turbine cash flow is C_i and farm cash flow is $C = \sum_i C_i$, then

$$Var(C) = \sum_{i=1}^{N} Var(C_i) + 2\sum_{i<j} Cov(C_i, C_i) \qquad (3.5)$$

This directly mirrors MPT: increasing the number of turbines can reduce relative risk if failures are not perfectly correlated. However, correlation is plausible due to shared maintenance strategies, common environmental exposure, shared supply chains for components, and common-mode failures (e.g., grid outages, storms, systematic component issues). Reliability and O&M research highlights that failure rates rise with age and that major components can drive low-frequency, high-severity downtime exactly the type of tail behaviour that variance alone can obscure (Tavner, 2012; Carroll et al., 2016).

Portfolio approaches have been used in energy investment to evaluate how diversification across generation technologies reduces cost and risk, particularly under fuel price volatility and uncertain policy conditions (Awerbuch, 2000; Roques et al., 2008). More broadly, the adoption of VaR and CVaR as tail-risk measures and their use with Monte Carlo simulation is well established in financial risk management and has been extended to infrastructure-type settings where losses are driven by rare events (Artzner et al., 1999; Rockafellar & Uryasev, 2000; Jorion, 2007; Glasserman, 2004). Within wind operations, reliability research details the stochastic nature of failures and

downtime and provides empirical grounding for modelling ageing-related operational uncertainty (Tavner, 2012; Carroll et al., 2016).

Study 1 operationalises these theoretical ideas by treating a wind farm as a portfolio of turbines whose net cash flows are subject to stochastic failure events. Each turbine is modelled as an "asset" producing uncertain revenue due to random downtime durations and failure occurrences, with uncertainty increasing with age as component reliability degrades (Carroll et al., 2016; Tavner, 2012). Wind farm size is therefore analysed as a diversification mechanism: as number of turbines increases, idiosyncratic turbine failures can partially diversify, reducing relative cash-flow volatility unless dependence (common-mode risks) dominates.

3.1.2.2 Concept evolution : from variance to downside and tail risk

Although mean-variance risk remains foundational, several developments motivated a broader view of risk. Empirical finance showed that asset return distributions are often non-normal, exhibiting fat tails and skewness, which weakens variance as a complete risk descriptor (Fama, 1965). In such settings, variance can understate the importance of rare, high-impact losses. Second, decision theory and behavioural economics demonstrated that decision-makers are typically loss-averse and evaluate outcomes relative to reference points; downside outcomes carry disproportionate weight (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). This reinforced the need for risk measures that focus explicitly on losses rather than symmetric volatility. Third, risk management and regulation pushed practice toward quantifying "worst-case" losses at high confidence levels. Value-at-Risk (VaR) became a standard tail-risk measure in institutions and regulatory frameworks (Jorion, 2007). However, VaR has known theoretical limitations, particularly that it may fail subadditivity (diversification should not increase measured risk), which undermines its consistency with portfolio logic. This critique motivated the development of coherent risk measures (Artzner et al., 1999) and popularised Expected Shortfall/Conditional Value-at-Risk (CVaR) as a coherent, tail-sensitive alternative (Rockafellar & Uryasev, 2000; Acerbi, 2002).

Value-at-Risk (VaR) summarises a loss distribution by a quantile. Let L be a loss random variable (higher L is worse). For confidence level α(e.g., 95% or 99%),

$$VaR_\alpha(L) = inf\{\ell \in \mathbb{R}: \mathbb{P}(L \leq \ell) \geq \alpha\} \quad (3.6)$$

Interpreting VaR: with probability α, losses will not exceed VaR_α. VaR is intuitive and widely used, but it does not indicate how severe losses are beyond that threshold (Jorion, 2007).

Conditional Value-at-Risk (CVaR), also termed Expected Shortfall (ES), addresses this by taking the expected loss in the tail beyond VaR:

$$CVaR_\alpha(L) = \mathbb{E}[L|L \geq VaR_\alpha(L)] \quad (3.7)$$

Rockafellar and Uryasev (2000) show that CVaR is particularly attractive because it is coherent under broad conditions and can be optimised effectively. Artzner et al., (1999) formalised coherence properties (monotonicity, translation invariance, positive homogeneity, and subadditivity) that align with the diversification logic central to portfolio theory; CVaR satisfies these properties, whereas VaR can fail subadditivity for some distributions.

In an end-of-life wind context, low-probability, high-impact failures (e.g., gearbox, generator, major blade damage) create heavy-tail loss behaviour losses that are rare but potentially large due to extended downtime, crane logistics, and high replacement costs. Tail-risk measures are therefore substantively aligned with the risk profile of ageing assets (Tavner, 2012; Carroll et al., 2016). VaR provides a clear threshold-type statement ("a bad year at the 95th percentile"), while CVaR quantifies the expected severity of truly adverse outcomes, which is especially relevant for investors and lenders concerned with downside protection.

3.1.2.3 Monte Carlo simulations as the link between theory and operational modelling

Financial risk theory emphasises distributions, not point forecasts. When analytic distributions are unavailable common when modelling failure processes, price uncertainty, and maintenance logistics, Monte Carlo simulation is a standard approach. In general, if cash flow C depends on uncertain drivers X (failures, downtime durations, prices), $C = f(X)$, Monte Carlo approximates the distribution of C by repeatedly sampling $X^{(k)}$ from assumed stochastic models and computing

$$C^{(k)} = f\left(X^{(k)}\right), k = 1, \ldots., K. \quad (3.8)$$

Losses can then be defined as $L = C^{\text{baseline}} - C$(or any other decision-relevant loss definition), and empirical estimates of VaR_α and CVaR_α can be computed directly from simulated loss samples (Glasserman, 2004; Rockafellar & Uryasev, 2000). Simulation therefore operationalises the portfolio logic (aggregation and dependence) and tail-risk measurement (VaR/CVaR) in a single workflow.

3.2 Real options theory and investment flexibility

Real Options Theory (ROT) extends financial option pricing logic to real, non-financial assets, allowing investment decisions to be evaluated as contingent claims under uncertainty. Whereas traditional discounted cash flow (DCF) and Net Present Value (NPV) analysis assume passive, now-or-never decisions, ROT recognises that managers possess flexibility: they may delay, expand, contract, switch, or abandon projects in response to evolving information. This flexibility has economic value when uncertainty is high, investment is partially irreversible, and timing is discretionary. These conditions characterise capital-intensive infrastructure assets, including wind farms at end-of-life.

The intellectual foundations of ROT lie in financial option pricing. The breakthrough came with the derivation of the Black-Scholes-Merton option pricing framework (Black & Scholes, 1973; Merton, 1973), which demonstrated that the value of a financial option can be expressed as a function of the underlying asset price, volatility, time to maturity, risk-free rate, and strike price. For a European call option, the Black-Scholes formula is:

$$C = S_0 N(d_1) - K e^{-rT} N(d_2) \quad (3.9)$$

Where

$$d_1 = \frac{\ln(S_0/K) + (r + \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}, d_2 = d_1 - \sigma\sqrt{T}. \quad (3.10)$$

Here, S_0 is the current asset value, K the exercise price, r the risk-free rate, T time to maturity, and σ volatility.

The insight that real investments resemble options emerged shortly thereafter. Myers (1977) introduced the term "real options" in corporate finance, arguing that many investment opportunities are analogous to growth options embedded within firms. Unlike financial options, real options concern physical assets plants, infrastructure, R&D projects where uncertainty and irreversibility create option-like characteristics.

The central principle of ROT is that uncertainty increases the value of waiting when investment is irreversible. In a simple NPV framework:

$$NPV = \sum_{t=0}^{T} \frac{E(C_t)}{(1+r)^t} - I_0 \qquad (3.11)$$

C_t is the expected cash flow at time *t*, and I_0 is the initial investment. NPV assumes immediate commitment.

Real options modify this by recognising that investment can be deferred until uncertainty resolves. The value of a project without options is E(NPV), the value of a project with options is E (Max (NPV,0)). Therefore, the value of the investment opportunity (option value) becomes:

$$OV = E((Max(NPV, 0))\text{-E(NPV)} \qquad (3.12)$$

Under uncertainty, the option value is increasing in volatility (σ) because greater variability increases the upside potential without proportionally increasing downside exposure (since losses are bounded by non-exercise).

Dixit and Pindyck, (1994) formalised this insight in irreversible investment theory. They demonstrated that the optimal investment trigger exceeds the static NPV break-even threshold. If project value V follows a stochastic process such as geometric Brownian motion:

$$dV = \mu V dt + \sigma V dW_t \qquad (3.13)$$

then the optimal trigger V^*satisfies:

$$V^* = \frac{\beta}{\beta - 1} I \qquad (3.14)$$

where I is investment cost and $\beta > 1$depends on parameters r, μ, σ. This implies that higher volatility raises the threshold required to invest, reflecting the value of waiting.

3.2.1 Evolution of real options theory

Early applications of real options theory concentrated primarily on the value of deferral, that is the option to wait before committing irreversible capital under uncertainty. Dixit and Pindyck, (1994) formalised this logic by demonstrating that when investment is sunk and project value follows a stochastic process, the optimal investment trigger exceeds the traditional NPV break-even level. Their analysis showed that uncertainty increases the value of waiting because postponement preserves upside potential while limiting downside exposure. In this framework, the investment opportunity itself is treated as a call option on the underlying project value, and optimal timing depends on volatility, irreversibility, and the opportunity cost of delay.

Subsequent developments broadened the scope of real options beyond simple timing decisions. Trigeorgis, (1996) systematised a taxonomy of real options embedded in corporate investment. These include: Expansion options, where firms retain the right to scale up operations if market conditions prove favourable; Abandonment options, allowing early termination and asset redeployment to limit downside losses; Switching options, which permit changes in input mix or output configuration in response to relative price movements; Compound options, where one investment creates follow-on opportunities (e.g., staged R&D); and Sequential and staged investments, in which learning over time reduces uncertainty and alters subsequent decision thresholds.

Trigeorgis also advanced practical valuation methods beyond closed-form Black-Scholes solutions. He demonstrated that binomial and trinomial lattice approaches could approximate dynamic decision trees while preserving option-theoretic rigor. These discrete-time models allow managerial decisions to be embedded at each node, making them suitable for strategic planning contexts where uncertainty evolves stepwise. Simulation-based methods were later adopted to address multi-factor uncertainty and path-dependent cash flows, which are common in infrastructure projects.

In energy economics, real options theory gained prominence because energy investments exhibit precisely the characteristics under which flexibility is valuable: large sunk costs, long asset lifetimes, volatile commodity prices, regulatory uncertainty, and technological change. Pindyck, (1991) applied real options logic to irreversible capacity investment under uncertainty, demonstrating that fuel price volatility substantially delays optimal entry relative to static NPV rules. His work showed that energy firms require higher price thresholds before committing capital when volatility increases, reinforcing the importance of option value in capital-intensive sectors.

In the context of renewable energy, Kitzing et al., (2017) examined investment under policy uncertainty, particularly support scheme instability. They demonstrated that fluctuating feed-in tariffs or renewable support mechanisms reduce investment by increasing the value of waiting. Policy risk, in this sense, functions analogously to price volatility in classical models, raising the investment trigger threshold. Similarly, switching options have been studied in thermal generation contexts where plants can shift between fuels (e.g., gas versus coal) depending on relative price spreads. These models treat fuel flexibility as a real option that mitigates input price risk. Carbon pricing uncertainty has also been analysed using real options frameworks. Investment in abatement technologies or low-carbon generation can be viewed as contingent on future carbon price trajectories. When carbon markets are volatile or policy credibility is weak, the option value of delay increases, often slowing decarbonisation investment unless credible long-term signals are provided.

Mun, (2005) segregate the real option process into eight simple steps. Qualitative management screening, time-series and regression forecasting, base case net present value analysis, Monte Carlo simulations, real option problem framing, real option modeling and analysis, portfolio and resource optimisation, and lastly reporting and update analysis. Theses process can be performed in isolation or together for a more robust ROA.

Roques et al., (2008) integrated portfolio theory with real options to analyse electricity generation investment under uncertainty. Their work showed that diversification across generation technologies reduces risk exposure while real options capture flexibility in investment timing. This combined approach is particularly relevant in

liberalised electricity markets, where investors must manage both market volatility and structural uncertainty. More recent studies have extended real options analysis to renewable deployment pathways, energy storage, and system flexibility investments. Tsiodra and Chronopoulos, (2022) applied real options methods to renewable energy investments in deregulated markets, demonstrating that volatility in electricity prices and policy support materially affects project valuation and optimal timing.

Despite this growing literature, most energy applications focus on initial development decisions whether and when to build new capacity. Comparatively limited research addresses end-of-life flexibility, where ageing assets present choices among repowering, lifetime extension, or decommissioning. These decisions involve different forms of embedded optionality: repowering may constitute an expansion option with technological upgrading; lifetime extension resembles a deferral option combined with operational risk; and decommissioning resembles an abandonment option. The underdevelopment of real options analysis in the context of wind farm end-of-life management represents a theoretical and empirical gap that this thesis addresses.

3.2.2 Real options theory methodological developments

Valuation techniques in real options analysis have progressed from analytically tractable, closed-form solutions toward more flexible numerical methods capable of handling multiple uncertainties and complex cash flow structures.

Black-Scholes-type continuous-time models: The earliest real options applications relied on adapting the Black-Scholes-Merton framework (Black & Scholes, 1973; Merton, 1973), in which the underlying project value follows a continuous-time stochastic process, typically geometric Brownian motion: Under risk-neutral valuation, expected cash flows are discounted at the risk-free rate, and the option value is derived analytically. This approach was influential in early irreversible investment models, including McDonald and Siegel, (1986), who applied option pricing logic to investment timing under uncertainty. Their work demonstrated that the option to wait substantially increases the threshold required to undertake irreversible projects. Continuous-time models provide elegant closed-form intuition but rely on strong assumptions, including constant volatility and complete markets.

Binomial and trinomial lattice models: To relax some of these assumptions and accommodate discrete decision points, binomial and trinomial lattice methods were developed (Cox, Ross, & Rubinstein, 1979). These models approximate the stochastic evolution of the underlying asset using a recombining tree, allowing the option value to be computed through backward induction. Trigeorgis, (1996) demonstrated how lattice approaches can incorporate managerial decisions such as expansion, contraction, or abandonment at each node of the tree. In energy economics, lattice models have been used to evaluate power plant investment under uncertain fuel prices, where decision flexibility must be incorporated at discrete intervals. Lattice approaches are particularly useful when decision rules depend on threshold conditions that evolve over time.

Dynamic programming: Dynamic programming generalises lattice logic to multi-stage decision problems with state-dependent strategies. It is particularly suited to sequential investments and compound options, where one decision influences future opportunity sets. Dixit and Pindyck, (1994) used dynamic programming techniques to derive optimal investment thresholds under uncertainty, solving the Hamilton Jacobi Bellman (HJB) equation associated with stochastic control problems. In energy applications, dynamic programming has been used to analyse optimal capacity expansion and retirement decisions under price volatility and regulatory uncertainty. The strength of this approach lies in its ability to capture path dependency and strategic interaction over time; however, it can become computationally intensive when the state space expands.

Monte Carlo simulation: Monte Carlo simulation provides a highly flexible numerical method for valuing real options when uncertainty arises from multiple interacting stochastic variables. Rather than relying on analytic solutions or discrete approximations, simulation generates a large number of possible paths for uncertain drivers such as electricity prices, demand growth, capital costs, or operational performance and computes the distribution of project values under different decision rules (Glasserman, 2004; Mun, 2005). Least-squares Monte Carlo methods, as introduced by Longstaff and Schwartz, (2001), allow the valuation of American-style (i.e., early-exercise) options under complex dynamics. In energy economics, simulation has been widely used to evaluate renewable investments where price

volatility, policy risk, and operational uncertainty interact nonlinearly. Monte Carlo methods are particularly appropriate when closed-form solutions are infeasible and when real-world cash flows exhibit path dependency or non-normal distributions.

Across these valuation approaches, real options analysis typically employs risk-neutral valuation, whereby expected cash flows are adjusted to reflect market risk and discounted at the risk-free rate, consistent with arbitrage pricing principles (Black & Scholes, 1973; Merton, 1973). However, many infrastructure investments occur in incomplete markets where underlying risks cannot be perfectly hedged. In such contexts, analysts often apply risk-adjusted discount rates or certainty-equivalent cash flow approaches, as discussed by Trigeorgis and Reuer, (2017). The choice of valuation technique therefore depends on the nature of uncertainty, market completeness, and the degree of managerial flexibility embedded in the investment opportunity.

Despite its theoretical appeal, ROT has been criticised for overestimating option value in cases of limited managerial flexibility, difficulty in estimating volatility for real assets, complexity relative to NPV, and assumptions of continuous trading and frictionless markets. Nonetheless, its conceptual contribution recognising flexibility as economically valuable under uncertainty remains widely accepted in infrastructure and energy finance.

In this thesis, real options theory underpins Study 2, which evaluates wind farm end-of-life pathways. Repowering, lifetime extension, and decommissioning are conceptualised as mutually exclusive real options embedded in ageing wind assets. The investment opportunity is framed as a contingent claim on future electricity price trajectories, operational reliability, and capital cost uncertainty. Electricity price P_t is modelled as a stochastic process:

$$dP_t = \mu P_t dt + \sigma P_t dW_t \qquad (3.15)$$

This captures volatility that directly affects revenue.

Each pathway has:

- Distinct investment cost I_j
- Distinct expected cash flow distribution $C_{t,j}$

- Distinct operational risk profile

The value of each pathway is computed through Monte Carlo simulation of cash flows, generating a distribution of NPVs:

$$NPV_j^{(k)} = \sum_{t=0}^{T} \frac{C_{t,j}^{(k)}}{(1+r)^t} - I_j \tag{3.16}$$

Flexibility is incorporated by allowing decision-makers to delay or switch pathways depending on realised price trajectories and performance outcomes. The option value of waiting or switching is measured as the difference between:

$$\begin{aligned} Option\ value = max_j\{\mathbb{E}[NPV_j \mid \text{optimal timing}]\} \\ - \ max_j\{\mathbb{E}[NPV_j \mid \text{immediate decision}]\} \end{aligned} \tag{3.17}$$

This approach captures the value of managerial flexibility in volatile electricity markets, particularly under policy and market uncertainty.

Real options theory performs three analytical functions in the thesis: It formalises end-of-life wind decisions as dynamic investment problems rather than static cost comparisons; It provides a valuation framework consistent with stochastic modelling from Study 1; and bridges financial risk analysis and strategic flexibility, linking objective uncertainty to decision timing. By embedding repowering and lifetime extension decisions within a real options framework, the thesis extends ROT beyond initial project development into the domain of ageing renewable infrastructure. It demonstrates that end-of-life wind decisions are not merely technical replacement choices but contingent investment options shaped by volatility, irreversibility, and policy uncertainty.

3.3 Behavioural finance and social theories of risk

Behavioural finance reasons that certain market outcomes are more convincingly explained by models in which at least some participants deviate from strict rationality. The framework rests on two core components. First, limits to arbitrage: even when mispricing arises from the actions of less rational traders, rational investors may be

constrained in their ability to correct those distortions due to risk, transaction costs, institutional frictions, or synchronization problems. Second, psychology: systematic cognitive biases and heuristic-driven judgments generate predictable departures from fully rational decision-making. Together, these elements provide a structured account of how persistent anomalies can emerge and endure in financial markets.

Some financial phenomena can be studied and understood using models that assume

Financial risk is not solely an objective, probabilistic construct derived from measurable variability in returns. A substantial body of behavioural and social research demonstrates that risk is also interpreted, framed, and acted upon through cognitive heuristics, social experience, and institutional context. Whereas financial risk theory models uncertainty as stochastic variability, behavioural and social theories emphasise how individuals and communities perceive and respond to uncertainty. This distinction is central to Study 3, which examines community investment decisions in wind farm end-of-life pathways. The analysis is grounded in the Psychometric Paradigm of Risk Perception, Diffusion of Innovation Theory, and the Affect Heuristic, complemented by social acceptance and institutional trust frameworks. Together, these perspectives provide a theoretically coherent basis for analysing subjective risk evaluation in energy infrastructure contexts.

3.3.1 The psychometric paradigm of risk perception

The Psychometric Paradigm originated in the 1970s within cognitive psychology and decision research, primarily through the work of Paul Slovic, Baruch Fischhoff, and Sarah Lichtenstein. Early studies sought to explain why public attitudes toward technological hazards such as nuclear power, pesticides, or aviation often diverged sharply from expert risk assessments based on statistical mortality rates (Slovic, Fischhoff, & Lichtenstein, 1979). Rather than treating these divergences as irrational, the psychometric programme proposed that lay evaluations of risk are structured, systematic, and predictable. Risk, in this framework, is not reducible to probability consequence; it is a multidimensional construct shaped by qualitative attributes.

Methodologically, the paradigm relies on large-scale survey instruments in which respondents rate various hazards along multiple characteristics (e.g., voluntariness, immediacy of effect, familiarity, controllability, catastrophic potential). Factor-

analytic techniques are then used to identify latent dimensions underlying these ratings. Slovic, (1987) demonstrated that two dominant factors consistently explain variance in perceived risk across hazards:

Dread risk- associated with catastrophic potential, fatal consequences, lack of control, inequitable risk distribution, and involuntariness.

Unknown risk- associated with newness, unobservability, delayed effects, and scientific uncertainty.

Hazards high on both dimensions such as nuclear power in early studies were perceived as particularly threatening, even when actuarial risk levels were comparatively low. The paradigm therefore reframed risk perception as an interplay between cognitive evaluation and affective response, rather than as a deficit of information.

Over subsequent decades, the psychometric approach has been applied across domains including environmental hazards, climate change, biotechnology, and energy infrastructure. In nuclear energy research, high dread and unknown risk scores were found to correlate with opposition to plant siting and expansion. In renewable energy studies, wind farms have typically scored lower on dread but may score higher on perceived environmental or visual impact depending on local context (Devine-Wright, 2005; Wolsink, 2007). Research has also shown that perceived controllability and familiarity significantly moderate acceptance levels (Siegrist, 2000; Terwel et al., 2009). For example, communities with prior exposure to wind projects often rate associated risks as more familiar and less severe, reducing opposition (Wolsink, 2010; Bidwell, 2016).

The paradigm has also been extended conceptually. Later work integrated insights from cultural theory and social amplification of risk, recognising that media, institutional trust, and social networks influence how risk characteristics are interpreted (Slovic, 2000). Importantly, the framework does not assume static perceptions; rather, perceptions evolve with experience, information, and institutional performance.

In the context of Study 3, the psychometric paradigm provides a structured analytical lens for measuring subjective risk associated with wind farm end-of-life investment. Repowering or lifetime extension decisions may trigger perceptions of renewed environmental impact, financial uncertainty, or procedural unfairness. By operationalising key psychometric dimensions such as perceived financial severity, controllability of investment outcomes, familiarity with wind technology, and perceived long-term consequences, the survey instrument captures how communities cognitively organise these risks.

This is analytically significant because community investment willingness is unlikely to respond solely to expected return metrics. If end-of-life repowering is perceived as high in dread (e.g., due to visual intrusion or mistrust) or high in unknown risk (e.g., uncertainty about turbine lifespan or policy stability), investment uptake may be constrained regardless of favourable financial modelling. Conversely, high familiarity and perceived controllability may attenuate perceived risk and increase openness to participation.

By embedding psychometric constructs into the empirical design, Study 3 enables direct comparison between objectively modelled financial risk (Studies 1 and 2) and subjectively perceived risk. This alignment allows the thesis to examine whether divergences between statistical risk and perceived risk influence co-investment decisions in Ireland and Tanzania. In doing so, the psychometric paradigm functions not merely as descriptive background theory but as a measurable bridge between behavioural interpretation and financial decision analysis.

3.3.2 Diffusion of innovation

Theory originated in rural sociology and communication studies, most prominently through the work of Everett Rogers, whose synthesis was consolidated in successive editions of *Diffusion of Innovations* (Rogers, 1962; 2003). The theory was initially developed to explain how agricultural innovations such as hybrid seed corn spread among farmers in the United States. Rogers integrated findings from sociology, anthropology, and communication research to construct a generalisable framework describing how new ideas and technologies propagate through social systems over time.

At its core, diffusion theory conceptualises adoption as a social process rather than an individual optimisation decision. An innovation is adopted not solely because it is objectively superior, but because it is perceived as advantageous within a given social and cultural context. Rogers, (2003) identified five perceived attributes that systematically influence adoption rates:

Relative advantage- the degree to which the innovation is perceived as better than existing practice.

Compatibility- consistency with existing values, norms, and experiences.

Complexity- perceived difficulty of understanding or using the innovation.

Trialability- the extent to which it can be experimented with before full commitment.

Observability -visibility of results to others.

These attributes function as mechanisms of uncertainty reduction. Adoption is more likely when uncertainty surrounding outcomes is reduced through observation, peer communication, and incremental experience. Diffusion is therefore mediated by communication channels and social networks, rather than occurring purely through isolated decision-making.

Rogers further categorised adopters into five groups, innovators, early adopters, early majority, late majority, and laggards, based on timing of adoption relative to the social system. These categories reflect heterogeneity in risk tolerance, access to information, and openness to change. Innovators and early adopters typically possess higher risk tolerance and greater exposure to novel information, whereas late adopters rely more heavily on social proof and established norms. Importantly, the diffusion curve is cumulative and path dependent: early adoption shapes subsequent perception and legitimacy of the innovation.

Over time, diffusion theory has been applied far beyond agriculture, including public health interventions, information technologies, environmental practices, and renewable energy adoption. In energy research, diffusion frameworks have been used to explain the uptake of rooftop solar photovoltaics, smart meters, electric vehicles,

and community energy schemes. Studies have shown that geographic clustering of renewable installations often reflects social contagion effects, where visibility and peer experience reduce perceived risk and increase perceived legitimacy. Empirical work on wind energy has similarly demonstrated that communities with prior exposure to operational wind farms tend to express higher levels of acceptance compared to communities encountering projects for the first time.

Diffusion theory is particularly relevant to renewable energy because energy infrastructure is both technologically complex and socially embedded. Unlike purely private consumer goods, wind farms alter landscapes, generate collective benefits and costs, and are mediated through regulatory and institutional structures. As such, community-level learning and observational experience become central to risk interpretation.

In the context of Study 3, diffusion theory provides a structured explanation for variation in investment willingness across communities with differing levels of wind energy exposure. Communities in Ireland, where wind deployment is relatively mature, may have progressed further along the diffusion curve. Prior interaction with wind projects may reduce perceived complexity and increase familiarity, thereby lowering perceived uncertainty associated with repowering or lifetime extension decisions. In contrast, communities in Tanzania with limited exposure may evaluate such investments under higher informational and experiential uncertainty, potentially increasing reliance on social narratives or institutional trust.

Operationally, diffusion theory informs the inclusion of survey variables capturing prior exposure to wind farms, perceived familiarity with wind technology, perceived community benefits, and awareness of others' experiences. These measures allow empirical testing of whether accumulated experience moderates the relationship between perceived risk and investment willingness. If diffusion dynamics are present, prior exposure should reduce perceived uncertainty and increase openness to co-investment, independent of objective financial projections.

By integrating diffusion theory into the analytical framework, Study 3 moves beyond purely individual cognitive models of risk perception and incorporates social learning and temporal dynamics. This complements the psychometric approach by situating

risk perception within evolving social systems and aligns with the thesis's broader argument that investment decisions in renewable infrastructure are shaped not only by financial returns and individual perception, but also by collective experience and institutional context.

3.3.3 The affect heuristic

The Affect Heuristic emerged from research in behavioural decision theory and risk psychology, primarily through the work of Slovic, Finucane, Peters, and MacGregor (Slovic et al., 2004). It builds on earlier findings from the psychometric paradigm and prospect theory, but shifts analytical focus from cognitive evaluation to affective response. The central proposition is that individuals frequently rely on immediate emotional impressions "affect" when evaluating risks and benefits, especially under conditions of complexity, uncertainty, or limited information.

Rather than conducting explicit probabilistic calculations, individuals often substitute the question "What are the risks and benefits?" with the simpler, affect-laden question "How do I feel about it?" Positive affect associated with an activity leads to lower perceived risk and higher perceived benefit, while negative affect produces the opposite effect. Empirical studies demonstrate a systematic inverse correlation between perceived risk and perceived benefit driven by affective evaluation rather than statistical reasoning (Slovic et al., 2004). This finding challenges classical rational-choice assumptions that risk and benefit assessments are independent dimensions.

The theoretical foundations of the affect heuristic are closely aligned with dual-process models of cognition. Kahneman, (2011) distinguishes between "System 1" (fast, intuitive, affect-driven processing) and "System 2" (slow, analytical reasoning). In many policy and infrastructure contexts, System 1 processes dominate initial judgments, particularly where uncertainty is high and outcomes are complex. Emotional cues trust, fear, optimism, resentment serve as cognitive shortcuts.

Over time, the affect heuristic has been applied to diverse domains including nuclear energy, biotechnology, climate change, and financial decision-making. Research has shown that affect can significantly influence investment behaviour, consumer preferences, and policy support. In energy contexts, emotional attachment to

landscape, perceptions of fairness, environmental identity, and prior interpersonal experiences with developers can shape overall sentiment toward projects. These emotional responses often persist even when objective risk information is provided, suggesting that affect may mediate or override statistical evidence.

In wind energy specifically, studies have found that aesthetic concerns, perceptions of community inclusion, and symbolic associations with environmental sustainability strongly influence support levels. Positive affect linked to climate mitigation goals can reduce perceived financial or environmental risk, whereas negative affect arising from perceived visual intrusion or mistrust can increase perceived threat regardless of objective performance data.

Within Study 3, the affect heuristic provides a mechanism linking subjective evaluation to investment willingness. The survey instrument includes attitudinal measures capturing overall sentiment toward wind energy, perceived community pride or frustration, perceived fairness of past engagement processes, and emotional reactions to potential repowering. These variables allow empirical examination of whether affect mediates the relationship between perceived financial risk and co-investment intention. If affect operates as theorised, positive sentiment toward wind energy should reduce perceived risk and increase investment willingness even when objective financial uncertainty remains constant. Conversely, negative affect may dampen participation despite favourable financial modelling in Studies 1 and 2.

3.3.4 Social acceptance and institutional trust

While the affect heuristic focuses on individual emotional processing, social acceptance and institutional trust theories situate risk perception within broader relational and governance contexts. Research on renewable energy deployment has consistently demonstrated that public acceptance is shaped not only by perceived technical or financial risk, but also by procedural fairness, distributive justice, and trust in institutions (Wolsink, 2007; Aitken, 2010).

Social acceptance theory distinguishes between several dimensions: socio-political acceptance (support at policy level), community acceptance (local approval of specific projects), and market acceptance (willingness to invest or purchase). Wolsink, (2007)

argued that opposition to wind energy is rarely reducible to simple “not in my backyard” (NIMBY) motivations. Instead, resistance often reflects perceived procedural injustices, lack of meaningful participation, or inequitable distribution of costs and benefits. Aitken, (2010) further emphasised that community benefit schemes and participatory governance structures significantly shape acceptance outcomes.

Institutional trust functions as a critical heuristic in this context. Trust reduces perceived uncertainty by allowing individuals to rely on institutional competence and integrity rather than evaluating technical details independently. When trust in developers, regulators, or policymakers is high, communities are more likely to accept uncertain outcomes. Conversely, low trust amplifies perceived risk and increases scepticism. Trust therefore interacts with both cognitive and affective processes in shaping decision-making.

Over time, research in environmental governance has shown that trust is closely linked to perceptions of transparency, accountability, and fairness. Community energy studies indicate that co-ownership and participatory investment models can strengthen institutional legitimacy and increase local support, particularly when decision processes are inclusive.

In the specific context of wind farm end-of-life decisions, trust may be especially salient. Repowering, lifetime extension, or decommissioning decisions can alter visual impacts, economic benefits, and long-term community relationships. If prior project phases were perceived as exclusionary or unfair, institutional distrust may persist and negatively influence willingness to reinvest. Conversely, positive engagement histories may facilitate acceptance of continued or expanded operations.

In this thesis, institutional trust is operationalised through survey measures assessing confidence in developers, regulatory authorities, and governmental oversight. Perceptions of procedural fairness and transparency are also captured. These variables enable examination of whether trust moderates the relationship between perceived financial risk and investment willingness. Specifically, the analysis tests whether higher institutional trust attenuates the negative effect of perceived risk on co-investment intention.

Together, social acceptance and institutional trust frameworks extend behavioural risk theory beyond individual cognition. They highlight that investment decisions in renewable infrastructure are embedded within relational systems shaped by governance quality, benefit distribution, and participatory processes. By integrating these perspectives, Study 3 captures the institutional conditions under which objective financial viability translates or fails to translate into community investment participation.

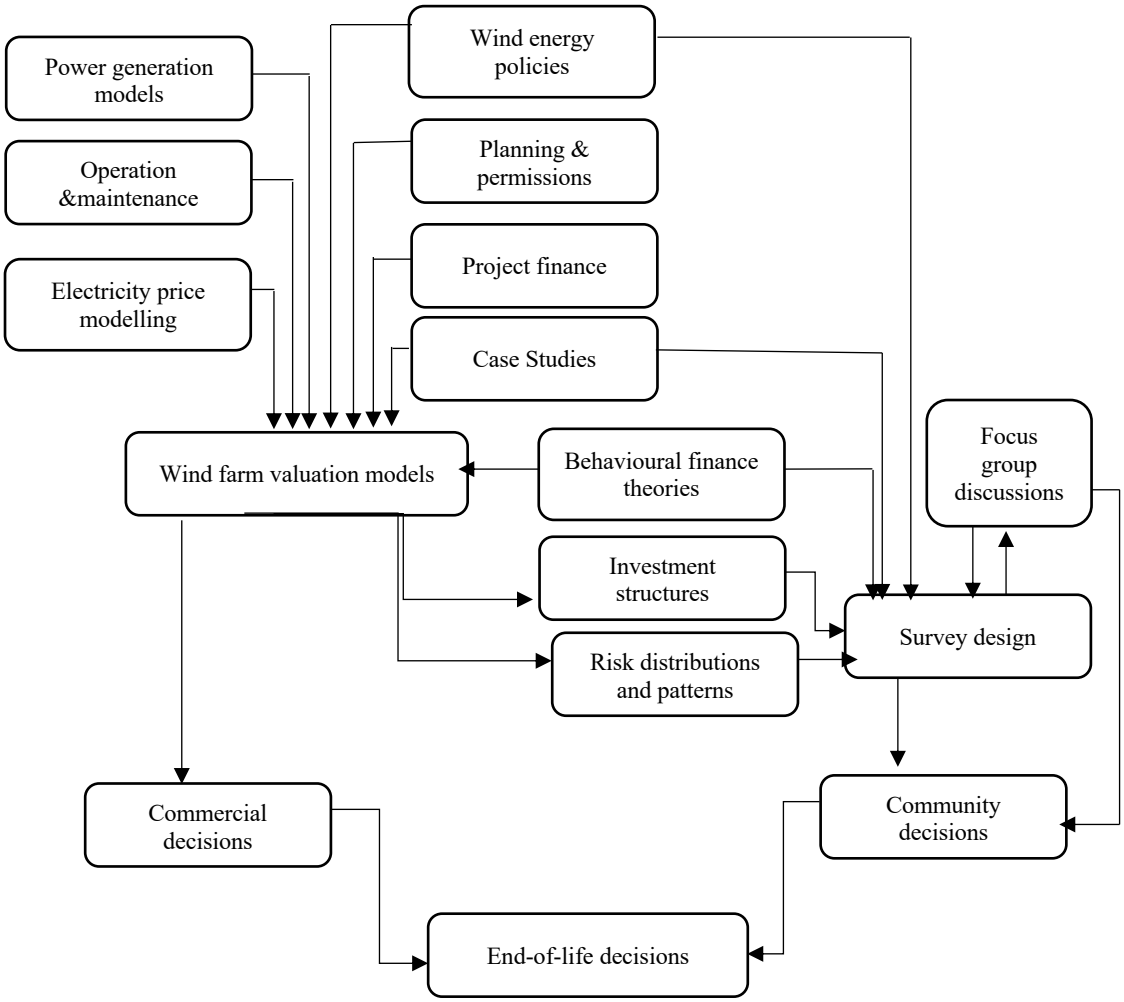
Chapter 4 . Methodology

The literature review identified a range of factors shaping end-of-life (EoL) decision making for wind farms, including the financial and technical uncertainties associated with ageing assets, evolving industry practices around lifetime extension and repowering, and emerging forms of community participation in renewable energy investment. These themes highlighted the need to examine not only the economic implications of different pathways, but also the risk perceptions, values, and interests of the diverse actors involved. A mixed research design was adopted given the multidimensional nature of research aims.

The purpose of this chapter is to provide an account of the methodological approaches underpinning the three studies in this thesis. It outlines the research design, including the rationale for the methodological choices, the steps taken to minimise potential limitations, and the measures implemented to ensure reliability, validity, and ethical integrity. The thesis employs a mixed-method, multi-study approach to investigate end-of-life decisions from complementary angles: two quantitative studies model financial risks and value the options of lifetime extension, repowering, and decommissioning, and a third study integrates qualitative and quantitative techniques to explore community risk perceptions relating to co-investment. This approach was chosen to support an in-depth examination of how financial considerations, operator decision making, and community perspectives intersect and influence end-of-life outcomes.

Figure 4.1 presents the methodological framework that ground this research. This framework is based on power generation, operations and maintenance costs, electricity prices, and community surveys. For power generation, existing models from wind farm power generation are matched to existing wind farms historical data. Operations and maintenance analysis draws on data from existing onshore wind farms and the broader wind energy literature. A price model is developed to provide an estimate of the mean price while allowing for the volatility in electricity prices. Financial attributes and risk patterns are used to develop a survey that measures community risk perceptions of investment in wind farms.

Figure 4.1: Methodological framework



4.1 Study aims and analytical objectives

The overall aim of this thesis is to understand how end-of-life decisions for wind farms are shaped by the interaction of financial, operational, and social factors. Specifically, the thesis examines how financial risks linked to turbine failures influence operators' strategic choices, how the economic value and uncertainty of end-of-life options can be assessed in a systematic way, and how community perceptions of risk affect the feasibility of co-investment and reinvestment models.

Decisions taken at the end of a wind farm's life are critical because they determine the future economic value, environmental impact, and social acceptance of the site. End-

of-life represents a point where several uncertainties converge, including the physical condition of ageing turbines, market conditions, regulatory requirements, and community expectations. The literature shows that lifetime extension, repowering, and decommissioning all involve important trade-offs related to cost, safety, environmental responsibility, and public acceptance. Making informed choices at this stage is therefore essential if wind farms are to continue contributing to the energy transition while remaining economically viable and socially legitimate.

There are several limitations in current approaches to wind farm end-of-life decision making. Existing studies often examine repowering, lifetime extension, and decommissioning separately with limited use of integrated methods that allow direct comparison between options. Environmental research has largely focused on specific issues such as blade waste and recycling, while broader life-cycle implications of different end-of-life pathways are less explored. Many studies rely on simplified assumptions due to limited access to real operational and financial data. Finally, the role of communities in shaping end-of-life outcomes remains underdeveloped, despite growing interest in community ownership and co-investment models. In response to these gaps, this thesis is structured around three empirical studies, each addressing a different but complementary dimension of end-of-life decision making. Rather than framing these as abstract research questions, each study is guided by clear analytical objectives that reflect its specific focus and contribution.

Study 1: The financial risks from wind turbine failures: a value at risk approach

The first study examines how turbine lifetime failures contribute to variation in realised profits in wind energy generation, focusing on two parts

(a) What are the financial risks of turbine failures over a wind farm's lifetime?

(b) Does the size of the farm (number of turbines) matter?

This study addresses the technical feasibility of wind farms, recognising that end-of-life decisions are strongly influenced by the ageing of turbine infrastructure. Whether operators choose to extend operational life, repower, or decommission depends partly on the physical condition of turbines and the likelihood of major component failures. Age-related failures introduce financial risks through unplanned outages, repair costs, and replacement of major components.

Part (a) seeks to quantify the financial risks (value at risk and conditional value at risk) that arise when major failures occur, particularly those involving the gearbox, generator, or blades components whose replacement can significantly affect operational expenditure and revenue loss.

Part (b) investigates how wind farm size influences financial risk exposure. Drawing on portfolio theory, diversification across multiple turbines is expected to reduce the overall value at risk because failures are random and uncorrelated events. Larger farms may therefore benefit from risk pooling, whereas smaller farms may be disproportionately affected by single turbine failures.

Study 2: Real options valuation for end-of-life investment decisions in wind farms
The second study evaluates the financial value of alternative end-of-life investment strategies lifetime extension, repowering, and decommissioning under electricity price uncertainty using a real options framework. Market conditions such as electricity prices, cost of capital, and policy incentives play a significant role in determining the expected returns associated with each pathway.

Wind farms can be viewed as assets with three strategic investment options at end-of-life: (1) repowering through the installation of modern, higher-capacity turbines; (2) extending the operational life of existing turbines; or (3) decommissioning and site restoration. Each pathway represents an investment option that gives owners the right, but not the obligation, to take a specific action now or in the future. This research therefore asks whether these options possess quantifiable economic value and how market uncertainty influences that valuation.

Study 3: Perceptions of risk and investment in wind energy in rural communities
The third study addresses the social dimension of end-of-life decision making by examining how community attitudes toward risk and investment shape willingness to engage with wind energy projects. As wind farms reach the end of their operational life, new opportunities arise for local communities to participate through co-investment or co-ownership arrangements, especially where existing infrastructure reduces development costs.

This study presents evidence how risk preferences, prior experience with wind farms, and socio-demographic factors influence investment behaviour. It explores whether communities perceive wind energy as an attractive and acceptable form of investment, and how familiarity with local projects affects trust and acceptance. By doing so, the study provides insight into the conditions under which community participation can support socially viable and durable end-of-life strategies.

4.2 Research design (epistemology and ontology)

Research on wind farm end-of-life decisions has often been fragmented with studies tending to prioritise either economic modelling (Leite et al., 2022) or social acceptance independently (Windemer, 2023) rather than adopting a holistic analytical perspective (De Laurentis and Windemer, 2024). Similar fragmentation has been noted in the broader wind energy studies where there is an overreliance on positivist paradigms that privilege quantifiable outcomes while overlooking the interpretive and contextual factors shaping community energy relationships (Ellis et al., 2007). Subsequent studies have demonstrated the value of broadening methodological approaches in wind energy research: (Barry et al., 2008) show that post-positivist and interpretive perspectives enable richer exploration of the narratives, values, and contested meanings surrounding wind energy development. This intellectual trajectory highlights the need for methodological approaches capable of capturing financial realities, technical uncertainties, and social dynamics simultaneously an approach that aligns with the mixed-method research design in this thesis.

This research adopts a pragmatic epistemological stance, which holds that the choice of method should be dictated by the research objective and the practical usefulness of the knowledge generated (Creswell and Clark, 2017; Morgan, 2007). Pragmatism is particularly well suited to end-of-life decision making in wind energy, where both measurable financial outcomes (e.g., failure risks, investment value, market conditions) and socially constructed interpretations (e.g., community risk perceptions, local attitudes toward co-investment) influence decision pathways whilst requiring different research methods. The quantitative paradigm often called scientific research is based on objectivism and positivism in which there is only one objective reality that is separated from the researcher's perceptions (Creswell and Creswell, 2014). The researcher neither affect nor affected by the phenomena. Differently, the qualitative

paradigm is based on subjectivism and interpretivism. Qualitative researchers believe in the existence of multiple realities based on researcher's construction of reality (Maarouf, 2019). Quantitative approaches enable the modelling of objective, market-facing realities such as turbine reliability, replacement costs, or option values while qualitative and mixed methods provide insight into the subjective and relational elements that shape community engagement and acceptance. In adopting a pragmatic epistemology, this thesis acknowledges that different kinds of knowledge are needed to understand the full decision landscape and that no single methodological tradition is sufficient on its own.

Ontologically, this research assumes a pluralistic view in which both material and social realities coexist and jointly shape end-of-life outcomes. On one hand, financial risks, component failures, and electricity prices are treated as objective phenomena that can be modelled and quantified. On the other hand, community perceptions, risk preferences, and lived experiences are understood as socially constructed and variable across contexts, aligning with interpretivist ontological assumptions (Berger and Luckmann, 2016; Schutz, 1967). This dual acknowledgement reflects the complex nature of renewable energy infrastructures, which operate simultaneously as technical systems and social institutions. Past work in energy social science emphasises the importance of such multiplicity; for example, (Wolsink, 2007) and (Aitken, 2010) show that social acceptance cannot be understood independently of the material realities of wind technology, nor can technical assessments be separated from the communities that host them.

This philosophical grounding informs the design of the three empirical studies in the thesis. The first two studies adopt a predominantly quantitative orientation to investigate financial risks, failure distributions, and the economic value of repowering, lifetime extension, or decommissioning. Their epistemological logic aligns with a positivist-influenced understanding that certain aspects of wind farm performance and valuation can be objectively measured and modelled. In contrast, the third study integrates qualitative and quantitative methods to explore community risk perceptions and investment preferences, reflecting an interpretivist assumption that social meaning, experience, and context shape public responses to energy infrastructure. Through pragmatism, these divergent methodological traditions are not viewed as

incompatible but rather as complementary tools for addressing different facets of the research problem.

Adopting this pragmatic pluralistic stance allows the research to engage with the full complexity of end-of-life decision making. Wind farms are not static entities but dynamic socio-technical systems whose futures depend on interactions between infrastructure ageing, market volatility, regulatory change, and evolving community relationships. Recognising this, the methodological approach in this thesis is designed to produce knowledge that is both analytically rigorous and practically relevant, supporting decisions that are technically sound, economically justified, and socially informed.

