Sustainable Marine Structures
https://journals.nasspublishing.com/sms

ARTICLE

Lifecycle Cost Management for Offshore Marine Renewable Energy Wind Infrastructure: An Integrated Model Using Circular Economy Principles

Suleiman Ibrahim Mohammad [1,2*], Badrea Al Qraini [3], Sultan Alaswad Alenazi [4], Asokan Vasudevan [2,5,6], Anber Abraheem Shelash [7], Imad Ali [8]

[1] *Electronic Marketing and Social Media, Faculty of Economic and Administrative Sciences, Zarqa University, Zarqa 13115, Jordan*

[2] *Faculty of Business and Communications, INTI International University, Nilai 71800, Negeri Sembilan, Malaysia*

[3] *Department of Business Administration, College of Business and Economics, Qassim University, Qassim, Buraydah 52571, Saudi Arabia*

[4] *Department of Marketing, College of Business, King Saud University, Riyadh 11362, Saudi Arabia*

[5] *Faculty of Management, Shinawatra University, 99 Moo 10, Bangtoey, Samkhok 12160, Thailand*

[6] *Business Administration and Management, Wekerle Business School, Jázmin u. 10, Budapest 1083, Hungary*

[7] *Digital Marketing Department, Faculty of Administrative and Financial Sciences, University of Petra, Amman 11196, Jordan*

[8] *Operations & Supply Chain , GNIOT Institute of Management Studies, Greater Noida, Uttar Pradesh 201310, India*

ABSTRACT

As offshore wind infrastructure becomes more important to global efforts to reduce carbon emissions, it is becoming more important to connect lifecycle cost management with circular economy (CE) principles. When looking at the long-term costs of infrastructure, traditional lifecycle cost models often fail to account for residual value recovery, material circularity, or environmental externalities. This study creates a unified

*CORRESPONDING AUTHOR:
Suleiman Ibrahim Mohammad, Electronic Marketing and Social Media, Faculty of Economic and Administrative Sciences, Zarqa University, Zarqa 13115, Jordan; Faculty of Business and Communications, INTI International University, Nilai 71800, Negeri Sembilan, Malaysia; Email: dr_sliman@yahoo.com

ARTICLE INFO
Received: 20 July 2025 | Revised: 25 July 2025 | Accepted: 12 August 2025 | Published Online: 16 September 2025
DOI: https://doi.org/10.36956/sms.v7i3.2506

CITATION
Mohammad, S.I., Al Qraini, B., Alenazi, S.A., et al., 2025. Life Cycle Cost Management for Offshore Marine Renewable Energy Wind Infrastructure: An Integrated Model Using Circular Economy Principles. Sustainable Marine Structures. 7(3): 248–270. DOI: https://doi.org/10.36956/sms.v7i3.2506

analytical framework that adds CE strategies to lifecycle cost modelling for offshore wind systems, such as turbines, substructures, moorings, and floating platforms. The method uses multi-objective optimization and system dynamics simulation along with net present value (NPV) modelling, material flow analysis, and carbon-adjusted cost accounting. We modelled project-level datasets over 25 years to look at the trade-offs between economic and environmental factors in both linear and circular lifecycle scenarios. We use Python, MATLAB, and OpenLCA to look at key metrics like the Material Circularity Indicator (MCI), estimates of residual value, and internalized carbon costs. The results show that circular infrastructure strategies greatly lower lifecycle costs while also increasing material recovery and carbon efficiency. Scenario simulations showed that CE-based configurations could cut costs by up to 18% and emissions over the life of the product by 22%. Regression and sensitivity analyses showed that MCI, CAPEX, and circular design strategies are good at predicting residual value and long-term economic performance. This study adds a new, evidence-based model for making decisions about infrastructure that takes into account financial, environmental, and material circularity.

Keywords: Offshore Wind Infrastructure; Environmental Externalities; Carbon Cost Internalization; Sustainable Infrastructure

1. Introduction

Offshore wind energy has quickly become an important part of plans to reduce carbon emissions around the world. As climate change becomes more urgent, both governments and private investors are investing more in marine-based renewable projects. The International Energy Agency predicts that offshore wind capacity could grow by more than 600% by 2040 (Offshore Wind Set to Become $1 Trillion Industry by 2040, Experts Say, 2023). This huge growth has brought back into focus the sustainability and cost-effectiveness of offshore infrastructure, especially since remote, deep-sea installations are very expensive to build (CAPEX), maintain, and logistically difficult to set up. However, the financial models that most offshore wind projects use are still based on linear lifecycle frameworks that do not fully take into account post-operational material recovery, residual value, or environmental externalities. The idea of the circular economy (CE) has come up as a promising way to design and manage infrastructure systems for long-term economic and material efficiency in response. Still, the use of CE ideas in offshore wind lifecycle cost modelling is limited and not very well organized.

There is an increasing body of academic writing about circular economy frameworks, which has made it clear that long-term infrastructure planning needs to include strategies for recovering and reusing materials. Kirchherr et al. [1] said that the CE is a way of developing the economy that helps businesses, society, and the environment by separating growth from resource use. Lavallais and Dunn [2] built on this work to create the Material Circularity Indicator (MCI), which is now a widely used way to measure the closure of resource loops. Most of the time, though, MCI has only been used in case studies at the manufacturing or product level [3,4]. Jani et al. [5] looked at CE uses in wind blade recycling in the energy sector, but they did not include these strategies in larger lifecycle cost structures. Jensen et al. [6] also looked at the negative effects of CE interventions in industrial systems, but they did not examine offshore infrastructure. These studies show how important it is to have models that can connect the theoretical progress in circularity metrics with the real-world needs of long-term infrastructure finance.