4.3 Methods

This research adopts a mixed-methods design supported by multiple case studies. Combining quantitative and qualitative approaches enables the study to address the breadth and diversity of the research objectives, while also generating deeper and more nuanced insights that could not be achieved through a single-method paradigm. The integration of methods helps to mitigate the limitations inherent in relying solely on either quantitative or qualitative techniques, thereby providing a more robust and comprehensive understanding of end-of-life decision making for wind farms. Mixed methods support both the generation and testing of theory, using words, narratives, and images to enrich the interpretation of numerical patterns, and numerical evidence to add precision and clarity to qualitative accounts (Migiro and Magangi, 2011).

Thereafter, the method of each study is elaborated by explaining research design and rationale, data collection process, data sources, data analysis, ethics and limitations. Table 4.1 presents the relationship between the research questions and methods.

Table 4.1: The relationship between the study aims and methods

This table shows different methods used in this research, the main method is marked by ● and complementary methods by ⊙.

	Study 1 How do turbine lifetime failures contribute to variation in realised profits in wind energy generation?	**Study 2** Is there financial value in the option to decommission, repower, or extend the life of a wind turbine?	**Study 3** What are community perceptions of risk and investment in wind energy projects?
Review and analysis of age, status, and operation of wind farms	●	⊙	⊙
Commercial analysis of wind farms	●	●	⊙
Modelling electricity prices	●	●	
Case studies		●	●
Simulations and model experimenting	●	●	
Semi-structured Surveys			●
Focus group discussions			●
Regressions Analysis			●

4.3.1 Method of study 1

The first study research how turbine lifetime failures cause variation in realised profit in wind energy generation. This study employs a quantitative modelling design grounded in financial risk assessment methods. The rationale for using a quantitative approach is the inherently numerical nature of turbine failure events, repair costs, downtime losses, and market-driven revenue variability. Importantly, the variability of energy markets requires predictability and modelling of scenarios that use quantitative techniques especially electricity pricing. A novel risk estimation model capable of capturing uncertainty in technical failures and market conditions. The financial modelling strategy was based on Value-at-Risk (VaR), Conditional Value-at-Risk (CVaR), and Monte Carlo simulation techniques. This design supports the study's aim to quantify the magnitude and distribution of financial risks associated with major turbine component failures, while enabling comparison across differently sized wind farms.

Monte Carlo simulation integrates rigorous mathematical reasoning with practical, experiment-based analysis. It operates on the principle that robust quantitative social science requires the alignment of both theoretical assumptions and statistical specifications within a well-defined data-generating process (Carsey and Harden, 2015). As explained by Chance and Rossman, (2006), the classical methods of statistical analysis rely on unverifiable assumptions about a true model and the impractical notion of repeated sampling, Monte Carlo simulations replicate this logic in a controlled environment. Monte Carlo simulations offer a clear advantage over classical statistical analysis by allowing researchers to work with a fully known data-generating process and to create as many samples as needed, conditions impossible in real-world frequentist inference. This enables a researcher to directly observe the stochastic behaviour of estimators, evaluate model assumptions, and gain intuitive insight into statistical inference without relying solely on abstract theory or mathematical proofs.

Data were collected from publicly available engineering failure rate studies, peer-reviewed literature, and energy market statistics. Component-specific failure frequencies were compiled and standardised to annualised rates. Repair and replacement costs were extracted from industry reports, and market price data were aggregated as annual mean and volatility measures. All data were cleaned to ensure consistency in units, time horizons, and cost bases before being incorporated into the risk model.

Data sources include:

- Annual turbine failure rates for major components (gearbox, generator, blades).
- Cost of repair or replacement for each failure type, drawn from published industry sources and academic literature (Lantz, 2013; Shaun Campbell, 2015; Tazi et al., 2017).
- Electricity market price data**,** representing variable revenue impacts during periods of turbine downtime from Sustainable Energy Authority of Ireland database (SEAI, 2023).

- Wind farm configurations (small, medium, large) used to evaluate portfolio effects based on number of turbines.

These datasets reflect typical generational and operational characteristics of onshore wind farms in mature markets.

Financial risk was assessed through a multi-stage modelling process: First, simulation of turbine failures where Monte Carlo simulation was used to generate a large set of possible lifetime failure paths for each turbine. Each simulation draw included both the probability of failure and the cost impact. Second, cashflows were estimated, here downtime caused by failures was matched with market price distributions to calculate revenue loss. Portfolio risk was assessed incorporating farms of different sizes (e.g., 10, 50, 100 turbines). These were modelled to measure diversification effects consistent with portfolio theory. Two portfolio financial risk measure Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) were used for risk analysis (Chi and Tan, 2011; Ma and Wong, 2010). VaR estimates the maximum expected loss under normal conditions. CVaR captures tail-risk, representing extreme but plausible worst-case loss scenarios. The output is a probabilistic risk profile demonstrating how turbine failures influence profitability and farm size moderates exposure.

Formal ethical approval was not required as this study does not involve human subjects or sensitive data. Nevertheless, ethical considerations were followed by ensuring transparency in data sources, maintaining accuracy in reporting, and avoiding misrepresentation of risk outcomes. All secondary data used were publicly available (open source) or derived from published sources.

Several limitations should be acknowledged. Data uncertainty remains a challenge, as failure rates and cost estimates vary by manufacturer, location, and turbine age. Available datasets may not fully capture this variability. Market price volatility affects the analysis, since future electricity prices are inherently uncertain and are modelled probabilistically. The results indicative rather than strictly predictive. In addition, operational differences such as maintenance practices, insurance arrangements, and contractual terms may influence financial outcomes in ways not fully represented in the model. Finally, while the findings illustrate typical risk patterns, they may not generalise to all wind farms or regulatory contexts.

4.3.2 Method of study 2

This study adopts a quantitative case-study design to assess the financial value present in the option to extend the life of a wind turbine, repower, or decommission onshore wind turbines. The rationale for a quantitative approach stems from the need to evaluate how market uncertainty, capital costs, operational conditions, and electricity prices interact to influence the financial attractiveness of each option. A Monte Carlo simulation framework, combined with Net Present Value (NPV) analysis, is used to estimate the real option value associated with repowering and lifetime extension. This approach allows the creation of a novel decision support model capable of capturing uncertainty in future cash flows dynamics.

The shortcomings of the valuation model in the first study are addressed in this work. By using a case study, the modelling is anchored in real operational parameters, enhancing both the relevance and credibility of the economic assessment. Building on the lessons from the first study, incorporating the long-term behaviour of electricity prices is inherently difficult; therefore, rather than relying on a single modelling assumption, we construct three plausible scenarios and calculate option values for each. The second model strengthens the stochastic representation of electricity prices by introducing three market scenarios that capture crisis-period volatility and drift (COVID-19 and the war in Ukraine), typical Irish electricity market dynamics, and broader European electricity trends.

The dataset was the performance parameters of a wind farm case study in Ballincurry Ireland. This involved annual generation, availability rates, operating time. CAPEX estimates, decommissioning and dismantling cost, operational expenditure, salvage value and project finance cost including cost of capital from industry publications and academic studies; downloading historical electricity market prices and constructing probabilistic distributions to reflect future uncertainty.

This study does not involve human participants. Instead, it draws on multiple technical and financial datasets:

- Case study site**:** An operational onshore wind farm located in *Ballincurry, Ireland*, with a rated capacity of 4.7 MW, consisting of two ENERCON turbines mounted on 77 m steel towers.

- Operational parameters: Turbine specifications, output characteristics, and site performance data from the case study.
- Capital expenditure (CAPEX) data**:** Derived from industry reports (WindEurope, 2022), and supplier cost estimates for repowering, lifetime extension, and decommissioning (Burke, 2023; Wind Measurement International, 2024; Interreg Europe, 2024).
- Electricity price distributions: Obtained from energy market data (ENTSOE, (2025) and verified by SEMOpx, (2025).
- Other financial costs such as the cost of capital and inflation rates are taken from academic literature and industry reports.
- Maintenance and operational cost assumptions**:** Sourced from academic literature and technical reports related to ageing turbine performance.

These inputs provide the financial and technical basis for modelling the option value of EoL decisions. All data were standardised into a consistent time horizon and cost base, ensuring compatibility within the financial model.

The modelling process proceeded in several stages. First, baseline NPVs were estimated for each end-of-life (EoL) option, repowering, lifetime extension, and decommissioning, under deterministic assumptions to establish comparative benchmarks. Next, key uncertain parameters, particularly electricity prices, were simulated using probability distributions, with each Monte Carlo run generating a distinct cash-flow trajectory and enabling stochastic valuation. The model then applied real options analysis to estimate the financial value of delaying or selecting among EoL choices, deriving option values by comparing expected NPVs across simulated scenarios and capturing the upside potential of flexibility. Finally, validation and sensitivity testing assessed the robustness of results under varying assumptions about price volatility and cost escalation.

No formal ethical approval was required ss this study uses only secondary data and operational parameters from publicly available or non-personal sources. Ethical considerations include maintaining data accuracy, transparent reporting of assumptions, and ensuring that proprietary or commercially sensitive information is not disclosed especially the case study financial stance.

Several limitations should be noted. The results are case-specific, reflecting the characteristics of a single wind farm and therefore not necessarily generalisable to other sites, turbine types, or regulatory environments. However, the methodology can be adopted to any renewable or wind energy project. Data uncertainty affects the analysis, as CAPEX and O&M estimates vary widely across projects and markets, and published figures may not fully capture site-specific realities. Finally, the model uses simplified operational assumptions, meaning that real-world constraints such as grid curtailment, planning restrictions, and financing conditions are not fully incorporated.

4.3.3 Method of study 3

This study explores community investment in onshore wind energy through behavioural decision-making frameworks, focusing on how risk attitudes, prior experience, and socio-demographic characteristics shape investment decisions. It adopts a mixed-methods design, combining a quantitative descriptive cross-sectional survey with qualitative focus group discussions. The cross-sectional approach allows for the assessment of perceptions and behavioural intentions at a single point in time, aligning with the aim of comparing communities in distinct geographical and socio-cultural settings. Cross-sectional research is characterised by observing participants at one point in time, examining natural rather than intervention-induced differences, and selecting groups based on pre-existing characteristics rather than random allocation (Hunziker & Blankenagel, 2024). The design is efficient, cost-effective, and appropriate for exploratory research involving multiple countries and resource constraints.

The mixed-method design enriches the analysis by integrating qualitative insights into behavioural decision-making processes, enabling a deeper understanding of how risk attitudes, experience, and socio-demographic characteristics influence willingness to invest in wind energy.

The two case studies (Ireland and Tanzania) were selected representing developed and developing countries, following different practices in wind energy, economic differences, and variation in power generation options. Ireland's electricity supply is privatised, has high wind energy penetration in the energy mix, and is well developed. Tanzania is still struggling to provide electricity throughout the country. Tanzania has

fourteen times Ireland's population (Worldometer, 2025), yet wind energy remains largely unfamiliar there. In Ireland, communities are accustomed to wind power, many live near turbines, participate in investment schemes, and understand the associated risks and benefits. In contrast, Tanzanian communities generally have limited awareness of the wind sector and its implications. The contrast between the two countries adds valuable depth to the analysis.

Data were collected using a questionnaire, comprising twenty-six questions, including consent. The questionnaire included: Part A**,** fifteen questions assessing individual risk attitudes, identifying whether respondents were risk-tolerant or risk-averse and Part B**,** ten questions focusing on sustainability values, perceptions of investment in wind energy, and demographic characteristics. Surveys were administered in person and distributed through community networks. The focus group discussions were guided by an interview protocol exploring themes such as trust in developers, familiarity with wind farms, perceived risks, and investment preferences. All data were anonymised and prepared following standard ethical and analytical procedures.

Participants were adults residing in Ireland and Tanzania. Sampling strategies differed across locations to reflect the context and feasibility of data collection. In Ireland, convenience sampling was used, targeting individuals who were readily accessible and who voluntarily agreed to participate. In Tanzania, purposive cluster sampling was employed, focusing on two villages in the Mpanda District selected for their relevance to the study's comparative aims and their contrasting socio-cultural and energy contexts relative to Ireland. A total of 125 survey responses were collected in Ireland and 267 responses in Tanzania. After data cleaning, usable samples consisted of 115 and 237 responses, respectively. Focus group discussions were held in Ireland, in county Donegal, with a total of twenty-eight participants. These discussions helped contextualise quantitative findings and offered deeper insights into community concerns, motivations, and perceptions of wind energy investment.

Data analyses were conducted in the following stages. The quantitative component involved data cleaning to remove missing or invalid responses, standardise coding, and ensure completeness. Descriptive statistics were then generated to summarise risk attitudes, investment willingness, and key demographic characteristics, followed by

multivariate regression analysis specifically ordered logistic models to examine how risk preferences, prior experience, socio-demographic factors, and geographical context influence willingness to invest in wind energy. The qualitative component entailed reviewing focus group transcripts and notes through thematic analysis to identify recurring themes related to trust, perceived risks, past experiences, and investment motivations. These qualitative insights were used to contextualise and triangulate the quantitative findings, resulting in a more comprehensive understanding of behavioural decision making in community wind energy investment.

Ethical considerations included an approval from the university Social Research Ethics Committee (SREC), informed consent, anonymity, and voluntary participation (Appendix C, D, and G respectively). All participants were briefed on the study's purpose, and consent was obtained before survey completion or focus group involvement.

Data were stored securely, and all identifying information was removed prior to analysis. The study was deemed low risk as it did not involve sensitive personal data or vulnerable populations. The cleaned data is stored in the Zenodo repository.

Several limitations should be acknowledged. The use of convenience sampling in Ireland and purposive sampling in Tanzania restricts the generalisability of the findings to wider populations. The cross-sectional design captures perceptions at only one point in time, limiting the ability to infer causality or observe changes in attitudes. Because the study relies on self-reported data, responses may be influenced by social desirability bias or inaccurate reporting of risk attitudes. Cultural differences between Ireland and Tanzania may also reflect broader socio-economic contexts that cannot be fully controlled for. Finally, focus groups were conducted only in Ireland, which constrains the cross-cultural depth of the qualitative interpretation.

4.4 Methodological integration and synthesis

This section explains how the methods employed across the three studies are integrated into a coherent and unified research strategy. Rather than treating the studies as isolated empirical exercises, the thesis adopts an intentionally integrative methodological design in which the findings, assumptions, and analytical outputs from

each study inform and reinforce one another. Such integration is necessary given the thesis aim of understanding wind farm end-of-life decision making as a complex socio-technical and financial process shaped by interacting forms of uncertainty, risk, and stakeholder behaviour.

Mixed-method research is most effective when integration occurs not only at the level of data collection, but also at the levels of conceptual framing, research design, and interpretation (Creswell and Clark, 2017; Teddlie and Tashakkori, 2010). In this thesis, integration is achieved through a shared conceptual lens centred on risk, a complementary division of analytical labour across studies, and a sequential flow of insights between quantitative modelling and social inquiry.

4.4.1 Logic of integration: complementarity rather than convergence

The methodological integration in this thesis follows a complementarity logic, rather than a strict triangulation or convergence model. Complementarity allows different methods to address distinct dimensions of the same phenomenon, producing a richer and more complete understanding than any single method could achieve alone (Carroll and Rothe, 2010).

Each study focuses on a different but interrelated component of wind farm end-of-life decision making:

- Study 1 examines operational and financial risks arising from turbine lifetime failures, focusing on realised profit variability and portfolio effects.
- Study 2 evaluates the economic value of strategic flexibility at end-of-life, using real options analysis to assess repowering, lifetime extension, and decommissioning under uncertainty.
- Study 3 explores how risk is perceived and negotiated by communities, and how these perceptions influence investment decisions.

Rather than seeking methodological convergence through identical measures or datasets, the studies collectively address different analytical levels technical, financial, and social of the same decision context. This design aligns with pragmatic mixed-methods research, which prioritises explanatory adequacy and practical relevance over

adherence to a single methodological tradition (Creswell and Clark, 2017; Morgan, 2007).

4.4.2 Conceptual integration through risk

Risk functions as the central integrative concept across all three studies, providing a common analytical language while allowing for methodological diversity. In mixed-method research, conceptual integration is often more important than procedural integration, as it ensures coherence in interpretation even when methods differ (Maxwell and Loomis, 2003).

Across the thesis, risk is conceptualised and operationalised in multiple, complementary ways:

- In Study 1, risk is treated as a probabilistic and quantifiable phenomenon, captured through failure distributions, revenue losses, and tail-risk measures such as Value-at-Risk and Conditional Value-at-Risk (Rockafellar and Uryasev, 2000).
- In Study 2, risk appears as uncertainty in future cash flows, electricity prices, and investment timing, addressed through Monte Carlo simulation and real options valuation (Trigeorgis and Reuer, 2017).
- In Study 3, risk is understood as a socially constructed perception shaped by experience, trust, affect, and contextual knowledge, drawing on behavioural and social risk theories (Slovic, 1988; Aitken, 2010).

This multi-dimensional treatment reflects established insights in energy and risk research that risk is simultaneously objective and subjective, measurable and interpreted (Renn, 2008; Sovacool and Ratan, 2012). By explicitly acknowledging these different manifestations, the thesis avoids reducing social judgments to purely financial metrics, while also avoiding interpretive analyses detached from material and economic constraints.

4.4.3 Sequential and informational integration across studies

Integration in this thesis also occurs through a sequential and informational logic, where earlier quantitative studies inform the design and interpretation of later social

research, and social findings contextualise economic results. Such sequential integration is a recognised strength of mixed-method designs, particularly when studying complex decision-making processes (Creswell and Clark, 2017).

Specifically:

1. Informing survey design: Outputs from Studies 1 and 2 particularly patterns of financial risk, uncertainty, downside exposure, and return variability directly informed the development of the survey instrument in Study 3. Financial attributes such as volatility, probability of loss, and long-term uncertainty horizons were translated into perceptual and attitudinal survey items, ensuring conceptual alignment between objective and perceived risk (Slovic et al., 2013).
2. Contextualising financial results: Findings from Study 3 provide interpretive context for the economic results of Studies 1 and 2. For example, even where repowering or lifetime extension demonstrates positive option value, community risk aversion, lack of trust, or limited familiarity may constrain the practical feasibility of these pathways, consistent with social acceptance literature(Devine-Wright, 2011; Wolsink, 2007).
3. Integrated interpretation: In the decision support framework chapter, results from all three studies are interpreted jointly, allowing financial viability, operational risk, and social feasibility to be considered simultaneously rather than in isolation.

This form of integration strengthens the explanatory power of the research and reflects calls in energy scholarship for decision frameworks that explicitly link techno-economic analysis with social dynamics(De Laurentis and Windemer, 2024; Ellis et al., 2007).

4.4.4 Integration through shared contexts and case anchoring

Methodological integration is further reinforced using shared contextual anchors, particularly Ireland as a recurring empirical reference point. Ireland features in electricity price modelling and operational assumptions in Studies 1 and 2, as well as in the community perception and investment analysis in Study 3. This overlap enables

analytical continuity between financial modelling and social research, ensuring that community perceptions are interpreted against realistic market and operational conditions rather than abstract or hypothetical scenarios.

The inclusion of Tanzania in Study 3 extends the analysis by testing how behavioural and perceptual insights vary across contrasting socio-energy contexts. Comparative case study research has been shown to enhance analytical depth by revealing how contextual factors shape decision making processes (Yin, 2018). Importantly, Tanzania is not introduced as a competing case to Ireland, but as a complementary context that broadens the interpretive scope of the social findings without fragmenting the overall methodological coherence.

4.4.5 Methodological integration and research quality

The integrated design enhances research quality by strengthening multiple dimensions of validity and robustness. Mixed-methods scholars argue that validity in integrative designs should be understood pluralistically rather than through a single criterion (Teddlie and Tashakkori, 2010)

In this thesis:

- Analytical validity is enhanced by grounding social research instruments in empirically modelled financial risk patterns.
- Interpretive validity is strengthened by situating quantitative outcomes within real-world social perceptions, trust dynamics, and experiential factors.
- Practical relevance is improved by addressing both investor-oriented decision metrics and community-facing considerations that increasingly shape renewable energy outcomes.

Rather than relying on method-specific notions of validity alone, the thesis achieves coherence through transparent assumptions, theoretical consistency, and alignment between research questions, methods, and interpretation.

4.4.6 Contribution of the integrated methodological approach

The methodological integration achieved in this thesis constitutes a contribution in its own right. Existing research on wind farm end-of-life decisions has largely treated

technical performance, financial valuation, and social acceptance as separate analytical domains. By integrating financial risk modelling, real options valuation, and behavioural analysis within a single conceptual framework, this research demonstrates how end-of-life decisions can be analysed as risk-mediated, multi-actor investment choices.

This integrated approach responds directly to calls in renewable energy research for holistic decision-making frameworks that recognise wind farms as dynamic socio-technical systems rather than purely economic assets (Sovacool et al., 2020; Wolsink, 2018). It also provides a transferable methodological template for future research on ageing renewable energy infrastructure, supporting decision making that is technically sound, economically robust, and socially legitimate.

4.5 Ethical considerations

4.5.1 Researcher stance

This research is undertaken from a pragmatic and reflexive researcher stance, consistent with the epistemological and ontological positions outlined earlier in this chapter. The researcher does not adopt a detached or purely positivist role, nor a fully relativist interpretivist position. Instead, the stance taken recognises that knowledge about wind farm end-of-life decision making is co-produced through the interaction of empirical modelling, theoretical framing, and interpretation of social meanings. Financial risks, operational performance, and market behaviour are treated as phenomena that can be modelled and analysed with a high degree of objectivity, while community perceptions, risk attitudes, and investment motivations are acknowledged as context-dependent and socially constructed. The researcher therefore moves between analytical roles, at times acting as a modeller of objective risk and value, and at others as an interpreter of subjective experience and perception.

Reflexivity is an integral component of this stance, acknowledging that researcher positioning influences every stage of inquiry (Berger, 2015). In quantitative studies, reflexivity is enacted through transparent documentation of assumptions, sensitivity analysis, and critical evaluation of model limitations, recognising that risk metrics such as Value-at-Risk and real options valuation are analytic constructs that structure,

rather than determine, future uncertainty (Rockafellar and Uryasev, 2000; Trigeorgis and Reuer, 2017). In the mixed-methods exploration of community perceptions, reflexivity extends to an awareness of contextual power relations and cultural norms that shape how questions about risk and investment are framed and interpreted (Charmaz, 2014). For example, differences in socio-economic context between Ireland and Tanzania suggest that assumptions of financial rationality may not translate uniformly across settings a point underscored in cross-cultural research on energy transitions (Sovacool and Dworkin, 2015).

Overall, the researcher stance is oriented toward analytical integration and practical relevance rather than advocacy for a particular end-of-life pathway or governance model. The objective is not to prescribe lifetime extension, repowering, or decommissioning as inherently superior choices, but to illuminate the conditions under which each becomes financially viable, operationally sensible, and socially acceptable. By maintaining this balanced and pragmatic stance, the research aims to produce insights that are credible to academic audiences while remaining meaningful and usable for practitioners, policymakers, and communities engaged in real-world wind energy decision making.

4.5.2 Research participants

Ensuring that participants clearly understood the nature of the research, the purpose of their involvement, and the voluntary basis of participation was central to the ethical design of this study, consistent with (Alhabsi, 2024) guidance on informed consent in social research. For all components involving human participants specifically Study 3, which included survey respondents and focus group participants an information sheet accompanied every invitation. This document outlined the aims of the research, the types of data to be collected, procedures for data storage and confidentiality, and the potential use of results in academic and policy-oriented contexts. Providing these details upfront ensured transparency and allowed participants to make an informed decision about taking part.

In line with University College Cork SREC recommendations, participants were given adequate time to review the information sheet, ask questions, and consider whether they wished to proceed. No individual was placed under pressure to participate, and

participation remained entirely voluntary throughout. Prior to taking part in focus group discussions, each participant signed a written consent form (see Appendix C). Consent procedures for the surveys (Ireland and Tanzania) were integrated into the first page of the questionnaire, where participants confirmed their agreement before proceeding.

Participants were also informed of their right to withdraw at any point without providing a reason and without any negative consequences. At the start of focus group, participants were asked for explicit permission to record the discussion. In the rare cases where recording was not permitted, detailed handwritten notes were taken to ensure accurate documentation while respecting participants' preferences.

Across both Ireland and Tanzania, careful consideration was given to ensuring that participants felt comfortable and respected during the research process, and that their contributions were treated with sensitivity given the diverse cultural, economic, and experiential contexts in which views about wind energy investments may differ.

4.5.3 Data storage

All data collected across the three studies were handled in accordance with institutional data management policies and established ethical guidelines. For Study 3, following the transcription of focus group discussions and the processing of survey responses, all digital files were stored on a secure, password-encrypted computer accessible only to the researcher. Quantitative datasets used in Studies 1 and 2 including turbine failure records, cost parameters, and electricity price series were similarly stored on encrypted institutional servers to ensure data integrity and confidentiality.

To protect participant anonymity, all qualitative and survey data were pseudonymised at the earliest stage using a numerical coding system, with no names or identifying characteristics retained in the working datasets. Survey data from Ireland and Tanzania were stored separately from consent forms to further minimise the risk of re-identification. Participants were informed of the data handling procedures, including how their information would be protected and how the anonymised data may be used in academic dissemination.

Long-term storage procedures follow the Ireland Data Service recommendations, whereby anonymised datasets will be retained for the period required under institutional policy and securely destroyed thereafter. All data, qualitative, quantitative, and model input parameters were managed to ensure confidentiality, security, and responsible stewardship throughout the research lifecycle.

4.6 Conclusion

This chapter has articulated and justified the methodological framework adopted in this thesis, demonstrating how a mixed-methods, multi-study design is necessary to examine the intertwined financial, technical, and social dimensions of end-of-life decision making for wind farms. Guided by a pragmatic epistemological stance, the research intentionally combines quantitative modelling and mixed-method social inquiry, recognising that no single methodological approach is sufficient to capture the complexity of investment decisions made under uncertainty. The framework prioritises analytical usefulness and real-world relevance, enabling the research to engage simultaneously with objective measures of risk and value and with socially constructed perceptions and behavioural responses.

The methodological approach developed in this chapter aligns closely with the broader aims of the thesis: to generate a holistic, empirically grounded understanding of how financial risk, investment flexibility, and community perspectives interact to shape wind farm end-of-life decisions. By integrating economic modelling with behavioural and social analysis within a coherent risk-based framework, the thesis bridges disciplinary boundaries and responds to calls for more holistic approaches to renewable energy research. The subsequent chapters present the empirical findings from each study, demonstrating how this integrated methodology supports a nuanced, policy-relevant, and socially informed understanding of wind farm end-of-life decision making.

Chapter 5 . The financial risks from wind turbine failures: a value at risk approach.

Abstract[1]
This chapter models the financial risk associated with the cost of turbine failures over the lifetime of a wind farm. These failures cause significant variation in realised profit on wind generation projects. A model of the fault generating process is presented and industry data is used to parameterise the model. The model is then used to measure the financial risk associated with the wind project. Risks are measured using the financial metrics Value at Risk (VaR) and Conditional VaR (CVaR) metrics. The study shows that the 95% lifetime VaR of a turbine is equivalent to 52% of the initial capital expenditure. However, as the number of turbines in a farm increases, this risk diminishes. These findings have significant implications for small scale projects, particularly community projects.

[1] This paper has been published in *Applied Economics* journal, Vol. 57, No 39. The research reported in this paper has been presented at the following conferences. RE-Wind, Wind Value, IAFA, CUBS, all in Ireland. Lead author, Dorcas Mikindani, co-authors, Peter Deeney, John O'Brien, Paul Leahy.

5.1 Introduction

There is a global effort to decarbonize power generation by using renewable energy in response to climate change (Balsalobre-Lorente et al., 2023), with wind energy becoming increasingly popular. Increased wind capacity lowers the mean and variance of production costs (Lynch and Curtis, 2016), strengthening financial resilience and market stability. However, wind farms face significant risks from turbine component failures. Initially, wind energy profitability relied on government subsidies, but as the industry moves towards full commercialization, understanding failure risks' impact on profitability is crucial, especially for new investors and community-based projects with smaller turbines which may not purchase a long-term guarantee from the manufacturer (Leaney et al., 2001)(Leaney et al., 2001). This paper aims to highlight the financial impact of failure risks, offering valuable insights for investors, insurers, and industry practitioners by developing a method to estimate and quantify these risks using investment finance measures.

The Chartered Institute of Management Accountants defines operational risks as those arising from an entity's structure, systems, people, products, or processes (Collier, 2005). In manufacturing, these risks involve physical asset damage, system failures, and employee safety. Financial losses from wind turbine failures include energy sales loss (opportunity cost) and replacement equipment costs (direct cost) (Rieger, 2004). This study focuses on uncertainty in random failures that can cause significant financial losses. High-risk projects, like small-scale community projects, often struggle to secure institutional finance, hindering renewable energy investment growth (Gabriel, 2016).

According to Modern Portfolio Theory, investors can reduce overall portfolio risk by diversifying their investments across uncorrelated assets (Mangram, 2013). In the wind energy industry, this means having multiple turbines in a farm to ensure continued power generation if one turbine fails. Turbines operate independently, so a failure in one, such as from a lightning strike, does not affect others. This is the same for failures of components such as generators, blades, and gearboxes. Financial theory uses measures like standard deviation and value at risk to analyze the benefits of this diversification given the industry characteristics of market fluctuations and technical

uncertainties (Du and Li, 2019). Whilst, regulatory authorities are faced with the challenge of developing policy measures that can mitigate these risks and encourage diversification of investment portfolios in renewable energy infrastructure.

Many studies on wind turbine failures are limited by data quality and availability(Li et al., 2016; Leahy et al., 2019). This study addresses this problem by using Weibull distributions fitted to industry turbine failure data, enhancing precision over studies relying solely on average failure rates. It extends the analysis to include financial risk and farm size, developing a model that captures random failure processes. This model generates failure profiles, measuring the financial risk of a wind project over its typical twenty-year life (Ziegler et al., 2018). Value at Risk (VaR) and Conditional VaR (CVaR) are adopted to measure risk consistently and effectively.

Results are normalized relative to initial CapEx to compare wind farm sizes. The total expected repair cost over a turbine's lifetime is 22% of CapEx. In 5% of worst-case scenarios (95% VaR), this cost exceeds 52%, with CVaR at 63%. VaR and CVaR values decrease as the number of turbines increases, suggesting risk reduction through diversification. The study highlights the importance of deploying multiple turbines to mitigate financial risks from individual failures. Focusing on the onshore wind industry, a 2.5MW turbine was analysed, reflecting typical capacities (Lantz, 2013; Serrano-González and Lacal-Arántegui, 2016; Tazi et al., 2017).

Figure 5.1 shows the number of turbines in European wind farms. Panel A details Ireland, where most farms have fewer than fifteen turbines, but larger projects are emerging. Panel B gives an overview of Europe. The UK leads with an average of sixty-one turbines per farm, indicating significant investment. The Netherlands follows with sixty, Germany with fifty, and Denmark with forty-two turbines per farm. These figures highlight a trend toward larger wind farms to meet renewable energy targets.

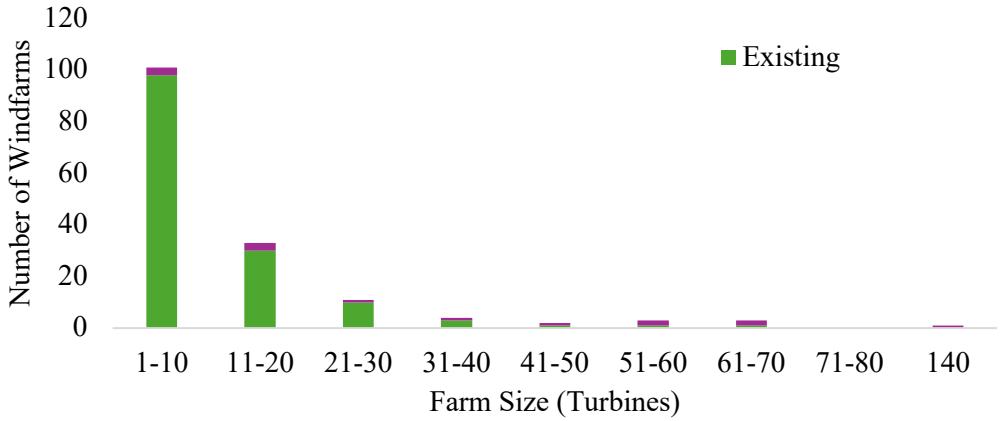
This study offers several contributions to the literature and wind energy industry. First, it provides a generic model for practitioners to assess risk profiles, applicable to any industry relying on complex equipment. Second, it scales standard financial metrics by CapEx, offering a common language for operators and investors to understand wind

farm risks, aiding in better risk hedging strategies. Third, it highlights the relationship between risk and wind farm size, relevant for small-scale and community projects. Lastly, it aids project planning by providing insights into the optimal number of turbines for efficient operations, particularly valuable for small community projects and wind energy initiatives in developing countries.

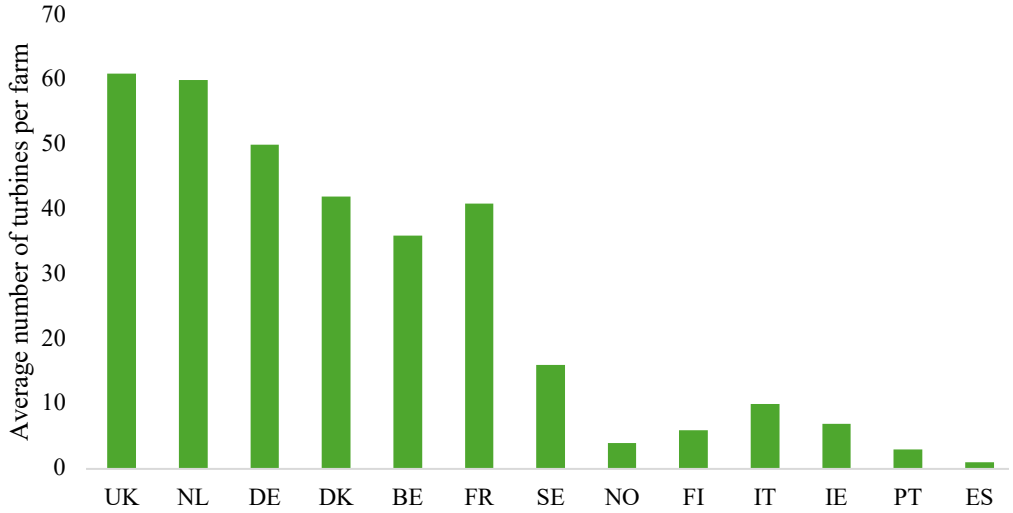
Figure 5.1: Turbines in European wind farms

This Figure presents the number of turbines in European wind farms. Panel A shows the distribution of turbines in the Republic of Ireland, for existing and under construction wind farms. Panel B shows the average of number of turbines in wind farms for different European countries commissioned in 2023.

Panel A: Ireland 2021



Panel B: Europe 2023



Source: Wind Europe 2023

The rest of the chapter is organised as follows: section 5.2 provides an extensive review of the existing literature. In section 5.3, the data and method are detailed, explaining how the random processes and parameters are modelled and failures are

transformed to financial risks. The results are presented in section 5.4. The chapter ends with discussion and conclusion in section 5.5.

5.2 Literature review

This section reviews the literature to first explain how risks affect wind energy industry focusing on risks from turbines' failures. Secondly, the effect of size in wind farms is reviewed to understand the studied relationship between size of the farm and the financial losses from operational risks.

5.2.1 Wind energy associated risks

The Global Wind Energy Council (GWEC) shows that wind energy industry is growing fast as nations pledge to meet 2030-2050 science-based targets for reducing greenhouse gas emissions (Lee and Zhao, 2022). In 2021 Europe installed 19.8 GW of new wind power capacity which is 18% more than in 2020 (Wind Europe, 2022). However, the technological advancement has shaped the wind energy industry resulting in more complex operational risks, requiring a more sophisticated approach to risk modelling. The wind energy sector requires substantial upfront investment(Pookpunt et al., 2020), expensive equipment, and long production cycles spanning up to twenty-five years(Zaoui et al., 2022). Operational and maintenance costs are uncertain, amidst political pressures for energy security and carbon emission reduction (Rashid Khan et al., 2021). These factors introduce risks challenging both investors and operators.

Previous studies have researched wind energy project risks. Sonnberger and Ruddat, 2017; Broughel and Wüstenhagen, (2022); and Lorente et al., (2023) showed that political risks can impact wind energy projects but Krane and Idel, 2021 proved that wind energy can reduce political risks from other non-renewable sources. Other risks affecting wind energy are environmental risks as studied in (Kucukali, 2016; Nazir et al., 2019), investment and financing risks (Erfani and Tavakolan, 2020; Lei et al., 2020; Qiu et al., 2020; Zhou and Yang, 2020), and risk from operations and maintenance as discussed in (Li et al., 2014; Weaver, 2012; Zhou and Yang, 2020).

To provide a comprehensive view of the topic, studies analysing the cost structure of wind energy projects have demonstrated that, after project commissioning, most of the

costs come from operation and maintenance (O&M) (Lau, 2020; Wagner, 2018). These costs which pose financial risks to projects account for 20%-25% of the total levelized cost of electricity (LCOE) of the current wind power systems (Costa et al., 2021). Unscheduled repairs due to random or unexpected failures is the biggest drivers of these costs (Kim et al., 2011). For a comprehensive review of operation issues in wind farms see Costa et al. (2021) and Ren et al. (2021).

Froger et al. (2018) find that wind turbine repairs are typically outsourced to third parties by investor-owned farms, leading to operational challenges due to conflicting interests. Investors aim to minimize costs post-initial investment, while repair companies (often the original equipment manufacturer) seek higher spending to uphold product reputation. They propose condition-based maintenance strategies for turbine failures. However, Tazi et al. (2016) argue that addressing reliability issues starts with meticulous project design, considering environmental constraints, manufacturing defects, costs, and the system's global warming potential.

Nielsen and Sørensen (2011) examined offshore wind turbine operations, finding that turbine failures significantly impact energy costs, necessitating risk mitigation planning. However, their analysis treated turbines as single components, overlooking their complex sub-assembly structure. Likewise, Li et al. (2016) assessed operational risks focusing solely on converters and condition monitoring, using wind turbine outage probability as a risk measure. Our study addresses this gap by analysing multiple turbine components, emphasizing those most prone to failures.

Bezrukovs and Sauhats (2017) evaluated economic and operational risks in wind projects, considering environmental (wind speed), economic (electricity market prices), and technical factors. Their study projected revenue and efficiency using stochastic models and Monte Carlo simulations. However, the study was limited to Latvia and only generators were considered. We fill this research gap by using a generic turbine structure and capacity and incorporate both financial and technical factors to assess risks posed by turbine failures.

5.2.2 Turbine failures in different wind farm sizes

The size of the farm is a crucial factor to considered when studying turbine failure risks in wind energy industry. Research has demonstrated the presence of economies of scale in various industries including power generation (Christensen and Greene, 1976; Hisnanick and Kymn, 1999; Triebs et al., 2016; Bejan et al., 2017). As firms expand their scale of operations, they can often achieve lower average costs per unit of output, benefiting from factors such as bulk purchasing, specialization, and efficient use of resources. However, alongside these cost advantages, there can also be increased risks associated with larger-scale operations. These risks arise due to the complexity and interdependencies that come with larger operations, including supply chain disruptions, technological failures, and regulatory challenges. To balance the risk versus farm size paradigm, Altuntas et al. (2021) argued that economies of scale benefits are best obtained with proper risk management practices.

Failure related risks are presented in (Lin et al., 2016), where the increase in capacity and turbine size is linked to increase in failures in turbine components. The findings showed that most wind turbine failures are due to failures of generators, gearboxes, or blades. The insurance market statistics listed that 85% of the failure claims come from these three components (Campbell, 2015). Giglio et al. (2018) show that management of assets including proper maintenance of infrastructure is essential for long-term economic viability of assets. Poorly maintained infrastructure causes risks of delays and damage in short run, while in the long run there is an increase in cost of disposal and reconstruction.

Nowakoski and Loomis (2023) analyze how project size influences the success of the wind energy industry, illustrating through case studies how scalability impacts product design and technology. The cost of electricity production was reduced more than six-fold over time. They highlight the industry's recognition of economies of scale, leading to the commercialization of larger wind turbines and a substantial reduction in electricity production costs over time. Yeter et al. (2020) propose a risk-based maintenance strategy for offshore wind turbines, determining the optimal number of turbines for minimizing the levelized cost of energy. Their assessment accounts for

various farm sizes, showing a significant decrease in electricity cost as the number of turbines increases, but costs begin to rise once the total exceeds sixty turbines.

Dismukes and Upton Jr. (2015) presented a model to test for economies of scale and learning effects. Both country-specific and industry-wide learning effects were analysed using a European offshore wind project. Their findings showed that the costs did not exhibit economies of scale and there was no robust evidence of a learning effect. However, although the sample was rich, it was heterogeneous in nature. Hence, they used the overnight cost (the cost of each project estimated separately) to aid comparison. Ederer (2015) evaluated the capital and operating cost efficiency of offshore wind projects. Cost was related to the issues of distance to the shore and water depth.

In contrast to other wind energy risk studies, this study analyses risks from wind turbine failures by using two risk metrics, VaR and CVaR. A combination of reliability analysis and financial analysis is presented by using Weibull distributions, Monte-Carlo simulations, and cost analysis. The paper investigates how the number of turbines in wind farms impacts the financial risk associated with turbine failures. The study approach involves assessing the risk profile of individual turbines and subsequently extending these findings to wind farms.

5.3 Data and method

5.3.1 Data

The analysis uses annual turbine failure rates data, cost of repair, and electricity market prices. Turbine failures are split into the three categories that dominate faults; generator, gearbox, and blades (Campbell, 2015). This allows a specific failure process to be modelled for each category. The study first examines an individual wind turbine, followed by aggregation of turbines to understand the effect of size in wind farms. The failure rates of generators and direct repair cost of the turbine components are obtained from Lantz (2013). Tazi et al. (2017) provides the failure rates of wind turbine gearboxes and blades, Table 5.1.

Table 5.1: Turbine components failures, ten years since commissioning

This table presents the observed failure rates for the three key turbine components, generators, gearboxes, and blades while in commercial use. Panel A presents the annual failure rate and Panel B presents average downtime per failure in hours. Data is taken from Lantz (2013) and Tazi et al. (2017).

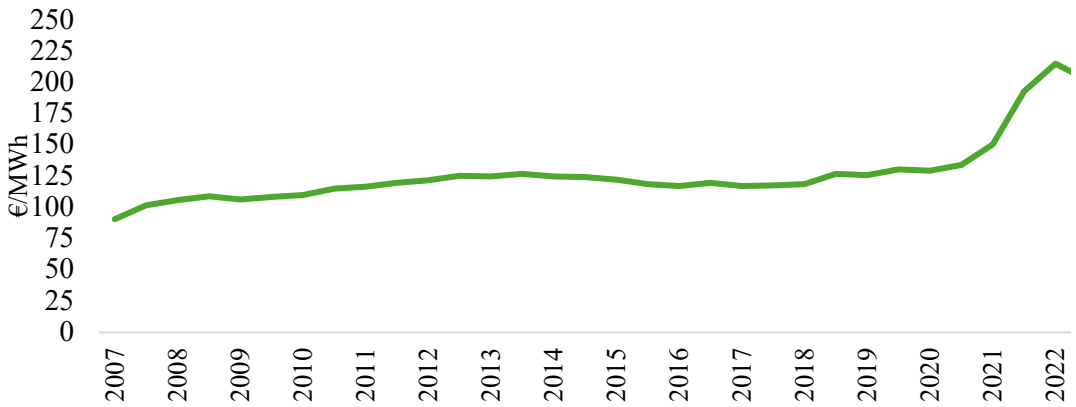
Panel A: Failure Rates			
	Generators	Gearboxes	Blades
1	0.008	0.005	0.035
2	0.009	0.027	0.015
3	0.027	0.036	0.021
4	0.033	0.078	0.028
5	0.028	0.100	0.034
6	0.063	0.058	0.026
7	0.078	0.040	0.013
8	0.036	0.074	0.010
9	0.040	0.050	0.016
10	0.024	0.036	0.004

Panel B: Downtime (hrs)		
Generators	Gearboxes	Blades
126	261	147

Electricity price data is taken from the Sustainable Energy Authority of Ireland (SEAI, 2023). The analysis uses the European (EU 27) long term average price €125.11 per MWh, taken over the period 2007 to 2023 (Figure 5.2). This price is used as a proxy to prices paid to wind farmers. The price is adjusted for inflation using the European average inflation rate of 2.05% (Webster, 2023; Eurostat, 2023 and Trading Economics, 2023).

Figure 5.2: Electricity prices (EU27)

Commercial electricity prices in Europe from January 2007 to June 2023. The data is from the Sustainable Energy Authority Ireland (SEAI).



5.3.2 Discount rates

This study uses a discount rate of 7% a typical representative value for discount rates in onshore wind projects, based on data collected for a wide range of EU countries. However, discount rates are specific to individual projects, as they can vary across countries (Steffan, 2020; Roth et al., 2021) and within countries, due to idiosyncratic differences across projects or industry factors (Saługa et al., 2021), including variables such as the investing company's age and size (Garcia et al., 2016).