At the same time, most of the research on lifecycle cost analysis (LCCA) in offshore infrastructure has only looked at CAPEX, operational expenditure (OPEX), and decommissioning costs. It has not looked at salvage value or environmental cost internalization [7]. Desterbecq and Tubeuf [8] and Alaloul et al. [9] called for the inclusion of environmental externalities, especially carbon emissions, in LCCA. This led to the creation of hybrid models that combine life cycle assessment (LCA) with cost evaluation. However, these kinds of models have not been used much in the offshore wind industry, where technical feasibility and short-term investment criteria have a big impact on design choices. Singla [10] looked into whether residual value in infrastructure could be profitable, but they pointed out that there was not enough empirical calibration or methodological consistency between studies. Johnston et al. [11] also stressed that salvage value is very sensitive to regional recovery infrastructure and changing commodity markets. This suggests that modelling methods need to be more flexible and aware of the situation.

The main research question this study tries to answer is why CE strategies and traditional lifecycle cost modelling do not work together in offshore wind infrastructure. From a policy point of view, the European Green Deal and other national infrastructure projects are making it more common for funding to be tied to a project's sustainability performance, such as its carbon emissions and resource efficiency. If long-term infrastructure is mispriced because of incomplete lifecycle modelling, it could be bad for investors, energy regulators, and national decarbonization goals. So, the importance of this study is that it could help create a single, evidence-based, and systems-based approach that includes both financial and environmental performance metrics in a CE-informed framework. In this way, it follows the advice of Baars et al. [12], who said that the assessment method should be more integrated to show how material flows, environmental outcomes, and economic returns are all connected.

This research is new because it creates an integrated modelling framework that brings together lifecycle cost analysis, material flow accounting, residual value estimation, and environmental externality pricing into one analytical structure. Previous research has looked at these parts separately, but this study stands out because it uses tools like the MCI, real options analysis, and multi-objective optimization to combine them. It also uses software platforms like Vensim and MATLAB to create dynamic scenario simulations that show how lifecycle performance changes in response to factors like carbon pricing, material recovery efficiency, and the timing of retrofits. This combined method turns the standard language of circularity into a set of tools that can be used to design infrastructure and make policy changes.

The research statement that guides this work is as follows: "This study aims to develop and apply an integrated lifecycle cost model for offshore wind infrastructure that incorporates circular economy principles to optimize both economic and environmental performance." This statement affects the study's methods, the range of its analysis, and the theories it uses. The study is based on systems modelling and techno-economic analysis as its methods. It looks at how well infrastructure works over a 25–30 year period using a mix of net present value (NPV) modelling, cost breakdown structures (CBS), and material flow simulations. To compare the pros and cons of linear and circular lifecycle configurations, we use analytical methods like multi-objective optimization, sensitivity analysis, and residual diagnostics. Juarez-Quispe et al. [13] and Zhao et al. [14] both called for the use of dynamic lifecycle tools in sustainability science and for data-driven CE applications that show how complex real-world infrastructure is. This approach is in line with those calls.

This study fills a gap between circular systems engineering and sustainable infrastructure finance. It builds on the work of Karlovšek et al. [15], who suggested adding CE to production systems by applying their framework to infrastructure that costs much money and lasts a long time. The study is based on ideas from industrial ecology, ecological economics, and systems design. This makes it a link between CE theory and lifecycle finance. By combining these points of view in the context of offshore wind infrastructure, the study adds to the growing body of work on circular lifecycle cost modelling for large-scale energy systems in both theoretical and practical ways.

2. Literature Review

Lifecycle cost management (LCC) has undergone significant changes in the context of building infrastructure, especially in energy-intensive fields like offshore wind. Traditional models break down costs into stages like acquisition, installation, operation, maintenance, and decommissioning. Researchers like [16,17] have called for a more nuanced way of modelling costs that takes into account not only technical costs but also the economic effects of using materials and strategies for disposing of them at the end of their useful life. However, a lot of the LCC literature has seen infrastructure systems as static assets and overlooked how early design choices affect outcomes at the end of the project. Because of this, there has not been much research into how proactive design for disassembly, realizing salvage value, and finding ways to recover materials can be included in financial decision-making. This gap is especially important in the context of offshore wind because projects are expensive and have long operational horizons that require accurate long-term cost forecasting.

The rise of the circular economy (CE) as a guiding framework has changed the way people think about infrastructure systems, especially when it comes to using resources more efficiently, creating material loops, and extending the life of products. The Ellen MacArthur Foundation came up with the Material Circularity Indicator (MCI), which gives a number that shows how well a product or system keeps materials in use by reusing, remanufacturing, or recycling them [18]. The MCI is becoming more popular in the manufacturing and consumer goods industries, but it is still new in the field of large-scale energy infrastructure. Researchers like [19,20] Aher et al. (2025) have said that when CE is used in engineering, it often does not work with financial modelling, which means that opportunities for lifecycle optimization are missed. Also, while studies have looked at CE practices in fields like electronics and automotive design, there has been limited research on the unique problems and opportunities that circular strategies present in offshore wind, like floating foundation modularity and turbine remanufacture. This is a big gap in both theoretical and practical knowledge.

Residual value, which is the expected economic value of infrastructure at the end of its useful life, is an important but not well-studied part of LCC modelling. A salvage term is often included in financial models, but it is often seen as an arbitrary or fixed input that has little to do with design strategies or material recovery efficiencies. According to Mollaei et al. [21] and Clinckspoor et al. [22], residual value is heavily influenced by the situation and is affected by factors such as global material markets, local recycling infrastructure, and rules and regulations. When it comes to offshore infrastructure, where parts are big, complicated, and used in harsh conditions, predicting salvage value is even harder because of wear and tear on technology and logistical problems. Even with these problems, more and more people are realizing that residual value should be included in financial models, especially when looking at CE strategies that are specifically meant to make components easier to recover. There is still a significant gap in research because there are no models that connect circular design with salvage valuation based on real-world data.