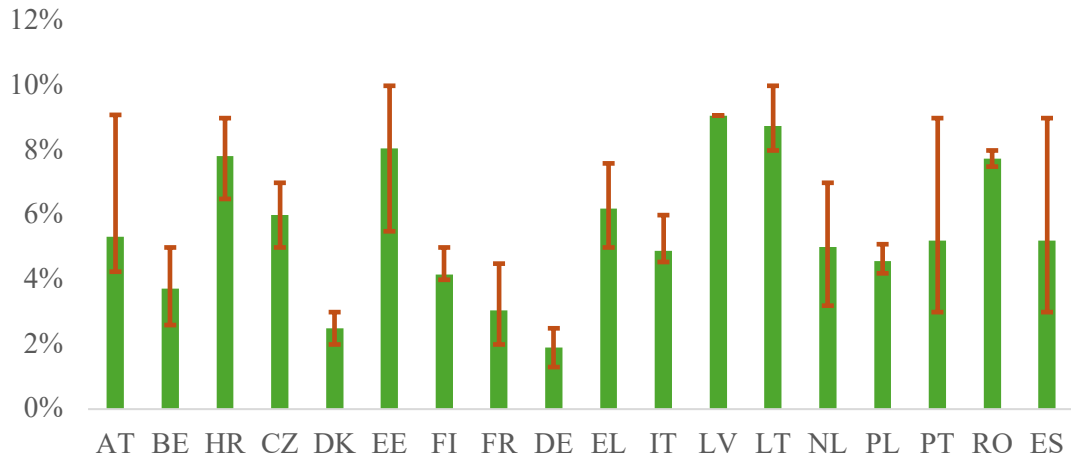
Steffan (2020) surveyed the literature for the cost of capital across a range of countries and renewable technologies over the period 2009-2017. He provided estimates for twenty-three EU countries for onshore wind. The results show significant differences across countries from 3.0% in Germany to 11.7% in Greece, with a mean value of 7.8%. However, most of the estimates are dated to 2014 and there is some evidence of a downward trend over time.

Roth et al. (2021) present a more recent survey of renewable energy projects across Europe. The paper presents the average cost of capital for onshore wind projects in nineteen countries, along with the maximum and minimum reported for each country, see Figure 5.3, gathered from November 2019 to April 2020. The average cost of capital is 5.5%, but again there is considerable variation between countries which ranges from 1.9% to 9.1%.

The representative rate of 7% selected for our analyses lies between the mean values of Roth et al. (2021) and Steffan (2020). It is also consistent with the generic 6.5% to 9% range noted by the International Energy Agency (IEA, 2020A) for renewable energy and their central estimate for commercial power generation of 7% (IEA, 2020B). The results of both Steffan (2020) and Roth et al. (2021) highlight the difficulty in defining a standard base rate. Both show significant cross-sectional variation across countries, while Roth at al. (2021) also identifies differences within countries with 63% of the countries have a range above 2% between maximum and minimum cost of capital, with a maximum range of 6%. Stress testing demonstrates that results are robust for any reasonable discount rate.

Figure 5.3: EU cost of capital for onshore wind projects

This figure shows the cost of capital for Onshore Wind Projects across nineteen European Union countries between September 2019 and April 2020 sourced from (Roth et al., 2021). The red bars mark the minimum and maximum values for countries.



5.3.3 Method

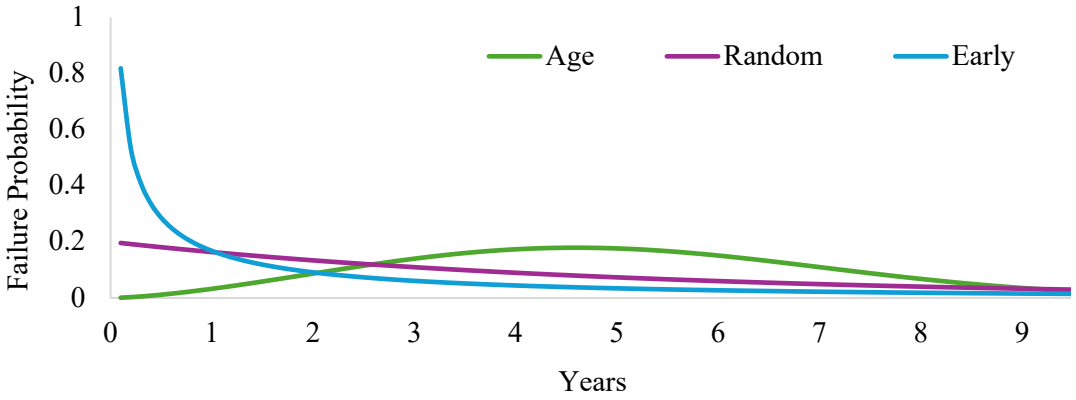
Turbine failure processes are modelled using Weibull processes, with unique parameters estimated for generators, gearboxes, and blades. An optimization process tailors the distributions using industry data. Monte Carlo simulation estimates fault distribution over a turbine's lifetime, converting simulated failures into financial costs and risk distributions. VaR and CVaR metrics describe the outcomes, where failure is defined as damage requiring a complete component replacement and halting power generation.

5.3.3.1 Optimisation process

The use of a Weibull distribution is a standard statistical method used in modelling engineering failures (Hribar and Duka, 2010) and has been used to model failures in power systems (dos Santos and de Barros, 2015), electrical components and space craft (Imken et al., 2018). The Weibull distribution is defined by two parameters, k and λ, referred to as shape and scale respectively. The value of k defines the dominant failure mode, with $k < 1$ indicating early failures and $k > 1$ indicating increasing failures from age. Random failures are indicated by $k = 1$, see Figure 5.4.

Figure 5.4: Weibull failure distributions

This figure shows three Weibull functions over time. Age related failures has a shape parameter $k>1$ representing failures due to wear and tear, early failures have a shape parameter $k<1$ indicating equipment damage or fault installation, and lastly random failures occur to any other reasons rather than age and early with a shape parameter $k=1$.



The probability density function (pdf) of the Weibull distribution is

$$f(t|k,\lambda) = \frac{k}{\lambda}.(\frac{t}{\lambda})^{k-1}.e^{-(\frac{t}{\lambda})^k}, t \geq 0 \qquad (5.1)$$

Where t is the time to failure, k is the shape parameter, determining the shape of the distribution and λ is the scale parameter, representing the characteristic life. The distribution is only defined for $t > 0$ and k and λ are positive, t and λ have the same units, in our case years, while k is a scalar. The cumulative distribution function (cdf) is

$$F(t|k,\lambda) = 1 - e^{-(\frac{t}{\lambda})^k}, \mathrm{t} \geq 0 \qquad (5.2)$$

An optimisation process is used to find the combination shape and scale parameters that provide the closest fit between the expected failure rates generated by the Weibull distribution and the failure rates observed in commercial wind farms. The best fit is defined as the lowest sum of square errors (the difference between the estimated and observed failure rates) across the range of observed data. The expected failure rate in a year, $\widehat{R_t}$, for a given pair of parameters k and λ is

$$\widehat{R_t} = F(t|k,\lambda) - F(t-1|k,\lambda). \qquad (5.3)$$

The optimisation process finds the values of k and λ that minimise the objective function $J(k,\lambda)$.

$$J(k,\lambda)=\sum_{t=1}^{T}(R_t-\widehat{R_t})^2 \quad (5.4)$$

R_t is observed failure rate in year *t* and *T* is the sample size.

4.3.3.2 Cost of faults

The cost of a single failure is the sum of direct cost (the cost of repair) and opportunity cost, (the lost energy sales due to downtime). All cost are discounted to the commissioning date of the turbine, that is $t = 0$.

$$C_n = \frac{DC_n + OC_n}{(1+d)^{t_n}} \quad (5.5)$$

C_n is discounted cost of fault n, t_n is the time of the fault, d is the discount rate, DC_n is the direct repair cost, OC_n is the opportunity cost, The simulated faults are summed over the life-time of a turbine to get the total cost of failure

$$LC = \sum_{n=1}^{N} C_n \quad (5.6)$$

The opportunity cost of a turbine failure is the lost revenue from energy sales that would have been made had the wind turbine remained operational. The opportunity cost is a function of the installed capacity, *IC,* utility factor, *U,* price, P, and downtime, DT.

$$OC = IC.U.P.DT \quad (5.7)$$

Installed capacity is the wind turbine's maximum production in megawatts (MW); utility factor, set at 24% according to IEA (2020), is the average power produced divided by installed capacity. Downtime is the loss of energy generation measured in hours from fault occurrence to repair completion. Price is in € per Megawatt-hour. fault occurring until repair is complete. Price is expressed in € per Megawatt-hour.

Financial risk is assessed using VaR and CVaR (Hull, 2014). VaR determines the maximum potential loss over a specified time and confidence level, commonly used by traders, fund managers, and financial institutions. It offers a single metric

summarizing portfolio risk. This study adopts a 95% confidence level over a turbine's twenty-year lifespan. CVaR, also known as estimated tail loss, calculates the average potential loss exceeding the VaR threshold. While VaR measures potential loss at a certain probability level, CVaR estimates the expected loss in worst-case scenarios beyond the VaR level. VaR and CVaR are measured through a Monte Carlo simulation. The present value of the total cost of faults is repeatedly measured. The values are then ranked, the 95^{th} percentile value is the VaR, and the average of all values above the 95^{th} percentile is the CVaR.

Results are presented as a percentage of the initial CapEx to enable comparisons across wind farms of varying sizes. The CapEx of wind energy generation encompasses turbine, foundation, electric installation, grid connection, control systems, consultancy, land, financial costs, and roads. This approach facilitates the assessment of cost-effectiveness and efficiency over a wind project's lifespan and allows for comparisons between wind farms of different scales. Wind Europe (2022) offers data on investments in Europe, reporting 19.8GW installed capacity at €24.8 billion, resulting in an average CapEx of €1.25 million per megawatt installed.

5.4 Results

The results are presented in three sections: the failure distributions that provide the basis of the Monte Carlo simulations, cost quantification of turbine component failures, and risk profiles of wind farms over their operational life. This final section presents the key findings of the paper, the distributions of costs due to random fault process, the quantification of the risk in terms of VaR and CVaR, and the relationship between windfarm size and investment risk.

5.4.1 Failure distributions

Weibull distribution parameters, derived from industry data through optimization (Section 4.3.3.1, Table 5.2), reveal distinctions among turbine components. Gearboxes and generators exhibit scales close to the turbine's typical lifetime, with shape values above one, suggesting wear as the primary failure cause. In contrast, blades have a shape parameter below one, indicating a longer lifespan, often surpassing other components. This corresponds with literature highlighting recycling challenges for used blades (Liu et al., 2022; Nagle et al., 2022).

Table 5.2: The modelled failure parameters

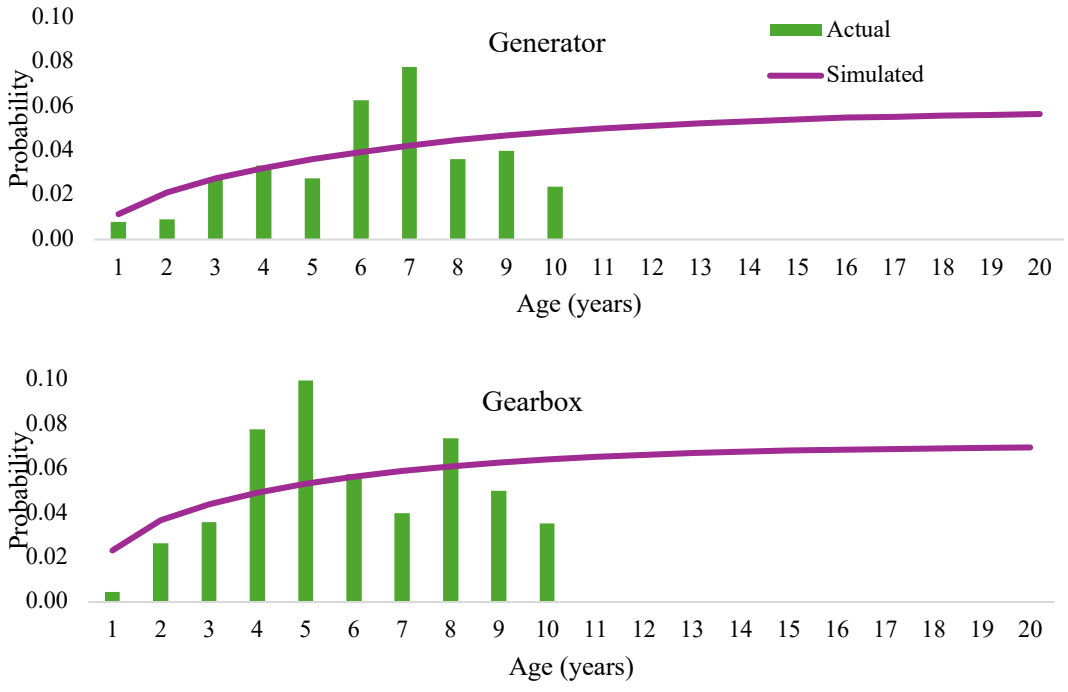
This table lists the pairs of parameters (shape and scale) for the Weibull distributions used to simulate turbine failure distributions.

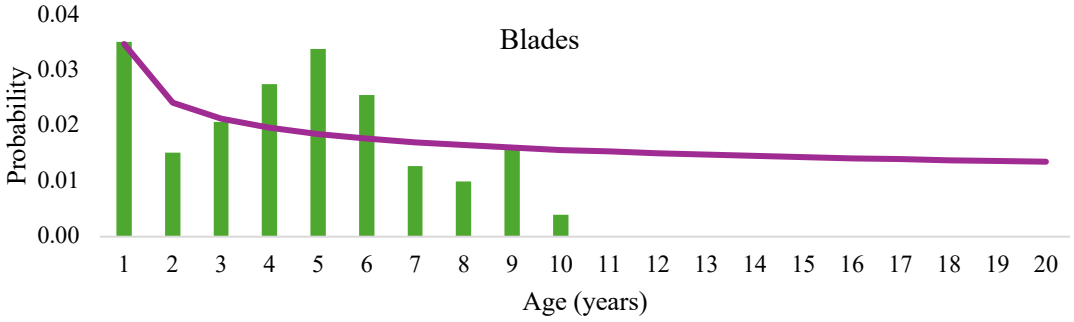
	Shape-k	Scale- λ (Years)
Generator	1.52	18.72
Gearbox	1.38	15.02
Blades	0.75	86.80

Industry data availability is limited to the first half of the turbines' operational life and statistical processes are used to model failure distributions over the lifetime of a turbine. The simulation uses Weibull distributions to model the failure behaviour of wind turbine components over time. Industry and simulated annual failure rates are presented in Figure 5.5.

Figure 5.5: Industry vs simulated failure probabilities

The figure shows the simulated failure probabilities over the lifetime of a turbine and the actual (Industry) data. The information is shown for three components Generators, Gearboxes, and blades. The X axes shows age in years and the Y axes shows failure probability.



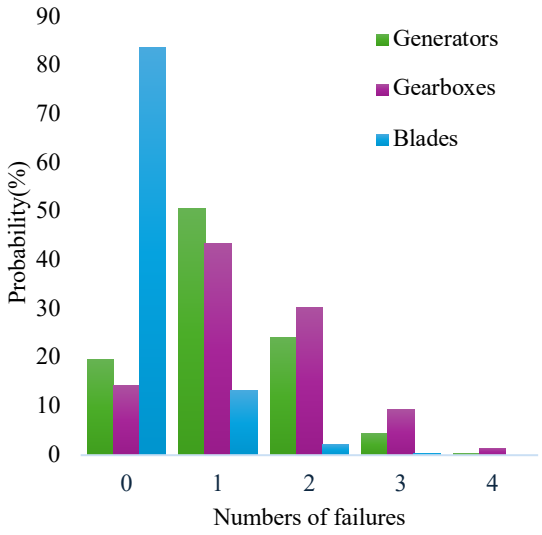


Failure distributions of a single turbine are presented in Figure 5.6, first showing failure probability in turbine components (Panel A) and then in total (Panel B). Gearboxes have the highest number of failures followed by generators and then blades. The probability of having one failure is 50% for generators and 43% for gearboxes. More failures are displayed in gearboxes compared to generators, with higher probability of multiple failures. There is an 83% probability that blades will not fail over the lifetime of a turbine.

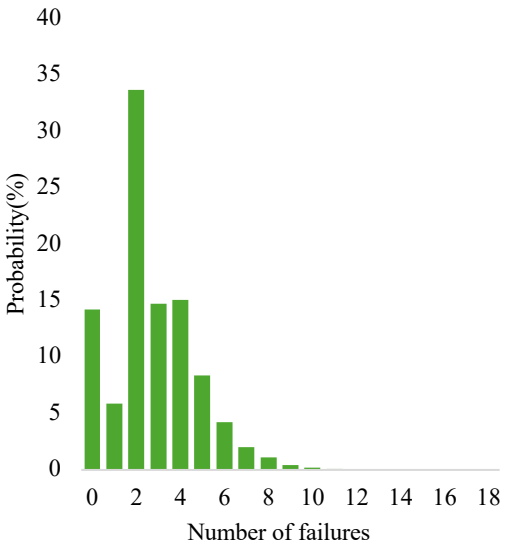
Figure 5.6: Turbine failure distributions

This figure presents the number of failures in a turbine's lifetime. Panel A shows the probability of failures for each component of a turbine, while Panel B the distribution of total failures over the lifetime of a turbine.

Panel A: Component failure distribution



Panel B: Turbine failure distribution



Panel B highlights the financial risk due to random faults in the components. While 15% of turbine have no faults over their lifetimes, another 15% is expected to have five or more faults. The costs associated with this faults will result in significantly

different economic outcomes and emphasises the importance of understanding and quantifying those risks.

Next, we group turbines into wind farms and analyze their fault profiles. Seven wind farms, with turbine counts ranging from one to one hundred, are modelled to estimate mean failure rates and standard deviations over their operational lives (Table 5.3). The average number of failures rises linearly with farm size, while the variability, depicted by the standard deviation, also increases but at a decreasing pace. This variability represents financial risk, quantifiable using VaR and CVaR metrics.

Table 5.3: Wind farms failure distribution

This table present the average number of failures, along with the standard deviation, for windfarms with sizes ranging from one to 100 turbines. The estimates are for failures across the windfarms' operational life.

Number of Turbines	1	5	10	20	40	60	100
Mean Failures	2.75	13.76	27.53	55.05	110.10	165.15	275.26
Standard Deviation	1.90	4.01	5.65	8.01	11.37	13.92	18.05

Unsurprisingly, the average fault increases linearly with windfarm size, and with that the expected cost. Standard deviation also increases with windfarm size, but in this case, it increases more slowly, proportional to the square root of farm size. The standard deviation reflects the variability, and consequently financial risk, in reliability of wind farms. The increase in standard deviation with farm size, indicates a growth in risk in absolute terms but the slower growth rate indicates a fall in relative terms. Understanding the link between farm size and risk is essential in the planning and financing stages of a windfarm project.

5.4.2 Estimated failure costs

In this section, failures are converted to financial cost. The typical cost of failure of each of the three components is first examined. The costs, the aggregate of the direct cost (repair) and opportunity cost (lost energy sales), are specified and presented in Table 5.4. The repair cost dominates, with opportunity cost accounting for less than 3.5% of the total across all three components.

Table 5.4: Turbine repair cost

This table presents the components of total cost (TC) of failure for the components of a turbine. The Opportunity Cost (OC) and Direct Cost (DC). The opportunity cost is calculated from the downtime (DT), Installed Capacity (2.5 MWh), Utility Factor (0.24), and price of electricity (€125.11 per MWh).

	DT (hrs)	OC (€)	DC (€)	TC (€)	OC (%)	DC (%)
Blades	147	9,289	374,689	383,978	2.42	97.58
Gearboxes	261	16,513	647,101	663,614	2.49	97.51
Generators	126	7,995	232,634	240,629	3.32	96.68

Repair costs are used to derive the cost of faults over the lifetime of a turbine, Table 5.5. Costs are broken down by the three components and express in present value terms. The average lifetime cost is €684,672. The main source of costs is faults in the gearbox, accounting for 73% of the total. This is followed by generators (21%) and blades (6%).

Table 5.5: Components discounted failure costs for 1MW

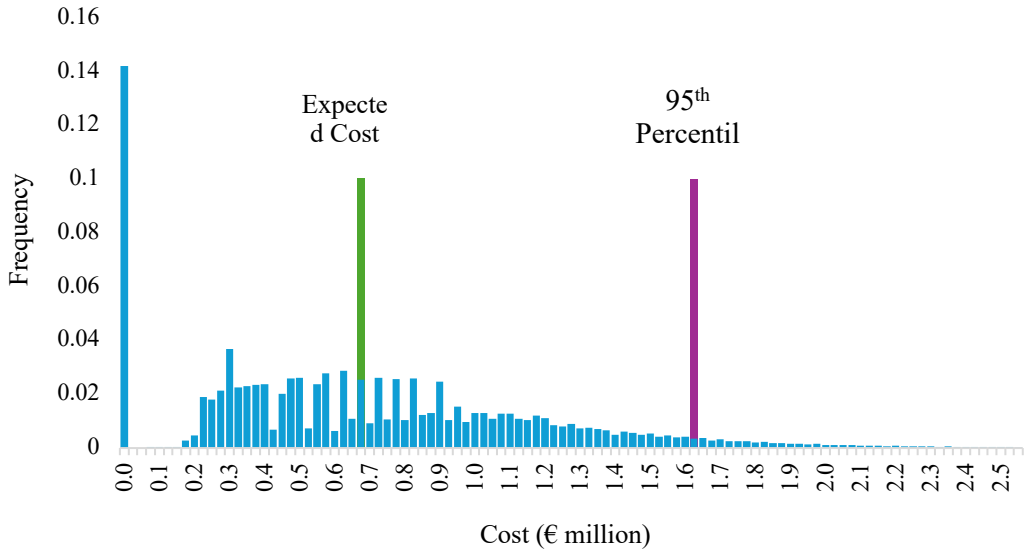
This table shows the present value of the expected cost of repairs over a turbine's lifetime. The costs are presented for each component and as an aggregate figure.

Component	Cost (€)	Total Cost (%)
Generators	146,679	21.42
Gearboxes	498,467	72.80
Blades	39,526	5.77
Total Cost	684,672	100.00

Figure 5.7 presents the discounted costs distribution. The average lifetime discounted failure cost is indicated by the green line and the red line identifies the 95% percentile of the distribution, that is the 95% VaR level. The distribution shows 14% of turbines do not have a single failure, highlighting the wide range of outcomes due to random failures

Figure 5.7: Turbine cost distribution

This figure presents the distribution of discounted failure cost for a single turbine. The green line indicates the expected cost, and the red line highlights the 95th percentile, the lifetime Value at Risk (VaR). Cost is in units of € million.



5.4.3 Risk metrics

The cost profiles allow quantification of the financial risk in a windfarm project due to random faults. The VaR and CVaR values for a single turbine are presented in Table 5.6, the results highlight the significant variation in realised profit due to random failures. The costs are scaled by the initial capital expenditure to allow comparison. The expected cost from failures is equivalent to 22% of CapEx. However, the 95% VaR from faults is equivalent to 52% of the CapEx. Significantly, in the worst 5% of cases, the average loss is equivalent to 63% of CapEx (the 95% CVaR), 41% above the expected value.

Table 5.6: Risk analysis for a single turbine

This table presents the expected cost, Value at Risk (VaR) and the Conditional Value at Risk (CVaR) of the wind turbine failures broken down by component. The Turbine costs is the aggregate of the three components and the normalised column shows the aggregate values relative to the initial capital expenditure. The cost values are in thousands of euros.

	Generator	Gearbox	Blades	Turbine	Normalised (%)
Expected Cost (€ '000)	147	498	40	685	21.91
95% VaR	354	1,159	283	1,624	51.98
95% CVaR	421	1,367	402	1,966	62.91

The final analysis is a study of the relationship between risk and wind farm size to understand the effect of diversification. The VaR and CVaR is calculated for a range of farm sizes, and then normalised relative to CapEx. The relationship between size and risk is presented in Figure 5.8. Panel A provides across a range of farm sizes from 1 to 100 while Panel B provides more detailed information on seven specific sizes. The focus is on normalised VaR and CVaR to allow comparison across wind farm size.

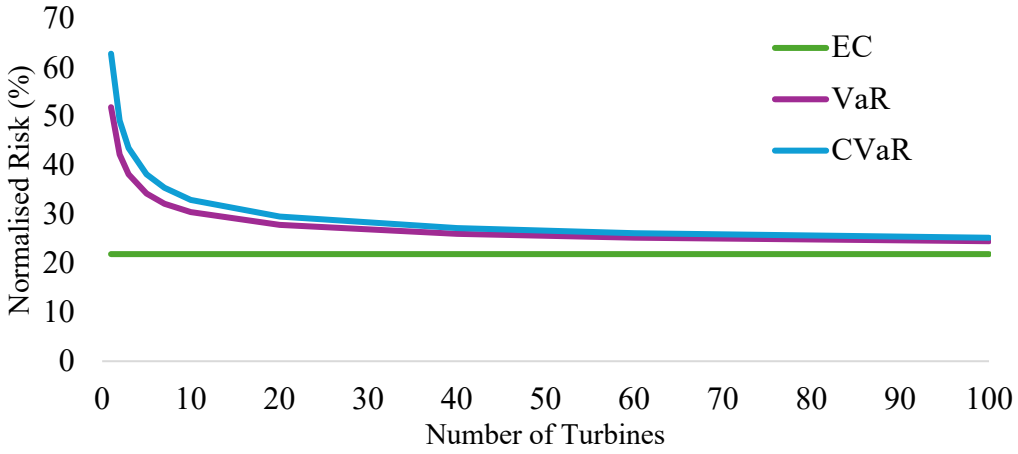
The general pattern is clear, as the number of turbines increases, the risk as a proportion of the investment declines, Figure 5.8, Panel A. Over the full range, VaR falls from 51.92% for a single turbine farm to 24.55% for a hundred turbine farm, the corresponding values for CVaR are 62.91% and 25.26%, respectively. The lower limit is 22%, the expected cost of repair. This represents a theoretical scenario in which all turbines incur the average repair cost, resulting in a zero-risk outcome. A single turbine has a VaR equivalent to 30% of CapEx above the minimum while this value falls to just 2.5% above the zero-risk level for one hundred turbines.

The relationship between size and risk, and consequently the benefits of diversification, is presented in more detail in Panel B. Over half the available reduction in risk can be achieved by increasing the size of a wind farm from one to five turbines. VaR falls from 51.98% to 34.77%. This represents a drop from 30% above the minimum level to 13%. A further increase to size to ten turbines brings the VaR down to 30.52%, only 8.5% above the minimum level, and capturing about three quarters of the available benefit from diversification. Beyond this level, the benefit of increasing farm size falls steadily.

Figure 5.8: Wind farms risk metrics

This figure gives the expected cost (EC), Value at Risk (VaR), the Condition VaR (CVaR) for wind farms ranging from one to one hundred turbines. The full range is shown in Panel A, while Panel B highlight the values for seven specific farms. The expected cost (22%) is the limit of risk reduction through increasing the number of turbines on a wind farm. Values in Panel B are presented in € '000.

Panel A: Variation of Risk and Farm Size



Panel B: Selected Farm Sizes

Number of Turbines	1	5	10	20	40	60	100
Expected Cost	685	3,423	6,847	13,693	27,387	41,080	68,467
95% VaR	1,624	5,371	9,540	17,449	32,598	47,500	76,716
95% CVaR	1,966	5,971	10,331	18,488	34,080	49,184	78,937
Normalised VaR (%)	51.98	34.37	30.52	27.91	26.08	25.33	24.55
Normalised CVaR (%)	62.91	38.21	33.06	39.58	27.26	26.23	25.26

5.4.4 Sensitivity analysis

The choice of discount rate is central to the analysis and the results presented here. Consequently, we perform stress tests the sensitivity of VaR estimates to discount rates. The results for a seven-turbine farm are analysed here but the results are similar for other farm sizes.

VaR is calculated for a range of values using the range of values of values for discount rate (6.5% to 9%) presented by the International Energy Authority (IEA, 2020). The results are presented in Table 5.7, along with the difference in value from the base case.

The change in Normalised VaR values ranges from 3.48% to -11.87% as a percentage of the central estimate as the discount rate moves from 6.5% to 9%. The results show the expected inverse relationship, VaR falls as the discount rate rises. More significantly, increasing the discount rate from 7 to 9% only decreases the VaR by 11.87%. This allows the conclusion that the findings presented are not sensitive to the selection of the discount rate, within a reasonable range.

Table 5.7: Discount rate sensitivity analysis

This table presents the normalised VaR for a seven-turbine farm, using a range of discount rates. The table also shows the difference of each estimate from the base case (7%) used in the analyses.

Discount rate (%)	5.0	5.5	6.0	6.5	**7.0**	7.5	8.0	8.5	9.0
Normalised VaR (%)	37.2	35.9	34.6	33.4	**32.3**	31.2	30.2	29.3	28.4
Difference from Base Case (%)	15.3	11.1	7.2	3.5	**-**	-3.2	-6.3	-9.1	-11.9

5.5 Discussion and conclusion

5.5.1 Implication of the findings

This paper outlines wind farm risk profiles based on industry data, revealing substantial variability in project cost due to random turbine failures across different farm sizes. The average repair cost of a single turbine nearly amounts to a quarter of CapEx, while in the 5% worst-case scenario, both 95% VaR and CVaR exceed half of CapEx. Despite similar average repair costs relative to CapEx across all farm sizes, risk decreases as farm size increases. Results indicate that compared to single turbine farms, excess risk decreases by over half for five-turbine farms and by three quarters for ten turbines. However, beyond this point, VaR declines at a notably slower rate. The findings highlight substantial financial risk for wind farms with fewer turbines. Larger commercial farms can offset risk through diversification with numerous turbines. As governments promote energy communities, they need to ensure robust risk mitigation measures are in place for these projects.

The findings have several economic policy implications for the wind energy sector.

1. Risk management policies. The wide fluctuations in costs caused by wind turbine failures highlight the need for strong risk management policies in wind

farm projects. We suggest policymakers create regulations or guidelines to address these risks, like mandating developers to maintain repair reserves or promoting advanced maintenance methods to reduce downtime.

2. Project Financing and Investment Decisions. Larger wind farms may entail comparatively lower risk than smaller ones, benefiting from economies of scale in maintenance and operation. Policymakers may need to ease financing access for larger projects to promote their growth and expansion.
3. Incentives for Scale. As wind farm size grows, the decreasing risk trend suggests potential economies of scale in managing turbine failure risks. Policymakers might incentivize project scaling to reduce sector-wide risk and enhance wind energy's viability as a renewable source.
4. Insurance and Risk Transfer Mechanisms. The findings highlight the potential financial impact of wind turbine failures, especially in worst-case scenarios. Policymakers might need to facilitate access to affordable insurance customized for wind farm developers and explore risk transfer methods like catastrophe bonds or public-private partnerships to manage risks efficiently.
5. Research and Development Support. Policymakers could allocate funding to research and development to enhance wind turbine reliability, performance, and maintenance technologies. These innovations could decrease failure rates, lowering overall risk and boosting wind energy's economic competitiveness.

Overall, these findings emphasize the need for proactive policy interventions to manage risks in wind farm development and operation, ensuring the sector's growth and sustainability. The study also informs end-of-life decisions for wind farms, such as repowering, lifetime extension, and decommissioning. When repowering involves deploying fewer turbines after permits expire, the increased risk from reduced turbine numbers must be quantified and addressed. The developed model can be expanded to assess risks beyond the normal lifetime, aiding in evaluating each end-of-life decision.

5.5.2 Conclusion

This study introduces a generic approach for modeling faults and quantifying financial risk arising from mechanical failure, using familiar metrics like VaR and CVaR. These methods aren't limited to wind energy but applicable across industries. When applied

to wind projects using proprietary data, they offer investors insights into financial risks early on. The study also underscores the higher relative investment risk for small-scale projects responsible for their own repairs, pertinent for policymakers considering community or developing country schemes often of smaller scale.

There are limitations to the results. Failure data is commercially sensitive, consequently a limited amount is publicly available. More data, and finer grained data would allow better estimates of the parameters of the failure processes. Similarly, the modelling could be improved by further subdivision of the failures beyond the three broad classes of generator, gearbox, and blades. This would allow improved allocation of costs beyond the averages used in this paper. Developing a comprehensive public database for reliability, availability, and maintainability is a significant challenge, but could bring far great reliability to planning and risk analysis in this area, encouraging investment.

Chapter 6 . Real options valuation for end-of-life investment decisions in wind farms

Abstract[2]

The European Union's climate targets necessitate a rapid expansion of wind energy; however, the aging turbine fleet presents challenges for end-of-life decisions, including repowering, lifetime extension, or decommissioning. This study applies real options analysis (ROA) with Monte Carlo simulations to evaluate these pathways, focusing on market uncertainties such as electricity prices and the cost of capital, based on a case study of an Irish wind farm. Results show that repowering yields significant option value across different market scenarios whilst the option value of lifetime extension is negligible, indicating minimal benefit from flexibility despite its potential short-term practicality. Decommissioning exhibits no option value and negative net present value (NPV), reaffirming its status as the least favourable alternative. The analysis underscores the advantages of ROA over traditional discounted cash flow methods by capturing flexibility and uncertainty in long-term energy investment. While case-specific, the framework is adaptable to other markets, providing a robust approach for optimising wind energy investments under uncertainty, offering insights for policymakers and investors, and supporting sustainable energy transitions.

[2] This paper has been submitted in *Annals of Operations Research* journal. The research reported in this paper has been presented at the following conferences. Wind Value, IAFA, CUBS, INFINITI in Ireland and UK. Lead author, Dorcas Mikindani, co-authors, Peter Deeney, John O'Brien, Paul Leahy

6.1 Introduction

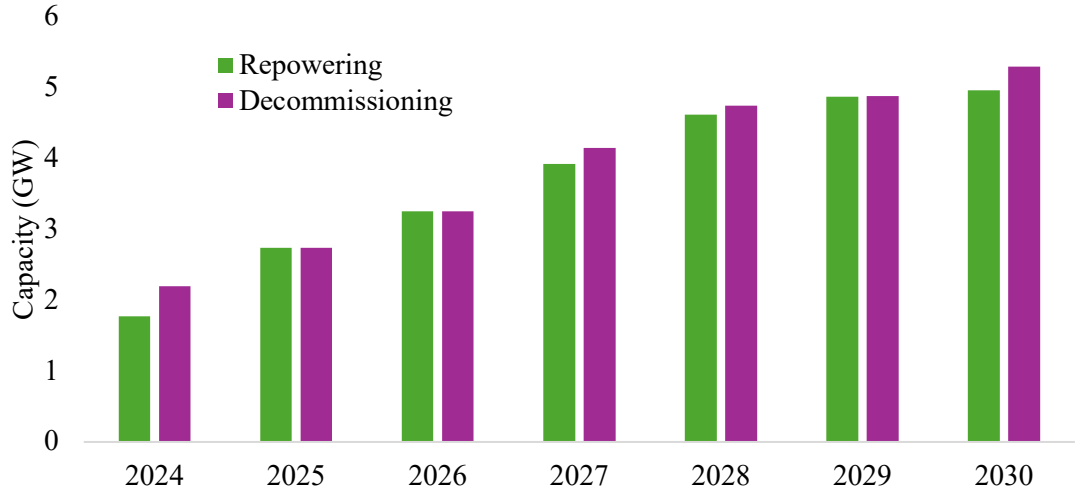
The European Union (EU) has set ambitious climate targets, aiming to increase greenhouse gas emission reductions from 40% to 55% by 2030 (European Commission, 2019). Central to this goal is the "Fit-for-55" package, which mandates an increase in the share of renewables in electricity supply from 32% to 40% within the same timeframe, necessitating a significant acceleration in wind energy investment. Specifically, the plan envisions the addition of 30 GW of new wind energy capacity annually (Wind Europe, 2021). Rapid transitions in the energy system demand significantly higher investment flows compared to the status quo (van Sluisveld et al., 2015). However, a growing challenge lies in the aging fleet of wind turbines, many of which are nearing the end of their designed operational lifespans. This presents critical implications for the overall installed wind energy capacity. Key decisions must be made regarding whether to repower these old turbines with modern technology, extend their operational lives, or to decommission them.

The end-of-life decisions are influenced by a complex interplay of economic, regulatory, and market factors (Agra Neto et al., 2024). This study aims to investigate how market dynamics shape investment strategies for wind farms at the end of their operational life. The study examines whether there is a value attached to wind farm operators' decisions regarding the future of their assets, focusing on changes in electricity prices and the cost of capital. These investment decisions are modelled using real options analysis to take account of the value of the choices available to the wind farm owner. Calculations are applied during a second operational phase beyond the typical 20-year lifespan of a wind turbine (Ziegler et al., 2018), supported by a data-driven case study of a wind farm in Ireland. The study is grounded in option pricing theory and uses a Monte Carlo simulation approach for option valuation. The wind farm is treated as an asset, with operators considering three investment pathways to optimise returns: repowering the wind farm by installing new, larger turbines, extending the life span of the wind farm, or decommissioning. Each investment pathway has an option that gives wind farm owners the right to take some specified action at present or in the future (Hull, 2014).

The urgency to accelerate wind energy capacity and meet ambitious decarbonization targets underpins the motivation for this study. Mitigating climate change requires deep, dynamic transformational change globally, which requires risk-opportunity analysis to be used in place of traditional cost-benefit analysis (Mercure et al., 2021). End-of-life strategies for wind farms have gained significant attention, with scholars examining investment optimisation methods and the factors influencing these critical decisions (Agra Neto et al., 2024). Among these strategies, repowering and lifetime extension have emerged as the most extensively explored options (Leite et al., 2022). These approaches offer several advantages, including the efficient use of existing sites, which mitigates environmental concerns and simplifies planning and permitting processes. Moreover, they often reduce costs associated with grid connection (Risso and Canale, 2022) and infrastructure, such as access roads. However, a 2023 report by Wind Europe underscores the challenges ahead: over the next seven years, 26 GW of capacity is expected to be added through repowered wind farms, while 27 GW will likely be decommissioned. At present there is 285 GW of wind capacity in Europe (Wind Europe, 2024 https://windeurope.org/data/products/wind-energy-in-europe-2024-statistics-and-the-outlook-for-2025-2030/) so the broader implications of end-of-life choices is significant, since these figures suggest that achieving climate targets will rely entirely on the deployment of new wind farms. Figure 6.1 shows the annual outlook of repowered and decommissioned wind projects in Europe up to 2030 (Wind Europe, 2023).

Figure 6.1: Repowering wind capacity in Europe

This figure presents the predicted repowering and decommissioning wind capacity in Europe, estimated by the repower EU project based on wind energy in Europe 2023 statistics and 2024-2030 outlook.



The results of this study highlight the critical role of option values in evaluating wind farm end-of-life strategies. Repowering demonstrates a significant option value across all scenarios, indicating that flexibility in timing and investment decisions can substantially enhance project value under uncertainty. In contrast, lifetime extension exhibits a negligible option value across all scenarios suggesting limited benefit from flexibility in this decision. While lifetime extension may still provide practical advantages in specific contexts, such as limited capital availability or regulatory constraints, its strategic option value is too small to influence investment outcomes meaningfully. Decommissioning remains the least favourable strategy, with negative NPV and no associated option value, and would only be rational under extreme market, technical, or regulatory environment that preclude continued operation.

The primary contribution of this study is not merely the application of real options analysis to wind energy, but the integration of institutional timing constraints into end-of-life wind farm decision-making. Existing literature typically evaluates repowering, life extension, or decommissioning separately, or applies static NPV analysis. Our study evaluates all three pathways within a unified framework and explicitly models the planning-permission timing gap as a source of managerial flexibility. A second contribution is the valuation of embedded flexibility under electricity price uncertainty using Monte Carlo simulation. The framework demonstrates that the strategic value of flexibility differs substantially across end-of-life strategies, with repowering exhibiting significant option value while life extension does not. A third contribution is the practical integration of real operational data from an Irish wind farm, creating a framework that is transferable to other jurisdictions through parameter adaptation.

The interplay between electricity markets and wind energy investments has been extensively explored in prior studies, particularly focusing on electricity prices, e.g., (Tao et al., 2012; Mulder and Scholtens, 2013; Rintamäki et al., 2017; Kyritsis et al., 2017; Csereklyei et al., 2019) and regulatory policies such as renewable energy subsidies (González and Lacal-Arántegui, 2016; Mytilinou et al., 2017; Sahu, 2018; Chaurasiya et al., 2019; Hitaj and Löschel, 2019). However, limited research has examined the relationship between electricity markets and end-of-life investment for wind farms (e.g., Chinmoy et al., 2019; Pandit and Kolios, 2020; Leite et al., 2022).

Electricity prices are significant in investment decision making due to their high uncertainty levels. For instance, Paraschiv et al. (2014) analysed the influence of renewable energy integration on day-ahead electricity prices, concluding that renewables decrease market spot prices by shifting the merit order curve, though final consumer prices rise due to feed-in tariffs. Similarly, Kök et al. (2018) investigated the impact of flat and peak pricing structures on investment levels in renewable and conventional energy sources. Their findings suggested that flat pricing incentivizes higher renewable energy investments, while peak pricing, favoured by industry experts, smooths demand and reduces supply system inefficiencies. McInerney and Bunn (2017) showed that turbine's over-installation is beneficial under both Feed-in Tariffs (FiTs) and feed-in premium schemes, although the benefits are greater under premiums linked to market electricity prices. These studies highlight how price volatility and policy mechanisms significantly influence investment returns and feasibility.

Additional studies have explored the relationship between wind energy penetration and electricity price dynamics. Martinez-Anido et al. (2016) used a production cost model to demonstrate that higher wind penetration increases price volatility, despite overall price reductions, with short-term effects being particularly pronounced. Benhmad and Percebois (2016, 2018) observed similar trends in Germany, noting heightened short-term price volatility due to wind penetration. Conversely, O'Flaherty et al. (2014) suggested that in the Irish market, increased wind penetration is unlikely to significantly impact future electricity pricing.

Previous studies on end-of-life decisions for wind farms have predominantly focused on environmental impacts, such as those related to turbine decommissioning (Gomaa et al., 2019; Hall et al., 2020; Mello et al., 2022) and blade waste management (Liu and Barlow, 2017; Leahy, 2019; Heng et al., 2021; Deeney et al.,2021; Beauson et al., 2022; Delaney et al., 2023). In contrast, this study extends the scope by investigating how uncertainties in electricity markets influence decisions to repower, extend the operational life, or decommission wind projects. This study adds to the literature by showing that there is value in the decision to be made for the second investment in

wind projects. Also, all three decisions are investigated in a single project to allow for comparison. Although the analysis is based on a case study of an Irish wind farm, the analysis is adaptable and can be applied to other regions by adjusting for market-specific conditions and regulatory frameworks.

Real Option Analysis (ROA) techniques are used in this study. Previous studies have shown that ROA can be more useful than the traditional Discounted Cash Flow (DCF) techniques under three conditions. First, when the investment decision is irreversible, as is the case for wind energy projects, where once resources are deployed, it is hard to reverse without substantial loss. Second, the decision-maker has some flexibility in when to carry out the investment, for example, capital deployment by stage or phase, which is typical in wind project investments. Third, the decision-maker faces uncertain conditions such as changes in market factors, and by waiting, new information can be gained regarding the success of the investment (Schwartz and Trigeorgis, 2004; Watkiss et al., 2015).

Real option methods were explored by scholars in end-of-life studies like Galay and Winter (2025) for oil wells in Alberta and Chen et al. (2024) for wind and solar in China. Unlike DCF, which adjusts risk at the aggregate cash flow level, ROA adjusts risk at the cash flow source and allows for decisions to be taken based on the cash flow model (Belz et al., 2025; Ito et al., 2024). Simply, the value of an investment decision is the net present value of its net revenue earned until it becomes obsolete (Hickey et al., 2021).

Three investment decisions are considered:

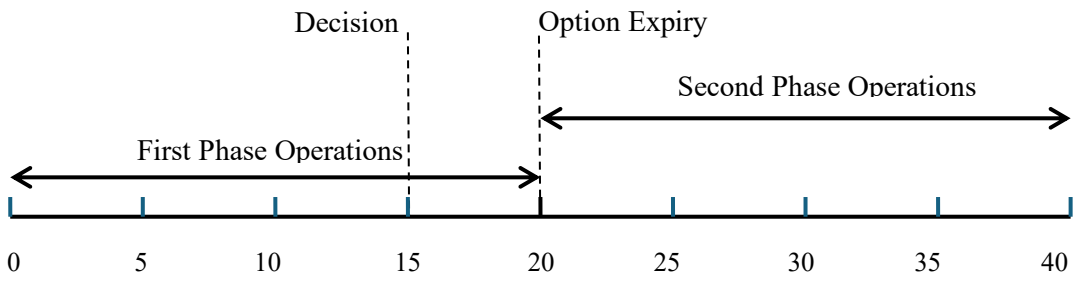
1. Expansion (Repowering): This option is to invest in new turbines to increase the capacity of the existing wind farm (the flexibility to invest was always present).
2. Wait-and-See (Lifetime extension): This option involves delaying a decision to either decommission or repower, allowing time to gather more information on market conditions.

3. Abandonment (Decommissioning): This option allows the wind farm to cease operations and decommission assets if market or regulatory conditions become unfavourable.