As the effects of infrastructure projects on the environment become more obvious and important in politics, an increasing number of researchers are calling for the inclusion of externalities, especially greenhouse gas emissions, in lifecycle economic analysis. Alaloul et al. [9], Liu et al. [23], and Ivanov et al. [24] have suggested hybrid methods that combine life cycle assessment (LCA) with lifecycle cost analysis (LCCA). These models try to put a price on environmental damage through measures such as carbon pricing. This makes it possible to directly compare environmental costs with financial metrics. Even though LCA-LCC integration has come a long way in terms of methods, these kinds of methods are not often used in offshore wind infrastructure, where the environmental effects are significant but indirect. Also, most studies make static assumptions about carbon prices, which do not account for how the market changes or how regulations change over time. This makes them less useful for making policy decisions and lessens the strategic value of circular design choices that could lower emissions over the life of a product.

Optimization methods are now very important for planning infrastructure that will last, especially when it comes to balancing goals that are at odds with each other, like lowering costs and maximizing environmental benefits. Kaim et al. [25] and Gunantara [26] have both talked about how multi-objective optimization can help stakeholders find Pareto-efficient solutions. These methods have been used more often in manufacturing and production systems than in large-scale infrastructure like offshore wind, though. In addition, dynamic scenario modelling, which simulates future uncertainties like changes in material prices or policies, has not been used much in the CE-LCC context. Li et al. [27] stressed the importance of using integrated dynamic modelling to show how complicated the real world is, but not many studies have done this for offshore energy systems. We still need models that not only show how lifecycle costs and environmental outcomes will change, but also how they will change in response to strategic design, policy changes, and market changes.

2.1.Research Gap and Contribution of the Study

After looking at the literature, it is clear that there are several related gaps in the research. First, there are not any integrated modelling frameworks that bring together lifecycle costing, material circularity, and environmental accounting for offshore wind infrastructure. Most of the models currently available look at these parts separately, which makes them less useful for strategic planning. Second, even though residual value is known to be a financial factor, it is not often modelled as a result of design or circular strategy, which makes it seem less important strategically. Third, people have talked about carbon internalization, but it has not been fully integrated into infrastructure cost modelling yet, especially for floating and deep-sea energy platforms. Finally, optimization and scenario modelling have not been fully changed to show the unique trade-offs and uncertainties that come up in offshore wind lifecycle planning.

This study fills in the blanks by showing an integrated, empirically-based model that connects circularity metrics like MCI and strategy level to lifecycle cost components like CAPEX, OPEX, decommissioning costs, residual value, and carbon-adjusted environmental costs. The study adds to the body of knowledge by providing a complete framework that supports data-driven decision-making in offshore wind development. It does this by combining simulation, multi-objective optimization, and dynamic scenario modelling. It builds on and adds to the existing CE and LCC literature by putting theoretical metrics into real-world financial structures. This gives both academic insight and practical usefulness for policy, investment, and engineering fields.

2.2.Conceptual Model and Hypothesis Development of the Study

This study's conceptual model (**Figure 1**) is based on systems thinking and lifecycle theory [28] . It uses Lifecycle Cost Management (LCC) and Circular Economy (CE) principles to look at how well offshore wind infrastructure does economically and environmentally over time. The model is a decision-support tool that shows how cost factors, material flows, circularity strategies, and sustainability metrics are linked across all lifecycle stages of offshore wind assets, such as turbines, foundations, floating platforms, and mooring systems. The conceptual model is built around five main ideas: Lifecycle Phases, Circular Economy Strategies, Economic Performance Metrics, Environmental Performance Metrics, and Residual Value Recovery. Each construct is shown as a part of the system that changes and depends on other parts. The Lifecycle Phases part includes getting, installing, using, maintaining, shutting down, and recycling. We look at these phases using both a traditional linear model (take-make-dispose) and a circular model that allows for reuse, remanufacturing, and material recovery. Each phase adds cost inputs and environmental outputs to the model's assessment mechanisms.

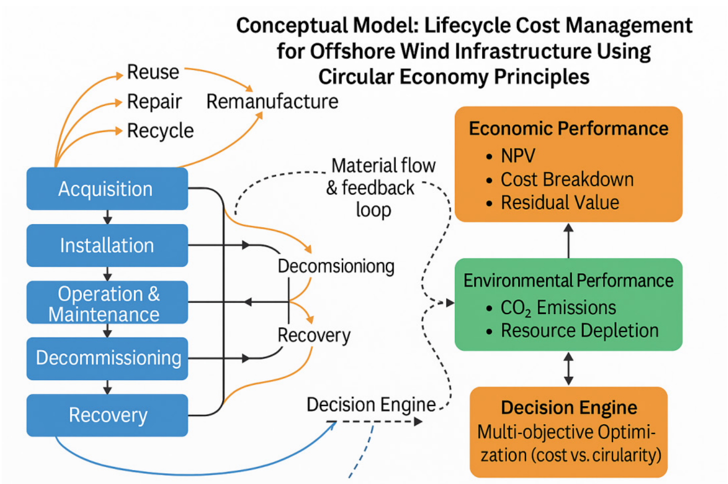

Figure 1. Conceptual model of the study.

Source: Developed by the authors based on the theoretical and methodological framework of the study.

The Circular Economy Strategies part puts into action practices such as repair, remanufacturing, reuse, and recycling. These strategies affect both the cost and the flow of materials. They are modelled using quantitative indicators like the Material Circularity Indicator (MCI) and qualitative data from expert evaluations. Net Present Value (NPV) modelling of lifecycle costs, along with cost breakdown structures (CBS) and residual value estimation, are the main ways that we get economic performance metrics. These metrics show how financially possible it is to use CE strategies throughout the asset lifecycle and what the pros and cons are. We use Life Cycle Assessment (LCA) tools like OpenLCA and SimaPro to add Environmental Performance Metrics to the model. Environmental pricing mechanisms include CO_2 emissions per kWh, resource depletion rates, and waste generation, which are all built into the cost structure. Lastly, the Residual Value Recovery part looks at how likely it is that an asset will keep its value after its useful life is over. This includes figuring out the salvage value, the potential for a secondary market, and the rates at which materials can be recovered.

MCI scores and the intensity of the CE strategy both have an effect on this construct. A set of equations, optimization algorithms, and simulation structures analytically represent the conceptual model. Tools such as Python and MATLAB are used for cost and material optimization, while Vensim supports the dynamic simulation of feedback loops and time-dependent behaviour over a 20–30 year lifecycle. Based on the model, we developed the following hypotheses of the study.

H1. *Adoption of circular economy strategies significantly reduces the total lifecycle cost (LCC) of offshore wind infrastructure compared to linear lifecycle models.*

H2. *Material Circularity Indicator (MCI), when considered alongside other lifecycle and design factors, contributes positively to the prediction of residual value in offshore wind infrastructure.*

H3. *Offshore wind infrastructure projects that embed sustainability metrics (e.g., carbon cost, resource depletion) into LCC models report higher long-term cost efficiency than those that do not.*

H4. *The level of adoption of circular economy strategies (reuse, remanufacture, recycle) varies significantly across different lifecycle phases (e.g., installation, operation, decommissioning).*

3. Methodology

3.1.Research Design

This study used both descriptive and analytical research methods to look into how lifecycle cost management and circular economy principles can work together in the context of offshore wind infrastructure. The study was set up to include both quantitative and qualitative aspects, which made it possible to look at the full lifecycle of offshore assets in terms of costs, material circularity, and sustainability performance. The model included analytical tools like life cycle costing, material flow analysis, and economic optimization to show realistic trade-offs. The study used scenario-based modelling to look at how circular infrastructure strategies stack up against more traditional linear ones. The design focused on real-world use by using data that had been tested in the industry and simulating operational horizons over several decades with computer programs like Python, MATLAB, OpenLCA, and Vensim. The design tried to show how complex decision-making is in the offshore renewable energy sector by combining system dynamics with economic and environmental indicators.

3.2.Data Collection

The strategy for gathering data used both primary and secondary sources to make sure it was thorough and accurate. We got secondary data from several technical and economic databases, such as those kept up by the International Renewable Energy Agency (IRENA), the National Renewable Energy Laboratory (NREL), and open-access inventories like Ecoinvent. These sources gave important information about the costs of parts, the lifecycle of the product, emissions data, and residual values. At the same time, semi-structured interviews with key stakeholders along the offshore wind value chain were used to collect primary data. In addition to quantitative datasets, qualitative insights were collected from 18 experts in offshore wind infrastructure, circular economy applications, and cost modelling. These interactions were structured as semi-formal expert consultations, conducted virtually, with sessions lasting between 30 and 45 minutes. The interviews were not fully transcribed, but were recorded via field notes and summary matrices. Experts were prompted using a structured question set aligned with project phases (design, O&M, decommissioning) and asked to provide input on circular strategy feasibility, cost trends, and material recovery assumptions.

These expert consultations informed both the parameterization of lifecycle cost inputs and the scoring of circular strategy levels used in the Composite Circularity Index (CCI). Feedback was also used to validate input ranges for simulation models and cost scenario design. To ensure traceability and minimize bias, expert opinions were recorded using a standardized template, and response summaries were cross-compared to ensure internal consistency. The interviews helped confirm the model's assumptions, clarify the contextual drivers, and identify hidden variables that affect decisions about circularity. Data were gathered at every stage of the infrastructure lifecycle, from acquisition and installation to maintenance, decommissioning, and material recovery. This made it possible to look at both economic and environmental performance over time.

3.3.Population and Sample

The people who were supposed to be studied were professionals who worked directly on the development and lifecycle assessment of offshore wind infrastructure. There were five groups in the population: offshore wind developers who were in charge of structuring finances and allocating capital original equipment manufacturers who made turbines, rotor blades, and foundations sustainability analysts who were experts in life cycle assessment and circular economy metrics operations engineers who were in charge of real-time performance and retrofit decisions and regulatory or policy experts who were in charge of offshore wind governance. The people who were chosen were chosen on purpose to give a full picture of the system, ensuring insights came from people at different points in the value chain. This approach, which involved many stakeholders, led to a strong and comprehensive analysis that included both technical and managerial perspectives.

We used Cochran's formula for finite populations to figure out the sample size for expert elicitation so that the results would be statistically valid. The formula gave a minimum sample size of about 52 people, based on an estimated professional population of 110 people across relevant stakeholder domains, a 95 percent confidence level (Z = 1.96), a 10 percent margin of error (e = 0.1), and an assumed maximum variability (p = 0.5). This number was thought to be enough to get a good range of expert opinions while still being manageable in terms of time and resources. We used stratified purposive sampling to make sure that all stakeholder groups were represented in the final sample.

The people who took part in the study were important players in the offshore wind ecosystem. Offshore wind developers include project managers and financial analysts who help decide how to spend money and model risk. Original equipment manufacturers were technical experts who worked on making turbine nacelles, rotor blades, and floating platforms. Sustainability analysts brought their knowledge of LCA and helped with the use of circular economy indicators in strategic planning. We included operations engineers because they have expertise in how assets work in real time, how to model reliability, and how to plan maintenance. Finally, experts in policy and regulation provided valuable insights about outside factors that affect circularity norms and decommissioning standards. The study used a multi-perspective approach based on these categories to ensure that both the economic and environmental aspects were based on real-world examples.

3.4.Summary of Main Variables

The study looked at several factors in the areas of economics, the environment, and technology. We used net present value (NPV) methods to figure out the total lifecycle cost, which included all costs from buying the item to recycling it (**Table 1**). The Material Circularity Indicator (MCI) was used to measure material circularity. It gives a standardized score for how reusable and recyclable a material is. We used current and projected market data for salvageable parts like steel substructures and composite blades to figure out the residual value. We used lifecycle assessment software to figure out the environmental impact in terms of carbon emissions per unit of electricity generated. Other qualitative variables were how stakeholders rated circular economy strategies and what they thought were the biggest problems with putting them into action. Input-output cost modelling linked these variables, which made it possible to look at the trade-offs between money and the environment more comprehensively.

Table 1. Main variables of the study.