We analyse a two-phase operation cycle from the first commissioning. In the first operation phase after initial commissioning, project parameters such as wind energy yield, initial capital expenditure, and operation cost are obtained. The investment decisions are calculated for a 20-year operation period. This follows an assumption that wind projects have a limited planning consent, typically 20 years after commissioning (Ziegler et al., 2018). We calculate option values at year 15, when decisions must be made regarding end-of-life. All investment paths end with the decommissioning of the project. For each investment decision, there is an embedded option in such a way that: repowering will lead to lifetime extension or decommissioning; lifetime extension will result in decommissioning; and decommissioning has no embedded option and its only value is the salvage value of the turbines (Figure 6.2).

Figure 6.2: Timeline: End-of-life investment decisions

This figure shows the timeline for the end-of-life investment decisions for a windfarm. The planning decision must be made five years before the end of the first operational phase to allow time to get an appropriate permission to apply the second stage. However, once permission is received the final decision does not need to be made until year twenty.



The rest of the chapter is arranged as follows. Section 6.2 provides a detailed explanation of the three end-of-life decisions and how they are affected by market factors. Section 6.3 presents the materials and methods of the study. Results and discussion are presented in section 6.4, followed by a conclusion in section 6.5.

6.2 End-of-life decisions

Wind turbines are designed to have an average operational life of twenty to twenty-five years, and as they age, their value gradually reduces to the point where they can become a liability rather than an asset (Ortegon et al., 2013). The operation and maintenance costs increase due to wear and tear (Byrne et al., 2020; Yang et al., 2020), and since operating permits usually have a specified end date, the value of the remaining income from a wind farm decreases. Planning for this situation means that wind farm operators must decide whether to carry out re-powering, lifetime extension, or decommissioning, and that this planning should begin perhaps 5 years ahead of the specified end date.

6.2.1 Repowering

Wind farm repowering refers to the process of replacing existing wind turbines with newer, more efficient models to maximize energy production while minimizing operational downtime. The new models are usually more powerful than those they replace, and it is often the case that the power output of the wind farm will increase despite using fewer turbines. This process leverages existing infrastructure, such as grid connections and access roads, to reduce project costs and streamline implementation. Key elements of repowering include replacing outdated turbines, upgrading supporting infrastructure, and conducting environmental impact assessments to ensure regulatory compliance and mitigate ecological disturbances. Repowering not only enhances the energy output and economic performance of a wind farm but also reduces long-term maintenance costs by incorporating more advanced technology. Comprehensive overviews of the repowering process are provided in studies by Nivedh et al. (2013), Hou et al. (2017), and Martínez et al. (2018).

Technical and economic considerations are critical for the successful execution of wind turbine repowering projects. Recent studies highlight significant advancements in wind turbine technology, including longer blades, higher hub heights, and smarter control systems, which can greatly improve the efficiency and capacity of repowered wind farms (Lucena, 2021; Bošnjaković et al., 2022). Key technical factors to address include grid compatibility and site-specific limitations. For instance, operators must assess whether upgraded turbines necessitate modifications to existing grid

infrastructure and evaluate wind conditions, land constraints, and the proximity of sensitive areas to determine the site's suitability for repowering. However, McInerney and Bunn (2017) proved that over-installation of wind turbines can increase economic benefits by achieving the maximum output limit imposed by the grid connection. On the economic side, the profitability of repowering depends heavily on electricity prices, demand forecasts, and the availability of government incentives or subsidies for renewable energy projects (Ahmed et al., 2024).

Despite its advantages, repowering faces several challenges. Community concerns often arise due to changes in turbine size or landscape impact, with larger turbines potentially meeting resistance from local stakeholders. For example, Kontogianni et al. (2014) identified turbine size as a significant factor in public opposition to wind energy projects. Additionally, decommissioning costs, particularly for rotor blades, can be substantial, adding to the financial burden of repowering projects. As a result, operators must carefully evaluate whether the long-term financial and energy gains from repowering justify the initial capital investment. Nevertheless, repowering plays a pivotal role in aligning wind energy projects with national and global renewable energy goals, supporting the transition to a more sustainable energy future.

6.2.2 Lifetime extension

Wind power lifetime extension involves implementing strategies to prolong the operational life of existing wind turbines beyond their original design lifespan. The primary objective is to maximize the return on investment while delaying the need for decommissioning or repowering. Key strategies for wind power lifetime extension include the following:

- Regular Maintenance: Proactive maintenance schedules are critical to identifying and addressing issues before they escalate, thereby ensuring continued reliable operation (Bocewicz et al., 2024).
- Component Upgrades: Upgrading or replacing specific turbine components, such as gearboxes, generators, or control systems, enhances performance and reliability while mitigating the risk of major failures.

- Monitoring and Data Analytics: Advanced sensors and data analytics are employed to continuously monitor turbine performance, enabling predictive maintenance and reducing unplanned downtime.
- Structural Assessments**:** Rigorous evaluations of structural integrity, including towers and foundations, ensure the physical durability of turbines over extended periods of operation.

Wind power lifetime extension requires meticulous planning to balance the costs of upgrades and maintenance against the potential revenue generated from extended operations. Economic feasibility depends on factors such as energy market conditions, regulatory frameworks, and the condition of the existing infrastructure, which, if not checked, may lead to operational risks (Kalatha et al., 2023; Mikindani et al., 2024). A particular advantage of lifetime extension is that it does not incur as much investment cost as repowering and therefore avoids substantial financial risk. For further insights, refer to Carriveau and Miller (2020) and Pakenham et al. (2021).

6.2.3 Decommissioning

Wind power decommissioning refers to the planned and systematic removal of wind turbines and associated infrastructure at the end of their operational life (Topham and McMillan, 2017). The decommissioning process involves several key steps.

- Dismantling: Wind turbines are disassembled and removed from their foundations. This process can be labour-intensive and may require specialized equipment.
- Site restoration: After removal, the land should be restored to its original state or repurposed for other uses, depending on the original contract and local regulations.
- Recycling or disposal: Wind turbine components, such as blades, towers, and nacelles, may be recycled, reused, or disposed of in an environmentally responsible manner (Nagle et al., 2020).

Proper decommissioning is essential to minimize the environmental impact of wind energy production.

Sakellariou (2018) and Deeney et al. (2025) explore potential decommissioning scenarios for wind turbine blades. These blades are particularly challenging for sustainable decommissioning due to their composite construction and their robust nature. These studies highlight the current state of markets for wind blades, advancements in supply chains, and the potential for cost-efficient decommissioning processes. Topham et al. (2019) emphasize the importance of integrating recycling considerations into the planning stage of wind farm development.

All investment decisions concerning wind turbines eventually finish with decommissioning, as these machines have a finite operational lifespan dictated by physical wear and technological obsolescence. However, decisions surrounding decommissioning during the second phase of a wind farm's life are more nuanced. Operators are unlikely to proceed with decommissioning unless market conditions, particularly electricity prices, render continued production economically unviable. For instance, low electricity prices may reduce the revenue potential of the wind farm to a point where operating costs exceed profits, making decommissioning the most rational choice. Conversely, if electricity prices remain favourable or other supportive market factors are present, operators may opt for lifetime extension strategies or repowering to maximize the asset's value before eventual decommissioning. This dynamic underscores the critical role of market factors in shaping the timing and nature of decommissioning decisions.

6.3 Method

A windfarm has a typical lifetime of twenty years (Ziegler et al., 2018). The owner has three alternatives for the windfarm at this point: repowering, lifetime extension and decommissioning. However, it is necessary to apply for planning consent to repower or extend life (at least) five years before the end of the period to ensure necessary permissions. Applying for repowering does not commit the operator to choose that, the final decision does not need to be made until the end of life, when the optimal strategy can be chosen based on electricity prices at that time. As a result, the decision to apply for either repowering or lifetime extension, contains an embedded real option, which should be accounted for in the decision to apply.

We estimate the value of the option using Monte Carlo methods. The NPV of each strategy is a function of the electricity price five years into the future and we treat this price as a stochastic variable. All other valuation parameters are well defined. For each iteration of the Monte Carlo simulation, we compare the value of the planned NPV against the best NPV. This is the value of the option for this price path. The value of the embedded option is then the average value of the option value across all iterations, discount back to the time of the decision.

In the case of a planned repowering, the operating can pick the best of the three strategies so the value of the option for a single iteration is:

$$O_{R,i} = max\{NPV_{R,i}, NPV_{L,i}, NPV_{D,i}\} - NPV_{R,i} \quad (6.1)$$

$O_{R,i}$ is the value of the embedded option for a single trial, *i*. $NPV_{R,i}$, $NPV_{L,i}$, and $NPV_{D,i}$ are the net present values of the repowering, lifetime extension and decommissioning strategies for a single trial, *i*.

The value of the option is then the average value across all options, discounted at the risk-free rate to the time of the application.

$$O_R = \frac{1}{M}\sum_{i=1}^{M}\frac{O_{R,i}}{(1+r_f)^5} \quad (6.2)$$

O_R is the value of the embedded option in the repowering decision, *M* is the number of trials in the Monte Carlo simulation, and r_f is the risk-free rate.

The repowering strategy cannot be selected in the case where permission is sought for the lifetime extension strategy. Under this circumstance, the value of the option for lifetime extension a single trial is:

$$O_{L,i} = max\{NPV_{L,i}, NPV_{D,i}\} - NPV_{L,i} \quad (6.3)$$

There is no option value associated with selecting the decommissioning strategy early as this eliminates the repowering or lifetime extension strategies which cannot be pursued without prior permissions.

6.3.1 Valuation models

The value of each decision is calculated as the NPV of the cashflows over the life of the second operational phase of the farm. Cashflows fall into three categories: capital investment (Moné et al., (2015) for more detail on the composition of initial investment), net cashflows from generation of electricity, and terminal value. The terminal value is the difference between the scrappage value of the equipment less the decommissioning costs. Cashflows are calculated over a planned lifetime of twenty years.

Repowering: Repowering decision includes all three classes of cashflow and its NPV is calculated as:

$$NPV_R = -I_0 + \sum_{t=1}^{T} \frac{\pi_t}{(1+r)^t} + \left(\frac{(s-d)(1+i)^T}{(1+r)^T} \right) \qquad (6.4)$$

I_0 is the initial capital investment, π_t is the net cash flow in year *t*, r is the discount rate, i is the inflation rate, *T* is the operational lifetime, *s* is the scrappage value, and *d* is the decommissioning cost.

The cash flow π_t from generating electrical power in a year is:

$$\pi_t = P_t . rp . cf . wt - opex(1+i)^t \qquad (6.5)$$

P_t is electricity price at time *t*. The windfarm's rated power (rp) is the maximum power output of the farm when all turbines are generating at full output. The capacity factor, cf, is the average proportion of the rated power that a farm generates, wt total available time for operation, and $opex$ is the operation and maintenance cost for the wind farm, adjusted for inflation over the lifetime of the farm. The annual energy production is the product of *rp*, *cf* and wt.

Lifetime extension: Lifetime extension does not require an initial capital investment but is otherwise similar to repowering. The net present value of a lifetime extension decision is:

$$NPV_L = \sum_{t=1}^{T} \frac{\pi_t}{(1+r)^t} + \left(\frac{(s-d)(1+i)^T}{(1+r)^T} \right) \quad (6.6)$$

The net cashflows, π_t, are estimated using Equation 5, but it should be noted that the rated power is lower and the operating costs higher than in the case of repowering, reflecting the older equipment.

Decommissioning: The value raised from decommissioning the wind farm is the difference between the scrappage value of the equipment and the costs associated with decommissioning:

$$NPV_D = (s-d) \quad (6.7)$$

6.3.2 Model parameters

The model parameters are derived from multiple sources. Those associated with capital expenditure are sourced from academic literature and industry reports, while operational parameters are based on an active wind farm. We also calculate the option values for this farm.

The focus of our case study is the onshore wind farm located in Ballincurry, Ireland. The farm has a rated capacity of 4.7 MW. This is generated by two turbines, manufactured by ENERCON and operating on 77m steel towers. The parameters are extracted from three consecutive annual operation reports that detail the farm's total operational time (wt), rated power (rp), and energy yield (Table 6.1).

Table 6.1: Ballincurry wind farm data 2020-22

This table shows key production data for the Ballincurry Windfarm. The farm has a rated power of 4.7 MW. wt is the total operating time of the wind turbine in hours for a year, and cf the capacity factor of the turbine.

Year	Energy Yield (MWh)	Key Production Parameters
2020	18,823	$wt = 8{,}760\ hours$
2021	14,581	$rp = 4.70$
2022	16,717	$cf = \frac{(Energy\ yield/wt)}{rp}\% = 41\%$
Average	16,707	

The other parameters for the model are set out in Table 6.2. The capital expenditure for repowering a wind turbine is €1.25 million/MW (Wind Europe, 2022). We include the value of removing the old turbines for the case of repowering, €60,000 (Burke, 2023). The annual maintenance and operational costs are 2% of capital expenditure for new turbines and 3% for older turbines, following Wind Measurement International (2024). All parameters are adjusted for inflation through the lifetime of the farm based on the European Central Bank's target rate of 2%.

We estimate the cost of decommissioning at €202,000 per MW consistent with the average decommissioning bond and a salvage value of €40,000 per MW per MW. These are based on estimates of decommissioning expenditure range from €85,000 to €320,000 per MW, with a corresponding salvage value between €30,000 and €50,000 per MW (Interreg Europe, 2024). These estimates are consistent with figures observed in markets outside Europe. McCullough (2024) reports that decommissioning bonds in Australia amount to AU$400,000 (approximately €244,000) per turbine. In the United States, the decommissioning bond was $106,000 per turbine in 2015 (Moné et al., 2015). This equates to approximately €208,000 per turbine after adjusting for inflation of 8%.

Rajgor (2011) shows that repowering avoids costs such as site access and staging and reuses 75% of electrical infrastructure. This results in a 5% drop in capital expenditure relative to initial construction (Moné et al., 2015). We include an increase in the capacity of the plant after repowering. This is based on a survey of European repowering trends (Grau et al., 2021; WindEurope, 2023) that shows rated power is on average 75% higher than the original rated power after repowering.

Table 6.2: NPV parameters

This table shows the parameter values used in the valuation models. The repowering scenario is a result of 75% increase in rated capacity from lifetime extension scenario, and capital expenditure (Capex) accounts for 5% reduction in Capex costs that happen when repowering. Costs are in Euros and for whole wind farm.

Variables	Repowering	Lifetime extension
Capacity (MW)	8.23	4.70
Capital Expenditure	9,773,125	-
Dismantling Cost	60,000	-
Operating Expense (Annual)	205,750	176,250
Salvage Value	329,200	188,000
Decommissioning Cost	1,662,460	949,400

6.3.2 Cost of capital

We use a cost of capital of 6.6% to estimate NPV. This is consistent with KPMG's most recent estimate of the appropriate value for energy projects (KPMG, 2024). It is also in line with other recent studies surveying of the cost of capital for renewable energy in Europe, including Steffen (2020), Roth et al. (2021), and IRENA (2024). These studies reveal a significant range of estimates for onshore wind projects in Europe. Steffen (2020), surveying the period 2009-2017, reports values from 3.0% in Germany to 11.7% in Greece, with a mean of 7.8% across twenty-three EU countries. Roth et al. find an average rate of 5.5% across nineteen countries over the period 2019 to 20, ranging from 1.9% to 9.1%. Finally, IRENA's latest data, covering the period 2020 to 2021 shows even lower values, from as low as 1.1% in Germany to over 12% in Ukraine giving an average of 6.5%. Given the variation in estimates, we test the sensitivity of core analyses to different estimates of this parameter.

6.3.3 Price modelling

Variation in electricity prices is the key uncertainty in planning power generating projects. We assume that electricity prices follow a log-normally distributed, stochastic process with drift. This is a standard model of financial market prices as used by (Hou et al., 2017) for electricity markets. The stochastic process is:

$$\frac{dP}{P} = \mu dt + \sigma dz \qquad (6.8)$$

P is the price of electricity, μ is the drift, σ is the volatility, and dz is a Wiener process generating random changes. This can be discretized in time for simulating a price path as:

$$P_{t+\Delta t} = P_t exp\left[\left(\mu - \frac{\sigma^2}{2}\right)\Delta t + \sigma\sqrt{\Delta t}\epsilon\right] \qquad (6.9)$$

P_t is the price at time t, Δt is the discrete time interval, μ and σ are drift and volatility respectively, while ϵ is randomly drawn from a standard normal distribution. Prices are simulated monthly, starting with the current price, P_0.

While Geometric Brownian Motion (GBM) provides a tractable framework for modelling uncertainty and is widely used in real options analysis, electricity markets exhibit characteristics that are not fully captured by this process. Unlike financial assets, electricity cannot be economically stored at scale, resulting in prices that are

influenced by short-term supply-demand imbalances, fuel costs, weather conditions, and regulatory interventions. As a consequence, electricity prices frequently display mean-reverting behaviour, where periods of unusually high or low prices tend to move back towards a long-run equilibrium level. Numerous studies have therefore employed mean-reverting processes when modelling wholesale electricity prices.

In addition to mean reversion, electricity markets are subject to structural breaks, whereby the underlying price process changes due to major economic, technological, or geopolitical events. The COVID-19 pandemic, the subsequent reopening of global economies, and the Russian invasion of Ukraine provide recent examples of such disruptions. These events led to sustained increases in both electricity prices and volatility across European markets, suggesting a shift in market conditions rather than a temporary fluctuation around a stable trend. Policy interventions can also generate structural changes in prices through mechanisms such as carbon pricing, renewable energy support schemes, market redesigns, or investments in interconnection capacity. For Ireland, the commissioning of the Celtic Interconnector and potential future links to continental Europe may alter the long-run relationship between Irish and European electricity prices.

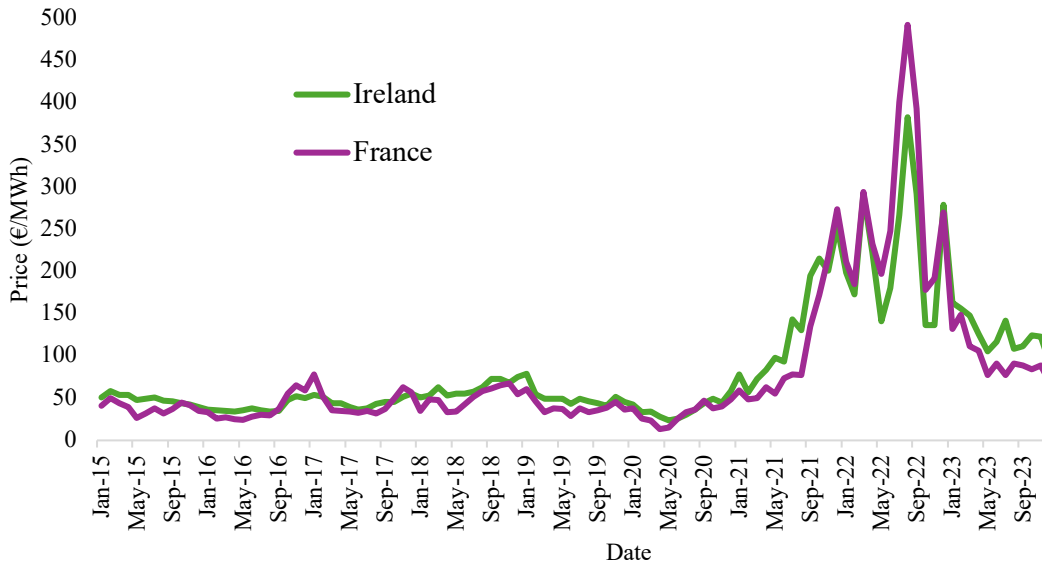
Modelling the stochastic price is key to estimating the value of the option. Given these uncertainties, it is difficult to identify a single stochastic process that can be assumed to remain valid throughout the remaining lifetime of the wind farm. Rather than imposing a specific mean-reverting or regime-switching model, this study adopts a scenario-based approach that captures a range of plausible long-term market outcomes. The three scenarios are designed to reflect alternative assumptions regarding the persistence of recent price shocks, the potential reversion of prices towards historical levels, and the increasing integration of the Irish electricity market with continental Europe.

The analysis uses prices from the European electricity market, focusing on Irish prices (Figure 6.3). Monthly prices are sourced from ENTSO-E, a central collection, repository and publication point for electricity generation, transportation and consumption data for the pan-European market (ENTSOE, 2025). The data was verified by comparison with SEMOpx data (SEMOpx, 2025).

We base our price models on the monthly price data from 2015 to 2024 (Figure 6.3), with prices reported in Euro per Megawatt-hour (MWh). This shows two distinct regimes. Prices were relatively stable from 2015-2020 but the level and volatility jumped from 2021, first due to disruption as the global economy reopened after Covid, followed by the war in Ukraine. The average price rose from €47.24/MWh from 2015 to 2020 to €149.01/MWh over the 2021-2024 period (Table 6.3), this was accompanied by a six-fold increase in volatility.

Figure 6.3: Electricity price data 2015-2024

This figure presents monthly electricity prices from January 2015 to December 2024 for the Irish and French electricity markets. Prices are in Euro per megawatt hour (€/MWhr).



We propose three reasonable scenarios and calculate option values under each. In all case the models start at the price on 31st December 2024, €99.05. The first scenario (S1: Step-Up) assumes that the recent structural break in electricity prices represents a persistent upward shift in the long-run price level. Under the second scenario (S2: Ireland), the recent price shock is assumed to be temporary, with prices gradually mean-reverting towards the pre-2020 Irish trend over the subsequent five years. Finally, we note that Irish prices are generally at a premium to European levels (Table 6.3), with average prices up to 11% above those in Germany and France (ENTSOE, 2025). This should disappear over the lifetime of the windfarm as Ireland's integration with European markets increases. The infrastructure to enable this is currently being

put in place, with the Celtic Interconnector to France due to come online in 2028 (EirGrid, 2025) and advance planning for a direct link to Spain (Murphy, 2025). This gives the third scenario (S3: EU_Market) where we model the premium declining to zero over the lifetime of the farm. We focus on France rather than a pan-European average as this is the closest market to Ireland and work on the Celtic Interconnector is progressing.

Table 6.3: Electricity price summary statistics: 2015-2024

This table key electricity price statistics for Ireland and France. Values are shown for the full period (2015-2024) and two subperiods (2015-20 and 2021-24)

		Average Price (€/MW)	Annualized Volatility (%)	Average Annual Increase (%)
Ireland	2015-2020	47.24	11.22	2.44
	2021-2024	149.01	68.68	14.94
	2015-2024	87.95	66.67	10.46
France	2015-2020	40.35	12.71	2.84
	2021-2024	134.77	105.22	13.34
	2015-2024	78.12	81.41	9.14

6.4 Results

6.4.1 NPV results

The NPV results for the three end-of-life pathways are presented in Table 6.4. Across all scenarios, repowering yields the highest project value, with NPVs ranging from €11.83 million to €27.35 million. Lifetime extension is consistently the second most attractive option, generating positive NPVs in all scenarios, although these are lower than those achieved through repowering. In contrast, decommissioning results in a negative NPV of €761,400 in every scenario, reflecting the absence of future revenue streams and the costs associated with site restoration and asset removal. The gap between repowering and life extension is largest in Scenario 1, where repowering provides an additional €7.05 million in value, whereas the difference narrows considerably in Scenarios 2 and 3.

Table 6.4: NPV results

This table presents the NPV results showing the value of each investment pathway without considering managerial flexibility.

	Scenario 1	Scenario 2	Scenario 3
Repowering (€)	27,345,791.15	13,383,664.02	11,831,797.92
Lifetime extension(€)	20,291,740.32	12,318,229.08	11,431,987.20
Decommissioning(€)	(761,400.00)	(761,400.00)	(761,400.00)

6.4.2 Real option values

The deterministic NPV estimates provide the benchmark values for evaluating the contribution of managerial flexibility through the real options framework developed in the subsequent section.

The option values were estimated for both repowering and lifetime extension under each of the three scenarios and are presented in Table 6.5, Panel A. The option values for repowering are substantial, ranging from €1.08 million in the S1:Step-Up scenario to €2.18 million in S3:EU_Market. There is unsurprisingly a significant inverse relationship between the central expectations for the price and the option value, with the value of options increasing as the price expectation drops.

The embedded option values for lifetime extension are negligible, below €10,000 across all scenarios. This reflects the relatively low capital expenditure relative to the income that can be generated by running the farm beyond its rated life. In all cases, except ultra-low prices, lifetime extension dominates decommissioning.

We assess the significance of the embedded option value by calculating the project value (NPV) of the repowering strategy with and without the embedded option. We then present the option value as a fraction of the NPV value (Table 6.5, Panel B). This shows that the value of the option is significant relative to the overall value of the project, notable in the case of S2: Irish and S3: EU_Market, with values of 15.1%, and 18.4% respectively.

These findings underscore that the inclusion of option valuation in investment appraisal fundamentally alters the evaluation of long-term asset strategies. Among the scenarios, the EU_Market scenario yields the highest relative option value for repowering (18.4%) suggesting that regional energy market conditions potentially

shaped by EU-level policy, carbon pricing, or support mechanisms amplify the benefits of managerial flexibility.

Table 6.5: Option values

This table presents the option values for three scenarios (S1: Step-Up, S2: Irish, and S3:EU_Market). Panel A shows the option values of the repowering and lifetime extension strategies. Panel B compares the relative value of the repowering project with the embedded option value.

Panel A: Option Values (€)			
	S1: Step-Up	S2: Ireland	S3: EU_Market
Repowering	1,075,000	2,018,000	2,182,000
Lifetime extension	1,000	5,000	6,000
Panel B: Project Values - Repowering			
	S1: Step-Up	S2: Ireland	S3: EU_Market
NPV (€m)	27.35	13.38	11.83
NPV + Option Value (€m)	28.42	15.40	14.01
Option Value to NPV (%)	3.93	15.08	18.44

These findings are consistent with those obtained under the conventional NPV framework. Even when managerial flexibility is incorporated, repowering remains the most economically attractive option, exhibiting the highest NPV and option values across the scenarios considered.

6.4.3 Risk analysis and option values

The distributions of the project values for repowering and lifetime extension are compared in Figure 6.4 to provide insights into the observed option values. The distributions were created using the Monte Carlo process developed to calculate the options values. The distributions are for S3: EU_Market, but the same pattern can be seen for all scenarios.

The distributions are driven by the variation of the NPVs in response to different price levels. Two factors drive the difference in distribution between repowering and lifetime extension, lower capital expenditure for the lifetime extension strategy and the greater income from increased capacity for repowering.

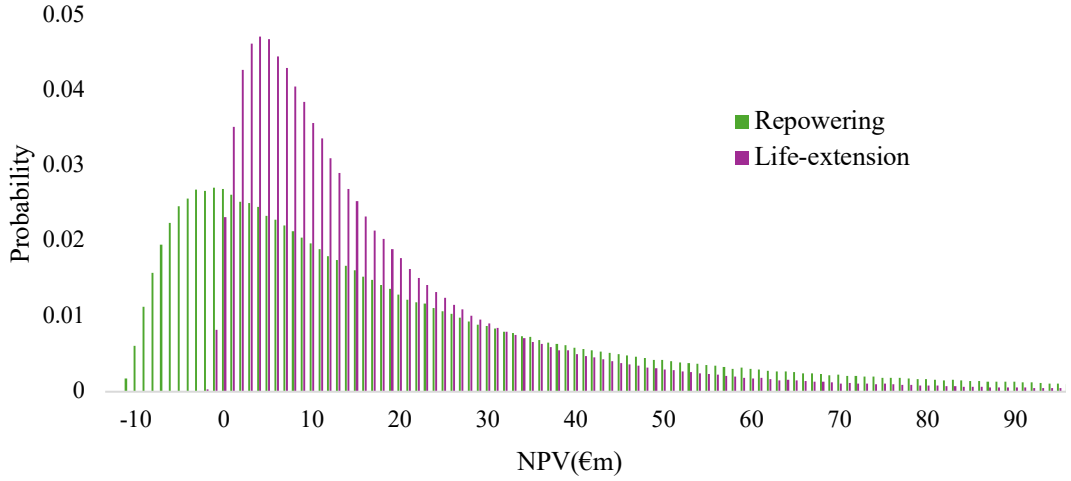
Both distributions are right-skewed, with significant positive exposure to high electricity prices. However, repowering has a greater exposure to price changes due to the extra capacity and the greater skew, associated with high prices, drives a higher expected NPV.

The significant capital expenditure associated with repowering can result in a loss-making project if the electricity price is low. In the case of the Ballincurry wind farm (1.6 %) of the outcome have a negative NPV, with a maximum loss of €12.5 million. This contrasts with the lifetime extension where losses are incurred only (0.8 %) of the time, and the maximum loss is €2.4 million.

This explains the difference in the real option values associated with the decision. The high frequency of losing outcome in the case of repowering mean it is valuable to have the option of switching to the generally profitable lifetime extension model if electricity prices are low close to the expiry of the option. In contrast, lifetime extension makes only a small number of losses so there is little value in being able to switch to the decommissioning in the case of low prices.

Figure 6.4: NPV distribution

This figure compares distributions of the NPV values for repowering and lifetime extension decisions under the S3: EU_Market scenario. NPV values are in € millions.



6.4.4 Sensitivity analysis: cost of capital

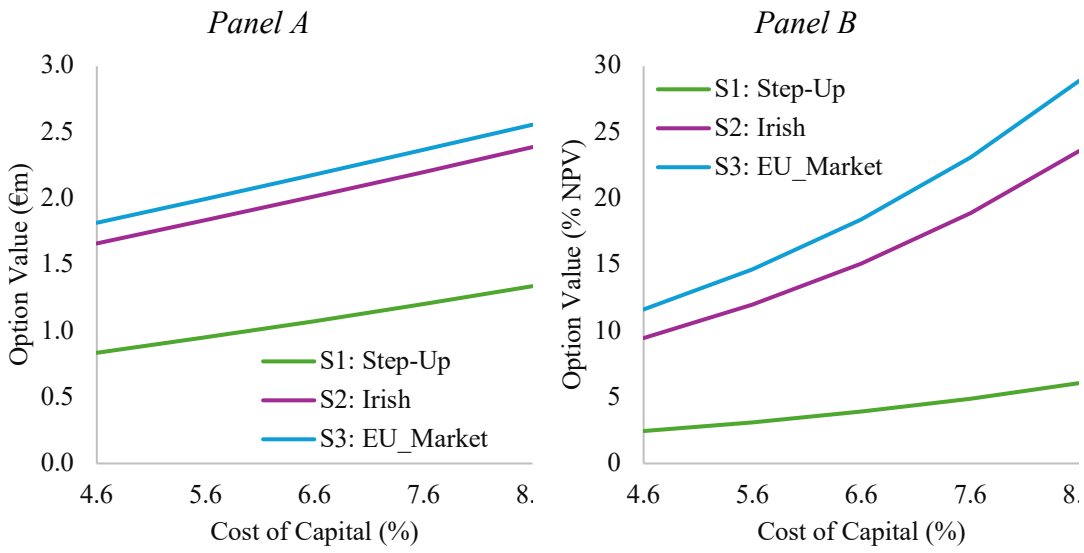
The sensitivity of the option price to the central estimate of the capital (6.6%), derived in Section 6.3.2, was tested by varying the rate between 4.6% and 8.6% and calculating both the option value and the NPV with the new discount rates.

The value of the option increased with the cost of capital across all three scenarios, although this increase did not cause significant differences in the value of option, Figure 6.5, Panel A, with values about 20% away from the central estimate at the extreme ends of the range.

However, looking at the difference in the significance of the option value relative to the project value, the results vary more as, while option values increase with Cost of Capital, project NPV falls (Figure 6.5, Panel B). This is also asymmetric with proportional increase as the Cost of Capital increases greater than the drop when the cost falls. In the case of S3:EU_Market, the relative value rises from 18.4% to 28.9% as the cost of capital moves from 6.6% to 8.6%. This emphasizes to potential importance of including the embedded option value when analysing the data for end-of-life decisions.

Figure 6.5: Sensitivity analysis: cost of capital

This figure shows the sensitivity of the option value (Panel A) and relative option value (Panel B) to changes in the Cost of Capital for the repowering strategy. The sensitivity is presented for each of the three scenarios: S1: Step-Up, S2: Irish, and S3: EU_Market.



6.5 Discussion and conclusion

The average life of a windfarm is twenty years and the decision on the next phase of the wind farm's life focuses on three strategies: repowering, lifetime extension and decommissioning. Extensive installation of wind generation began at the start of the century, so now these wind farms are coming to the end of their useful life, Repower-EU reporting over 8GW capacity annual coming to the end of life for the rest of the century.

The decision on the second life strategy must be taken five years in advance of the end of a windfarm's life. However, applying for planning permission does not commit to taking that action, and investors can wait until. The combination of the lag between applying for permission and the decision to go head with a given course of action, creates a real option which can affect the investment decision.

We adapt financial techniques to develop a method to value the embedded option in the decision to apply for repowering and lifetime extension. The model focuses on the uncertainty in electricity prices, the key parameter in valuing the different strategies.

We validate the model by applying it to the second life decision for the Ballincurry wind farm in Ireland. For robustness we model the values under three different central assumptions for price process, and the results are consistent across all three. We show that the value of the option in for the repowering option is significant, while there is negligible value for lifetime extension.

The value of the option for repowering ranges from 4% to 18% of the projects value, depending on price expectation. There was an inverse relation between the expected price and the value of the option across the three price scenarios. Further robustness test show that while the value of the option was consistent with variations in the discount rate, the option value relative to the project value increased significantly, reaching 28.9% for an increase in the discount rate of 2%.

In contrast, the lifetime extension strategy has negligible option value across all specifications. The distribution of possible outcomes from the Monte Carlo distribution explains this. Very few outcomes lose money so there is very little value in being able to switch to the decommission strategy. This is tied to the very low initial capital cost which is covered by generation income even at low price outcomes.

There is significant difference in real option value between repowering and lifetime extension. This is large enough to change the ranking of the two strategies compared to an evaluation it is not accounted for. This highlights the importance of properly valuing the options.

The distribution on the outcomes of the Monte Carlo simulations highlights the difference in risk between the repowering and lifetime extension. While repowering generally has the highest mean value, lifetime extension has a significantly lower number of losing outcomes. This finding is relevant to projects, such as community projects, where the investor may have high risk aversion.

The focus of this study has been the real option value in repowering decisions, however, across the renewable universe there is a significant lag between applying for permission which creates a real option. It is necessary to evaluate this value to properly assess projects. The methods used here, are applicable to other renewable energy projects in areas such as offshore wind, solar, and tidal electricity generation. The method developed here can be used to value real options across the industry.

Chapter 7 . Perceptions of risk and investment in wind energy in rural communities

Abstract[3]

This study examines community investment in onshore wind energy through behavioural finance frameworks, focusing on how risk attitudes, prior experience, and socio-demographic factors shape investment decisions in developed (Ireland) and developing (Tanzania) countries. Using ordered and generalised ordered logistic regression models, the results show that in Ireland, risk tolerance is a strong and consistent predictor of a higher investment propensity. Investment return expectations, electricity choice preferences, and selected demographic factors, particularly age and gender, also significantly influence investment decisions. The Tanzanian results, based on the first survey of community attitudes to wind farm investment, reveal few significant predictors, with education and selected attitudinal variables displaying only threshold-specific effects. This indicates that investment propensity is shaped by broader contextual and institutional factors than by individual risk attitudes or experience. Overall, the findings indicate that mature renewable energy markets, such as Ireland, can benefit from strategies that leverage risk tolerance, energy preferences, and transparent communication of project benefits, while emerging markets require building foundational awareness, trust development, and simplified mechanisms for community participation to effectively support renewable energy investments.

[3] This paper has been submitted in the *Journal of Rural Studies*. The research reported in this paper has been presented at the following conferences. Wind Value, IAFA, in Ireland. Lead author, Dorcas Mikindani, co-authors, Peter Deeney, John O'Brien, Paul Leahy, Jeremiah Makindara, Judith Valerian.

7.1 Introduction

The transition to wind energy is crucial for achieving a sustainable and low-carbon energy future. The successful implementation of wind energy projects depends not only on policy, technical, and economic factors but also on social acceptance and participation by local communities (Ishola et al., 2024). The likelihood of public support and overall project success increases significantly when communities are involved in decision making processes (Hobson et al., 2019; Olajide, 2024). Inclusive participation fosters trust between developers and residents, ensures that local interests and concerns are addressed, and promotes an equitable distribution of benefits. This study explores the risk perceptions of communities of investment in wind energy projects, with particular attention to the roles of community participation, social acceptance, and investment opportunities in wind farms.

Wind farms are typically granted permission to operate for twenty to twenty five years corresponding to the assumed operational and economic lifespan of turbines (Ziegler et al., 2018). Extending the lifespan of the windfarm through repowering or extending the lifetime of the existing infrastructure provides both economic and environmental benefits, particularly when local ownership models are adopted (Philpott and Windemer, 2022). The lower cost investing in lifetime extension creates new opportunities for rural communities to invest in local projects.

Previous studies have demonstrated that social acceptance of wind energy projects varies according to prior exposure to and experience with wind turbines (Delicado et al., 2016). Communities living near operational wind farms tend to have a greater understanding of the industry than areas where wind energy represents a new technology (Sirr et al., 2023). These lived experiences shape community perceptions, positioning local residents as key stakeholders in discussions on wind energy expansion. Understanding community risk perceptions toward investing in such projects is critical for determining their feasibility and long-term sustainability while easing the planning process.

This study contributes to the literature in several ways. It examines community risk preferences for investing in onshore wind farms, assessing whether familiarity and socio-demographic factors influence the acceptability of projects. Previous research

has largely focused on the planning and development stages of wind energy projects (Higgs et al., 2008; Schlenker and Bosch, 2024) but limited attention has been paid to the end-of-life phases of wind farms. This study addresses this gap by examining rural community perceptions of continued investment in and ownership of aging wind farms. It offers new insights into the long-term viability of community-driven wind energy initiatives. Importantly, this study contributes to a deeper understanding of the formation and development of energy communities.

Building on this, this study adopts a comparative research design to examine whether community risk preferences and investment attitudes toward onshore wind energy vary across different socio-economic and demographic contexts. Analysing contrasting development settings allows for a more nuanced understanding of the factors that influence decision making as the formation and sustainability of energy communities are shaped by broader institutional, economic, and social conditions. This study compares a high-income (Ireland) and a lower-income (Tanzania) country. Both countries possess viable wind resources ensuring that investment considerations are grounded in realistic energy opportunities.

Ireland and Tanzania were selected as analytically contrasting cases rather than as directly comparable national samples. The two countries differ substantially in renewable energy market maturity, institutional development, electricity access, governance arrangements, and public exposure to wind energy. Ireland represents a mature European renewable energy market characterised by extensive wind deployment, liberalised electricity markets, widespread electricity access, and established opportunities for citizen participation in renewable energy projects. Tanzania represents an emerging renewable energy context with limited wind deployment, lower electricity access rates, and a different institutional environment for energy investment. Examining attitudes across these contrasting settings provides an opportunity to explore how investment perceptions may vary under different socio-institutional conditions and to assess the extent to which behavioural explanations are context dependent.

This study identifies differences in communities' attitudes to wind energy investments and integrates behavioural decision-making theories, specifically the psychometric paradigm of risk perception, diffusion of innovation theory, and the affect heuristic, to explain the differences. A behaviour framework is essential as investment decisions in renewable energy are not driven solely by economic rationality but also by individuals' perception, emotional evaluation, and social interpretation of risk. The analysis demonstrates that subjective risk appraisals, affective responses, and exposure to innovation jointly influence community eagerness to invest. This is consistent with recent renewable energy research that emphasizes behavioural and social drivers of investment and technology adoption (Perlaviciute et al., 2018; Brambati et al., 2022). This theoretical integration is particularly important in cross-country comparisons. Differences in socio-institutional contexts shape culturally embedded risk interpretations, emotional reactions to emerging technologies, and varying levels of familiarity with wind energy which can lead to divergent investment attitudes.

The rest of this chapter is set out as follows. Section 7.2 offers a comprehensive discussion of the relevant literature. Section 7.3 sets out the theoretical framework and Section 7.4 details the materials and methods used in the study. Section 7.5 presents the results, Section 7.6 discuss the findings, and Section 7.7 concludes the chapter.

7.2 Literature review

Wind farms are a cornerstone of the global transition to renewable energy, offering a clean and sustainable alternative to fossil fuels (Afridi et al., 2024; Hassan et al., 2024). The evolution of wind energy has involved a shift from subsidy or government supported initiatives (Tisheva, 2026) to fully commercial projects, providing a dual opportunity to address climate change while delivering economic benefits to energy communities (Phimister and Roberts, 2012). Over the past two decades, the global wind energy installed capacity has expanded at an average rate of 42 GW per year, resulting in an annual wind power generation of 2,304 TWh by 2023 and an additional 113 GW of capacity added in 2024 (IRENA, 2025). Despite this substantial growth, community acceptance remains a significant barrier to further deployment (Maleki-Dizaji et al., 2020).

A growing body of literature emphasizes the importance of a social license, defined as a community's ongoing approval and support for energy infrastructure, as a central determinant of project viability (Gaynor & MIPI, 2018; Minadakis & Vega-Araújo, 2024). Knauf and le Maitre (2023a) empirically demonstrated that citizen investment is positively correlated with community acceptance of wind energy projects. In a follow-up study, Knauf and Wüstenhagen (2023b) found that project developers frequently offer co-investment opportunities, not solely for financial reasons, but as a strategic tool to enhance community support and engagement.

The Co-Wind project in Ireland provides a robust framework for understanding effective community engagement. Its findings highlight that early stage consultation, compensation for nearby residents, and the provision of local amenities significantly enhance social acceptance (le Maitre, 2024a). Proximity to wind farms plays a crucial role, as individuals living closer to turbines tend to be more sensitive to both perceived risks and benefits, often making them more vocal in expressing support or opposition. Community ownership models have also demonstrated the potential to increase local buy-in. However, le Maitre (n.d.) argues that while co-ownership can improve perceptions, it is not a universal solution, as community preferences and levels of trust vary. These findings are reinforced by Wind Energy Ireland's 2024 national survey, which reported that 80% of respondents supported wind energy development and 62% were open to having wind farms in their local area. Key drivers of support included affordability, emissions reduction, and environmental benefits (WEI, 2024).

While social acceptance is essential, the literature indicates that community investment decisions are shaped by broader risk perceptions rather than attitudes toward renewable energy alone. These perceptions are influenced by multiple interrelated factors, including demographic characteristics, such as age, education, and income (Witkowska-Dabrowska et al., 2021); geographic considerations, including land use and visual impacts (Hammami and Triki, 2016); institutional trust and policy stability (Karakislak et al., 2023; Mey and Diesendorf, 2018); environmental concerns related to biodiversity and land disturbance (Delicado et al., 2016); and economic risks, such as financial uncertainty and long-term project viability (Broughel and Hampl, 2018; Gatzert and Kosub, 2016). These multidimensional risk perceptions

highlight the limitations of simplistic acceptance models and emphasize the need for integrated frameworks that account for trust, incentives, and communication.

The formation of risk perceptions is deeply embedded in social contexts. Although individual risk behaviour may appear autonomous, it is often shaped by social networks and peer influence. Studies by de Boer et al. (2017) and Gioia (2017) show that individuals tend to mirror the risk preferences of their peers, leading to behavioural clustering. Kasperson et al. (1988) introduced the concept of social schemata, whereby communities develop shared risk perceptions through collective experiences and social discourse. This process of collective sensemaking suggests that prevailing local narratives, whether supportive or oppositional, can strongly influence the interpretation and actions regarding new information about wind energy projects.

Co-investment mechanisms play a pivotal role in reducing perceived risks and strengthening local commitment. When communities are offered opportunities to invest in wind energy projects, they are more likely to support them and actively engage in risk mitigation and long-term project stewardship (le Maitre, 2024a; Knauf and Wüstenhagen, 2023b). These mechanisms, which range from cooperative ownership structures to joint ventures, can also function as trust-building instruments, particularly when supported by transparent governance and equitable revenue-sharing arrangements. Importantly, co-investment aligns financial and social incentives, helping to bridge the gap between top-down infrastructure development and bottom-up community engagement.

Overall, the literature demonstrates that community perceptions of wind energy are shaped by a complex interplay of factors, including proximity, socio-demographic characteristics, perceived risks, and opportunities for meaningful engagement. While social acceptance is a necessary condition, it is insufficient on its own to stimulate citizen investment. A deeper understanding of community risk perceptions formed through individual behaviour, collective norms, and participatory structures, such as co-investment, is essential for the design of inclusive and successful wind energy projects. This review highlights the need for future research and policy to move beyond assessing whether communities support wind energy and toward understanding why and how shared perceptions of risk can be transformed into collective commitments to a sustainable energy future.

7.3 Behavioural finance framework

Behavioural finance emerged from behavioural psychology discipline as a response to the restrictive assumptions of full rationality embedded in classical economics and the efficient market hypothesis. Early work by Simon (1955) introduced the concept of bounded rationality, arguing that individuals rely on heuristics to make satisfactory rather than optimal decisions. Subsequent research, notably by Bem (1972), confirmed deviations from rational behaviour, which Barberis and Thaler (2003) later categorised into belief-based and preference-based biases. Kahneman and Tversky in the 1970s demonstrated that heuristics such as availability and representativeness lead to predictable errors under uncertainty, including overconfidence, misinterpretation of probabilities, and excessive reliance on recent or salient information (Kahneman and Tversky, 1972, 1973). Later research extended these insights to risk attitudes recognising that decision making is shaped by psychological (Batel and Devine-Wright, 2015), cultural (Opoku-Okuampa, 2024; West et al., 2010), and emotional factors (Jaiyeoba, 2025; Perlaviciute et al., 2018).