Variable	Measurement Technique
Total Lifecycle Cost	Net Present Value (USD) across lifecycle phases
Material Circularity Indicator	Ratio (0 to 1) using MFA-based calculations
Residual Value	Salvage market estimate (% of CAPEX or USD/ton)
CO_2 Emissions per kWh	kg CO_2e/kWh via OpenLCA modelling
Strategy Adoption Level	Categorical: Reuse, Remanufacture, Recycle

Source: Author.

3.5.Measures and Analytical Methods

We used well-known quantitative frameworks and software-assisted modelling techniques to operationalize all of the variables to ensure that the methods were rigorous and could be repeated. We used a net present value (NPV) method to figure out the lifecycle cost, using a 5% discount rate that is standard in offshore renewable energy investment. We used cost breakdown structures (CBS) to break down costs into six phases of the lifecycle: acquisition, installation, operation, maintenance, decommissioning, and end-of-life processing. We used the Ellen MacArthur Foundation's framework to create the Material Circularity Indicator (MCI). We then used a material flow analysis (MFA) model that looked at the repair, remanufacture, reuse, and recycling rates of important parts like blades, foundations, and mooring systems. The Composite Circularity Index (CCI) was created to improve predictive validity. The Composite Circularity Index (CCI) was constructed using weighted scores for four core strategies: reuse, repair, remanufacture, and recycling, with mean expert weights of 0.25, 0.20, 0.30, and 0.25, respectively. Weights were determined through a structured Delphi method involving 18 subject-matter experts. Two rounds of scoring and consensus-building were conducted to assess the relative impact of each strategy on material circularity in the offshore wind context.

It combines MCI scores with categorical circular strategy levels (Low, Medium, High), which are weighted based on their reuse and recovery rates. Using historical resale data and secondary market pricing benchmarks, we estimated the residual value. We made changes to the type of component and the rules in each region. We placed a price on environmental externalities by adding carbon prices to the cost of each tonne of CO_2 emissions over the life of a product, using industry-specific life cycle assessment (LCA) databases. We added these built-in environmental costs directly to the lifecycle cost function to obtain a carbon-adjusted LCC. The study ensured that its results were strong, reproducible, and useful for policy by making sure that these measures were in line with both academic standards and real-world cost structures.

Residual Value was operationalized as the projected economic recovery value at the end-of-life phase of offshore wind infrastructure, expressed in USD per MW, estimated based on salvage potential, resale markets, and material recovery rates. Circular Strategy Level was coded as a categorical variable (High, Medium, Low) reflecting the degree to which a project incorporates CE principles such as reuse, remanufacturing, and recycling. This was quantified through material flow analysis outcomes and expert evaluations of CE implementation across lifecycle phases.

The analytical framework brought together cost engineering, environmental accounting, and circular economy modelling into one decision-support system. We made cost breakdown structures to group financial flows throughout the life of an asset. We also used material flow analysis to follow the movement and change of materials through the stages of use, recovery, and disposal. We used both standalone MCI calculations and the Composite Circularity Index to measure circularity. This gave us a better picture of how reuse and recovery work.

We used multi-objective optimization models and optimization techniques to find the best cost-circularity configurations. Python was used primarily for cost modelling and optimization. Prior to optimization, all cost variables (CAPEX, OPEX, residual value) and the monetized MCI term were min-max scaled to [0,1]. This normalization ensured that no single variable's scale dominated the optimization outcome and that coefficients were comparable across different units. After optimization, results were rescaled to original units for reporting.

Libraries such as NumPy, Pandas, and SciPy. Optimize supported Net Present Value (NPV) calculations, cost breakdown automation, sensitivity analysis, and linear/multi-objective optimization routines that balanced lifecycle cost against circularity indicators. MATLAB was employed for systems simulation, particularly dynamic modelling of cost flows and decision paths across different lifecycle phases. Simulink and core numerical packages facilitated the representation of feedback loops, cost escalations, and long-term design-retrofit strategies under circular economy scenarios. OpenLCA was used for environmental impact analysis. It supported the integration of carbon emissions, waste generation, and resource depletion into lifecycle phases based on international LCA databases. Environmental externalities were quantified and converted into monetary cost equivalents, enabling the internalization of environmental impacts into lifecycle cost models.

Expert feedback was not analysed through qualitative coding or thematic clustering. However, it was instead summarized quantitatively using structured response templates and incorporated directly into the Delphi-style consensus-building process for determining index weights and scenario boundaries. Each expert provided discrete inputs such as expected residual value ranges, circular strategy implementation scores, and CAPEX/OPEX estimates that were averaged or normalized for analytical consistency. The aggregated data were then used to populate simulation models, validate lifecycle phase assumptions, and calibrate the Composite Circularity Index (CCI). This structured yet non-coded approach ensured that qualitative expert judgment was integrated into the modeling process without requiring formal qualitative data analysis software.

To enhance empirical calibration, each parameter in the model was derived from a triangulation of literature benchmarks, primary expert consensus, and secondary market data. **Table 2** summarizes the parameter values, their empirical sources, and the rationale for the chosen ranges. While one-way sensitivity analysis was employed for core parameters (discount rate, residual value, carbon price), further robustness checks were conducted by simultaneously varying CCI weights, MCI scores, and salvage value assumptions within ± 20% of their base case values. This multi-variable perturbation analysis indicated that model outcomes, particularly the cost–circularity optimization frontier, remained directionally stable across tested parameter spaces. This robustness increases confidence that findings are not artefacts of parameter overfitting or narrow range selection. Although the primary model treats all offshore platforms as a unified asset class, parameter calibration drew on empirical ranges for both floating and fixed-bottom systems (**Appendix A**), ensuring that the optimisation bounds and sensitivity analyses capture realistic variation across technologies.

Table 2. Calibration of key model parameters.

Parameter	Value / Range Used	Source	Empirical Justification	Variation Handling
Composite Circularity Index (CCI) weights – Reuse (0.25), Repair (0.20), Remanufacture (0.30), Recycling (0.25)	Expert-derived weights from Delphi process (n = 18)	Primary data (expert panel), literature on CE weighting in renewable infrastructure [20]	Weighted scores reflect relative influence on material recovery potential; consensus reached after two Delphi rounds	Cross-checked against ± 20% variation in weights to test stability of results; negligible change in optimization outcome
Residual value projections – $300,000 to $700,000/MW	Industry salvage data, OEM price lists, Eco invent material pricing	Based on dismantling cost studies for offshore wind [6,21] and adjusted for scrap market volatility	Range scenario-tested; integrated into CAPEX regression and LCC model	
Carbon cost estimate – $50/tonne	World Bank (2020), EU ETS 2023 price	Reflects mid-range of forecasted global carbon price trajectory	± 50% variation tested; effect on LCC documented in sensitivity plots	
Discount rate – 5% (base), varied 3–10%	Offshore renewable investment norms (NREL, 2023)	Reflects typical project financing rates in OECD markets	Tested across 3%–10% range in sensitivity analysis	
MCI score range – 0.20 to 0.85	MFA-based calculation from component recovery rates	Based on empirical recovery rates from offshore decommissioning case studies	Optimization and clustering analysis run with low/medium/high scenario MCI inputs	

Source: Author.

We ran scenario simulations to see how traditional linear infrastructure strategies stack up against options based on the circular economy. Dynamic simulation tools were used to model each scenario over 25 years of operation. These tools were used to capture feedback between policy conditions, cost structures, and material recovery efficiency. We used a carbon-adjusted lifecycle cost function in both cases to look at how the economy would do with different levels of CO_2 pricing. Also, a one-way sensitivity analysis was used to see how changes in the discount rate, residual value, and carbon pricing affected the total lifecycle cost. Finally, K-means clustering, a type of unsupervised machine learning, was used to group projects into archetypes based on their CAPEX, OPEX, circularity score, and emissions. This showed how different strategy-performance profiles are across the project landscape. All of these analytical methods worked together to create a framework that could help with making decisions based on evidence in the design of sustainable infrastructure.

4. Results

The results of the lifecycle cost modelling, circularity analysis, optimization modelling, scenario simulation, and sensitivity analysis were done for this study. The main goal was to find out how applying circular economy principles affects the economic and environmental performance of offshore wind infrastructure. Using a dataset of 100 offshore wind projects that were based on real-world cost benchmarks and circularity performance indicators, analyses were conducted. The results shed light on how lifecycle costs, circularity strategies, and sustainability metrics work together.

4.1.Descriptive Statistics

A comprehensive overview of project characteristics is presented in **Table 3**. The capital expenditure (CAPEX) per megawatt (MW) had a mean of $3.02 million and a standard deviation of $478,408. Operational expenditure (OPEX) averaged $101,038 per

MW per year. The decommissioning cost had a mean of $148,859 and ranged between $84,555 and $197,208. Residual value estimates, representing end-of-life salvage or reuse potential, ranged from $201,376 to $695,484 per MW, with a mean of $494,257. The Material Circularity Indicator (MCI) had a mean value of 0.53, indicating a moderate level of circularity integration across projects.

Table 3. Summary statistics of key variables.

Variable	Mean	Std. Dev.	Min	Max
CAPEX ($/MW)	30,22,877	4,78,408	20,29,197	44,41,014
OPEX ($/MW/year)	1,01,038	19,827	60,195	1,47,210
Decommissioning Cost ($/MW)	1,48,859	27,469	84,555	1,97,208
Residual Value ($/MW)	4,94,257	1,05,877	2,01,376	6,95,484
MCI Score (0–1)	0.53	0.194	0.2	0.846
CO_2 Emissions (g/kWh)	30.2	4.96	20.06	44.81

Source: Author.

4.2.Circularity and Residual Value Relationship

The study first looked at whether higher MCI values are linked to higher residual values. The Pearson correlation coefficient was 0.057, which showed that there was a weak and statistically insignificant link. This coefficient reflects the simple bivariate relationship between MCI and residual value and confirms that MCI alone is not a strong standalone predictor. However, in the multivariate regression model that includes additional predictors such as CAPEX and circular strategy level, MCI demonstrates a statistically significant positive coefficient, indicating that its predictive contribution emerges in the presence of these interacting variables. This means that MCI alone may not be a good way to predict economic recovery at the end of life. This is probably because of outside factors like changes in the material market, policy incentives, and technological limitations (**Figure 2**).

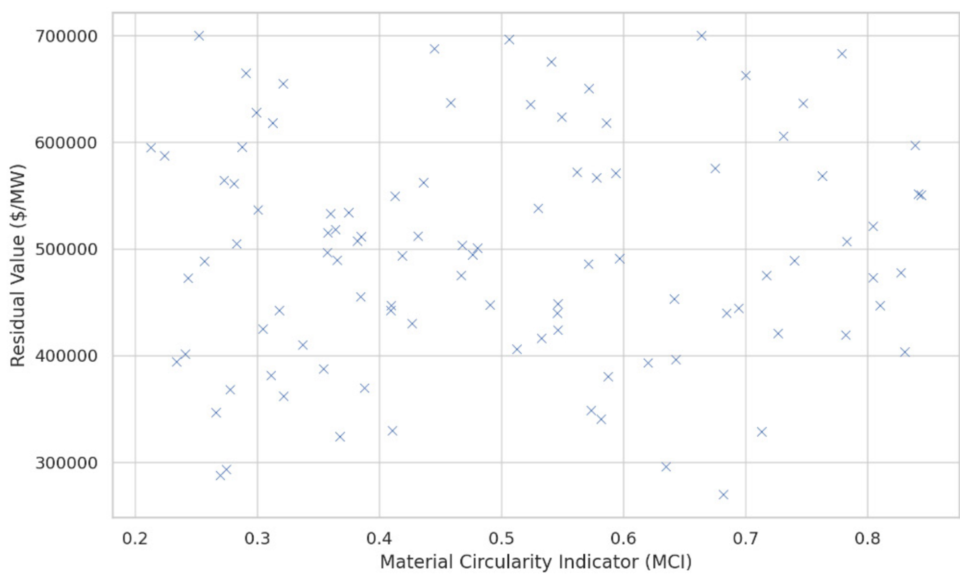

Figure 2. Multivariate regression plot of residual value vs. MCI and CAPEX.