This framework is grounded in three core theories: the psychometric paradigm of risk perception, diffusion of innovation theory, and the affect heuristic, complemented by insights from social acceptance and institutional trust theory. Together, these perspectives enable a nuanced interpretation of how cognitive, experiential, emotional, and contextual factors shape community investment behaviour. Grasping the complexity of the rural investment decisions in these terms demands not only a relational understanding, but also an epistemological commitment to relationality or theoretical pluralism (Heley and Jones, 2012)

The psychometric paradigm of risk perception theory challenges traditional models that treat risk as an objective function of probabilities and outcomes. Developed by Slovic and colleagues, it shows that individuals assess risk using qualitative characteristics, such as familiarity, controllability, voluntariness, dread, and perceived benefits, rather than relying solely on statistical information (Fischhoff et al., 1982; Slovic, 1988). Applied to energy technologies, this framework explains why public perceptions often diverge from expert assessments, particularly for complex or contested technologies (Sovacool, 2010; Hamza et al., 2022). In renewable energy contexts, acceptance is shaped more by perceived environmental impacts, trust in

developers, and perceived fairness than by technical risk estimates (Huijts et al., 2012; Perlaviciute and Steg, 2014). For wind energy investments, the paradigm explains how risk perceptions are formed without direct experience. In communities where wind energy infrastructure is relatively established, perceptions are often grounded in lived experience, including visual intrusion, noise, and opportunities for economic participation (Brennan and Van Rensburg, 2016). In contrast, where exposure remains limited, risk perceptions are more likely to be shaped by abstract evaluations, institutional trust, and anticipated development benefits rather than direct observation (Katikiro, 2016; Makorere, 2012).

These perceptual processes are further shaped by social learning and exposure over time, as emphasised by Diffusion of Innovation (DOI) theory. Originally developed by Rogers in 1962, as cited by Miller (2015), DOI explains how new technologies spread through social systems via communication, observation, and peer influence, rather than through purely rational economic calculations. The theory has been widely applied in studies of renewable energy adoption to explain variations in acceptance and participation across communities (Orr, 2003; Sovacool, 2009; Wolsink, 2007). DOI highlights the importance of the perceived characteristics of an innovation, such as relative advantage, compatibility, complexity, trialability, and observability, in reducing uncertainty and perceived risk. In the context of wind energy investment, familiarity and visibility play a central role: communities with prior exposure to wind farms tend to exhibit higher levels of trust and acceptance due to observable outcomes and shared experiences (Wüstenhagen et al., 2007). DOI further categorises adopters into innovators, early adopters, early majority, late majority, and laggards, reflecting systematic differences in risk tolerance and openness to innovation. Empirical studies have shown that early adopters exert a disproportionate influence by shaping social norms and facilitating peer learning, thereby encouraging wider participation over time (Rai and Robinson, 2013).

Recent advances in behavioural decision theory highlight the central role of emotions in risk-related judgments. The affect heuristic, proposed by Slovic et al. (2002), suggests that individuals rely on immediate emotional responses when evaluating complex or unfamiliar risks. Rather than analytically weighing probabilities, people often assess how they feel about a technology, and these affective responses guide

judgments of both risk and benefit. For example, positive affect, such as associating wind energy with sustainability, progress, or national development, has been shown to reduce perceived risk and increase perceived benefits, whereas negative affect, such as perceiving wind farms as environmentally disruptive or socially divisive, produces the opposite effect (Finucane et al., 2000; Siegrist, 2021). Empirical evidence across energy technologies demonstrates that affect significantly influences public attitudes and investment-related behaviour, particularly under conditions of uncertainty (Bidwell, 2013; Bessette, 2022). Importantly, affect does not operate in isolation but interacts with familiarity, experience, and social influence, reinforcing or moderating the risk perceptions described in the psychometric and diffusion perspectives.

Finally, institutional trust and social acceptance provide a broader contextual lens through which individual perceptions and behaviours can be understood. A substantial body of research shows that trust in government institutions, regulators, and project developers plays a critical role in shaping community responses to renewable energy projects (Devine-Wright, 2011; Rottenberg and Gross, 2007). Low levels of institutional trust tend to amplify perceived risk and resistance, whereas high trust can facilitate acceptance even when outcomes are uncertain or contested. This perspective is particularly salient in cross-country settings, where differences in governance quality, transparency, and perceived fairness in benefit distribution influence how communities interpret both risks and investment opportunities (Firestone et al., 2018; Mueller, 2020). Incorporating institutional trust allows risk perception and investment behaviour to be understood not merely as individual-level judgments but as outcomes embedded within wider socio-political and institutional environments.

7.4 Data and methods

The analysis adopts a comparative case study approach that focuses on the Republic of Ireland and Tanzania, representing developed and developing economies respectively. The two countries were selected to capture structural differences in demographic profiles, institutional quality, and renewable energy deployment practices (Table 7.1). Ireland represents a mature economy that is advanced in wind energy initiatives, whereas Tanzania is a typical developing country with relatively small-scale wind energy development.

Table 7.1: Context of the study area

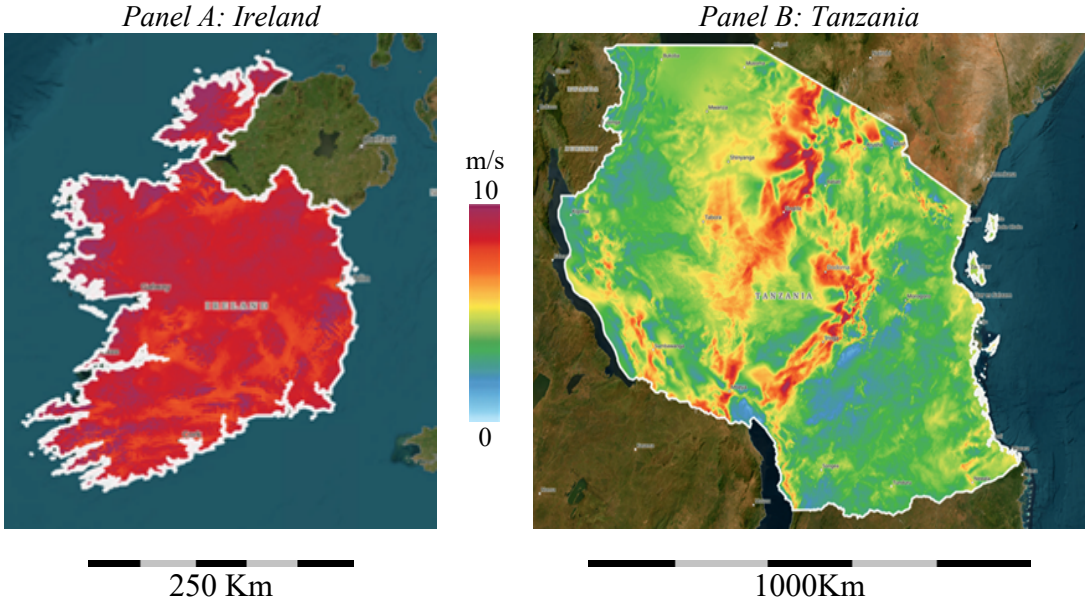
This table show characteristics of the two study areas focusing on wind potential, population and electricity supply coverage.

	Ireland	Tanzania
Land area (Km^2)	70,273	947,303
Population (Million)	5	71
GDP ($ Billion)	708.77	87.44
Electricity grid access (%)	100	48
Wind resource potential (MW)	11,200	17,000
Wind energy installed capacity (MW)	4,836	2.4
Electricity Supply	Privatised	Central Government

Both countries have sufficient wind resources for significant electricity generation (Figure 7.1). Ireland has high wind potential (red) across the entire country. Wind potential is geographically concentrated Tanzania, occurring predominantly within the central regions of the country. Overall wind energy potential is similar, as Tanzania's landmass is approximately thirteen times larger than that of Ireland.

Figure 7.1: Wind resource maps of the study areas

This figure shows the wind resource of the two study countries. The wind maps show mean wind speed at 100m from the Global Wind Atlas. The scale ranges from 0m/s in blue to 10m/s in red.



Electricity supply is fully liberalised in Ireland, with multiple private suppliers offering a range of renewable and non-renewable energy sources (Gaffney et al., 2017). There is strong capacity for investment in emerging energy technologies.

Onshore wind energy development is well established, with the first wind farm commissioned in 1992 (WEI, 2025). There are over 300 operational wind farms (WEI, 2025), supported by abundant wind resources and robust national policies aligned with European Union climate targets. Their capacity is currently 4,836 MW, accounting for 33% of the national electricity mix, the second highest in Europe (Wind Europe, 2024).

Tanzania is a lower middle-income country with electricity generation is dominated by hydropower and natural gas (Kichonge, 2018). The electricity sector is primarily operated by a single state-owned utility, the Tanzania Electric Supply Company (TANESCO). Only 48% of the population had access to the electricity grid, with power outages frequently exceeding twelve hours due to grid congestion and ageing infrastructure (IBRD-IDA, 2023). Many households rely on small-scale solar systems to meet basic energy needs, such as mobile phone charging (Okika et al., 2025). Tanzania has substantial untapped wind energy potential, estimated at up to 17 GWh annually (Kulaba, 2023). However, progress in exploiting this resource is limited. Tanzania's first wind farm was completed in late 2020 in the Mwenga District. This 2.4 MW project, supported by a USD 1.2 million loan from the UK Government-funded renewable energy performance platform, aims to enhance energy security for surrounding communities (Michael et al., 2023).

In Ireland, rural communities generally have a high level of familiarity with wind energy; many live near wind farms, have access to investment platforms, or possess prior knowledge of both the risks and benefits associated with wind technology. In contrast, wind energy remains a relatively new concept in Tanzania. Local communities often have limited awareness of the energy sector and minimal experience with large-scale renewable energy infrastructure. These contrasting contexts provide a valuable basis for examining how experience and socio-economic conditions shape community risk perceptions and investment behaviour.

7.4.1 Institutional context

The two study contexts differ not only in social-economic factors but also in institutional characteristics that may shape renewable energy investment attitudes. Ireland operates within a mature European regulatory framework characterised by

relatively high levels of institutional trust, established renewable energy policies, extensive wind energy deployment, and universal electricity access. Trust in public institutions and project developers has been consistently identified as an important determinant of public acceptance of renewable energy projects and associated investment opportunities (Devine-Wright, 2011; Firestone et al., 2018; Mueller, 2020). Ireland's wind energy sector has developed over more than three decades, supported by national and European climate policies, creating a social environment in which wind energy is familiar to many rural communities (WEI, 2025). Furthermore, recent policy developments have increasingly promoted community participation through energy communities, shared ownership models, and local investment mechanisms, providing citizens with greater opportunities to engage directly in renewable energy projects (European Commission, 2019; le Maitre, 2024a).

In contrast, Tanzania's renewable energy sector remains at a comparatively early stage of development. Electricity access remains uneven, particularly in rural areas, and wind energy deployment is limited, with only a small number of operational projects (IBRD-IDA, 2023; Michael et al., 2023). Previous studies have shown that where renewable energy technologies remain relatively unfamiliar, perceptions are often shaped less by direct experience and more by institutional trust, expectations of development benefits, and broader socio-economic conditions (Katikiro, 2016; Makorere, 2012). In addition, participation in formal investment markets is generally less widespread than in developed economies, potentially affecting familiarity with investment mechanisms and perceptions of financial risk. Research on renewable energy adoption in developing countries highlights the importance of governance quality, regulatory stability, access to information, and equitable benefit-sharing arrangements in shaping public engagement with energy projects (Mey and Diesendorf, 2018; Karakislak et al., 2023).

These institutional differences are important because they may influence how respondents interpret investment opportunities, evaluate risks, and assess the credibility of project developers and public authorities. Consequently, observed differences between the Irish and Tanzanian samples should not be interpreted solely as reflecting differences in individual attitudes or behavioural preferences. Rather, they may also reflect broader differences in institutional trust, renewable energy

market maturity, energy access, investment experience, and governance environments. The comparison should therefore be viewed as an exploratory contrast between two distinct socio-institutional settings rather than as a harmonised comparison of national attitudes toward renewable energy investment.

7.4.2 Research design and data collection

This study employs a quantitative, descriptive, cross-sectional research design to assess community perceptions of risk and investments in wind energy projects. Cross-sectional research designs involve observing participants at a single point in time, examining naturally occurring differences rather than intervention-induced effects, and selecting groups based on pre-existing characteristics rather than random assignment (Hunziker and Blankenagel, 2024).

Theoretical perspectives presented in section three inform the survey design. Questions related to proximity to wind farms, knowledge of climate issues, and formal education serve as indicators of familiarity with wind energy and its outcomes, key components of observability and compatibility. Questions concerning willingness to invest, investment amounts, and expected returns assess respondents' positions along the adoption curve and their perceptions of relative advantage and risk.

Data were collected using a questionnaire, supplemented by follow-up semi-structured group discussions to enrich and contextualize the quantitative findings. Convenience sampling was employed in Ireland, targeting individuals who were readily accessible and who voluntarily chose to participate in the survey. A purposive cluster sampling approach was adopted in Tanzania, with two rural villages in the Mpanda District selected based on their contextual relevance.

The questionnaire comprised a total of twenty-six questions, including an informed consent item. Section A contained fifteen questions to assess individuals' risk attitudes, specifically whether respondents exhibited risk-tolerant or risk-averse tendencies. Section B consisted of ten questions focusing on sustainability, wind energy investment perceptions, and demographic characteristics.

A total of 125 responses were collected in Ireland and 267 in Tanzania. Data were cleaned to remove incomplete or invalid responses, including cases in which participants did not answer key questions or provided responses outside the scope of the survey. Following this, the final sample had 115 respondents from Ireland and 237 respondents from Tanzania (Table 7.2).

Table 7.2: Survey descriptive statistics

This table shows the number of responses collected, omitted, and the clean data for analysis.

	Ireland	Tanzania
Total response	125	267
Less		
Incomplete responses	(9)	(18)
Irrelevant responses	(1)	(12)
Final sample	115	237

7.4.3 Attitude to risk and investment

7.4.3.1 Risk tolerance

Respondents' risk preferences were measured using two complementary approaches. First, a set of fourteen questions was used to create an objective measure of risk-taking behaviour. Participants were asked for their preferences in a series of hypothetical probabilistic scenarios. The answers were processed to generate participants risk tolerance, referred to as *assessed risk.*

Respondents were then asked to self-evaluate their own level of risk tolerance, generating a subjective measure of risk preference, referred to as *self-rated risk*.

The assessed risk questions were adapted from Colasante and Riccetti (2020). These questions systematically evaluate risk preferences through hypothetical decision making scenarios involving varying levels of uncertainty, potential gains, and potential losses. The scenarios span a range of financial situations, allowing for the identification of risk-averse and risk-seeking behaviour. The financial risk scoring method proposed by Colasante and Riccetti (2020) was adopted[4]. Responses were coded as zero for risk-averse choices and one for risk-tolerance choices, and the assessed-risk was measured as the average value of these across the fourteen questions.

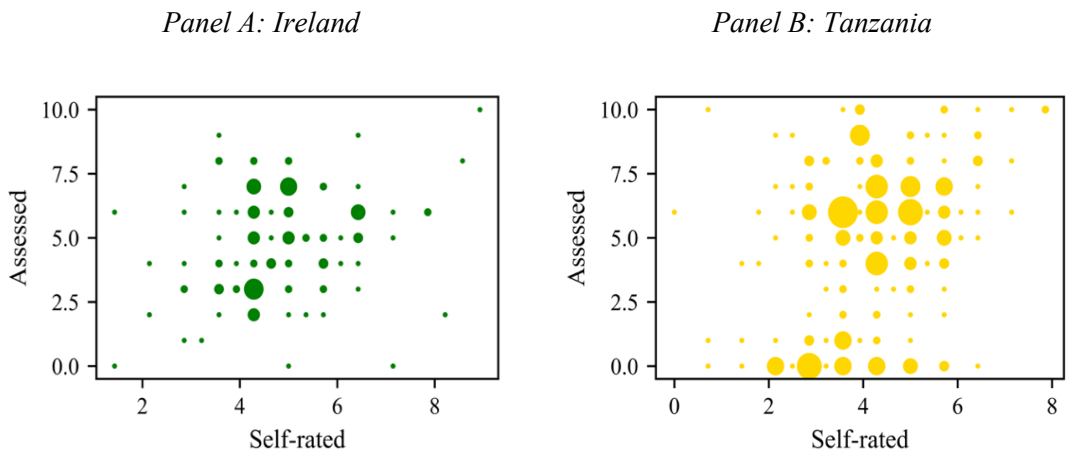
[4] A complete list of questions and the corresponding risk ranking procedure is provided in Appendix C

The self-rated risk measure allowed participants to rate their own level of risk tolerance on a scale of one to ten, where lower values indicate greater risk aversion and higher values indicate greater risk tolerance. The responses for assessed risk were rescaled to a range of one to ten, consistent with the scale of the self-rated risk, to facilitate comparison.

The two measures of risk tolerance have a positive but weak correlation (Figure 7.2). The correlation was 0.21 with a slightly higher value of 0.28 in Tanzania. Overall, the results suggest that self-perceived and assessed risk tolerance are related but capture distinct dimensions of individual risk preferences.

Figure 7.2: Risk correlation measures

This figures present the relationship between two measures of risk perception, self-rated risk and assessed risk for respondents in Ireland (Panel A) and Tanzania (Panel B). The size of the dot represent the intensity of responses.



7.4.3.2 Investment propensity

The core empirical analysis identifies the factors that can influence an individual's willingness to invest in a wind project. We refer to this willingness as investment propensity, term is adapted from the economic concept of the marginal propensity to invest (MPI), which describes the proportion of additional income allocated to investment. While MPI typically refers to investment responses to income changes, the concept is used here to represent an individual's inclination to allocate resources toward an investment opportunity. Investment propensity is measured using a five-point ordinal scale indicating likelihood to invest: 1 = "very unlikely", 2 = "somewhat unlikely", 3 = "neither likely nor unlikely", 4 = "somewhat likely", and 5 = "very

likely". This ordinal measure is the dependent variable in the regression models in the empirical analysis.

7.4.4 Empirical analysis

The core statistical analysis identifies the factors that affect the propensity to invest. An Ordered Logistic Regression Model (also known as a proportional odds model) is preferred to a standard linear regression as the dependent variable, investment propensity, is ordinal. Under the model, categories have a natural order, but the exact spacing between them is not defined (Casinillo, 2023; Hamidi et al., 2013). It assumes the existence of an unobserved latent variable Y^* that is continuous, and the observed categories arise when Y^* crosses a threshold.

$$Y_i^* = \beta X_i^T + \varepsilon_i, \quad \varepsilon_i \sim Logistic(0,1) \tag{7.1}$$

X_i is the vector of covariates for observation i, β is the vector of coefficients, and ε is the error term assumed to follows a standard logistic distribution (Equation 2). Y_i^* is the latent propensity underlying the observed ordinal outcome.

$$F(z) = \frac{e^z}{1 + e^z} \tag{7.2}$$

The observed ordinal response Y_i is determined by a set of threshold (cut-off point) parameters τ_j:

$$Y_i = j \text{ if } \tau_{j-1} < Y_i^* \leq \tau_j \text{ , j=1, ..., J} \tag{7.3}$$

The value of τ range from $\tau_0 = -\infty$ to $\tau_j = +\infty$. In this study Y_i represents the observed ordinal investment propensity measured on a five point like scale: 1 = "very unlikely" to 5 = "very likely". The thresholds τ_j determine how the latent propensity Y_i^*maps into the observed categories.

The cumulative probabilities to covariates X_i in the jth category, is

$$P(Y_i \leq j|X_i) = P(Y_i^* \leq \tau_j|X_i) \tag{7.4}$$

Therefore, the probability of being in exact category j is:

$$P(Y_i = j|X_i) = P(Y_i \leq j|X_i) - P(Y_i \leq j-1|X_i) \quad (7.5)$$

The estimated ordered logistic regression equation for this study model is:

$$logit\big(P(Y_i \leq j)\big) = \tau_j - (\beta_1.risk_i + \beta_2.controls_i) + \varepsilon_i \quad (7.6)$$

This formulation ensures that a positive coefficient β increases the probability of being in higher categories, which is intuitive for most ordinal outcomes. To isolate the effect of individual risk tolerance on stated wind-investment propensity, the model incorporates theoretically grounded controls that capture alternative determinants of choice under uncertainty.

We include a series of variables to control for factors that can independently influence willingness to invest. Investment decisions reflect both risk preferences and anticipated payoffs under expected utility theory (Pratt, 1976). Required return (*Investment Return*) controls for pay-off and investment amount (*Investment Amount*) proxies for risk. Social benefits influence evaluation of renewable energy projects and their associated risks (Huijts et al., 2012; Perlaviciute and Steg, 2014). We include a variable that captures wind farm purpose (*Wind farm*) to analyse the extent to which investment is based on social (climate change) or economic (profitability) motives.

Trust in energy institutions and project developers has been shown to influence public responses to renewable energy projects and associated investment opportunities (Devine-Wright, 2011; Firestone et al., 2018). The variable *Electricity choice* captures whether consumers prioritize price or renewable energy solutions when selecting an electricity provider.

Individuals living closer to wind infrastructure tend to have stronger perceptions of both the risks and benefits of projects, influencing their support and engagement (Brennan and Van Rensburg, 2016; le Maitre, 2024a). This is captured by *Location* which is a categorical variable, checking if the respondent lives within one, five, or more than ten kilometres of an existing wind farm. Policy awareness (*Knowledge*) is included to capture respondents' familiarity with the regulatory context of renewable energy development, which can shape perceived credibility and risk (Rottenberg and Gross, 2007). Finally, demographic characteristics systematically influence risk attitudes and financial decision-making (Dohmen et al., 2011; Witkowska-Dabrowska

et al., 2021) and so *Age*, *Gender* and *Education* are included. Including these variable, the specified model is:

$$logit\big(P(Y_i \leq j)\big) = \tau_j - (\beta_1.Risk_{score_i} + \beta_2.Location_i + \beta_3.InvesmentReturn_i + \beta_4.InvestmentAmount_i + \beta_5.Knowledge_i + \beta_6.Electricity_i + \beta_7.Farm_i + \beta_8.Age_i + \beta_9.Gender +_i \beta_{10}.Education_i) + \varepsilon_i \quad (7.7)$$

The model parameters (β and τ_j) were estimated using Maximum Likelihood Estimation (MLE)[5]**.** The model's fit was measured with McFadden's Pseudo-R^2 and Likelihood-Ratio (LR) Chi-Square used to test if the predictors have a statistically significant effect on the outcome.

A Brant test assessed the proportional odds assumption underlying the standard ordered logistic regression model. Specifically, this tests whether each predictor exerts a constant effect across all thresholds of the ordinal outcome (Brant, 1990). Violation of this assumption indicates that the parallel lines constraint does not hold, necessitating the use of a generalised ordered logistic regression framework that allows predictor effects to vary across outcome categories.

Correlation matrices (Spearman) for Ireland and Tanzania (Figure 7.3) indicate that multicollinearity is not a concern, as most coefficients are small, with all having a magnitude 0.7, a commonly accepted threshold for multicollinearity (Dormann et al., 2013). Overall, the variables capture distinct constructs and can be jointly included in the regression analysis without the risk of inflated standard errors or unreliable estimates.

[5] All statistical analyses were conducted in Python, using the `statsmodels` library to fit the ordered logistic regression model

Figure 7.3: Variables correlation measures

This figure presents the correlation of the study variables using Spearman's correlation matrix for Ireland (Panel A) and Tanzania (Panel B).

Panel A: Ireland

Investment propensity	1											
Self-rated risk	0.34	1										
Assessed risk	0.03	0.21	1									
Investment return	0.19	-0.01	-0.12	1								
Investment amount	0.23	0.09	0.01	0.37	1							
Location	0.00	0.06	-0.13	0.04	0.13	1						
Electricity choice	0.14	-0.04	-0.04	0.07	-0.02	-0.21	1					
Wind farm	-0.07	0.15	-0.02	0.06	0.03	-0.07	-0.07	1				
Knowledge	0.20	-0.03	0.01	-0.02	-0.07	-0.08	0.03	-0.17	1			
Age	-0.16	-0.07	0.19	-0.11	-0.01	-0.20	-0.06	-0.08	0.01	1		
Gender	-0.18	-0.08	0.02	-0.16	-0.18	-0.08	0.24	-0.18	0.08	-0.04	1	
Education	-0.50	-0.01	-0.18	-0.01	0.18	-0.10	-0.02	0.04	0.11	0.14	0.14	1
	Investment propensity	Self-rated risk	Assessed risk	Investment return	Investment amount	Location	Electricity Choice	Wind farm	Knowledge	Age	Gender	Education

Panel B: Tanzania

Investment propensity	1											
Self-rated Risk	-0.08	1										
Assessed Risk	0.00	0.28	1									
Investment return	-0.02	0.30	0.15	1								
Investment amount	-0.10	0.50	0.14	0.22	1							
Location	0.00	0.06	0.08	-0.04	0.08	1						
Electricity choice	-0.09	0.46	0.15	0.11	0.46	0.18	1					
Wind farm	0.03	-0.04	0.01	0.03	0.09	-0.26	-0.03	1				
Knowledge	0.00	0.25	0.01	0.10	0.05	-0.08	0.17	0.17	1			
Age	0.01	0.00	-0.05	-0.01	-0.05	0.17	0.10	0.10	0.16	1		
Gender	0.00	-0.12	-0.08	-0.11	0.02	-0.11	-0.13	-0.13	0.04	-0.14	1	
Education	0.03	0.11	0.07	0.07	0.13	0.00	0.21	0.21	0.19	-0.13	0.06	1
	Investment propensity	Self-rated Risk	Assessed risk	Investment return	Investment amount	Location	Electricity choice	Wind farm	Knowledge	Age	Gender	Education

7.5 Results

7.5.1 Survey demographics

The survey has a gender representation difference. The Irish sample has a balanced split between male and female, while the Tanzanian sample is predominantly male (Figure 7.4, Panel B). This pattern reflects social norms common in many developing

countries and rural communities, where men are often viewed as the public representatives of households and women's roles are more focused on the domestic sphere (Lamphere, 2024). In both countries, there is a high average of respondents that fall within the twenty five to sixty five year age range (Figure 7.4, Panel A).

Figure 7.4: Age and gender

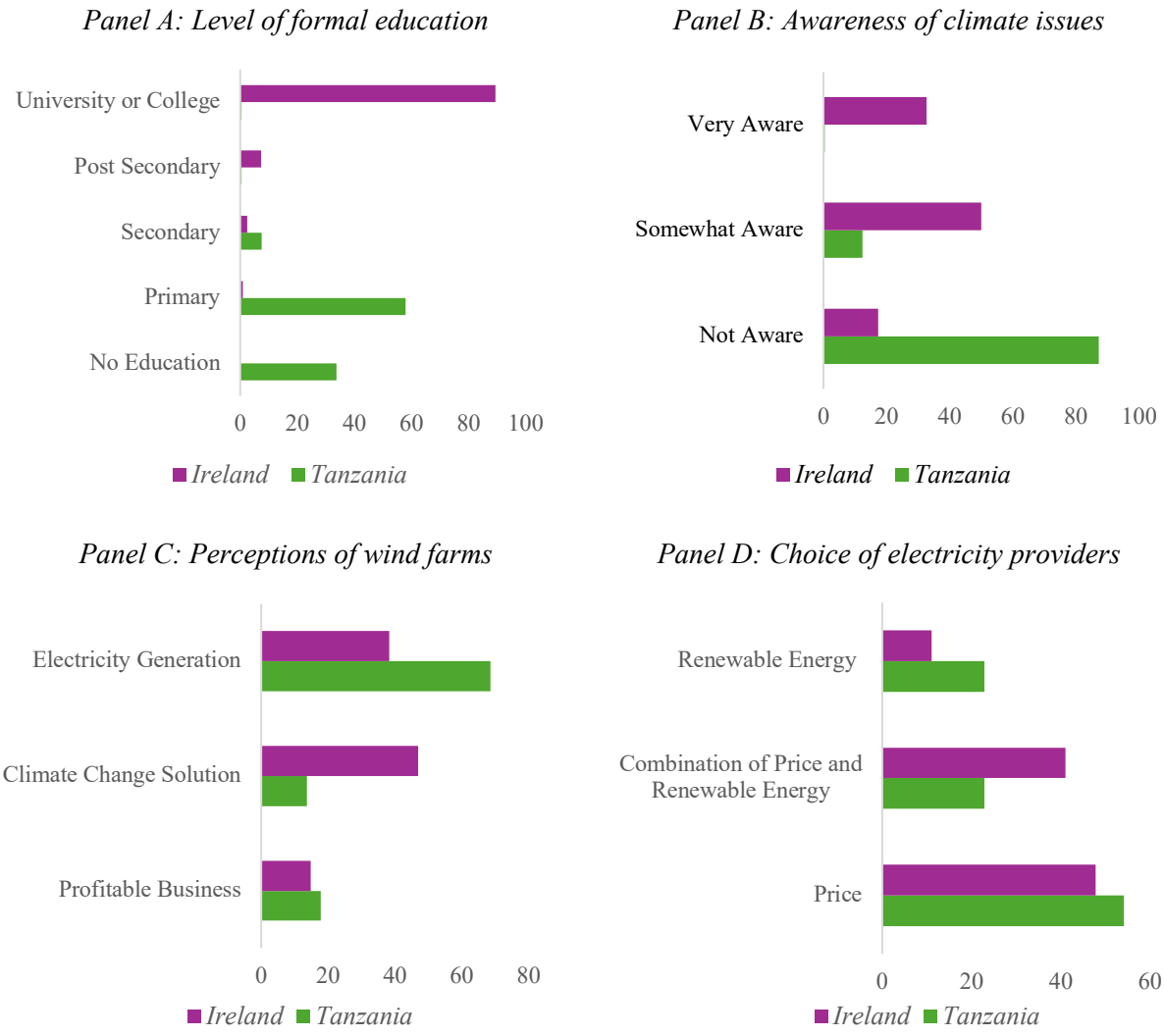
This figure presents the age (Panel A) and gender (Panel B) distributions of the survey participants in Ireland and Tanzania.



There are clear differences between the two study groups in education, climate change awareness, and perceptions of wind energy (Figure 7.5). Nearly 90% of Irish respondents have a university or college degree, whereas most Tanzanian respondents have only primary education or no formal education. These differences are reflected in how wind energy is viewed: Tanzanians tend to view wind farms mainly as sources of electricity, while Irish respondents view them as a way to address climate change. Awareness of environmental policy also differs, with most Irish participants being at least somewhat aware of the EU's 2030 emissions targets, while almost 90% of Tanzanian respondents are unaware of a similar national target. Irish respondents place greater importance on renewable energy or a balance between cost and sustainability choosing electricity providers, whereas Tanzanians focus on affordability.

Figure 7.5: Education and awareness

This figure shows the awareness status of respondents regarding the formal level of education, knowledge of climate-related issues including renewable energy topics, and electricity provision.



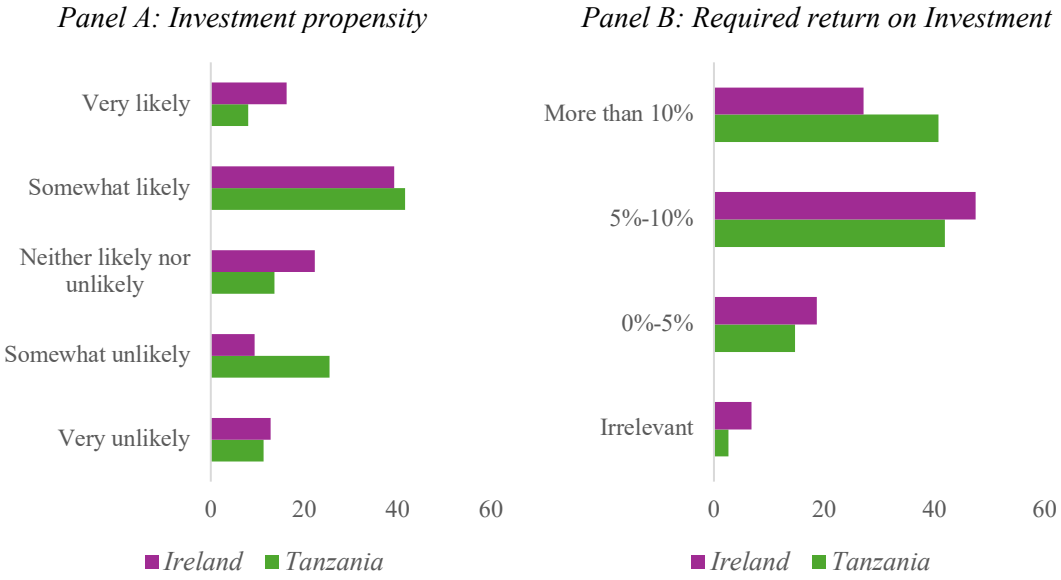
7.5.2 Investment propensity

The proportion of respondents in both countries likely to invest in a wind energy opportunity was greater than those unlikely to (Figure 7.6, Panel A), although the proportion was greater in Ireland. In Ireland, 56% were likely to invest against 22% that were unlikely, the corresponding figures in Tanzania were 50% against 37%. Tanzanian participants had a higher required return for their investment with 40% requiring a return above 10% per annum. This is consistent with Tanzanians have a

greater perceived risk or Irish participants accepting lower returns as a price for fighting climate change.

Figure 7.6: Investment and return perceptions

This figure presents respondents' investment propensity (Panel A) and the required investment return (Panel B) to invest in a wind energy project. Participants who would not consider investing marked the required return as irrelevant.

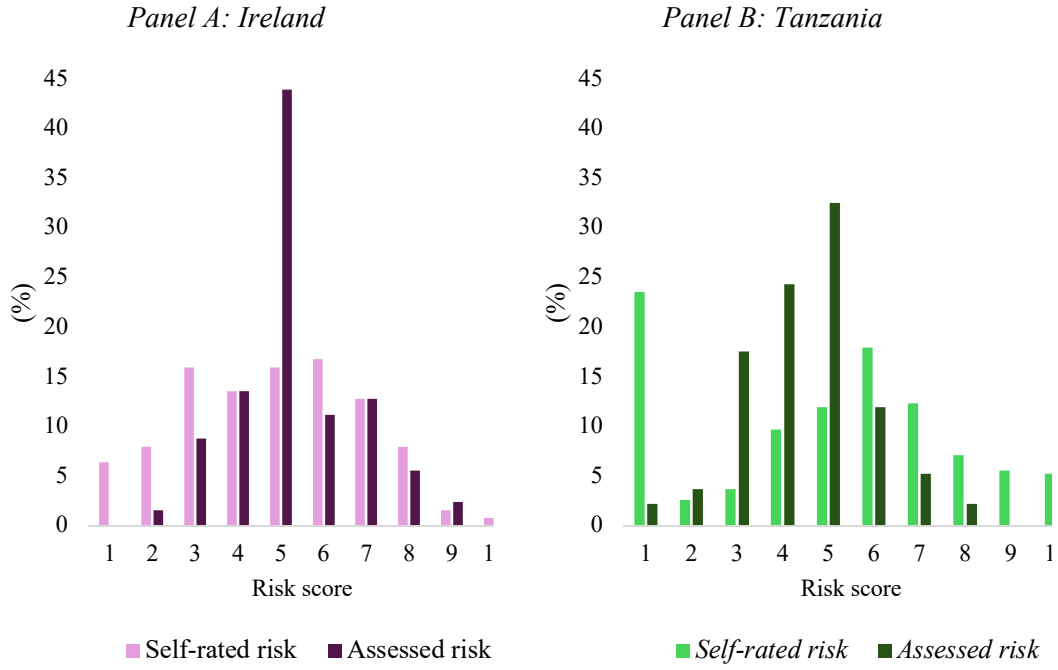


7.5.3 Risk tolerance

Risk scores, both assessed and self-rated, are centred between three and seven in Ireland, a relatively balanced and moderate risk tolerance across respondents (Figure 7.7). The absence of substantial clustering at the extremes indicates Irish participants evaluate risk scenarios with stable and differentiated preferences. The distribution of Tanzanian responses differs between the two risk measures. The distribution of assessed risk is similar to the Irish pattern, albeit slightly more risk averse. The self-rated risk has a bimodal distribution. One cluster of respondents peaking around five, similar to the Irish pattern. However, there is a second peak where 24% of respondents assign themselves the minimum score of one. Overall, Tanzanian respondents display higher self-rated and assessed risk aversion than their Irish counterparts.

Figure 7.7: Risk distribution

This figure shows the respondents' risk preference distributions under the self-rated risk scores and assessed risk scores for Ireland (Panel A) and Tanzania (Panel B).



7.5.4 Factors affecting investment propensity in wind farms

The section identifies the factors that influence an individual's propensity to invest in a wind project. We first regress investment propensity against a series of potential explanatory variables, including self-assed risk. We use a standard ordered logistic regression model, consistent with the ordinal dependent variable. This is followed by two robustness tests. A Brant test indicates a potential violation of the proportional odds assumption, that is the assumption that the explanatory coefficients are consistent across all categories of the dependent variable. We use the generalized ordered logistic regression method to allow for this, with the same dependent and independent variables. Finally, we repeat that regression but use rated risk in place of self-assessed risk as an explanatory variable.

The ordered regression presents a number of statistically significant factors impacting investment propensity in Ireland (Table 7.3). Investment propensity is positively associated with risk ($\beta = 0.434$, $p < 0.001$). Investment propensity also increases with higher returns and investment amount. A preference for preference for sustainable electricity also has a positive effect. Demographics also effects investment, with both

younger and male participants more likely to invest. Other factors, including location, and education, are not statistically significant. A Brant test ($\chi^2 = 369.823$, $p < 0.001$) indicates that there may be a violation of the proportional odds assumption and these results must be treated with caution. This motivates the use of the generalised ordinal least squares as a robustness check.

In contrast, the regression analysis of the Tanzanian study showed no statistically significant relationships. This is surprising as the sample size in Tanzania was twice that of Ireland.

Overall, the findings point to a clear cross-country contrast. In Ireland, investment willingness is shaped by risk attitudes, financial expectations, and sustainability preferences, whereas in Tanzania, these factors appear largely irrelevant, suggesting that unobserved economic or structural constraints may play a more dominant role.

Table 7.3: Factors affecting investment propensity in wind farms

Standard ordered regression results of the factors affecting investment propensity using self-rated risk as the primary explanatory variable. The dependent variable is ordinal variable ranked from 1 to 5, low to high propensity.

	Investment propensity (Ireland: n=115)		Investment propensity (Tanzania: n=237)	
Variable	Coef	P>|Z|	Coef	P>|Z|
Self-rated risk	0.434***	0.001	-0.007	0.891
Location	-0.043	0.847	0.075	0.631
Investment return	0.514**	0.033	0.018	0.919
Investment amount	0.483*	0.083	-0.302	0.237
Knowledge	0.658	0.160	0.072	0.854
Electricity choice	0.725*	0.051	-0.244	0.408
Wind farm	-0.515*	0.070	0.131	0.429
Age	-0.248*	0.080	-0.019	0.833
Gender	-0.644*	0.054	-0.013	0.961
Education	-0.051	0.914	0.231	0.252
LR Chi-sq		49.927 (0.001)		5.810 (0.971)
McFadden R^2		0.146		0.008
Brant test		369.823 (0.001)		221.301 (0.001)

* p < 0.1, ** p < 0.05, *** p < 0.01

The regression is re-run with generalized ordered logistic (GOL) regression (Areo and Gershon, 2020; De Lucia et al., 2021). This allows predictor effects to vary across thresholds (Table 7.4). The GOL estimates provide a more nuanced understanding of how predictors influence different levels of investment propensity and complement the earlier findings (Table 7.3).

Risk tolerance is a statistically significant predictor across all thresholds in Ireland, confirming that higher risk tolerance consistently increases the likelihood of greater investment willingness. The significance of other factors is reduced. Investment returns are significant at the lower thresholds ($\tau_{1/2}$ and $\tau_{2/3}$) and right-signed at the others, indicating that expected returns primarily distinguish those who are unwilling from those at least moderately open to investment. Age and gender are negative across all thresholds consistent with the ordered regression results but only statistically significant at the lower bounds (gender) and higher bounds (age).

In Tanzania, the predictor effects remain generally weak, reflecting the insignificant findings from the standard ordered model. Most variables do not significantly influence investment propensity across thresholds. However, two threshold-specific effects emerge: electricity choice and education are significant at the lowest threshold ($\tau_{1/2}$), predicting that choosing an electricity provider based on price and lower educational attainment are associated with remaining in the lowest willingness category. However, it must be noted that four out of forty significant variables in in line with random chance so greater care should be taken in interpreting these results.

Table 7.4: Factors affecting investment propensity using GOL

Odds-specific results (effects differ across cut points of the ordinal outcome) using self-rated risk as the key explanatory variable, $\tau_{1/2}$ present a transition from very unlikely to somewhat unlikely, $\tau_{2/3}$presents somewhat unlikely to neither likely nor unlikely, $\tau_{3/4}$ presents neither likely nor unlikely to somewhat likely, and $\tau_{4/5}$ presents somewhat likely to very likely.

	Investment propensity (Ireland)				Investment propensity (Tanzania)			
Variable	$\tau_{1/2}$ Coef	$\tau_{2/3}$ Coef	$\tau_{3/4}$ Coef	$\tau_{4/5}$ Coef	$\tau_{1/2}$ Coef	$\tau_{2/3}$ Coef	$\tau_{3/4}$ Coef	$\tau_{4/5}$ Coef
Self-rated risk	0.597*** (0.004)	0.314** (0.049)	0.421*** (0.001)	0.517*** (0.009)	0.026 (0.755)	-0.047 (0.407)	-0.0019 (0.972)	-0.004 (0.969)
Location	1.0494 (0.123)	0.079 (0.792)	-0.252 (0.355)	-0.327 (0.319)	0.260 (0.368)	0.267 (0.136)	0.089 (0.601)	-0.594 (0.125)
Investment return	1.274** (0.045)	0.698* (0.069)	0.026 (0.934)	0.134 (0.692)	0.132 (0.575)	0.034 (0.863)	-0.109 (0.564)	0.010 (0.972)
Investment amount	1.354 (0.416)	0.162 (0.761)	0.719 (0.103)	-0.177 (0.665)	-0.602 (0.162)	-0.317 (0.264)	-0.157 (0.567)	-0.563 (0.415)
Knowledge	0.257 (0.741)	0.580 (0.127)	0.604* (0.076)	0.639 (0.222)	-0.269 (0.678)	0.057 (0.898)	0.188 (0.652)	-0.425 (0.6260)
Electricity choice	1.827* (0.060)	0.406 (0.467)	0.560 (0.216)	0.576 (0.341)	-0.988** (0.037)	-0.369 (0.310)	-0.018 (0.956)	-0.007 (0.906)
Wind farm	-0.907 (0.204)	-0.647 (0.125)	-0.727* (0.054)	0.195 (0.677)	0.218 (0.476)	0.362* (0.062)	0.114 (0.538)	-0.221 (0.522)
Age	-0.156 (0.482)	-0.156 (0.424)	-0.247 (0.143)	-0.370* (0.089)	0.348 (0.57)	0.010 (0.928)	-0.034 (0.745)	-0.544** (0.011)
Gender	-1.338** (0.036)	-0.925** (0.033)	-0.523 (0.196)	-0.243 (0.694)	0.657 (0.277)	0.035 (0.917)	-0.194 (0.530)	-0.247 (0.654)
Education	-1.026 (0.350)	0.300 (0.559)	0.167 (0.774)	-0.595 (0.325)	1.085*** (0.002)	0.255 (0.268)	-0.056 (0.798)	0.418 (0.232)
Constant				-1.937 (0.345)				0.570 (0.382)
McFadden R^2				0.449				0.319

* p < 0.1, ** p < 0.05, *** p < 0.01

The final test used the assessed risk in place of the self-assigned score (Table 7.5). The assessed risk score is a far weaker predictor of investment propensity among Irish respondents. Unlike the previous model, where self-rated risk was strongly significant across all thresholds, assessed risk is largely not significant, reaching only marginal significance at the highest threshold, where it slightly increases the likelihood of moving into the "very likely" category. It does have positive sign across all four thresholds which is consistent with the self-rated model. Other patterns are broadly consistent with earlier findings, such as the positive effects of investment returns at

lower thresholds and the significant negative effect of gender at the lowest levels of willingness.

Table 7.5: Factors affecting investment propensity using GOL and assessed risk.

Odds-specific results (effects differ across cut points of the ordinal outcome). $\tau_{1/2}$ present a transition from very unlikely to somewhat unlikely, $\tau_{2/3}$presents somewhat unlikely to neither likely nor unlikely, $\tau_{3/4}$ presents neither likely nor unlikely to somewhat likely, and $\tau_{4/5}$ presents somewhat likely to very likely. The analysis uses assessed risk score.

	Investment propensity (Ireland)				Investment propensity (Tanzania)			
Variable	$\tau_{1/2}$ Coef	$\tau_{2/3}$ Coef	$\tau_{3/4}$ Coef	$\tau_{4/5}$ Coef	$\tau_{1/2}$ Coef	$\tau_{2/3}$ Coef	$\tau_{3/4}$ Coef	$\tau_{4/5}$ Coef
Assessed risk	0.068 (0.747)	0.295 (0.149)	0.062 (0.729)	0.283* (0.082)	0.034 (0.745)	–0.068 (0.511)	–0.204 (0.218)	0.283* (0.082)
Location	1.047* (0.053)	0.103 (0.719)	–0.128 (0.590)	0.120 (0.665)	0.254 (0.151)	0.116 (0.499)	–0.491 (0.200)	0.120 (0.665)
Investment return	1.109* (0.055)	0.536 (0.122)	–0.009 (0.975)	0.135 (0.725)	–0.098 (0.704)	–0.024 (0.908)	–0.053 (0.784)	0.183 (0.525)
Investment amount	1.218 (0.268)	0.244 (0.617)	0.734* (0.054)	–0.054 (0.895)	–0.641* (0.079)	–0.407 (0.127)	–0.130 (0.614)	–0.481 (0.422)
Knowledge	0.407 (0.582)	0.559 (0.139)	0.526* (0.091)	0.553 (0.266)	–0.207 (0.748)	–0.019 (0.964)	0.191 (0.644)	–0.453 (0.588)
Electricity choice	2.159** (0.021)	0.472 (0.394)	0.569 (0.187)	0.496 (0.405)	–0.983* (0.066)	–0.447 (0.210)	–0.020 (0.950)	–0.074 (0.897)
Wind farm	–0.245 (0.614)	–0.489 (0.142)	–0.413 (0.169)	0.359 (0.387)	0.111 (0.720)	0.372* (0.051)	0.129 (0.481)	–0.167 (0.604)
Age	–0.248 (0.241)	–0.251 (0.174)	–0.225 (0.175)	–0.376 (0.112)	0.316 (0.100)	–0.001 (0.996)	–0.018 (0.865)	–0.505** (0.024)
Gender	–1.405** (0.029)	–1.020** (0.021)	–0.485 (0.191)	–0.381 (0.511)	0.720 (0.278)	0.053 (0.876)	–0.181 (0.559)	–0.251 (0.663)
Education	–0.699 (0.347)	0.053 (0.925)	0.166 (0.759)	–0.440 (0.454)	1.007*** (0.006)	0.249 (0.280)	–0.032 (0.884)	0.495 (0.153)
Constant	-0.745 (0.717)				0.550 (0.457)			
McFadden R^2	0.369				0.323			

* p < 0.1, ** p < 0.05, *** p < 0.01

In Tanzania, the results confirm the earlier conclusion that predictors exert limited influence on investment propensity, regardless of whether risk is measured through self-rating or assessed using hypothetical questions. Risk measures remain non-significant across all thresholds. While a small number of variables reach statistical significance, this is no different to the number that would be achieved by chance, so any inference should be treated with caution. A few threshold-specific patterns may

be worth noting. Education remains significant at the lowest threshold, and age becomes negatively significant at the highest threshold, predicting that the most educated respondents are more likely to move out of the "very unlikely" category, while older respondents are less likely to reach the "very likely" category. The positive effect of wind farm sentiment at $\tau_{2/3}$ mirrors the subtle attitudinal sensitivities observed earlier.

7.6 Discussion

Overall, the results show an openness to wind energy in Ireland and Tanzania, with the numbers willing to invest greater than those unlikely to invest in both countries. However, there are differences between the countries across both investment propensity and risk tolerance. Respondents in Ireland demonstrated a greater willingness to invest coupled with lower return requirements. In contrast, Tanzanian respondents exhibited greater risk aversion and, consistent with this a more cautious investment propensity and greater return requirement. The statistical analysis linked increased willing to invest with risk tolerance, financial factors and climate concerns in Ireland. Demographic factors also effected the propensity to invest with younger and female respondents linked to higher propensity. In contrast, no statistically significant factors affecting investment propensity were found in Tanzania.

These differences can be interpreted through several established theoretical frameworks. The psychometric paradigm, diffusion of innovation, the affect heuristic, and institutional trust provide complementary insights into how subjective risk construction, experiential familiarity, social learning, emotional evaluation, and governance environments shape investment perceptions. Collectively, these perspectives explain why individuals with broadly comparable objective risk profiles may nevertheless arrive at different investment decisions across national contexts, indicating that community investment behaviour extends beyond purely financial reasoning.

The observed differences between the Irish and Tanzanian samples are consistent with several behavioural frameworks. However, they should not be interpreted as evidence that respondents differ solely because of individual risk attitudes or psychological characteristics. The two study contexts differ across a wide range of institutional,

economic, and infrastructural dimensions that were not directly measured. Consequently, country effects may act as proxies for broader contextual influences rather than reflecting behavioural differences alone. In Ireland, higher levels of education attainment and greater climate awareness appear to support more differentiated assessments of investment risk. This interpretation is reinforced by the modelling results: in Ireland, self-rated risk consistently predicts investment propensity across both ordered and generalised ordered logistic specifications, whereas assessed risk plays a weaker explanatory role. In Tanzania, neither risk measure is statistically significant, and both exhibit a negative association with investment willingness. This is consistent with psychometric risk evaluations become behaviourally relevant only when a technology is sufficiently embedded within everyday economic and social contexts to be cognitively framed as an investment risk.

Diffusion of innovation theory offers further explanatory power. In Ireland, wind energy appears to have progressed to a mature stage of diffusion, in which investment decisions are shaped by perceived relative advantage and practical considerations, such as expected returns and minimum investment thresholds. The generalised ordered logit results indicate that these factors operate across distinct decision thresholds, consistent with movement along the adoption continuum. In Tanzania, the near absence of significant predictors aligns with an earlier diffusion stage in which wind energy remains largely abstract. Under such conditions, individual preferences exert limited influence because market infrastructure, financing mechanisms, and social learning channels remain underdeveloped.

The weak influence of individual-level variables in Tanzania highlights the dominant role of institutional trust and social acceptance. While education and electricity preferences appear to reduce strong opposition, they do not translate into active investment interest. This can be taken as evidence that investment reluctance is shaped more by uncertainty about institutional credibility, project governance, and benefit sharing than by personal risk attitudes. In contrast, Ireland's results reflect higher baseline social acceptance (Cronin et al., 2021; Strain and Barry, 2017), which allows individual attitudes and preferences to meaningfully influence investment behaviour. Overall, the findings align with prior research showing that institutional trust and

perceived procedural fairness are critical conditions for community investment in renewable energy projects (Mueller, 2020).

7.6.1 Institutional context and omitted variables

An important consideration when interpreting the results is that country membership is likely acting as a proxy for numerous unobserved variables. Although the analysis controls for demographic characteristics, risk attitudes, and selected energy-related preferences, several potentially important determinants of investment behaviour were not directly measured. These include household income and wealth, financial literacy, access to investment capital, trust in government institutions, trust in project developers, perceptions of corruption, previous investment experience, energy security concerns, and awareness of renewable energy financing mechanisms.

Consequently, observed differences between Ireland and Tanzania should not be interpreted as reflecting intrinsic national differences in risk attitudes or investment behaviour. Rather, they may reflect broader institutional and socio-economic conditions within which respondents form investment preferences. Future research would benefit from explicitly measuring these contextual variables to better distinguish behavioural effects from institutional influences.

7.6.2 Policy implications

Taken together, these findings indicate that policies aimed at promoting community investment in wind energy must be context-specific and aligned with the diffusion stage. In mature markets such as Ireland, policy interventions should focus on reducing perceived investment barriers and enhancing affectively positive signals, such as transparent returns, manageable investment sizes, and visible community benefits, to leverage existing risk tolerance and social acceptance.

In early-stage contexts, such as Tanzania, policies targeting individual risk attitudes are unlikely to be effective in isolation. Instead, priority should be given to strengthening institutional credibility, building demonstrator projects, and establishing trusted mechanisms for community participation and benefit sharing. Stable leadership and the legitimacy of municipal strategy can support the strategic development of rural areas (Mustakangas and Vihinen, 2024). Only as wind energy becomes socially visible

and institutionally credible are behavioural factors, such as risk perception and affect, likely to translate into meaningful investment propensity.

7.6.3 Limitations and future research

This study has several limitations. First, the cross-sectional design restricts causal inference, as relationships between risk tolerance and investment propensity reflect associations rather than changes over time. Given that renewable energy investment decisions evolve as technologies diffuse, institutions mature, and policy contexts change, future longitudinal studies would provide deeper insights. In addition, reliance on self-reported risk measures may introduce response or framing biases. Future research could therefore strengthen validity by integrating behavioural experiments, revealed-preference data, or qualitative approaches to better capture actual investment behaviour and underlying affective and social processes.

Another limitation pertains to the sample composition and cross-country comparability. Educational attainment is unevenly distributed across samples, with primary education dominating the Tanzanian data and tertiary education being more prevalent in Ireland, potentially introducing bias. Larger and more balanced samples would improve representativeness. Moreover, the findings are context-specific and care should be taken in generalizing to all low- or high-income countries, as institutional capacity, market maturity, and community engagement can vary widely. The weak explanatory power of individual-level variables in Tanzania also indicates the need for future research to incorporate institutional and structural factors, such as access to finance, regulatory clarity, and benefit-sharing mechanisms, alongside behavioural theories.

A further limitation concerns the sampling strategy and comparability of the two samples. The study employed non-probability sampling approaches, with convenience sampling used in Ireland and purposive village-based recruitment used in Tanzania. Consequently, neither sample should be regarded as nationally representative. Differences in recruitment methods, internet access, literacy levels, and survey administration environments may also have influenced responses. Participants in Ireland were more likely to be recruited through online channels, whereas Tanzanian respondents were recruited through field-based approaches within specific rural

communities. These differences introduce potential self-selection bias and may affect the comparability of measured attitudes. The substantial differences observed in gender balance, educational attainment, and access to information further suggest that the samples capture distinct respondent populations. Accordingly, the findings should be interpreted as exploratory evidence from two contrasting case-study contexts rather than as definitive national comparisons.

7.7 Conclusion

Perceptions regarding risk and investments in onshore wind energy vary significantly between developed and developing communities. The results indicate that attitudes toward wind energy investment differ between the Irish and Tanzanian samples. However, these differences should be interpreted cautiously because the two study contexts differ across numerous institutional, economic, and infrastructural dimensions that were not directly measured. The findings therefore provide exploratory evidence that renewable energy investment attitudes are shaped not only by individual risk perceptions but also by broader socio-institutional conditions.

The statistical analysis reveals clear contrasts between the two study contexts. Self-rated risk is a strong and consistent predictor of investment propensity across both ordered and generalised ordered logistic models in Ireland, indicating that subjective risk perceptions play a central role in shaping investment propensity in wind energy. Investment decisions are also influenced by expected returns and other individual preferences, reflecting a context in which wind energy is familiar and socially embedded. In Tanzania, neither self-rated nor assessed risk significantly explains investment propensity, and most individual-level variables show weak or inconsistent effects.

Overall, the study concludes that community investment in wind energy is a socially and institutionally mediated process rather than a purely economic one. Effective policies and project designs must therefore move beyond assumptions of rational risk-return calculations and prioritize trust-building, social acceptance, and context-sensitive pathways that reflect the maturity of the energy system and the lived experiences of communities.

Chapter 8 . Discussion: decision support frameworks

This chapter draws on the findings and lessons from the studies conducted in this thesis to formulate and discuss end-of-life (EoL) decision support frameworks. The purpose of these frameworks is to assist wind farm stakeholders in making informed EoL decisions namely whether to extend the operational life of existing assets, repower, or decommission by placing risk analysis at the centre of the decision process. The first decision framework is commercial and the second is community (social) based.

8.1 Commercial decision support framework

The first framework integrates two complementary sources of uncertainty (component failures and electricity prices). First, it captures operational financial risk arising from turbine component failures, as quantified in study 1, by explicitly modelling expected repair costs alongside downside risk using Value at Risk (VaR) and Conditional Value at Risk (CVaR), expressed relative to capital expenditure (CAPEX) and accounting for diversification effects associated with wind farm size. Second, it incorporates the market-driven value and risk of alternative EoL investment pathways under uncertain electricity prices, drawing on the real options framework developed in study 2 to reflect both upside potential and downside exposure across different market scenarios. The tool produces a risk-adjusted ranking of EoL options, complemented by recommended risk-mitigation measures and clearly defined trigger points for re-evaluation as asset condition, market conditions, or stakeholder risk appetite evolve (Figure 8.1).

8.1.1 Stakeholder objectives and constraints

The first step is clear identification of stakeholder objectives and constraints, as these fundamentally shape the feasible set of end-of-life (EoL) decisions and the interpretation of subsequent risk and value metrics. Stakeholder objectives may vary widely and often extend beyond the simple maximisation of expected financial returns. For example, an operator may seek additional revenue generation from an existing site by repowering with larger, more efficient turbines, thereby increasing energy yield and extending the economic life of the asset. In other cases, objectives may include meeting decarbonisation targets and complying with climate change and energy transition policies, maintaining portfolio scale to support long-term strategic growth, or preserving stable cash flows by continuing to exploit the current benefits of an

operating wind farm through lifetime extension. Crucially, these objectives are closely linked to the stakeholder's risk appetite, which determines the acceptable level of downside exposure associated with capital-intensive investments such as repowering, as opposed to lower-risk but lower-return alternatives.

At the same time, EoL decisions are subject to a range of binding constraints that may significantly limit strategic flexibility. Regulatory and physical constraints, such as grid connection capacity and operational permits, play a central role, as many wind farms are originally granted operating licences for periods of only twenty to twenty five years, beyond which continued operation or repowering may require renegotiation or face regulatory uncertainty. Financial constraints are equally important: CAPEX availability and financing conditions can restrict the ability of an operator to undertake repowering projects, which involve substantial upfront investment, or even to fund major component replacements required for lifetime extension. These constraints must be explicitly recognised at the outset, as they determine which EoL pathways are technically, financially, and institutionally feasible, and they provide the contextual foundation upon which the subsequent risk-based evaluation within the decision support tool is built.

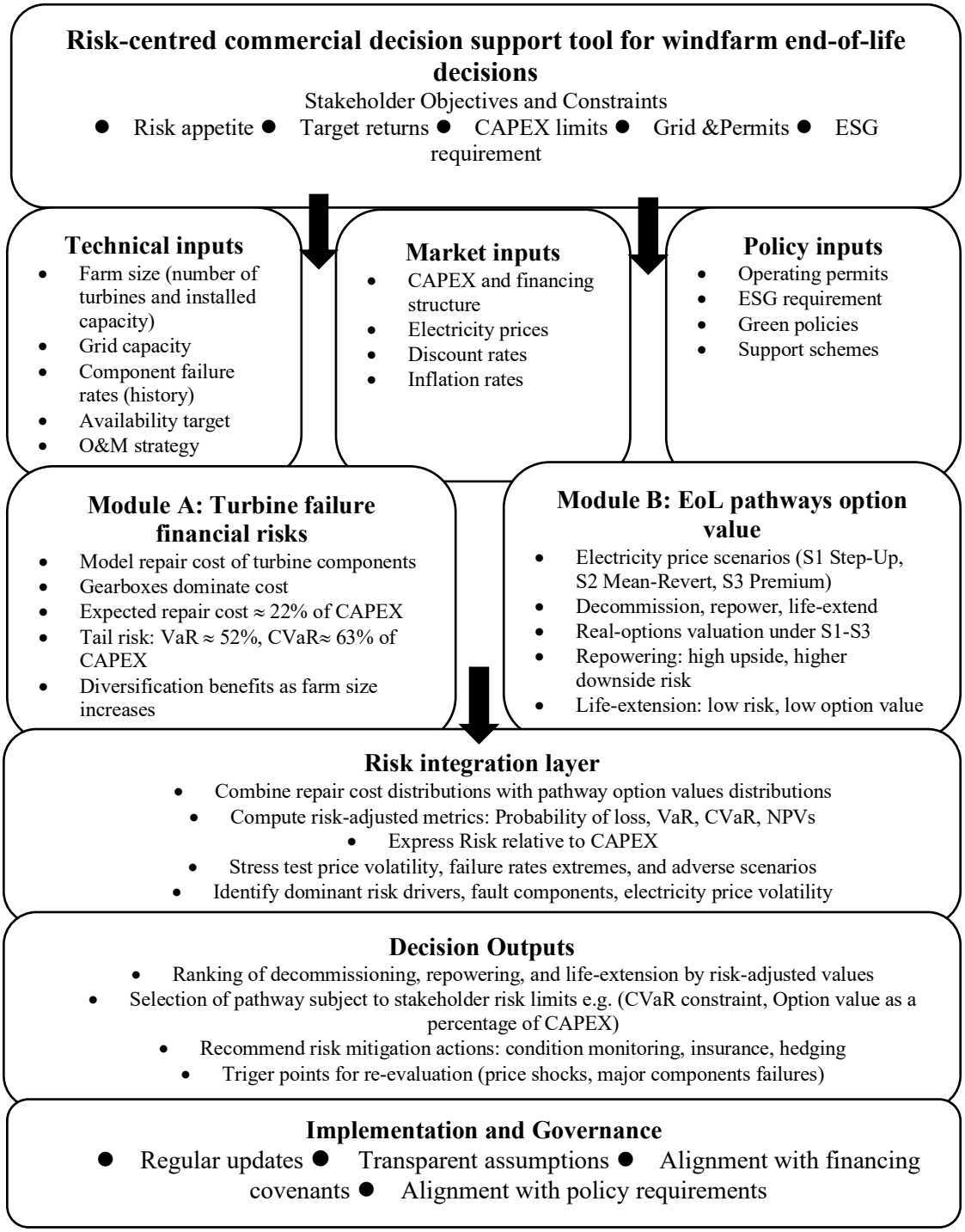
8.1.2 Technical, market, and regulatory inputs

Following the identification of stakeholder objectives and constraints, the second stage of the commercial decision framework involves a structured evaluation of three interrelated domains that critically influence decisions for ageing wind farms: technical condition, market factors, and policy and regulatory considerations. As illustrated in the framework (Figure 8.1), this stage provides the essential inputs required for the subsequent quantitative risk and value assessments.

The technical assessment focuses on the physical condition and performance history of the wind farm assets. This includes an evaluation of structural elements such as foundations and towers, as well as the condition of key turbine components that are prone to failure or degradation, including blades, gearboxes, and generators. Historical records of component faults, replacements, and maintenance interventions provide valuable insight into future failure risk and remaining useful life. In addition, operational performance indicators such as availability and capacity factor, along with

detailed records of energy output during the first operational phase, are assessed to establish baseline performance and degradation trends. The size of the wind farm relative to the available grid connection capacity is also a critical technical consideration, particularly if repowering is under consideration, as existing grid constraints may limit the feasible increase in installed capacity or necessitate costly grid upgrades.

Figure 8.1: Commercial decision support framework



The market assessment captures the financial and economic conditions under which EoL decisions are made. Key inputs include capital expenditure requirements associated with different investment pathways, prevailing and expected financing costs, discount rates, and inflation assumptions, all of which directly affect the valuation of future cash flows. Among market factors, electricity price dynamics represent the largest source of revenue uncertainty, given their inherent volatility and sensitivity to broader energy market conditions. Expectations regarding future price levels, trends, and volatility play a decisive role in determining the attractiveness and risk profile of repowering and lifetime extension options, and therefore must be explicitly incorporated into the decision-making process.

Finally, the policy and regulatory assessment addresses the institutional framework governing wind farm operation and investment. This includes the status and duration of operating permits, planning consents, and grid access agreements, which may constrain or enable continued operation, repowering, or decommissioning. Broader energy and climate policies, such as decarbonisation targets and renewable energy mandates, shape the long-term strategic value of wind assets and influence investor confidence. In addition, the availability and design of support mechanisms, including renewable tariffs, subsidies, or other market-based incentives, can significantly alter both the expected returns and the risk exposure associated with different EoL pathways.

8.1.3 Module A: Turbine failure financial risks

Module A (see Figure 8.1) translates the empirical findings of Paper 1 (Chapter 5) into a practical framework for assessing operational financial risk in ageing wind farms. Rather than relying on average failure costs, the module represents how turbine component failures generate a distribution of potential losses over time, allowing decision makers to see how both routine and extreme outcomes affect economic viability. By embedding observed failure behaviour into a probabilistic structure, the tool enables operators and investors to evaluate when increasing repair exposure begins to undermine the case for continued operation.

By incorporating component-level risk and portfolio scale effects, Module A supports risk-aware end-of-life planning across wind farms of different sizes and ownership

structures. It allows stakeholders to compare financial exposure across assets, identify where failure risk becomes critical, and determine when lifetime extension is no longer a prudent strategy. In this way, the first paper provides the quantitative basis for recognising when ageing assets move from being productive generators into financially vulnerable infrastructure that requires strategic intervention.

8.1.4 Option value in EOL pathways

Module B (see Figure 8.1) evaluates the market-driven value of alternative end-of-life investment pathways using the real options framework developed in Paper 2 (Chapter 6). By modelling electricity price uncertainty through transparent scenarios, the module enables decision makers to compare lifetime extension, repowering, and decommissioning as flexible investment strategies rather than fixed, one-off choices. This approach captures how different market conditions alter both the upside potential and downside exposure associated with each pathway.

Through this structure, Module B supports strategic timing and capital allocation at the end of a wind farm's life. It allows investors and policymakers to identify when reinvestment through repowering is justified, when conservative lifetime extension may be preferable, and when exit becomes the rational choice. By embedding uncertainty and flexibility directly into the evaluation of EoL options, the second paper provides a market-responsive framework for managing ageing wind assets in volatile energy systems.

8.1.5 Risk integration layer: central decision engine

At the centre of the diagram (Figure 8.1) lies the risk integration layer, which constitutes the core contribution of the decision support framework and the thesis as a whole. This layer combines the operational loss distributions generated in Module A with the pathway value distributions generated in Module B to form a unified, risk-consistent basis for decision making.

Specifically, the tool integrates repair and replacement loss distributions including component-level cost dominance, VaR, CVaR, and diversification effects with EoL pathway value distributions under each electricity price scenario. This integration enables the computation of risk-adjusted performance metrics for each pathway,

including expected value, probability of loss, VaR and CVaR of net present value, and downside risk expressed as a proportion of CAPEX. In addition, the framework identifies dominant risk drivers, which are typically gearbox replacement costs on the operational side and electricity price volatility on the market side.

Decision making within the tool follows a risk-first principle. Rather than selecting the pathway with the highest expected value alone, stakeholders are supported in maximising expected returns subject to explicit downside risk constraints. For example, a pathway may be selected if it delivers the highest expected net present value while keeping CVaR below a threshold determined by financing covenants, liquidity constraints, or organisational risk appetite. This approach ensures that the preferred option reflects both return potential and tolerance for extreme but plausible adverse outcomes.

8.1.6 Decision outputs, risk controls, and trigger rules

The final stage of the framework translates analytical outputs into actionable guidance. The tool produces a risk-adjusted ranking of lifetime extension, repowering, and decommissioning strategies under each market scenario. Consistent with the empirical findings, lifetime extension tends to be preferred under conditions of high uncertainty, limited capital availability, or low risk tolerance. Repowering is typically favoured when stakeholders are willing to accept higher downside risk in exchange for potentially large option values, particularly where price support mechanisms or hedging strategies are available. Whilst decommissioning becomes optimal when combined operational and market tail risks exceed acceptable limits or when non-financial constraints dominate.

To support implementation, the tool also recommends targeted risk controls linked directly to dominant risk drivers. Given the concentration of replacement costs in gearboxes, priority measures include enhanced condition monitoring, predictive maintenance, spare-part strategies, and insurance or warranty arrangements for high-severity failures. On the market side, especially for repowering decisions, contracting and hedging strategies, floor price mechanisms, and long-term power purchase agreements are emphasised as key risk mitigation instruments.

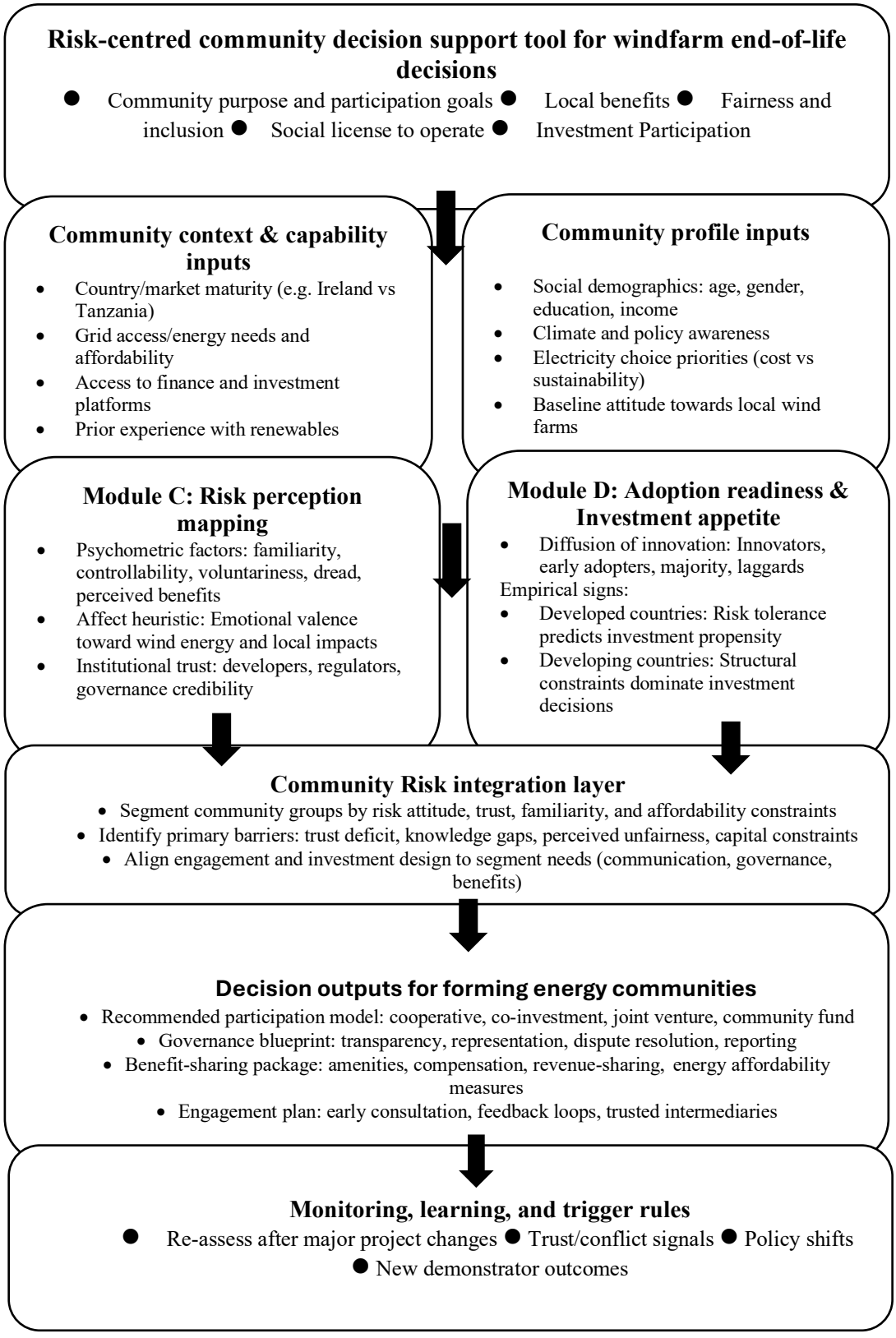
Finally, the framework incorporates explicit trigger rules that prompt re-evaluation of EoL decisions as conditions evolve. These include predefined thresholds for electricity price movements, accumulated fault counts indicating entry into the high-failure tail of the distribution, major component replacement events, and changes in financing terms or covenants. In this way, the tool supports not only a one-off decision but an adaptive, risk-aware approach to wind farm end-of-life management.

8.2 Community decision support framework.

This section introduces a community decision support framework developed using the empirical evidence presented in the third paper, *"Perceptions of risk and investment in wind energy in rural communities"*. In contrast to the commercially focused framework discussed earlier in this chapter, this tool is designed to support energy communities and local stakeholders who are considering participation in, or ownership of, wind energy projects. The framework is grounded in an analysis of how local communities perceive risk, return, and uncertainty in relation to wind energy investments, and how these perceptions shape willingness to invest and engage in collective energy initiatives.

The community decision support tool organises and translates observed patterns in risk attitudes, investment preferences, and socio-demographic characteristics into practical guidance for the formation and structuring of energy communities (Figure 8.2). The third paper demonstrates that attitudes toward financial risk, alongside factors such as income, age, education, and exposure to renewable energy projects, exert a significant influence on investment appetite and participation decisions. These empirically identified relationships are embedded within the tool to highlight critical areas that require consideration when designing community-led wind energy initiatives. As a result, the framework assists policymakers, developers, and community organisers in aligning project design, governance structures, and engagement strategies with the heterogeneous preferences and risk perceptions of local communities, thereby improving the likelihood of successful and inclusive community investment in wind energy.

Figure 8.2: Community decision support framework



8.2.1 Community purpose and participation goals

The first step in this framework is to clarify the community's purpose and participation goals, because community-led wind investment is not driven by financial criteria alone, but by a broader set of social, environmental, and distributional objectives. As presented in the framework (Figure 8.2), the tool begins by establishing what "success" means for the community and how that success should be assessed. Typical objectives include securing tangible local benefits, improving energy affordability or reliability, strengthening local energy autonomy, and contributing to decarbonisation outcomes. Equally important are procedural goals, such as achieving fairness and inclusion in decision making, building a durable social license to operate, and ensuring that participation opportunities are meaningful rather than symbolic. In this context, participation is itself a value: when communities are engaged early and consistently, trust is strengthened, local concerns are surfaced before they escalate, and the legitimacy of project outcomes increases. These goals provide the reference point for later stages of the tool, which translate heterogeneous perceptions of risk, trust, and benefit into practical design choices for community ownership and governance.

8.2.2 Community context and profile inputs

Following the articulation of community goals, the tool requires a structured assessment of two sets of inputs shown at the top of Figure 8.2: (i) community context and capability, and (ii) community profile characteristics. Community context captures the broader structural conditions that shape whether investment is feasible and how risk is perceived. The empirical comparison between Ireland and Tanzania in Chapter 7 demonstrates that market maturity and institutional settings materially affect both understanding of wind energy and confidence in participating financially. Therefore, the tool explicitly considers country or market maturity (for example, whether wind energy is established and visible), the level of electricity access and energy needs, the salience of affordability constraints, and the availability of investment platforms and financing channels. Prior experience with wind or other renewables, including proximity and visibility, is treated as a key factor because it shapes familiarity and observability, consistent with diffusion of innovation theory.

In parallel, community profile inputs capture the socio-demographic and attitudinal characteristics that influence investment propensity and the formation of shared local narratives. These include age, gender, education, and income, alongside climate and policy awareness and electricity choice priorities (for example, whether households prioritise cost, sustainability, or a balance of both). Paper 3 shows that in developing countries, higher education levels and climate awareness align with more differentiated risk assessments and higher willingness to invest, whereas in developing countries, lower awareness and higher risk aversion are more prevalent and investment attitudes are less responsive to individual-level predictors. For decision support purposes, these inputs are not used to stereotype communities, but to diagnose which barriers are likely to be binding and which engagement strategies are likely to be credible and effective.

8.2.3 Module C: risk perception mapping

Module C (Figure 8.2) operationalises the core behavioural insight of Chapter 7. Community investment decisions in wind energy are mediated through subjective perceptions of risk rather than purely rational risk-return calculation. As shown in Figure 8.2, the tool maps risk perception through three complementary lenses. First, the psychometric paradigm is used to identify qualitative attributes that amplify or dampen perceived risk, including familiarity, perceived controllability, voluntariness, dread, and perceived benefits. This is particularly relevant for wind projects because communities often respond more strongly to issues of fairness, trust, and lived experience than to technical probability statements.

Second, the module incorporates the affect heuristic by recognising that communities form rapid judgments based on emotional associations with wind energy and local impacts. Positive affect such as perceiving wind energy as progress, sustainability, and community benefit tends to reduce perceived risk and increase perceived benefit, whereas negative affect such as associating wind farms with disruption, unfairness, or distrust can produce the opposite effect. Third, the module explicitly incorporates institutional trust in developers, regulators, and governance processes, reflecting evidence that low trust amplifies perceived risk and weakens willingness to invest, while credible institutions and transparent processes can sustain support even when

uncertainty remains. Together, these dimensions provide an integrated diagnosis of why a community might oppose, tolerate, support, or actively invest in wind energy.

8.2.4 Module D: adoption readiness and investment appetite

Module D (Figure 8.2) translates risk perception into an assessment of adoption readiness and investment appetite using diffusion of innovation theory. The tool recognises that communities occupy different positions along an adoption curve ranging from innovators and early adopters to later adopters and laggards and that these positions reflect systematic differences in familiarity, risk tolerance, and willingness to commit capital. Paper 3 provides clear evidence that these dynamics differ by context. In Ireland representing developed countries, wind energy is socially embedded and visible, and the empirical models show that self-rated risk tolerance is a strong predictor of investment propensity, alongside expected returns and other preferences. This pattern is consistent with a more advanced diffusion stage where individuals can evaluate wind investment using a mix of experiential knowledge, peer effects, and perceived relative advantage.

In Tanzania, by contrast, the statistical analysis indicates that individual-level predictors including risk measures are generally weak, suggesting that investment appetite is constrained less by personal preference and more by structural and institutional conditions, such as limited access to finance, weaker investment channels, lower policy visibility, and affordability pressures. In practical terms, Module B therefore distinguishes between communities where behavioural levers (communication, transparency, opportunity design) may shift investment participation, and contexts where structural preconditions (credible institutions, demonstrator projects, access mechanisms) must be strengthened before meaningful community investment can be expected.

8.2.5 Community risk integration layer: segmentation and barrier diagnosis

At the centre of the community decision support tool is the community risk integration layer which functions as the decision engine that converts the diagnostics of Modules A and B into design implications for forming energy communities. The tool first segments the community into groups with distinct combinations of risk attitude, trust

levels, familiarity, and affordability constraints. This segmentation reflects the empirical and theoretical finding that communities are not homogeneous: individuals differ in their openness to innovation, their emotional responses to local infrastructure, and their tolerance for financial uncertainty. The tool then identifies the primary participation barriers within each segment. Typical barriers include trust deficits (low confidence in developers or regulators), knowledge and awareness gaps (limited understanding of wind technology or policy context), perceived unfairness (concerns about who bears burdens and who receives benefits), and capital constraints (inability to meet minimum investment amounts or withstand uncertain cash flows).

Once barriers are diagnosed, the tool aligns engagement and investment design with segment needs. For instance, where trust is the primary constraint, the design emphasis shifts to governance credibility, transparency, and independent oversight. Where familiarity is limited, the priority becomes social learning, demonstrator effects, and communication that improves observability and perceived controllability. Where affordability dominates, participation pathways must be structured to reduce financial exposure, lower minimum investment thresholds, or emphasise non-financial benefits that matter locally (such as reliability or community services). This integration layer is therefore the mechanism through which behavioural evidence becomes actionable guidance.

8.2.6 Decision outputs: participation model, governance, benefit sharing, and engagement plan

The outputs of the community decision support tool provide practical guidance for forming energy communities and designing participation mechanisms. First, the tool recommends an appropriate participation model consistent with local conditions and risk perceptions. Options include cooperative ownership structures, co-investment arrangements, joint ventures, or community benefit funds. Importantly, the tool treats these as design choices rather than universal solutions: the literature and Paper 3 both indicate that co-ownership can increase acceptance, but it is not always sufficient if trust, fairness, or capability constraints are unresolved.

Second, the tool produces a governance blueprint that specifies transparency requirements, representation and decision rights, dispute resolution mechanisms, and

reporting obligations. These governance elements operationalise institutional trust: the goal is to ensure that community members can observe how decisions are made, how revenues are distributed, and how conflicts are handled. Third, the tool specifies a benefit-sharing package that matches local priorities and addresses fairness concerns. This can include local amenities, compensation for proximate residents, revenue-sharing arrangements, and where relevant measures aimed at energy affordability. Finally, the tool defines an engagement plan emphasising early-stage consultation, iterative feedback loops, and the use of trusted intermediaries, reflecting evidence that meaningful participation strengthens social acceptance and investment willingness over time.

8.2.7 Monitoring, learning, and trigger rules

The final stage of the community tool introduces monitoring and trigger rules to ensure the framework remains adaptive as social conditions and project characteristics evolve. Community perceptions are dynamic and may shift with new information, project changes, or emerging local narratives. The tool therefore recommends periodic reassessment after major project modifications, the emergence of trust or conflict signals (for example, disputes over benefits, governance, or local impacts), policy shifts that alter the credibility of support schemes, or the outcomes of new demonstrator projects that change familiarity and perceived controllability. In this way, the community decision support tool supports not only the initial formation of an energy community but also the long-term sustainability of community participation by embedding learning, transparency, and responsiveness into the investment process.

Chapter 9 . Conclusion

Drawing on three interlinked studies, the thesis examined operational financial risk arising from turbine failures, market-driven real options associated with EoL investment pathways, and community perceptions of risk and investment in wind assets. This final chapter reflects on how these strands collectively address the research objectives, articulates the theoretical and practical contributions of the work, and discusses implications for the energy transition, policy, and future research.

9.1 Studying end-of-life decision making for wind farms

An increasing share of assets are approaching the end of their originally permitted operational lifetimes as wind energy matures, creating an urgent need for structured approaches to evaluating lifetime extension, repowering, and decommissioning. This thesis shows that end-of-life decision making is not a narrow technical or accounting exercise, but a multidimensional investment problem shaped by interacting sources of uncertainty. Asset degradation, electricity price volatility, financing conditions, regulatory requirements, and community acceptance jointly determine whether continued operation, reinvestment, or exit is viable, and none of these factors can be considered in isolation.

Each end-of-life investment decision entails a distinct risk profile and set of trade-offs. Lifetime extension offers short-term capital efficiency but exposes operators to increasing failure risk and rising maintenance costs as assets age. Repowering enables higher output and improved performance, yet requires substantial new investment and renewed regulatory and community approval. Decommissioning, while sometimes unavoidable, entails significant financial and environmental liabilities associated with dismantling, waste management, and site restoration. Taken together, these findings confirm that wind farm end-of-life choices are fundamentally strategic investment decisions embedded within complex socio-technical systems, rather than simple technical or regulatory endpoints.

9.2 Addressing the research objectives

The first objective of the thesis was to quantify the financial risks associated with turbine lifetime failures and to examine how these risks affect realised profitability across wind farms of different sizes. The analysis demonstrates that component

failures, particularly major replacements, generate substantial downside financial exposure, with repair cost distributions exhibiting strong skewness. Value at Risk (VaR) and Conditional Value at Risk (CVaR) were shown to represent a significant proportion of initial capital investment, especially for smaller wind farms. Gearbox failures emerged as the dominant source of loss, while portfolio size was found to provide meaningful diversification benefits that reduce the intensity of financial risk. These results establish failure-driven risk as a central driver of late-life economic viability.

The second objective was to evaluate the option value of alternative end-of-life strategies under market uncertainty using a real-options framework. The analysis shows that repowering offers substantial upside potential through increased output and technological upgrading, but also exposes investors to significant downside risk due to high capital intensity and sensitivity to electricity price uncertainty. Lifetime extension, by contrast, provides a lower-risk and lower-return pathway that may be attractive to risk-averse investors or those facing capital constraints. Decommissioning was the most unattractive decision having negative financial values. The scenario-based modelling further demonstrates that optimal end-of-life choices are highly sensitive to market conditions, reinforcing the importance of flexible, risk-aware investment frameworks rather than static financial appraisal.

The third objective was to assess how community risk perceptions, experience, and socio-demographic factors influence investment behaviour in wind energy, particularly in an end-of-life context. The comparative analysis of Ireland and Tanzania reveals that in mature markets, investment propensity is strongly shaped by subjective risk tolerance, expected returns, and energy preferences, indicating scope for community participation in late-life reinvestment. In contrast, in emerging market contexts, investment behaviour is driven more by institutional and informational constraints than by individual risk attitudes. These findings demonstrate that community engagement and co-investment potential are context dependent and must be embedded within the design of end-of-life strategies if socially legitimate and implementable outcomes are to be achieved.

Lastly, the thesis aimed to integrate financial, operational, and social dimensions into coherent decision-support frameworks for wind farm end-of-life planning. This

objective is met by linking the quantitative risk and real-options models with the empirical analysis of community investment behaviour, enabling end-of-life strategies to be evaluated not only in terms of financial viability but also social feasibility.

9.3 Research contribution

This thesis makes a single overarching contribution by establishing an integrated, risk-based and socio-technical framework for wind farm end-of-life decision making that links financial exposure, investment flexibility, and community behaviour. Through the combined use of failure-risk modelling, real options analysis, and behavioural evidence, it reframes end-of-life from a technical or regulatory endpoint into a strategic investment and governance problem, and provides a coherent basis for evaluating lifetime extension, repowering, and decommissioning under uncertainty.

9.3.1 Insights for the energy transition

The findings of this thesis show that the effective management of existing renewable energy assets is a critical component of the energy transition. As decarbonisation increasingly depends on sustaining and upgrading current wind capacity rather than relying solely on new developments, end-of-life decision making becomes central to maintaining system performance and economic value. The results show that both lifetime extension and repowering can deliver significant climate and financial benefits by preserving and enhancing existing infrastructure, but only where the associated technical, financial, and social risks are explicitly accounted for in investment and governance processes.

More broadly, the research highlights that the energy transition is fundamentally a challenge of long-term infrastructure governance as well as technology deployment. Managing ageing renewable assets requires balancing efficiency and resilience while maintaining public trust. In this context, community participation and risk-aware investment design are essential. Aligning ownership structures, benefit-sharing arrangements, and governance models with local risk perceptions can improve acceptance, reduce conflict, and support the long-term sustainability of renewable energy systems as they move beyond their initial operating lives.

9.3.2 Consideration of risk in EoL decisions

A central insight of the thesis is that risk, particularly downside and tail risk, should be a primary criterion in EoL decision making. Traditional approaches that prioritise expected values can obscure the severity of low-probability, high-impact outcomes associated with component failures or adverse market conditions. By demonstrating the magnitude of VaR and CVaR relative to CAPEX, the thesis shows that ignoring tail risk can lead to systematically biased decisions, especially for smaller or less diversified operators. The risk-first decision framework developed in the thesis provides a structured means of aligning EoL choices with stakeholder risk appetite, financing constraints, and resilience objectives.

Importantly, the research shows that risk is not perceived uniformly across stakeholders, particularly when community participation and investment are involved. Community investors tend to evaluate wind energy investments through subjective lenses shaped by familiarity, trust in institutions, affective responses, and socio-economic context, rather than through probabilistic risk metrics alone. In mature markets, where wind energy is socially embedded, higher risk tolerance and positive affect can support willingness to invest despite uncertainty. In contrast, in less mature or lower-income contexts, heightened risk aversion, limited institutional trust, and affordability constraints can amplify perceived downside risk and suppress investment appetite, even when objective risk-return profiles appear favourable. Effective EoL decision making must account not only for quantified financial risk, but also for how risk is perceived, communicated, and governed, particularly where community ownership or co-investment models are pursued.

9.3.3 Technical considerations in end-of-life decisions

From a technical perspective, the thesis highlights the importance of asset condition, component reliability, and operational history in shaping EoL outcomes. Component-specific failure behaviour, particularly for gearboxes, has a disproportionate influence on financial risk and therefore on the viability of lifetime extension strategies. The findings suggest that technical assessments should not only evaluate remaining useful life but also inform probabilistic risk modelling and maintenance prioritisation. Grid capacity and compatibility with repowering options further constrain technical

feasibility, reinforcing the need for integrated technical-economic evaluation rather than siloed assessments.

9.3.4 Commercial considerations in end-of-life decisions

Commercially, the thesis demonstrates that EoL decisions are shaped by the interaction of capital availability, financing conditions, market volatility, and scale effects. Repowering can generate significant value under favourable market conditions, but it exposes investors to heightened downside risk if prices fall. Lifetime extension offers a more conservative pathway, particularly where capital is constrained or uncertainty is high. The commercial decision support tool developed in this research provides a structured approach for evaluating these trade-offs, enabling stakeholders to select EoL pathways that maximise value subject to explicit risk constraints.

9.3.5 Social considerations in end-of-life decisions

The thesis shows that social factors are not peripheral but integral to EoL decision making, particularly where community ownership or participation is envisaged. Community perceptions of risk, fairness, and trust significantly influence investment decisions and social acceptance. Importantly, these perceptions are context-dependent and shaped by familiarity, institutional credibility, and lived experience with wind energy. The community decision support tool developed in this research provides guidance on aligning governance structures, benefit-sharing mechanisms, and engagement strategies with heterogeneous community preferences, thereby increasing the likelihood of successful and inclusive outcomes.

9.4 Policy implications

The findings of this thesis highlight the need for proactive and risk-aware policy frameworks to support wind farm end-of-life (EoL) decisions and the long-term sustainability of the wind energy sector. Given the magnitude of operational and market-related downside risks identified, policies that rely solely on average performance metrics are insufficient.

First, there is a clear role for risk management policies that explicitly address the financial consequences of turbine failures. Policymakers should encourage or require the establishment of repair reserve funds, support the adoption of advanced condition monitoring and preventive maintenance practices, and promote standards that reduce downtime and failure severity over the asset lifetime.

Second, the results indicate that scale matters for risk reduction. Larger wind farms benefit from diversification effects that substantially lower downside risk relative to CAPEX. Policy frameworks may therefore need to facilitate access to finance for larger projects and consider incentives that enable project aggregation or scaling, while ensuring that smaller and community-scale projects are not exposed to disproportionate financial vulnerability.

Third, the scale and severity of worst-case failure outcomes underscore the importance of insurance and risk-transfer mechanisms. Policymakers can play a facilitating role by supporting access to affordable, tailored insurance products for wind assets and by exploring innovative risk-sharing arrangements, such as public-private partnerships or catastrophe-style instruments, to manage extreme but plausible loss events.