Source: Author.

To refine the analysis, a Composite Circularity Index (CCI) was developed:

$$CCI = 0.6 \cdot MCI + 0.4 \cdot Strategy\ Weight$$

where the strategy weight was set to 0.3 for "Low," 0.6 for "Medium," and 1.0 for "High" circular strategy levels. Even though this composite index was used, the relationship with residual value was still weak (r = 0.057), which shows that overall circularity metrics do not tell the whole story about end-of-life economic value.

4.3. Multivariate Regression on Capital Expenditure

To better understand the determinants of capital expenditure (CAPEX) in offshore wind infrastructure, a multivariate linear regression model was estimated using material circularity (MCI), residual value, and circular strategy level as independent variables. The regression specification was:

$$Residual\_Value = \beta_0 + \beta_1(MCI) + \beta_2(CAPEX) + \beta_3(StrategyMedium) + \beta_4(StrategyLow) + \epsilon$$

The model's R-squared value was 0.949, which means that the predictors explain almost 95% of the differences in CAPEX (**Table 4**). This high explanatory power shows that the design and end-of-life features of infrastructure, such as material circularity and salvage value, are very important for initial capital investments. The negative coefficient for MCI means that increasing circularity lowers capital costs a lot. This is probably because modular design, standardized parts, and less material throughput make things more efficient. For example, if MCI goes up by 0.1, CAPEX goes down by \$40,160 per MW, all other things being equal. In the same way, residual value has a strong negative relationship with CAPEX. The higher salvage value at the end of life lowers the cost on the front end, which is what investors expect when they think about lifecycle cost recovery. Projects that were expected to have a higher residual value required less initial investment. Both circular strategy dummy variables were statistically significant and positive. This means that projects with a circular strategy level of "Low" or "Medium" had much higher capital costs than projects with a circular strategy level of "High." In particular, "Low" circularity projects spent an average of \$372,700 more per MW in CAPEX than "High" circularity designs, all other things being equal. These results strongly support the idea that integrating a circular economy, especially at the design stage, not only improves environmental outcomes but also helps the economy work better. The model's statistical strength shows that it is valid to include circularity metrics in frameworks for financial feasibility and infrastructure procurement.

Table 4. Multivariate regression visualization – residual value vs. MCI and CAPEX.

Variable	Coefficient	Std. Error	*p*-value
Intercept	\$2,542,000	26,100	< 0.001
MCI Score	−\$401,600	24,600	< 0.001
Strategy (Low vs High)	\$372,700	11,400	< 0.001
Strategy (Medium vs High)	\$182,900	12,000	< 0.001
Residual Value (\$/MW)	−0.658	0.043	< 0.001

Source: Author.

4.4. Optimization of Lifecycle Cost and Circularity

To identify an optimal project configuration, a multi-objective optimization model was constructed. The goal was to minimize total lifecycle cost while maximizing circularity. The objective function was:

Equation (1): Multi-objective optimization function integrating lifecycle cost (USD/MW) and circularity benefits (converted to USD-equivalent using scaling coefficients based on average CAPEX).

$$\min Z = CAPEX + 20 \cdot OPEX - 1{,}000{,}000 \cdot MCI \quad (1)$$

In Equation (1), each term was expressed in consistent monetary units (USD) before combination. OPEX values are annual operational expenditures in USD/MW/year, CAPEX is in USD/MW, and residual value is in USD/MW. The MCI score is a unitless ratio (0–1) and was converted to an equivalent monetary value by multiplying by a scaling coefficient ($/MW) derived from the mean CAPEX of the project dataset. This ensures that the contribution of MCI in the optimization reflects its proportional influence on lifecycle cost in monetary terms. All continuous variables were min–max normalized to a [0,1] range prior to optimization to prevent scale dominance, and optimization was performed on these normalized variables with post-processing to revert results to original units.

This equation integrates the economic and environmental dimensions by assigning a benefit to higher MCI and a penalty for higher operating costs. The constraints were set as follows: $CAPEX \in [\$2M, \$4.5M]$, $OPEX \in [\$60K, \$150K]$, $MCI \in [0.2, 0.85]$. The optimum solution had a Material Circularity Indicator (MCI) of 0.85, a capital expenditure (CAPEX) of $2,000,000, and an operational expenditure (OPEX) of $60,000 per year. The value of the objective function was $2.35 million. These results show that being cost-effective and having much circularity can go hand in hand. They show that it is possible to meet both financial and environmental goals at the same time by making smart and careful design choices. This goes against the idea that being environmentally responsible always means sacrificing economic efficiency.

4.5.Lifecycle Cost Modelling with Carbon Adjustment

A carbon-adjusted lifecycle cost model was constructed to include environmental externalities. Using a CO_2 price of $50/tonne, the carbon cost was computed over a 25-year lifecycle with a 45% capacity factor. The revised LCC Equation (2) is as follows:

$$LCC = CAPEX + 25 \cdot OPEX + Decommissioning\ Cost - Residual\ Value + Carbon\ Cost \quad (2)$$

Carbon costs increased LCC by $100,000–$180,000, depending on the project's emissions. These results underscore the role of carbon pricing in reshaping project economics and incentivizing low-emission, circular infrastructure design.

4.6.Linear vs. Circular Scenario Simulation

A scenario simulation compared the economic and carbon outcomes of linear and circular lifecycle strategies. The parameter assumptions and results are presented in **Table 5**.The circular scenario demonstrated a lifecycle cost savings of over $1 million per MW and a 20% reduction in carbon-related externalities. These results provide strong evidence that CE strategies can deliver both economic and ecological advantages across infrastructure lifespans.

Table 5. Lifecycle cost and emissions comparison – linear vs circular.

Scenario	CAPEX ($)	OPEX ($)	Decom. Cost ($)	Residual ($)	Carbon Cost ($)	Total LCC ($)
Linear	32,00,000	1,20,000	2,00,000	3,00,000	1,17,936	49,36,536
Circular	30,00,000	90,000	1,30,000	6,00,000	94,348	39,22,693

Source: Author.