Fourth, continued investment in research and development remains essential. Targeted support for improving turbine reliability, component durability, and maintenance technologies can reduce failure rates over time, lowering operational risk and strengthening the economic competitiveness of wind energy, particularly as assets age and enter EoL decision phases.

Finally, policies aimed at promoting community investment in wind energy must be context-sensitive. In mature markets, interventions should focus on reducing perceived investment barriers by enhancing transparency, offering manageable investment structures, and ensuring visible and equitable community benefits. In early-stage contexts, however, priority should be given to building institutional credibility, supporting demonstrator projects, and establishing trusted mechanisms for participation and benefit sharing. Only when wind energy becomes socially visible and institutionally credible are community risk perceptions likely to translate into sustained investment and engagement.

Collectively, these policy implications reinforce the central conclusion of the thesis: effective wind energy governance at end of life requires integrating technical, financial, and social risk considerations into coherent, adaptive policy frameworks that support both commercial resilience and community participation.

9.5 Limitations and future studies

This research is subject to several limitations. The operational risk analysis relies on failure data that are commercially sensitive and only partially available, which constrains the granularity of the modelling and may not fully capture site-specific conditions or future technological improvements. Failures are grouped into broad component categories, which limits the precision of cost allocation and risk estimation. Electricity price uncertainty is addressed through scenario analysis, but future prices remain inherently unpredictable and subject to structural market and policy changes. In addition, the community investment study adopts a cross-sectional design, limiting causal inference and the ability to observe how risk perceptions and investment attitudes evolve over time. Differences in sample composition and socio-economic context further restrict the generalisability of the findings beyond the case study settings.

Future research could extend this work in several directions. Access to more detailed and disaggregated reliability and cost data would enable more refined modelling of failure processes and operational risk, while longitudinal datasets could capture changes in both technical performance and community perceptions over time. Further studies could examine end-of-life decisions for offshore wind, integrate climate related physical risks, and explore hybrid ownership and financing models that combine commercial and community participation. Deeper investigation into institutional and structural factors such as access to finance, governance quality, and benefit-sharing mechanisms would also enhance understanding of how risk-aware decision making can support a resilient and socially inclusive energy transition.

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Appendices

Appendix A: Code for Study 1

```
clear
rng("default")

% Define parameters for Generators
L = 40; % Lifetime of turbine operation in years
D = 0.06; % Discount Rate
T=1;  % number of turbines in a farm
M = 1000000; % M is number of Monte Carlo simulations

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

% Weibull Parameters HereDCFSimulation
% Generator
A_SHAPE = 1.5240;
A_SCALE = 18.72;
A_COST  = 232634;
% Gearbox
B_SHAPE = 1.3840;
B_SCALE = 15.02;
B_COST  = 647101;
% Blades
C_SHAPE = 0.7480;
C_SCALE = 86.80;
C_COST  =374689;

% expected value of Weibull distribution of Times To Fail
A_Expectation_TTF = A_SCALE*gamma(1+1/A_SHAPE);
B_Expectation_TTF = B_SCALE*gamma(1+1/B_SHAPE);
C_Expectation_TTF = C_SCALE*gamma(1+1/C_SHAPE);

% Create Weibull distributions from the above given parameters
wb1 = makedist('Weibull','A', A_SCALE,'B',A_SHAPE);
wb2 = makedist('Weibull','A', B_SCALE,'B',B_SHAPE);
wb3 = makedist('Weibull','A', C_SCALE,'B',C_SHAPE);

%Creating a matrix to store the simulations
failure_at_start_A = 0;
failure_at_start_B = 0;
failure_at_start_C = 0;

fail_record_A = nan(L,M);
fail_record_B = nan(L,M);
fail_record_C = nan(L,M);

for c =1:M % Start of Monte Carlo Loop

   for period = 1:L

      failure_at_end_A = 1 + failure_at_start_A;
      failure_at_end_B = 1 + failure_at_start_B;
      failure_at_end_C = 1 + failure_at_start_C;

      prob_of_failure_A = (cdf(wb1,failure_at_end_A)-cdf(wb1,failure_at_start_A))...
         /(1-cdf(wb1,failure_at_start_A));
```

```
        prob_of_failure_B = (cdf(wb2,failure_at_end_B)-cdf(wb2,failure_at_start_B))...
           /(1-cdf(wb2,failure_at_start_B));

        prob_of_failure_C = (cdf(wb3,failure_at_end_C)-cdf(wb3,failure_at_start_C))...
           /(1-cdf(wb3,failure_at_start_C));

    % Generate a random number such that if the probability of failure
    % is greater than the random number generated we record it as a failure
    % else we record as zero

        rand_number = rand();

        if rand_number < prob_of_failure_A
           fail_record_A(period,c) =1;
           failure_at_start_A = 0;

        else
           fail_record_A(period,c) =0;
           failure_at_start_A =failure_at_start_A+1;
        end

        if rand_number < prob_of_failure_B
           fail_record_B(period,c) =1;
           failure_at_start_B = 0;

        else
           fail_record_B(period,c) =0;
           failure_at_start_B =failure_at_start_B+1;
        end

        if rand_number < prob_of_failure_C
           fail_record_C(period,c) =1;
           failure_at_start_C = 0;

        else
           fail_record_C(period,c) =0;
           failure_at_start_C =failure_at_start_C+1;
        end
      end
    end
    % ----------------------------------------------------------------------------------------------------

    % Variation in number of Turbines
    %create fail number for wind farms by grouping together T coulumns of the
    %fail records
    %There are M/T wind farms (make sure this is an interger)

    F  = floor(M/T); % this is the number of simulated wind farms

    WF_results_A= zeros(L,F);
    for f= 1:F
     WF_results_A(:,f) =sum(fail_record_A(:,(f-1)*T+1:f*T),2);
    end

    WF_results_B= zeros(L,F);
    for f= 1:F
     WF_results_B(:,f) =sum(fail_record_B(:,(f-1)*T+1:f*T),2);
    end

    WF_results_C= zeros(L,F);
```

```
for f= 1:F
 WF_results_C(:,f) =sum(fail_record_C(:,(f-1)*T+1:f*T),2);
end
%-------------------------------------------------------------------------------------------------
%Components Results
%Generator
fail_annual_count_A = sum(WF_results_A,2);
fail_rate_A  = mean(WF_results_A,2);
fail_Tot_per_Simulation_A = sum(WF_results_A);
Expected_fail_per_Simulation_A =fail_annual_count_A .* fail_rate_A ;
MeanFails_OverLifetime_A = sum(fail_rate_A);
StdDev_FailsPerSimulation_A     = std(fail_Tot_per_Simulation_A);
Confidence_Interval_NoOfFails_A = [mean(fail_Tot_per_Simulation_A) -
StdDev_FailsPerSimulation_A*1.96/sqrt(M), ...
                        mean(fail_Tot_per_Simulation_A) +
StdDev_FailsPerSimulation_A*1.96/sqrt(M)];
TableOfNoLifetimeFails_A =tabulate(fail_Tot_per_Simulation_A);

%Gearbox
fail_annual_count_B = sum(WF_results_B,2);
fail_rate_B  = mean(WF_results_B,2);
fail_Tot_per_Simulation_B = sum(WF_results_B);
Expected_fail_per_Simulation_B =fail_annual_count_B .* fail_rate_B ;
MeanFails_OverLifetime_B = sum(fail_rate_B);
StdDev_FailsPerSimulation_B     = std(fail_Tot_per_Simulation_B);
Confidence_Interval_NoOfFails_B = [mean(fail_Tot_per_Simulation_B) -
StdDev_FailsPerSimulation_B*1.96/sqrt(M), ...
                        mean(fail_Tot_per_Simulation_B) +
StdDev_FailsPerSimulation_B*1.96/sqrt(M)];
TableOfNoLifetimeFails_B =tabulate(fail_Tot_per_Simulation_B);

%Blade
fail_annual_count_C = sum(WF_results_C,2);
fail_rate_C  = mean(WF_results_C,2);
fail_Tot_per_Simulation_C = sum(WF_results_C);
Expected_fail_per_Simulation_C =fail_annual_count_C .* fail_rate_C ;
MeanFails_OverLifetime_C = sum(fail_rate_C);
StdDev_FailsPerSimulation_C     = std(fail_Tot_per_Simulation_C);
Confidence_Interval_NoOfFails_C = [mean(fail_Tot_per_Simulation_C) -
StdDev_FailsPerSimulation_C*1.96/sqrt(M), ...
                        mean(fail_Tot_per_Simulation_C) +
StdDev_FailsPerSimulation_C*1.96/sqrt(M)];
TableOfNoLifetimeFails_C =tabulate(fail_Tot_per_Simulation_C);
%-------------------------------------------------------------------------------------------------

%Turbine results
Turbine_WF_results = WF_results_A + WF_results_B + WF_results_C;
Turbine_fail_annual_count = sum(Turbine_WF_results,2);
Turbine_fail_rate = mean(Turbine_WF_results,2);
Turbine_fail_Tot_per_Simulation = sum(Turbine_WF_results);
Turbine_Expected_fail_per_Simulation =Turbine_fail_annual_count .* Turbine_fail_rate ;
Turbine_MeanFails_OverLifetime = sum(Turbine_fail_rate);
TSTD2 = std(Turbine_fail_rate);
Turbine_StdDev_FailsPerSimulation = std(Turbine_fail_Tot_per_Simulation);
Turbine_Confidence_Interval_NoOfFails = [mean(Turbine_fail_Tot_per_Simulation) -
Turbine_StdDev_FailsPerSimulation*1.96/sqrt(M), ...
                        mean(Turbine_fail_Tot_per_Simulation) +
Turbine_StdDev_FailsPerSimulation*1.96/sqrt(M)];
Turbine_TableOfNoLifetimeFails =tabulate(Turbine_fail_Tot_per_Simulation);
```

```
%-------------------------------------------------------------------------------------
%Financial Analysis
% Calculate the Discounted Cash Flows for the expected cost of repairs over
% the length of the project
% We assume the cost of the first year is not discounted but the second and
% subsequent years are.

% Calculate the Discount Vector DV
DV = zeros(L,1);
for i = 1:L
 DV(i) = (1-D)^(i-1);
end

% Now apply the discount vector to the expected value of the fail cost
DCFAnnual_A = A_COST.*DV.*fail_rate_A;
DCFAnnual_B = B_COST.*DV.*fail_rate_B;
DCFAnnual_C = C_COST.*DV.*fail_rate_C;

DCFTotal_A  = sum(DCFAnnual_A);
DCFTotal_B  = sum(DCFAnnual_B);
DCFTotal_C  = sum(DCFAnnual_C);

% Next apply the discount vector to the fail_record to calculate the DCF
% for each simulation, in this way the distribution of the DCFs can be
% obtained for VAR and ETL calculations
% For each column in fail_record calculate the DCF and store the answer in
% a DCFSimulation Row vector

%Generator
DCFSimulation_A = zeros(1, F);
for i = 1:F
   DCFSimulation_A(i)  = sum(A_COST.*(DV'* WF_results_A(:,i)));
end
VAR95_A = prctile(DCFSimulation_A, 95);

ETLList_A  = 0;
for i = 1:F
   if DCFSimulation_A(i) >= VAR95_A
  ETLList_A = [ETLList_A, DCFSimulation_A(i)];
   end
end
if length(ETLList_A) > 1 % There is a possibility that the DCFSimulation is very short
  ETLList_A = ETLList_A(2:end);
end
ETL95_A = mean(ETLList_A);

%Gearbox
DCFSimulation_B = zeros(1, F);
for i = 1:F
   DCFSimulation_B(i)  = sum(B_COST.*(DV'* WF_results_B(:,i)));
end
VAR95_B = prctile(DCFSimulation_B, 95);

ETLList_B  = 0;
for i = 1:F
   if DCFSimulation_B(i) >= VAR95_B
  ETLList_B = [ETLList_B, DCFSimulation_B(i)];
   end
end
```

```
if length(ETLList_B) > 1 % There is a possibility that the DCFSimulation is very short
  ETLList_B = ETLList_B(2:end);
end
ETL95_B = mean(ETLList_B);


%Blades
DCFSimulation_C = zeros(1, F);
for i = 1:F
   DCFSimulation_C(i)  = sum(C_COST.*(DV'* WF_results_C(:,i)));
end
VAR95_C = prctile(DCFSimulation_C, 95);

ETLList_C  = 0;
for i = 1:F
   if DCFSimulation_C(i) >= VAR95_C
  ETLList_C = [ETLList_C, DCFSimulation_C(i)];
   end
end
if length(ETLList_C) > 1 % There is a possibility that the DCFSimulation is very short
  ETLList_C = ETLList_C(2:end);
end
ETL95_C = mean(ETLList_C);

%Farm(Turbine)
Turbine_DCFAnnual = DCFAnnual_A + DCFAnnual_B + DCFAnnual_C;
DCFTotal  = sum(Turbine_DCFAnnual);

Turbine_DCFSimulation = DCFSimulation_A + DCFSimulation_B + DCFSimulation_C;
Turbine_VAR95 = prctile(Turbine_DCFSimulation, 95);

Turbine_ETLList  = 0;
for i = 1:F
   if Turbine_DCFSimulation(i) >= Turbine_VAR95
  Turbine_ETLList = [Turbine_ETLList, Turbine_DCFSimulation(i)];
   end
end
if length(Turbine_ETLList) > 1 % There is a possibility that the DCFSimulation is very short
  Turbine_ETLList = Turbine_ETLList(2:end);
end
Trbine_ETL95_ = mean(Turbine_ETLList);

Dist= tabulate(Turbine_DCFSimulation);
```

Appendix B: Code for Study 2

```
clear
rng(1)

% .............DEFINING PARAMETERS.....................................

%%%Constants
wt = 8337;  % Time factor representing operational hours
r = 0.066;  % Discount rate
T = 25; % Time horizon/Option window (Investment years)
nSim = 1000000; % Number of Monte Carlo simulation
i= 0.02; %Inflation rate
r_f = 0.024; % risk free rate
r_m = (1+r)^(1/12)-1; % monthly discount rate
i_m = (1+i)^(1/12)-1; % monthly inflator
r_f_m = (1+r_f)^(1/12)-1; % monthly inflator


% Repowering option variables
rp_repower = 8.23;  % Capacity in MW
I0_repower = 9833125;% Capex (investment cost+ DISMANTILING COST)
opex_repower = 0.02 * I0_repower;  % Annual Maintenance cost
cf_repower = 0.4255;  % Capacity factor
s_repower = 329200;  % Salvage value
d_repower = 1662460;  % Decommissioning cost

% Life extension option variables
rp_life_ext = 4.7;  % Capacity in MW
opex_life_ext = 176250 ;  % Annual Maintenance cost
cf_life_ext = 0.4255;  % Capacity factor
s_life_ext = 188000;  % Salvage value
d_life_ext = 949400;  % Decommissioning cost

% Decommissioning option variables
s_decommissioning = s_life_ext;  % Salvage value for decommissioning
d_decommissioning = d_life_ext;  % Using the lifetime extension decommissioning cost

%Price parameters
S0 = 99.05;      % Initial electricity price
mu1 = 0.002039; % 5 years drift
mu2 = 0.002039;% rest 20 years drift
% mu1 = -0.005097; % 5 years drift
% mu2 = 0.002039;% rest 20 years drift
% mu1 = -0.005471; % 5 years drift
% mu2 = 0.001666;% rest 20 years drift
sigma1 = 0;   % Monthly volatility
sigma2 = 0;
n= T * 12;       % Total months (25 years)
dt = 1;          % Time step in months
t = 0:dt:n;      % Time vector in months


%...................MONTE CARLO SIMULATIONS.........
% Preallocate storage for results
repowering_values = zeros(nSim, 1);
life_extension_values = zeros(nSim, 1);
```

```
highest_npv_values_repower = zeros(nSim, 1);
highest_npv_values_life_extension = zeros(nSim, 1);
P1 = zeros(nSim, length(t)); % Store yearly prices
% sim_end = zeros(nSim, 1);
% sim_std = zeros(nSim, 1);
% sim_skew = zeros(nSim, 1);
% sim_kurt = zeros(nSim, 1);

% ..... MONTE CARLO SIMULATIONS .....

for s = 1:nSim
    % Simulate price paths
    P = zeros(1, n+1);
    P(1) = S0;
    for t = 1:n
        Z = randn;  % Standard normal random variable

        % Determine which drift to use
        if t <= 60   % First 5 years (60 months)
            mu = mu1;
            sigma = sigma1;
        else        % Years 6–25
            mu = mu2;
            sigma = sigma2;
        end

        %P(t+1) = P(t) * exp((mu - 0.5 * sigma^2) * dt + sigma * sqrt(dt) * Z);
         P(t+1) = P(t) * exp(mu*dt + sigma*sqrt(dt)*Z);
    end
P1(s, :) = P;

    % --- NPV Calculations ---
    % Use only years 6 to 25 for cash flow calculations

    selected_months = 61:300;
    num_selected_months = length(selected_months);


    % Adjusted discount and inflation factors for years 6 to 25 (years 6 = t=5)
    % Preallocate vector for efficiency

    nMonths = 300;
% Preallocate discount factor array
DF = zeros(nMonths, 1);

% Compute discount factors
for t = 1:nMonths
    if t <= 60
        % Before month 61
        DF(t) = 1 / (1 + r_f_m)^t;
    else
        % From month 61 onwards
        DF(t) = (1/(1 + r_f_m)^60) *(1 / (1 + r_m)^(t-60));
    end
end
DVi = DF.';

    inflator = (1+i_m).^(selected_months);

    % Decommissioning adjustment factor
```

```
    V = ((1 + i_m)^300);
    V1 = (1 + i_m)^60;
   opex_repower1 = opex_repower/12.*inflator;
   opex_life_extension1= opex_life_ext/12.*inflator;

% Decommissioning NPV
decommissioningNPV_Total= (s_decommissioning - d_decommissioning);
dx_repower = (s_repower-d_repower)*V;

% Calculate monthly cash flow with inflation-adjusted OPEX

% Repowering cash flows
power_repower= rp_repower * cf_repower * wt/12;
repower_CF = P(selected_months+1) * power_repower - opex_repower1; % I add one to the selected
month to skip the next month

% Life extension cash flows
power_extension= rp_life_ext * cf_life_ext * wt/12;
extension_CF = P(selected_months+1) * power_extension - opex_life_extension1;
dx_life_extension = decommissioningNPV_Total * V;

Capex_A = I0_repower* V1 * DVi(60);


% Discounted NPVs
 repowerNPV_Total = sum(repower_CF .* DVi(selected_months)) - (Capex_A) +
dx_repower*DVi(300);
 extensionNPV_Total = sum(extension_CF .* DVi(selected_months))+ dx_life_extension*DVi(300);

 % Store results
 repowering_values(s) = repowerNPV_Total;
 life_extension_values(s) = extensionNPV_Total;

 highest_npv_repower = max([repowerNPV_Total, extensionNPV_Total,
decommissioningNPV_Total]);
 highest_npv_life_extension = max([extensionNPV_Total, decommissioningNPV_Total]);

 highest_npv_values_repower(s) = highest_npv_repower;
 highest_npv_values_life_extension(s) = highest_npv_life_extension;
end


% ..... OUTPUT RESULTS .....
% we discount the option value using risk free rate, so we bring back to
% year 1 all npv values.
%
% median_repowering_NPV = median(repowering_values);
% median_life_extension_NPV = median(life_extension_values);

Repowering_NPVb = mean(repowering_values);
Repowering_NPVo = mean(highest_npv_values_repower);

Life_extension_NPVb = mean (life_extension_values);
Life_extension_NPVo = mean (highest_npv_values_life_extension);

OV_repowering = Repowering_NPVo -Repowering_NPVb;
OV_life_extension = Life_extension_NPVo-Life_extension_NPVb;

% Display Results
```

```
% fprintf('Median NPV for Repowering: €%.2f\n', median_repowering_NPV);
% fprintf('Median NPV for Life Extension: €%.2f\n', median_life_extension_NPV);

fprintf('OV for Repowering: €%.2f\n', OV_repowering);
fprintf('OV for life_extension: €%.2f\n', OV_life_extension);

fprintf('Mean NPV for Repowering: €%.2f\n', Repowering_NPVb);
fprintf('NPV_R0 for Repowering: €%.2f\n', Repowering_NPVo);

fprintf('Mean NPV for Extension: €%.2f\n', Life_extension_NPVb);
fprintf('NPV_L0 for Extension: €%.2f\n', Life_extension_NPVo);
%
fprintf('Mean NPV for Decommissioning: €%.2f\n', decommissioningNPV_Total);
%

fprintf('OV/NPV PERC: €%.2f\n', (OV_repowering/Repowering_NPVb)*100);
```

Appendix C: Online questionnaire for Ireland

Thank you for considering participating in this research project. The purpose of this introduction is to explain to you what the study is about and what your participation would involve, to enable you to make an informed choice.

The purpose of this study is to assess attitudes towards wind energy and the possibility of community ownership of onshore wind farms. This part of the study is an online survey to assess your attitude to financial risks. The online survey should take less than 6 minutes. Participation in this study is completely voluntary. There is no obligation to participate, and should you choose to do so, you can refuse to answer specific questions, or decide to withdraw from the survey entirely. You maintain the right to withdraw from the study at any stage up to the point of data submission. At this point, your data will be collated with that of other participants and can no longer be retracted.

The information you give on the survey is stored on a University College Cork supported cloud storage platform, namely the Wind Value Microsoft Forms Account which may only be accessed from the researchers' UCC login. The data will be stored for minimum of ten years. The anonymized information you provide may contribute to research publications and/or conference presentations as well as a PhD thesis and research reports available on the project website at https://windvalue.ie/ . We do not anticipate any negative outcomes from participating in this study. Should you experience distress arising from the interview, the contact details for support services provided below may be of assistance.

This study has obtained ethical approval from the UCC Social Research Ethics Committee. If you have any queries about this research, you can contact me at dorcas.mikindani@umail.ucc.ie or peter.deeney@ucc.ie.

1. Consent.

   The purpose and nature of the study has been explained to me in writing.

   I am participating voluntarily. I am 18 or more years old.

   I understand that I can withdraw from the study, without repercussions, at any time, whether before it starts or while I am participating.

   I understand that anonymity will be ensured in the write-up by disguising my identity.

   I understand that disguised extracts from my interview and online survey (e.g. my name / location won't be used) may be quoted in presentations and publications (e.g. article, book chapter, student thesis, social media publicity of the study's findings, etc.), if I give permission below (please tick one box): *

   ☐ Yes, I agree to participate in this study
   ☐ No, I do not agree to participate in this study

Risk attitude questions
Please choose the option for which you have a preference from the following Scenarios

2. You have the opportunity to participate in a lottery in which you have an equal chance (50%) of winning €100 or winning nothing. There is no fee to take part.
   Option A: you participate in the lottery
   OR
   Option B: you do not participate.
   Which option do you choose?
   ☐ Option A
   ☐ Option B
   ☐ Skip to Next Question

3. You can choose between two investments:
   Option A: offers an equal chance (50%) to gain €5 or €15
   OR
   Option B: offers you a certain gain of €10.
   Which option do you choose?
   ☐ Option A
   ☐ Option B
   ☐ Skip to Next Question

4. Suppose you have been fined and you have the opportunity to choose between two
   alternatives.
   Option A: pay a fine of €10

OR
Option B: have an equal chance (50%) of paying either €5 or €15.
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

5. You may decide to participate to a lottery in which you have an equal chance (50%) to gain or
lose €5000.
Option A: you will take part in the lottery
OR
Option B: you do not participate.
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

6. You may decide to take part in a lottery in which you have an equal chance (50%) to gain
or lose €5.
Option A: you will take part in the lottery
OR
Option B: you do not participate.
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

In the following scenarios you are faced with a choice of two options
Choose the option for which you have a preference

7. Option A: you have an equal chance (50%) of winning or losing €5000
OR
Option B: you have an equal chance (50%) of winning or losing €5.
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

8. Option A: you have an equal chance (50%) of winning either €5000 or €15,000
OR
Option B: you a sure gain of €10,000.
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

9. Option A: pay a fine of €10,000
OR

Option B: have an equal chance (50%) of paying either €5,000 or €15,000.
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

10. Option A: you have one chance in a million to win one million euro
OR
Option B: gain €1 for sure
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

11. Option A: you have a one in one thousand chance (0.1%) of losing €1,000, otherwise you lose nothing (zero)
OR
Option B: pay €1 for sure
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

12. Option A: 1% chance to lose €10,000 and 99% chance to win €101
OR
Option B: equal chance (50%) to win €1000 or lose €1000.
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

13. Option A: 1% chance to lose €10,000 and 99% chance to win 101
OR
Option B: equal chance (50%) to win €1,000 or lose €1,000.
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

14. Option A: You have an Equal chance (33%) of, €0 or €5,000 or −€5,000 (negative number means losing)
OR
Option B: You have an Equal chance (25%) to gain €0 or €2,100 or €7,900 or €10,000 or −€5000.
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

15. Option A: You have an Equal chance (33%) of, €0 or €5000 or −€5000 (negative number means losing)
OR
Option B: You have an Equal chance (25%) of, €2900 or €5000 or −€2900 or −€5000.
Which option do you choose?
☐ Option A
☐ Option B
☐ Skip to Next Question

Social-Demographic and Sustainability Questions

16. How do you see yourself: are you in general a person who takes risk or do you try to evade risk? Please self-grade your choice between 0 (I do not take risks at all) to 10 (I love to take risks).

1	2	3	4	5	6	7	8	9	10

17. If you were to consider investing in a windfarm project, what is the minimum rate of return you would expect to receive on your investment annually?
☐ 0%-5%
☐ 5%-10%
☐ more than 10%
☐ The return on investment is irrelevant, I would not invest in a wind farm project
☐ Skip to Next Question

18. If you were to consider investing in a windfarm project with an attractive rate of return, what is the maximum amount you would be willing to invest?
☐ €1-€20,000
☐ €20,000-€50,000
☐ more than €50,000
☐ Nothing, I would not invest in a wind farm project
☐ Skip to Next Question

19. Approximately, what is the distance from your home to the nearest wind turbine?
☐ Less than 1km
☐ 1km-5km
☐ 5km-10km
☐ More than 10km
☐ Skip to Next Question

20. What is the main deciding factor in your choice of electricity provider?
☐ Price
☐ Renewable Energy
☐ Combination of Price and Renewable Energy
☐ Skip to Next Question
☐ Other

21. Given your knowledge about the benefits of using wind energy, how likely are you
    to consider investing in a wind farm project?
    - ☐ Very likely
    - ☐ Somewhat likely
    - ☐ Neither likely nor unlikely
    - ☐ Somewhat unlikely
    - ☐ Very unlikely

22. What option below do you believe most accurately describes the purpose of wind farms?
    - ☐ Profitable Business
    - ☐ Climate Change Solution
    - ☐ Electricity Generation
    - ☐ Skip to next question

23. Are you aware of the EU Targets for Reducing Emissions by 2030?
    - ☐ Not Aware
    - ☐ Somewhat Aware
    - ☐ Very Aware
    - ☐ Skip to Next Question.

24. What is your age?
    - ☐ 18-24
    - ☐ 25-34
    - ☐ 35-44
    - ☐ 45-54
    - ☐ 55-64
    - ☐ 65-74
    - ☐ 75+

25. What is your gender?
    .....

26. What is the highest level of education you have completed?
    - ☐ Primary
    - ☐ Secondary
    - ☐ Post Secondary
    - ☐ University or College

Appendix D: Online questionnaire for Tanzania

DODOSO

Asante kwa kuzingatia mradi wa utafiti wa Wind Value. Hati hii inaeleza kuhusu utafiti huu na vile ushiriki wako unahusishwa ili uweze kufanya maamuzi.

Lengo la utafiti huu ni kutathmini mitazamo kuhusu nishati mbadala na uwezekano wa umiliki wa jamii wa nishati mbadala. Ikiwa utaamua kushiriki, utaombwa kushiriki katika mahojiano ya ana kwa ana na mwanachama wa timu ya utafiti na kisha kujaza dodoso la mtandaoni baadaye. Mahojiano haya yatanakiliwa kwa sauti na yanatarajiwa kuchukua dakika 15-20. Dodoso la mtandaoni linapaswa kuchukua chini ya dakika 6. Ushiriki katika mahojiano haya na dodoso ni wa hiari kabisa. Hakuna sharti la kushiriki, na ikiwa utaamua kufanya hivyo, unaweza kukataa kujibu maswali fulani au kuamua kujiondoa kutoka kwa mahojiano; vivyo hivyo, unaweza kujibu maswali machache au mengi utakavyo katika dodoso. Unaweza kushiriki katika mahojiano tu, dodoso tu, au vyote viwili. Ukishakamilisha mahojiano, unaweza kuchagua kujiondoa wakati wowote ndani ya mwezi mmoja baada ya mahojiano. Katika hali hii, taarifa ulizotoa katika mahojiano hazitatumika. Vivyo hivyo kwa dodoso, unaweza kujiondoa hadi mwezi mmoja baada ya kuwasilisha dodoso lako, na taarifa zako hazitatumika. Haki ya kujiondoa kutoka kwa mahojiano au dodoso haiwezi kuwa ya kudumu kwani ripoti na makala za utafiti zitaandikwa kulingana na taarifa zilizotolewa kwa njia isiyoweza kutambulika kutoka kwako na washiriki wengine wote.

Taarifa zote utakazotoa zitahifadhiwa kwa siri na bila majina, na zitapatikana tu kwa timu ya utafiti ya Wind Value (kwa orodha ya sasa ya wanachama wa timu, angalia https://windvalue.ie/?page_id=14). Isipokuwa tu ni pale ambapo taarifa zitakazoonesha kuwepo kwa hatari kubwa kwako au kwa wengine. Katika hali hiyo, mamlaka husika za kisheria zitaarifiwa. Baada ya mahojiano kukamilika, rekodi hiyo itahamishwa mara moja kwenye jukwaa salama la kuhifadhi data la Chuo Kikuu cha Cork (UCC) na kufutwa kutoka kwenye kifaa cha kurekodi. Mahojiano hayo yataandikwa na mmoja wa wanachama wa timu ya utafiti, na taarifa zote zinazotambulika zitaondolewa. Baada ya hatua hii kukamilika, rekodi hiyo pia itafutwa na kinachobaki ni maandishi yasiyo na majina. Vivyo hivyo, matokeo kutoka kwa dodoso yatafanywa kuwa bila majina na kuhifadhiwa kwa usalama. Taarifa zako zitahifadhiwa kwenye jukwaa la uhifadhi la wingu linaloungwa mkono na UCC, kwenye akaunti ya Microsoft Teams ya Wind Value ambayo inaweza tu kufikiwa kutoka kwa kuingia kwa watafiti wa UCC. Data itahifadhiwa kwa angalau miaka kumi. Taarifa zako zisizo na majina zinaweza kuchangia machapisho ya utafiti na/au mawasilisho ya mikutano pamoja na tasnifu ya PhD (shahada ya uzamivu) na ripoti za utafiti zinazopatikana kwenye tovuti ya mradi https://windvalue.ie/.

Hatuoni uwezekano wa matokeo yoyote mabaya kutoka kwa kushiriki katika utafiti huu. Mwishoni mwa mahojiano, nitajadili nawe jinsi ulivyopata uzoefu huu na jinsi unavyojisikia. Ikiwa utapata mfadhaiko kutokana na mahojiano haya, tafadhali tazama maelezo ya mawasiliano ya msaada yaliyo hapa chini.

Utafiti huu umepewa idhini ya kimaadili kutoka kwa Kamati ya Maadili ya Utafiti wa Kijamii ya UCC. Ikiwa una maswali yoyote kuhusu utafiti huu, wasiliana nami kwa peter.deeney@ucc.ie.

Ikiwa unakubali kushiriki katika utafiti huu, tafadhali saini fomu ya ridhaa iliyo nyuma.

Tovuti ya Mradi:
https://windvalue.ie/
Akaunti ya Twitter ya Mradi:
@WindValue
Maelezo ya Mawasiliano ya Msaada:

- **The Samaritans:** ☏ 116123
- **MABS:** ☏ 0818 07 2000

Mawasiliano ya Mradi:
Dkt. Peter Deeney
G0.3 Kitengo cha Kukuza Uzalishaji Safi, Taasisi ya Utafiti wa Mazingira, Jengo la Ellen Hutchins, Barabara ya Lee, Cork T23X10
peter.deeney@ucc.ie

1. Ridhaa
Lengo na asili ya utafiti vimeelezewa kwangu kwa maandishi.
Ninashiriki kwa hiari.
Nina umri wa miaka 18 au zaidi.
Ninaelewa kuwa naweza kujiondoa kutoka kwa utafiti huu wakati wowote bila madhara, iwe kabla ya kuanza au wakati ninashiriki.
Ninaelewa kuwa utambulisho wangu utahifadhiwa siri na kufichwa wakati wa kuandaa ripoti ya utafiti.
Ninaelewa kuwa dondoo zilizofichwa kutoka kwa mahojiano yangu na utafiti wa mtandaoni (mfano, jina langu / eneo langu halitatumika) zinaweza kunukuliwa katika mawasilisho na machapisho (mfano, makala, sura ya kitabu, tasnifu ya mwanafunzi, uhamasishaji wa utafiti kwenye mitandao ya kijamii, n.k.), ikiwa nitatoa idhini hapa chini (tafadhali weka alama kwenye kisanduku):
☐ Ndio, nakubali kushiriki katika utafiti huu
☐ Hapana, sikubali kushiriki katika utafiti huu

Maswali Kuhusu Mtazamo wa Hatari
Tafadhali chagua chaguo unalopendelea kutoka kwa hali zifuatazo:

2. Una nafasi ya kushiriki katika bahati nasibu ambapo una nafasi sawa (50%) ya kushinda Tsh10000 au kutoshinda chochote. Hakuna ada ya kushiriki.
Chaguo A: Unashiriki katika bahati nasibu
AU
Chaguo B: Hushiriki.
¿Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

3. Unaweza kuchagua kati ya wekezaji mbili:
Chaguo A: hutoa nafasi sawa (50%) ya kupata Tsh5000 au Tsh15000
AU
Chaguo B: hukupa faida ya uhakika ya Tsh10000.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

4. Fikiria umepigwa faini na una nafasi ya kuchagua kati ya mbadala mbili:
Chaguo A: Kulipa faini ya Tsh10000
AU
Chaguo B: Kuwa na nafasi sawa (50%) ya kulipa Tsh5000 au Tsh15000.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

5. Unaweza kuamua kushiriki katika bahati nasibu ambapo una nafasi sawa (50%) ya kupata au kupoteza Tsh 500000.
Chaguo A: Utashiriki katika bahati nasibu
AU
Chaguo B: Hushiriki.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

6. Unaweza kuamua kushiriki katika bahati nasibu ambapo una nafasi sawa (50%) ya kushinda au kupoteza Tsh5000.
Chaguo A: Utashiriki katika bahati nasibu
AU
Chaguo B: Hushiriki.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

Katika hali zifuatazo unakutana na chaguo la mambo mawili. Chagua chaguo unalopendelea:
7. Chaguo A: Una nafasi sawa (50%) ya kushinda au kupoteza Tsh500000
AU
Chaguo B: Una nafasi sawa (50%) ya kushinda au kupoteza Tsh5000.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

8. Chaguo A: Una nafasi sawa (50%) ya kushinda ama Tsh500000 au Tsh1,500,000

AU
Chaguo B: Una faida ya uhakika ya Tsh1,000,000.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

9. Chaguo A: Kulipa faini ya Tsh1,000,000
AU
Chaguo B: Kuwa na nafasi sawa (50%) ya kulipa Tsh500,000 au Tsh1,500,000.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

10. Chaguo A: Una nafasi moja kati ya milioni kushinda Shilingi milioni moja
AU
Chaguo B: Kupata Tsh1000 kwa uhakika.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

11. Chaguo A: Una nafasi moja kati ya elfu moja (0.1%) ya kupoteza Tsh100,000 vinginevyo hupotezi chochote
AU
Chaguo B: Kulipa Tsh1000 kwa uhakika.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

12. Chaguo A: Nafasi ya 1% ya kupoteza Tsh10,000 na nafasi ya 99% ya kushinda Tsh101
AU
Chaguo B: Nafasi sawa (50%) ya kushinda Tsh1,000 au kupoteza Tsh1,000.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

13. Chaguo A: Nafasi ya 1% ya kupoteza Tsh10,000 na nafasi ya 99% ya kushinda Tsh101
AU
Chaguo B: Nafasi sawa (50%) ya kushinda Tsh1,000 au kupoteza Tsh1,000.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

14. Chaguo A: Una nafasi sawa (33%) ya kupata Tsh0 au Tsh5,000 au −Tsh5,000 (nambari hasi inamaanisha kupoteza)
AU
Chaguo B: Una nafasi sawa (25%) ya kupata Tsh0 au Tsh2,100 au Tsh7,900 au Tsh10,000 au −Tsh5,000.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

15. Chaguo A: Una nafasi sawa (33%) ya kupata Tsh0 au Tsh5000 au −Tsh5000 (nambari hasi inamaanisha kupoteza)
AU
Chaguo B: Una nafasi sawa (25%) ya kupata Tsh2900 au Tsh5000 au −Tsh2900 au −Tsh5000.
Je, utachagua chaguo gani?
☐ Chaguo A
☐ Chaguo B
☐ Ruka kwa Swali Lijalo

Maswali ya Jamii na Demografia
Neno Nishati mbadala linamaanisha nishati itokayo kwenye vyanzo endelevu kama vile jua, upepo, na maji.

16. Je, unajiona jinsi gani: kwa ujumla wewe ni mtu ambaye huchukua hatari au unajaribu kuepuka hatari? Tafadhali jipe kiwango kati ya 0 (sichukui hatari kabisa) hadi 10 (napenda kuchukua hatari).
1 2 3 4 5 6 7 8 9 10

17. Ikiwa ungezingatia kuwekeza katika mradi wa nishati mbadala, kiwango cha chini cha faida ungependa kupokea kila mwaka kingekuwa kipi?
☐0%-5%
☐5%-10%
☐Zaidi ya 10%
☐ Kurudishiwa faida si muhimu, nisingewekeza katika mradi wa nishati mbadala
☐ Ruka kwa Swali Lijalo

18. Ikiwa ungezingatia kuwekeza katika mradi wa nishati mbadala wenye kiwango cha kuvutia cha faida, kiwango cha juu ungekuwa tayari kuwekeza kingekuwa kipi?
☐Tsh1000-Tsh2,000,000
☐Tsh 2,000,000-Tsh5,000,000
☐Zaidi ya Tsh5,000,000
☐Hakuna, nisingewekeza katika mradi wa nishati mbadala
☐ Ruka kwa Swali Lijalo

19. Takribani, umbali kutoka nyumbani kwako hadi kwenye mradi wa nishati mbadala ulio karibu zaidi ni upi?

☐ Chini ya 1km
☐1km-5km
☐5km-10km
☐ Zaidi ya 10km
☐ Ruka kwa Swali Lijalo

20. Ni nini kigezo kikuu cha uamuzi wako wa mtoa huduma wa umeme?
☐Bei
☐Nishati mbadala
☐Mchanganyiko wa Bei na Nishati mbadala
☐Ruka kwa Swali Lijalo
☐Nyingine

21. Kwa kuzingatia maarifa yako kuhusu faida za kutumia nishati mbadala, una uwezekano gani wa kuzingatia kuwekeza katika mradi wa nishati mbadala?
☐ Uwezekano mkubwa sana
☐ Uwezekano kiasi
☐ Wala uwezekano wala si uwezekano
☐ Uwezekano mdogo kiasi
☐ Uwezekano mdogo sana

22. Unafikiri chaguo gani hapa chini linaeleza kwa usahihi madhumuni ya miradi ya nishati mbadala?
☐ Biashara Yenye Faida
☐ Suluhisho la Mabadiliko ya Tabianchi
☐ Uzalishaji wa Umeme
☐ Ruka kwa swali lijalo

23. Je, unajua kuhusu Malengo ya Umoja wa dunia ya Kupunguza Uzalishaji wa Hewa Chafu ifikapo 2030?
☐ Sijui
☐ Najua kiasi
☐ Najua sana
☐ Ruka kwa Swali Lijalo

24. Umri wako ni upi?
☐ 18-24
☐ 25-34
☐ 35-44
☐ 45-54
☐ 55-64
☐ 65-74
☐ 75+

25. Jinsia yako ni ipi?
……

26. Kiwango cha juu zaidi cha elimu ulichomaliza ni kipi?
☐ Msingi
☐ Sekondari

☐ Baada ya Sekondari
☐ Chuo Kikuu au Chuo

Appendix E: Survey consent form

Survey Information

Thank you for considering participating in this research project. The purpose of this document is to explain to you what the study is about and what your participation would involve, to enable you to make an informed choice.

The purpose of this study is to assess attitudes towards wind energy and the possibility of community ownership of onshore wind farms. This part of the study is an online survey to assess your attitude to financial risks. The online survey should take less than 6 minutes.

Participation in this study is completely voluntary. There is no obligation to participate, and should you choose to do so, you can refuse to answer specific questions, or decide to withdraw from the survey entirely. You maintain the right to withdraw from the study at any stage up to the point of data submission. At this point, your data will be collated with that of other participants and can no longer be retracted.

The information you give on the survey is stored on a University College Cork supported cloud storage platform, namely the Wind Value Microsoft Forms Account which may only be accessed from the researchers' UCC login. The data will be stored for minimum of ten years. The anonymized information you provide may contribute to research publications and/or conference presentations as well as a PhD thesis and research reports available on the project website at https://windvalue.ie/ .

We do not anticipate any negative outcomes from participating in this study. Should you experience distress arising from the interview, the contact details for support services provided below may be of assistance.

This study has obtained ethical approval from the UCC Social Research Ethics Committee.

If you agree to take part in this study, please sign the consent form overleaf.



This project is funded by the Irish Research Council No. IRC*21/PATH-A/9348

Survey Consent Form

I _____ (Print Name) agree to participate in the Wind Value research study.

The purpose and nature of the study has been explained to me in writing.

I am participating voluntarily.

I understand that I can withdraw from the study, without repercussions, at any time, whether before it starts or while I am participating.

I understand that anonymity will be ensured in the write-up by disguising my identity.

I understand that disguised extracts from my interview and online survey (e.g. my name / location won't be used) may be quoted in presentations and publications (e.g. article, book chapter, student thesis, social media publicity of the study's findings, etc.), if I give permission below (please tick one box):

I agree to participate in this study ☐

I do not agree to participate in this study ☐

Signed: …….

Date: ……..

PRINT NAME: …….



This project is funded by the Irish Research Council No. IRC*21/PATH-A/9348

Appendix F: Risk analysis

Appendix F1: Risk Analysis Classification

This table explains how risky behaviour is ranked and classified by using (Colasante and Riccetti, 2020) mixed risk aversion and love method (criteria). Panel A show the original risk ranking from the paper, and panel b show the adopted risk ranking to be used in this study.

Panel A: Ranking from the original paper														
Question	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Risk averse option		B	A	B	B	B	B	A	X	B	X	B	B	B
Risk tolerant option		A	B	A	A	A	A	B	A	X	A	X	A	A
Panel B: Adopted ranking for the study														
Question	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Risk averse Option	B	B	A	B	B	B	B	A	B	B	B	B	B	B
Risk tolerant option	A	A	B	A	A	A	A	B	A	A	A	A	A	A

Appendix F2: Survey part A (Risk analysis modelling)

This table explains how risky behaviour is coded follows the adopted risk classification in appendix 3A

Question ID	Actual Survey Question	Chosen Option	Justification
Q1	You have the opportunity to participate in a lottery in which you have an equal chance (50%) of winning €100 or winning nothing. There is no fee to take part. Option A: you participate in the lottery OR Option B: you do not participate.	A	Gains domain – choosing the uncertain €100 demonstrates risk tolerance, contrary to expected risk aversion.
Q2	You can choose between two investments: Option A: offers an equal chance (50%) to gain €5 or €15 OR Option B: offers you a certain gain of €10.	B	Gains domain with equal expected value; preferring certainty reflects risk aversion.
Q3	Suppose you have been fined and you have the opportunity to choose between two alternatives. Option A: pay a fine of €10 OR Option B: have an equal chance (50%) of paying either €5 or €15.	B	Loss domain – choosing the gamble aligns with loss-domain risk-seeking behavior.
Q4	You may decide to participate to a lottery in which you have an equal chance (50%) to gain or lose €5000. Option A: you will take part in the lottery OR Option B: you do not participate.	A	High-stakes mixed outcome; preferring the gamble shows high risk tolerance.
Q6	You may decide to take part in a lottery in which you have an equal chance (50%) to gain or lose €5. Option A: you will take part in the lottery OR Option B: you do not participate.	B	Small stakes, Expected Value = 0; choosing the safe option reflects risk aversion.

Q6	Option A: you have an equal chance (50%) of winning or losing €5000 OR Option B: you have an equal chance (50%) of winning or losing €5.	A	Higher variance indicates greater risk tolerance when a safer option exists.
Q7	Option A: you have an equal chance (50%) of winning either €5000 or €15,000 OR Option B: you a sure gain of €10,000.	A	Preferring a variable gain over a sure gain shows risk tolerance in the gain's domain.
Q8	Option A: pay a fine of €10,000 OR Option B: have an equal chance (50%) of paying either €5,000 or €15,000.	B	Loss framing – preferring the gamble over the sure loss indicates risk-seeking in the loss domain.
Q10	Option A: you have a one in one thousand chance (0.1%) of losing €1,000, otherwise you lose nothing (zero) OR Option B: pay €1 for sure	A	Choosing a rare loss over a certain cost shows risk-seeking in the loss domain.
Q11	Option A: 1% chance to lose €10,000 and 99% chance to win €101 OR Option B: equal chance (50%) to win €1000 or lose €1000.	A	Potential large loss with a small, expected gain reflects strong risk-seeking.
Q12	Option A: 1% chance to lose €10,000 and 99% chance to win 101 OR Option B: equal chance (50%) to win €1,000 or lose €1,000.	A	Similar to Q12; again, reflects risk tolerance despite the potential downside.
Q13	Option A: You have an Equal chance (33%) of, €0 or €5,000 or −€5,000 (negative number means losing) OR Option B: You have an Equal chance (25%) to gain €0 or €2,100 or €7,900 or €10,000 or −€5000.	A	Wider outcome range including large win/loss shows preference for variability.
Q14	Option A: You have an Equal chance (33%) of, €0 or €5000 or −€5000 (negative number means losing) OR Option B: You have an Equal chance (25%) of, €2900 or €5000 or −€2900 or −€5000.	A	Similar to Q14 – Option B has higher upside but greater downside, indicating risk-seeking.

Appendix G: Survey social-demographics & sustainability ranking

Appendix I: Survey Part B (Variables Ordinal Ranking)

This table shows the variable names, original survey questions, and the ranking of variable categories to be used in coding and execution of the empirical model. The questions constitute part B of the survey.

Category / Variable	Original Survey Question	Response Options (with codes below)
Investment Decision	Given your knowledge about the benefits of using wind energy, how likely are you to consider investing in a wind farm project?	Very likely (5) Somewhat likely (4) Neither likely nor unlikely (3) Somewhat unlikely (2) Very unlikely (1)
Investment 1 (Expected Return)	If you were to consider investing in a windfarm project, what is the minimum rate of return you would expect to receive on your investment annually?	0%-5% (1) 5%-10% (2) More than 10% (3) The return is irrelevant; I would not invest (0) Skip to Next Question (NA)
Investment 2 (Amount Willing to Invest)	If you were to consider investing in a windfarm project with an attractive rate of return, what is the maximum amount you would be willing to invest.	€1–€20,000 (1) €20,000–€50,000 (2) More than €50,000 (3) Nothing, I would not invest (0) Skip to Next Question (NA)
Location	Approximately, what is the distance from your home to the nearest wind turbine?	Less than 1 km (0) 1–5 km (1) 5–10 km (2) More than 10 km (3) Skip to Next Question (NA)
Electricity Source Preference	What is the main deciding factor in your choice of electricity provider?	Price (0) Renewable Energy (1) Combination of Price & Renewable Energy (1) Skip to Next Question (NA)
Wind Farm Purpose	What option below do you believe most accurately describes the purpose of wind farms?	Profitable Business (2) Climate Change Solution (1) Electricity Generation (0) Skip to Next Question (NA)

Knowledge	Are you aware of the EU Targets for Reducing Emissions by 2030?	Not Aware (0) Somewhat Aware (1) Very Aware (2) Skip to Next Question (NA)
Age	What is your age?	18–24 (1) 25–34 (2) 35–44 (3) 45–54 (4) 55–64 (5) 65–74 (6) 75+ (7)
Education Level	What is your highest level of education you have completed?	Primary (0) Secondary (1) post-secondary (2) University/College (3)
Gender	What is your gender?	Male (0) Female (1) non-binary (2)

Appendix H: Offshore-repowering analysis

Economic impacts of repowering wind turbines: A comparative analysis of advanced wind turbine technologies

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Abstract[6]

Many of Europe's wind farms are nearing the end of their operational lives, threatening overall wind energy capacity. This study examines wind turbine repowering as a solution, particularly through the deployment of advanced turbine technologies. It compares the novel X-ROTOR turbine with traditional horizontal axis wind turbines (HAWT) by using the International Jobs and Economic Development Impact (I-JEDI) model to assess regional impacts of deploying 5GW capacity. Results suggest that X-ROTOR offers notable cost advantages, which can improve the economic viability of wind farms particularly under manufacturing localization scenarios. Sensitivity analyses confirm that these outcomes are consistent across a range of manufacturing input assumptions, supporting the robustness of the findings. This research highlights the potential of innovative turbine technologies to boost energy efficiency, reduce costs, and support the EU's decarbonisation goals.

Key words: Economic Impacts, Offshore Wind, I-JEDI, X-ROTOR.

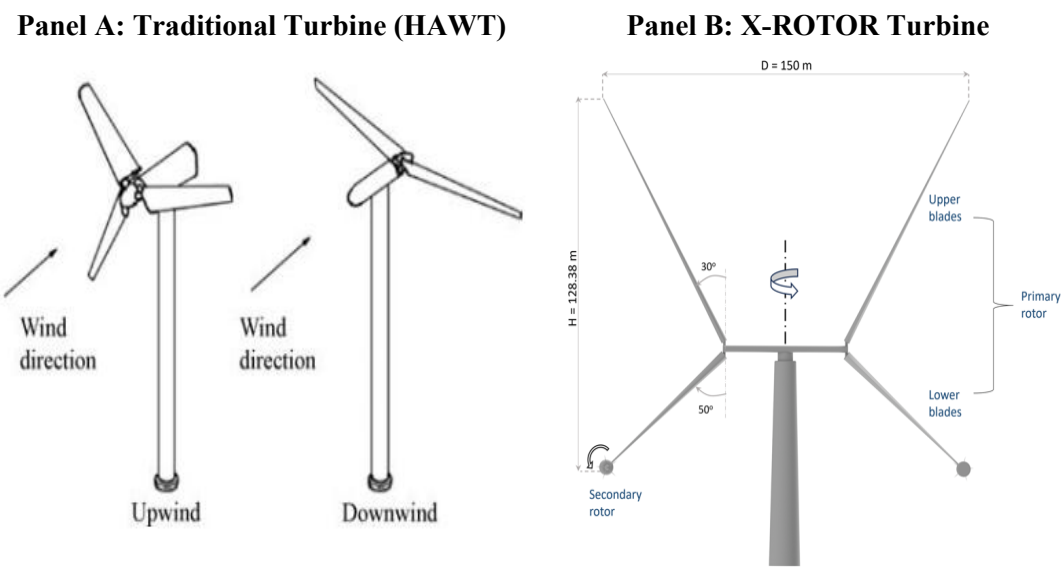
[6]This paper has been published in *Sustainable Energy Research* journal, Vol. 12, No 37.

1.Introduction

The increase in climate change effects, prompts Europe to intensify efforts to combat this global challenge. In the so called the “Fit-for-55 package”, contains a goal to raise the share of renewables from 32% to 40% by 2030 (European Commission 2019). Achieving this target requires a significant increase in wind energy investment. The plan aims to add 30 gigawatts (GW) of new wind energy capacity each year (Wind Europe 2021). Advancement in wind energy provides a promising future towards achieving this target. Therefore, new turbine technologies are being developed with the aim of reducing capital cost and increasing efficiency.

Wind turbines are subject to ageing resulting in increased failure rates, inefficiencies, and reduction of output. Research has shown that wind turbine failures increase with time leading to economic loss from maintenance cost and output loss (Mikindani et al. 2024b). Investment decisions of whether to repower, extend the life or decommission turbines have to be made to avoid these consequences. Of these alternatives, repowering was shown to be the most popular decision (Jadali et al. 2021; Leite et al. 2022). In this paper, we assess how a novel technology can add to the economic benefits of repowering wind farms by analysing two types of wind turbine (Figure 1) one having horizontal axis wind Turbine (HAWT) and the other using X-shaped Radical Offshore wind Turbine for Overall cost of energy Reduction (X-ROTOR).

Figure 1: A Comparison of Turbine Technologies



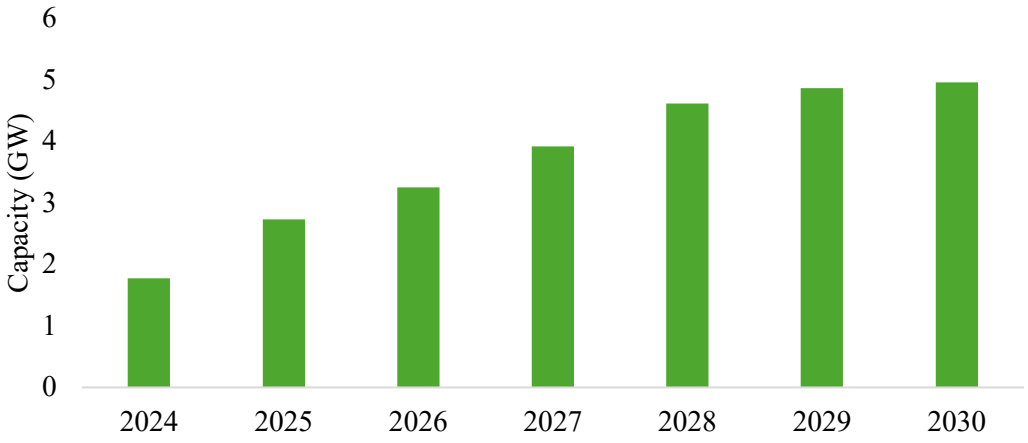
We take a case study of two technologies, the X-shaped Radical Offshore wind Turbine for Overall cost of energy Reduction (X-ROTOR) and compare it with a traditional horizontal axis wind turbine (HAWT). The holistic assessment of potential X-ROTOR economic impact provide the ground for this work (Mikindani et al., 2024a). We use the International Jobs and Economic Development Impact (I-JEDI) model, an Input-Output (IO) methodology as a bottom-up approach to assess the regional economic impact of deploying 5GW of wind farm capacity while comparing the two technologies.

The X-shaped Radical Offshore wind Turbine for Overall cost of energy Reduction (X-ROTOR) is a new offshore wind turbine concept (Leithead et al. 2019). The primary objective of X-ROTOR is to create a wind turbine with significantly reduced initial investment and operational expenditures for offshore wind energy production. Should the feasibility of the X-ROTOR concept be validated, it stands poised to revolutionize offshore wind energy. This disruptive innovation not only promises to unlock fresh opportunities within the European wind energy sector but also to fortify the European Union's position as a vanguard in renewable energy technology globally. The results show that X-ROTOR has positive effects on GDP, income, and earnings, whilst requiring less maintenance in comparison with a typical HAWT.

The motivation of this study comes from two areas, first, a large number of wind farms are reaching their end-of-life (Doukas et al. 2022), therefore decisions have to be made. Second, a novel technological advancement has been made with the X-ROTOR vertical axis wind turbine. This new design can cause a multiplier effect to repowering benefits making it an important topic for research. Theoretically, drawing from the principle of innovation and efficiency developed in the 1990s (Nelson and Winter 1977; Sundbo 1998), advanced technologies often enhance project outcomes by improving performance, reducing cost, and increasing reliability. Integrating a state-of-art turbine technology can lead to higher energy yields, better efficiency, and lower maintenance requirements.

Figure 2 presents the predicted repowering wind capacity in Europe, estimated by the Repower EU project based on wind energy in Europe 2023 statistics and 2024-2030 outlook.

Figure 2. Repowering Wind Capacity in Europe



Wind turbine Repowering is the process of upgrading or replacing existing wind turbines with newer, more efficient models. Repowering is undertaken to maintain the operational life of a wind farm, improve its energy generation, and take advantage of advancements in wind turbine technology. Repowering involves removing existing turbines and replacing them with new higher capacity models that can produce more electricity. Existing infrastructure, such as foundations and electrical systems, may need to be upgraded or modified to accommodate the new turbines. Repowering projects often require environmental impact assessments to ensure compliance with regulations and minimize ecological disturbances. Repowering can significantly boost the energy output and economic viability of a wind farm, while also reducing maintenance costs. For wind farm repowering process see Nivedh et al. (2013); Hou et al. (2017); and Martínez et al. (2018).

Historically, wind turbine technology has evolved with time, with repowering using turbines that are bigger and more efficient, proving itself to be a useful direction for the industry. A growth of rotor diameter from 50m in 2000 up to 170m in 2025 was projected (Bošnjaković et al. 2022). The literature shows the technological evolution of wind turbines especially in the early 2000s, see Ackermann and Söder (2002, 2000), Herbert et al. (2007), and Iglesias et al. (2011). Repowering will become even more important at present as more wind turbines reach their end of operational life across Europe (Wind Europe 2023).

The shift towards zero-carbon technologies in the energy sector yields significant environmental, social, and economic implications for societies. The scale of these impacts varies depending on the technology, prompting experts to conduct research on the effects of deploying different renewable energy sources in specific economic regions (Jenniches 2018). Diverse impacts are anticipated not only among various sources of energy such as solar or wind (Bulavskaya and Reynès 2018), but also within the same category, such as offshore wind versus onshore wind (Aslan 2020), or variations in wind energy based on different turbine types (Savino et al. 2017). The economic impact assessments play a crucial role in informing decision-making processes, maximizing the benefits, and minimizing potential risks associated with renewable energy projects, thereby facilitating the transition to a more sustainable energy future (IRENA 2014).

Offshore wind energy is expected to continue growing significantly in the coming years following factors like, advancement in turbine technology, policy support, the increase in the availability of offshore sites, declining cost, and economic growth (Díaz and Soares 2020; Dinh and McKeogh 2019; Soares-Ramos et al. 2020). Offshore wind projects have the potential to create significant numbers of jobs, infrastructure investment, developments in supply chain, added tax revenue and other fiscal implications, community benefits, and social impacts. A number of studies have researched the environmental, social, and economic impacts of offshore wind energy. However, much emphasis was given to environmental impact analysis given the perceived effect of the projects on the marine ecosystem. For a review of environmental impacts studies see Abramic et al. (2022), and for economic impacts studies see Pires et al. (2021).

The importance of wind energy is centred on its ability to reduce carbon emissions. However, it is generally agreed that the wind energy sector is transitioning to be fully commercial rather than relying on renewable energy support schemes. Wind energy requires large capital investment which results in a large sum of money being poured into the economy (Nanda 2015). However large capital deployment does not necessarily mean economic efficiency as the goal of renewable energy technology is to provide zero carbon energy (Baruch-Mordo et al. 2019). The economic structure of

a region together with the type of technology to be deployed play significant roles in the magnitude of the impacts to be realised (Blazejczak et al 2014).

Various methodologies are used to assess the impacts of a particular project, policy, or event on the economy of a specific region or area. These methodologies typically involve a combination of quantitative and qualitative techniques to estimate changes in economic activity, employment, income, and other relevant indicators. Two common approaches are input output (IO) analysis and Computable General Equilibrium (CGE). The IO analysis uses a detailed economic model to trace the direct and indirect effects of changes in economic activity through interconnected sectors of the economy, see for example (Noori et al. 2015). The CGE modeling, accounts for changes in prices, wages, and other economic variables that result from the initial shock or change being analysed (Connolly 2020).

Other methods are cost benefit analysis (Adeyeye et al. 2020; Snyder and Kaiser 2009), particularly for evaluating the relative costs and benefits of different projects or policies; econometric modeling, which uses statistical techniques to estimate relationships between economic variables; and case study analysis, which examines specific examples or instances to understand the economic effects in greater detail (Varela-Vázquez et al. 2019). Qualitative methods such as surveys, interviews, and focus groups may also be used to gather information on the non-economic impacts of a project or policy, such as its effects on community well-being or environmental quality.

This study uses an IO model (NREL,2025) which captures how the output of one industry (e.g., wind turbine manufacturing) becomes an input for another (e.g., construction, logistics). This makes it ideal for tracking the ripple effects (direct, indirect, and induced impacts) of a specific investment across the entire economy.

The rest of the paper is arranged as follows; section two presents the description of the case study explaining the I-JEDI model and the data used. Section three presents result, section four discussion, and section five conclusion.

2.Case description

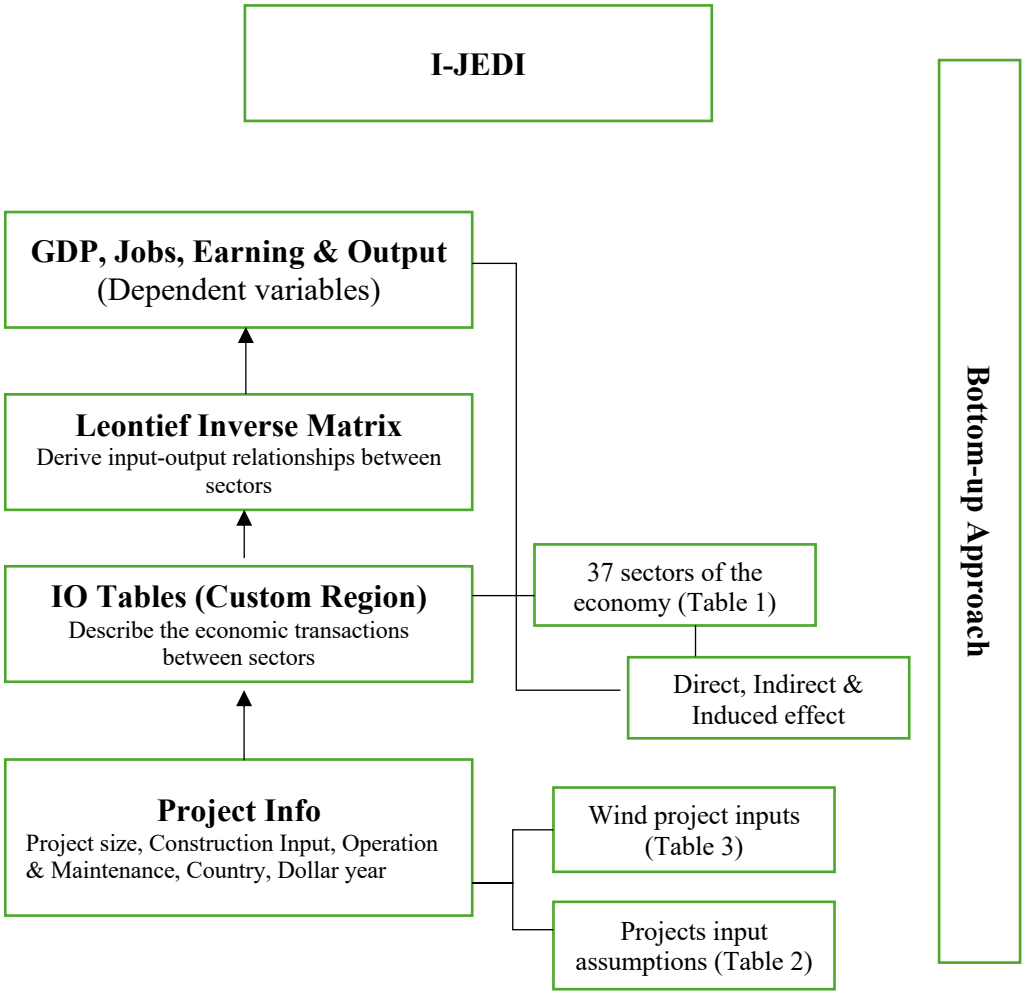
2.1 The I-JEDI model

This study uses the I-JEDI model, similar to Darghouth et al. (2020) which analyses the economic impact of distributed photovoltaic cells in Indonesia, and Woollacott et al. (2023) for renewable energy investment in Kenya. The scenario and data follow results from (McAuliffe et al. 2024) where both X-ROTOR and HAWT cost structure are provided.

The I-JEDI model was developed by the National Renewable Energy Laboratory (NREL) with support from the U.S. Agency for International Development, as a free tool for assessing the economic impacts of renewables around the world (NREL,2025). The model estimates the Gross Domestic Product (GDP), employment, earnings, and output from the construction and operation of renewable energy projects across the domestic supply chain and channels the results to other sectors like manufacturing and banking services. The I-JEDI model has three custom regions with different IO matrices that can be edited to match different economic regions in the world. We adjust the model to fit the three countries used in this report by using the current IO tables. Figure 3 shows the I-JEDI framework.

The I-JEDI model follows a bottom-up approach where the analysis starts with specific project inputs like number of turbines, cost of equipment, labour, operations, local content percentages (e.g., % of materials sourced domestically). These are then applied to sector-specific data (from Input-Output tables) to model. Then, direct, indirect, and induced effects are calculated from the ground up. This approach build the national or regional economic impact by summing these detailed contributions.

Figure 3: I-JEDI Framework



The region chosen for analysis is customised by 37 sectors which capture direct, indirect, and induced effect from the project investment (Table 1). Direct impacts represent the economic impacts that are directly linked to construction, operation, and decommissioning of the project for example employment on the construction site. Indirect effects are connected to the business in the value chain, and induced effects occur when workers involved in construction and operations of the wind project spend their money in other economic activities.

Table 1: Custom region sectors

1	Agriculture, hunting, forestry, and fishing
2	Mining and quarrying
3	Manufacturing: Food products, beverages, and tobacco
4	Manufacturing: Textiles, textile products, leather, and footwear
5	Manufacturing: Wood and products of wood and cork
6	Manufacturing: Pulp, paper, paper products, printing, and publishing
7	Manufacturing: Coke, refined petroleum products and nuclear fuel
8	Manufacturing: Chemicals and chemical products
9	Manufacturing: Rubber and plastics products
10	Manufacturing: Other non-metallic mineral products
11	Manufacturing: Basic metals
12	Manufacturing: Fabricated metal products except machinery and equipment
13	Manufacturing: Machinery and equipment not classified elsewhere
14	Manufacturing: Office, accounting, and computing machinery
15	Manufacturing: Electrical machinery and apparatus not classified elsewhere
16	Manufacturing: Radio, television, and communication equipment
17	Manufacturing: Medical, precision, and optical instruments
18	Manufacturing: Motor vehicles, trailers, and semi-trailers
19	Manufacturing: Other transport equipment
20	Manufacturing: Manufacturing not classified elsewhere; recycling
21	Electricity, gas, and water supply
22	Construction
23	Wholesale and retail trade; repairs
24	Hotels and restaurants
25	Transport and storage
26	Post and telecommunications
27	Finance and insurance
28	Real estate activities
29	Renting of machinery and equipment
30	Computer and related activities
31	Research and development
32	Other Business Activities
33	Public admin. and defence; compulsory social security
34	Education
35	Health and social work
36	Other community, social and personal services
37	Private households with employed persons

In a technical form, the economy in the IO analysis is expressed as

$$x = Ax + y \qquad (1)$$

where x represents the vector of total gross output of a sector and y represents the vector of final demand and includes domestic consumer spending, assets, changes in inventories, and exports. “A” represents the matrix of intermediate consumption per unit of output.

The Leontief inverse $L = (I - A)^{-1}$ is determined from the following mathematical transformation given by the vector matrix below

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} A & I \\ I - A & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

with I as the identity matrix, then $x = (I - A)^{-1} y$, with x, the output triggered by a given demand y, the corresponding gross value added can be derived using country and sector-specific ratios of Gross Value Added (GVA) to output.

GDP is calculated as the gross value added (GVA) across all sectors impacted by the project. It represents the contribution of each sector to the economy as a result of direct, indirect, and induced activities stemming from renewable energy investments. After calculating the gross output (x) using the Leontief-inverse, GDP is derived by applying sector-specific GVA-to-output ratios to the results (Equation 2).

$$GDP_{sector} = Output_{sector} * \frac{GVA}{Output_{sector}} \qquad (2)$$

Employment represents the number of full-time equivalent (FTE) jobs created or supported by the renewable energy project, including those in construction, manufacturing, services, and operations. The I-JEDI model uses sector-specific employment multipliers (jobs per unit of output) to convert sector outputs into job estimate (Equation 3).

$$Employment_{sector} = Output_{sector} * jobs\ per\ unit\ output \qquad (3)$$

Earnings refer to labour income generated across all impacted sectors, wages and salaries from direct, indirect, and induced jobs. Earnings are calculated by applying sector-specific earnings-to-output ratios (Equation 4)**.**

$$Earnings_{sector} = Output_{sector} * \frac{Earning}{Output_{sector}} \qquad (4)$$

Output (x) is the total economic activity generated in each sector due to the initial investment (final demand) in the renewable energy project.

2.2 Model Assumptions

Apart from the IO tables and Leontief inverse matrix, the model requires specific inputs from the project (Table 2). These include: the currency year, later to be

interpreted by adjusting for inflation and the currency used; the total capacity of the project to be deployed with the corresponding number of turbines and the cost of equipment, construction, and OPEX. Each variable must be matched with the specific economic region where operation is taking place.

The local manufacturing percentages in Table 2 are estimated based on each country's offshore wind maturity, relevant industrial base, and the characteristics of the turbine technology. X-ROTOR have smaller blades, light weight, do not need gearboxes, close to the surface of the sea, 20-25m, and have lower centre of thrust and reduced overturning moments allowing for a smaller or cheaper float (Leithead et al., 2019). Therefore, X-ROTOR can be manufactured in a broader range of facilities, even in regions lacking large-scale heavy industry. In contrast, HAWT require larger specialized factories for blade fabrication and nacelle assembly. These distinctions justify the higher local content assumptions for X-ROTOR in countries like Ireland.

All assumptions are grounded in existing industrial capabilities, publicly reported offshore wind projects, and government-supported supply chain reports. UK ranked as the 8th largest manufacturing nation globally in 2023 (ONS,2024), Spain the second largest in Europe for automotive industry (INE,2024), and Ireland is dominated by chemical, pharmaceutical, and food sectors (CSO,2024). The offshore wind capacity is led by UK, Ireland, then Spain (IEA, 2019; Soares-Ramos et al., 2020). Sensitivity test is conducted to confirm the robustness of results within a ±10% margin in manufacturing shares.

Assumptions are made by considering the percentage share of each cost to the specific country. In the sectors 13 and 22, equipment and construction, we refer to how much of the turbine components are manufactured and purchased in each region in Table 2. While Ireland has a significant amount of industrial activity, little of it is in heavy industry, vehicle manufacturing or shipbuilding which are the types of industry which would be expected to take up work on offshore wind. The UK already has active blade manufacturing[7] and has approximately 15 GW[8] of offshore wind installed. Spain[9] is

[7] See Powering ahead in the UK: Siemens Gamesa to double offshore blade facility and Siemens – Green Port Hull: A £310m renewable energy project | Mace (macegroup.com) accessed on 21 Feb 2024
[8] See Wind Energy Statistics - RenewableUK, accessed on 21 Feb 2024
[9] See Car Makers Pour Money Into Spain, accessed on 21 Feb 2024

the second largest car manufacturer in Europe and is at an advanced stage of planning for its offshore wind deployment[10]. Regarding operation and maintenance, the UK and Spain lead Ireland with more money going to their economy since they have more local staff. The pattern is therefore that more local spending will happen in UK than in Spain and more in Spain than in Ireland. In addition, since the X-ROTOR turbines are smaller, more local production of X-ROTOR is expected than HAWT. For a description of how the percentages were allocated, see Table 2.

Table 2: Project's input assumptions

Variable	Ireland (%)	Spain (%)	UK (%)
% Manufactured and Purchased in the region			
Turbine (Generator, Gearbox, Nacelle) HAWT	30	70	90
Turbine (Generator, Gearbox, Nacelle) X-ROTOR	40	80	100
Blades HAWT	20	60	80
Blades X-ROTOR	60	70	100
Tower HAWT	70	80	90
Tower X-ROTOR	70	80	90
Equipment Shipping/Transportation (both)	100	100	100
% Purchased in the region			
Electrical Balance of Plant (both)	80	90	90
Construction (Excluding Site Improvements) (both)	100	100	100
% Spent in the region			
Engineering and Other Professional Services (both)	60	90	90
Site Improvement (i.e., Road Construction) (both)	100	100	100
% Spent in the region			
Plant Operations (staff, equipment such as trucks) (both)	80	90	90
Replacement Parts (both)	40	80	100

2.3 IO tables and Leontief inverse matrices

The Organisation for Economic Co-operation and Development (OECD) is used to extract region specific IO tables. This source of data was chosen as the data format match the I-JEDI model economic sectors. The OECD data are sourced from OECD (2024). This data is used to fill the direct and indirect requirement part of the model. The model also requires information on annual average earning, gross domestic product, and total labour compensation per sector. Statistical bodies of each country provided this information. In Ireland the Central Statistics Office (CSO 2024) supplied the input output document for 2020. In Spain, Insituto Nacional de Estadistica (INE 2024) and the Office for National Statistics (ONS 2024) provided the data for UK.

[10] See Spain maps out first boundaries for offshore wind parks | Reuters, accessed on 21 Feb 2024

2.4 Wind project inputs

The X-ROTOR project inputs are sourced from (McAuliffe et al., 2024). Generally, X-ROTOR is shown to have lower costs and in particular lower levelised cost of energy than typical HAWT. Lower capital cost for an X-ROTOR turbine is a result of having no gearbox, no requirement for a bespoke multi-pole generator, and no twist in blade designs (Leithead et al. 2019). The X-ROTOR turbines OPEX costs are expected to be less than the HAWT due to the power take-off systems being situated closer to sea level, meaning that almost all repair and maintenance operations can be completed without the need for a heavy-lift vessel, which accounts for half the vessel charter costs for HAWT wind farms (McMorland et al. 2022).

In this analysis we use an average of the LCOEs modelled for offshore HAWT from (Devoy McAuliffe et al. 2023), giving a figure of 50.415 €/MWh and an estimated LCOE for X-ROTOR of 46.74 €/MWh (See Figure 6.1 on page 26 of 28 of McAuliffe et al. 2024). Table 3 provides a list of each input used for the two technologies, X-ROTOR, and the traditional offshore wind turbine. A 5 GW capacity is studied as it represents the renewable energy "Future Framework" target for offshore wind energy in Ireland as presented by the Department of the Environmental, Climate and Communication (DECC 2024). 5 GW is used as a benchmark for all three countries, allowing comparisons to be made between X-ROTOR and HAWT on an equal basis.

Table 3: Wind project inputs

Variable	X-ROTOR	HAWT
LCOE figures are from Devoy McAuliffe et al. (2023)		
Project capacity = 5GW		
LCOE €/MWh	46.74	50.42
€ m		
Turbine (Generator, Gearbox, Nacelle)	2,671	2,881
Blades	666	719
Tower	1,273	1,373
Equipment Shipping/Transportation	230	249
Electrical Balance of Plant	2,597	2,801
Construction (Excluding Site Improvements)	844	910
Engineering and Other Professional Services	1,651	1,781
Site Improvement	0	0
Plant Operations (staff, equipment such as trucks)	1,524	1,644
Replacement Parts	4,968	5,359
Civil Works (Access Road Maintenance, Etc.)	0	0

Table 3 show zero costs in civil works such as access road maintenance and site improvements. Repowering wind energy projects tend to avoid these costs as the area was developed and being in operation before. Therefore, it is likely that, similar access roads will be used. See Hou et al. (2017), and Martínez et al. (2018). The comparison in our study is based on the I-JEDI (International Jobs and Economic Development Impacts) model, which requires only the total installed capacity (in this case, 5 GW) as an input parameter and does not consider the specific turbine size, number of units, or detailed design characteristics such as rotor diameter or hub height. As such, the analysis is conducted at a system level rather than a component or unit level. Both the HAWT and the X-ROTOR configurations are evaluated assuming the same total installed capacity of 5 GW, which ensures consistency and fairness in comparing their economic impacts under the model's framework.

3.Results

This section presents the results of the analysis. Four areas are considered to capture the economic impact of deploying each technology to specific country: jobs created, earnings, total output, and GDP (value added). The number of jobs created are weighted to each country's working population in this analysis (People aged from 16 to 65). All other categories are normalised as a percentage of gross domestic product.

Results from this analysis are similar to most IO analysis findings using direct effect, indirect effect, and induced effect. For example, as quoted from the NREL user guide *"generator manufacturer that purchases copper wire, the direct effect would be the purchase of a generator, and the indirect effect would be the purchase of copper wire by the generator manufacturer. Indirect effects could include business-to-business services, natural resources, and any other activity that is supported by industry expenditures. Other indirect economic impacts from the example above include purchasing a coil-winding machine and hiring a consultant to diagnose faulty generators. The induced impact are activities that could occur from household expenditures made by worker earnings that are supported by direct and indirect impacts. For example, if workers from the generator manufacturer and the wire manufacturer go to a restaurant, their payments to the restaurant would be the induced impact"*(Keyser et al. 2016).

3.1 Jobs

Table 4 presents the number of total number jobs required for each technology in the three economic regions. On average over the three countries there are 10% fewer jobs required to generate 5GW using X-ROTOR technology compared with HAWT. This is because X-ROTOR technology delivers energy more cheaply than traditional HAWT. In Ireland there is a small 1.8 % higher number of jobs for the X-ROTOR technology than for HAWT, this small difference is due to more indirect jobs from X-ROTOR technology than for HAWT.

The total number of jobs created in the UK and Spain is on average 4,709 for both, this is 60% higher than the number of jobs on average for Ireland for both technologies. This is due to the expectation that the UK and Spain have the engineering and manufacturing jobs already in place which can take on X-ROTOR or HAWT deployment. The small number of jobs figures in Ireland can be explained by the smaller percentage contribution of manufacturing services allocated to the Irish economy, see Table 2. However, the percentage of jobs created within the total work force in Ireland is considerably bigger than the other regions because of the smaller working population present in the country.

In all regions, indirect effects account for more than 80% of the jobs created whilst there are no jobs created in induced effect. The large percentage of direct effect in Spain and the UK is due to the greater presence of industries relevant to the deployment of offshore wind (*e.g.,* engineering). Note the size of the work force in each country in 2022 in millions: Ireland 2.67, UK 34.38, and Spain 23.69 (World Bank[11]). The gross annual salary in Ireland was €46,264 in 2022 (CSO.ie); in Spain the gross annual salary was €25,897 in 2021 (PR AWSS 2021 (ine.es)), which allowing for Spanish inflation[12] in 2021 of 6.6%, gives €27,606; UK Gross annual

[11] See https://data.worldbank.org/indicator/SL.TLF.TOTL.IN accessed on 27th February 2024
[12] See https://ec.europa.eu/eurostat/documents/2995521/14176359/2-20012022-AP-EN.pdf/ce642dc8-1f96-fb6e-a7fc-a667762c5d37 accessed on 26th February 2024

salary was €37,276 ONS.gov.uk[13] using the mean annual conversion rate of GB 0.85276[14] from the Irish Central Bank.

The lower numbers of jobs required for X-ROTOR is not a surprise as it requires less investment because the LCOE of X-ROTOR is 3.68€/MW less than for HAWT. For a 5GW project capacity this is equivalent to a reduction in costs of €120 million.

Table 4: Number of jobs created from construction and O&M in a project lifetime.

Country	Effect	X-ROTOR	Jobs to work force (%)	HAWT	Jobs to work force (%)
Ireland	Direct	395	0.0148	405	0.0152
	Indirect	2570	0.0963	2,507	0.0939
	Induced	-	-	-	-
	Total	2965	0.1111	2,912	0.1091
UK	Direct	624	0.0018	660	0.0019
	Indirect	3702	0.0108	4,593	0.0134
	Induced	-	-	-	-
	Total	4,326	0.0126	5,252	0.0153
Spain	Direct	691	0.0029	731	0.0031
	Indirect	3,699	0.0156	4,137	0.0175
	Induced	-	-	-	-
	Total	4390	0.0185	4,868	0.0205

3.2 Earnings

This section presents the money obtained in return for labour (Table 5). The values are normalised as a percentage of GDP to aid interpretation and for easy comparison of different economic regions. There is a difference of 0.0003% for Ireland with X-ROTOR having a slightly larger effect. For UK the difference is 0.0008% and 0.0009% for Spain with HAWT showing larger impacts. This reflects the slightly larger number of jobs required in Ireland and the reduced numbers in Spain and the UK. Ireland shows the highest total earnings as a percentage of GDP, indicating a significant contribution from the projects, particularly in indirect earnings. This is due to Ireland's smaller GDP. Similarly, the earnings per GDP for Spain is larger than the UK.

[13] |See https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/averageweeklyearningsingreatbritain/december2022 accessed on 26th February 2024

[14] See https://www.centralbank.ie/statistics/interest-rates-exchange-rates/exchange-rates accessed on 26th February 2024

The difference in countries' total GDP plays a great role for these results. The gross domestic product (GDP) of Ireland is relatively small, compared to the larger economies in Spain and the UK. Note that the GDP figures are €3,654 billion, €2,209 billion, and €651 billion for UK, Spain, and Ireland respectively (OECD 2024). Another factor to consider is the number of jobs created in each region, recall Table 4.

Table 5: Earnings as €millions and % of GDP.

Country	Effect	X-ROTOR		HAWT	
		€ millions	% GDP	€ millions	% GDP
Ireland	Direct	15	0.0023	15	0.0023
	Indirect	90	0.0139	88	0.0136
	Induced	-	-	-	-
	Total	105	0.0162	103	0.0159
UK	Direct	21	0.0006	23	0.0006
	Indirect	126	0.0035	158	0.0043
	Induced	-	-	-	-
	Total	148	0.0041	181	0.0049
Spain	Direct	19	0.0009	20	0.0009
	Indirect	120	0.0054	138	0.0063
	Induced	-	-	-	-
	Total	139	0.0063	159	0.0072

3.3 GDP (Value added)

The value added reflects the additional income generated by producing goods and services, in other words, the contribution of capital and labour to the production process (Table 6). In Ireland, the X-ROTOR technology creates more value added as a percentage of GDP than traditional HAWT, most of which is from indirect effects. The opposite is seen for the UK and Spain where traditional HAWT add more value to the economy than X-ROTOR. This pattern was expected as HAWT require a larger amount of capital to be in invested creating more value in countries where they can be manufactured. The additional GDP for HAWT compared with X-ROTOR is 0.0017% for UK, and 0.0016% Spain (Table 6). As is seen, the smaller economy in terms of the GDP captures larger effects when such a big project as 5 GW of offshore wind is deployed. Ireland shows a X-ROTOR effect on GDP of 0.0581%, followed by Spain 0.0154% and lastly UK 0.0099%. However, the small numbers should not be underestimated as the GDP of these three regions are quite large.

Table 6: Value added as a % of GDP.

Country	Effect	X-ROTOR	HAWT
Ireland	Direct	0.0084	0.0057
	Indirect	0.0497	0.0318
	Induced	-	-
	Total	0.0581	0.0375
UK	Direct	0.0014	0.0015
	Indirect	0.0085	0.0101
	Induced	-	-
	Total	0.0099	0.0116
Spain	Direct	0.0022	0.0023
	Indirect	0.0133	0.0146
	Induced	-	-
	Total	0.0154	0.0170

3.4 Total output

The last part of the results presents total output generated in each region by each technology (Table 7). The first thing to note is that the output is on average more than double the input for each region. However, depending on the total percentage of spending and manufacturing in each country, Spain and UK have the largest output of €52 billion. As with the number of jobs the effect on total output from X-ROTOR in Ireland is slightly larger, 0.0409% of GDP, than the effect from HAWT. It is the reverse for Spain and the UK, and by larger margins of 0.1448% and 0.1209% respectively.

Looking at the normalised results, the output generated as a percentage of GDP is very high for Ireland due to the fact that it's a smaller country than Spain, leaving UK with the largest GDP with the smallest normalised effect. It is important to note the induced effect is captured in the total output results (Table 7). In each region and by all technologies, the total output from induced effect exceeds the total output from direct effect. This shows that the model successfully captured the amount of money from direct activities that are spent (several times) in other economic sectors.

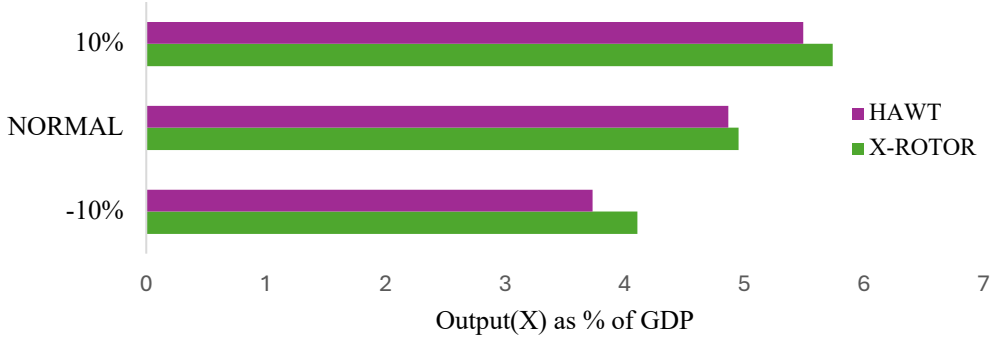
Table 7: Total Output Generated by a 5GW Deployment Over 30 Years in € Million.

Country	Effect	X-ROTOR		HAWT	
		Total Output Generated € m	GDP (%)	Total Output Generated € m	GDP (%)
Ireland	Direct	9,709	1.4914	9,617	1.4773
	Indirect	13,310	2.0446	13,088	2.0104
	Induced	9,227	1.4173	8,959	1.3764
	Total	32,246	4.9533	31,664	4.8639
UK	Direct	15,721	0.4303	16,526	0.4523
	Indirect	19,943	0.5458	22,830	0.6248
	Induced	15,594	0.4268	16,319	0.4466
	Total	51,904	1.4028	61,822	1.5237
Spain	Direct	13,866	0.6277	14,597	0.6608
	Indirect	24,566	1.1121	20,007	0.9057
	Induced	13,472	0.6099	14,098	0.6382
	Total	51,904	2.3497	47,702	2.2047

3.5 Model assumptions' stress test

A stress test is conducted to check the robustness for the percentages of manufacturing shares assumptions. The total output generated in Ireland was tested for subtracting 10 percent contribution of each project input assumption and repeating the analysis for an additional 10 percent. The results where normalised as a percentage of NPV. Figure 4 show that, the total output generated from repowering either X-ROTOR or HAWT, depend on the percentage of manufacturing assumptions discussed in Table 2. By adding more contribution of such manufacturing activities from a specific economy (in this case Ireland) there is a noticeable increase in total output generated and vice versa. These finding have been tested for other sections (jobs, earnings, and GDP value added) and proven to be the same. However, regardless of the manufacturing assumption scenarios, X-ROTOR leads HAWT by having higher output in all scenarios.

Figure 4. Sensitivity analysis.



4. Discussion

The results of the study showed that, technology choice has an effect on wind projects and the overall regional economy. The earnings, GDP (value added) and the total output both support these findings with the difference noted between X-ROTOR and HAWT.

In detail the findings can be used to support regional development policies in relation to wind energy industry. If the goal of the country is to boost the economy whilst combating climate change, then X-ROTOR is the optimal technology. However, if the goal is to solve an unemployment problem by creating a greater number of jobs, then it is better to stick to the traditional horizontal turbines.

The geographical location and economy of the country are important factors to consider when choosing a repowering technology. HAWT as the old technology is already widespread making it easier adopted for small countries like Ireland which are not heavily industrialised as well. Nevertheless, industrially advanced countries like UK and Spain can capture the benefits of X-ROTOR easily. But this should not be a hindrance to countries with smaller GDP, the X-ROTOR technology will be easier to implement than HWAT as the X-ROTOR uses shorter blades needing less customized manufacturing facilities.

These results depend heavily on the exact costs of the two technologies (Table 3), the assumptions for local spending (Table 2), and on the average gross salaries in each country. As X-ROTOR is more efficient, it requires a smaller investment, which has a smaller direct and indirect impact on local economies. The assumptions in Table 2 are based on the smaller size of the turbines and shorter blades of X-ROTOR compared with HAWT, and hence the greater ease of manufacturer with less need to import the components. The figures for salaries, though based on reliable sources, are without the effect of wage convergence which may happen in the offshore wind industry as workers move across borders, but speculation about such convergence is beyond the scope of this paper.

There are clear differences between the three countries. There are fewer jobs projected to be created in Ireland. This is because of the lack of a tradition of heavy industry, shipbuilding, and mechanical engineering. There are more local jobs in Spain which has such industries and yet more in the UK which already has an offshore wind industry. The effect of offshore wind of either technology on GDP is largest for Ireland, less for Spain, and least for the UK. This is due to the relative sizes of the three economies.

The economic impact analysis presented here does not account for the costs or regional economic benefits associated with the research and development (R&D) phase of either technology. While this omission simplifies the comparison, it may disproportionately benefit the X-ROTOR, which is at a lower technology readiness level and would likely require substantial additional investment in R&D before commercialization. In contrast, HAWT are mature and past the costly early stage development phase. As such, the exclusion of R&D costs may present a somewhat optimistic picture of the near-term economic competitiveness of X-ROTOR.

5. Conclusion

The study's objective was to examine the effects of repowering technology in three European countries, Ireland, UK, and Spain as an initiative to support optimal repowering of wind turbines. The study has used a "bottom up" approach using the I-JEDI model from NREL to calculate estimates for the effect of X-ROTOR and HAWT on employment, earnings, GDP, and total output. While the authors are more than aware of the estimated nature of the results in this report, it seems clear that X-ROTOR's greater efficiency means that it can produce power for a lower cost than HAWT, and that the costs during the lifetime of an X-ROTOR wind farm will be lower than HAWT.

The limitation of the study stand by the fact that the result of each country depends on the assumptions made and the sectors of the economy chosen from the I-JEDI model. A slightly difference in results magnitude might be observed if a different sector region were chosen. However, we anticipate that this might not change the overall effect of each technology on the economy. This study, like any, is limited by the choice of countries, and the assumptions used in the input output model. It may well be the case

that slight differences in magnitude might be observed if different countries are chosen, however it is not anticipated that this would change the overall conclusions of the study.

The findings of this study underscore the need for a tailored approach to wind farm repowering and end-of-life decisions, one that considers the broader economic goals and industrial capabilities of different countries or economic regions. As wind farms reach the end of their operational lifespan, careful assessment of the trade-offs between technologies will be critical to maximizing both economic and environmental benefits.