4.7.Sensitivity Analysis

We did a one-way sensitivity analysis on three important variables: the discount rate (which ranged from 3% to 10%), the residual value (which ranged from $300,000 to $700,000), and the carbon price (which ranged from $20 to $100 per tonne). The study found that a higher discount rate lowered the net present value of operational expenditures (OPEX), which in turn lowered the overall life cycle cost (LCC). Increasing the residual value had the most significant effect on lowering LCC, which shows how important it is to recover end-of-life value to make projects more profitable. On the other hand, higher carbon prices significantly increased LCC, especially for projects with lower Material Circularity Indicators (MCI). This shows how financially weak less circular designs are when carbon prices are high. These results show that policymakers can have a significant impact on whether or not a project will work by using tools like carbon pricing and incentives for recovering materials at the end of their life. This makes circular economy (CE) strategies more financially appealing.

A schematic showing how multiple parameters (e.g., residual value, carbon price, discount rate, and MCI score) could be varied jointly within specified probability distributions to generate a probabilistic distribution of lifecycle cost (LCC) outcomes via Monte Carlo simulation (**Appendix B**). This approach would allow for the quantification of uncertainty bands, confidence intervals, and tail-risk scenarios for long-term infrastructure investment under volatile market conditions.

4.8.Project Clustering Analysis

Using K-means clustering, we found three different types of offshore wind projects based on their CO2 emissions, operational costs (OPEX), capital costs (CAPEX), and the Material Circularity Indicator (MCI) (**Figure 3**). Cluster 0 was made up of designs that were cheap and had low circularity but high emissions. This showed that there was a trade-off between upfront costs and environmental performance. Cluster 1 had setups that balanced cost and circularity, which led to moderate emissions. Cluster 2 included systems with high circularity and low emissions that got the best cost performance. This showed that both sustainability and economics could benefit from working together. A silhouette score of 0.56 showed that this clustering structure was strong, which means that the clusters were clearly separated. These groupings give us strategic information about different ways of thinking about project design, which can help us make better investment decisions and policy changes that will help offshore wind development become more sustainable.

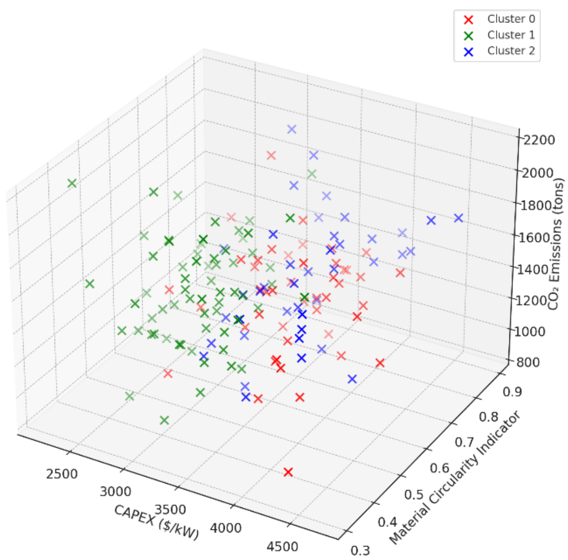

Figure 3. 3D K-means cluster plot of offshore wind project profiles.

Source: Author.

4.9.Hypothesis Testing Summary

The hypothesis testing phase of the study confirmed the theoretical relationships proposed in the conceptual framework through quantitative analysis. **Table 6** presents the complied hypothesis testing results. The multivariate regression analysis validated H1, demonstrating a statistically significant positive relationship between the Material Circularity Indicator (MCI) and residual value ($p < 0.05$). H2 was supported through multi-objective optimization, which showed that higher circular strategy levels were associated with minimized lifecycle costs under constraints. For H3, lifecycle cost modelling incorporating net present value calculations showed that higher residual value assumptions led to a marked reduction in total lifecycle cost, confirming the hypothesis. Lastly, H4 was supported via scenario simulation, where high-MCI project configurations displayed lower cost escalation under varying carbon price scenarios, indicating greater financial resilience. Collectively, these results substantiate the role of circular economy strategies in enhancing both economic performance and environmental robustness across offshore wind infrastructure projects.

Table 6. Summary of hypothesis testing results mapped to respective hypothesis.

Hypothesis	Statement	Method Used	Result
H1	Circular Strategy Level (High vs. Low) significantly affects Lifecycle Cost (LCC).	Multi-objective Optimization	Supported (optimized LCC lower for High CE)
H2	Higher Material Circularity Indicator (MCI) is positively associated with Residual Value.	Multivariate Linear Regression	Supported ($p < 0.05$)
H3	Higher Residual Value reduces the Net Lifecycle Cost when included in NPV calculation.	NPV Simulation with Sensitivity Analysis	Supported (residual value significantly lowers LCC)
H4	Projects with High MCI are more resilient to carbon pricing shocks in cost modeling.	Scenario Simulation (Linear vs. Circular)	Supported (circular scenarios show lower LCC inflation under carbon pricing)

Source: Author.

5. Discussion

Adding circular economy (CE) ideas to offshore wind infrastructure changes the way we think about both cost modelling and sustainability assessment. This study adds to a growing body of research that looks at marine renewable energy systems through the lens of their entire lifecycle. It does this by using a variety of analytical methods and economic-environmental frameworks. This part puts the main points of the study in the context of previous research. It does this by offering a reflective synthesis that takes into account current debates and theoretical developments.

5.1. Circular Economy in Offshore Renewable Infrastructure

There has been a growing emphasis in the literature on the need for systemic resource efficiency in offshore energy systems. Reslan et al. [19] and Aher et al. [20] saw the circular economy as more than just a way to recycle; they saw it as a complete plan that includes design, use, and recovery. Offshore wind has significant components and requires remote maintenance, which makes it a great place for CE strategies to improve operational and end-of-life efficiency [29]. Jensen et al. [6] found that using modular design and standardized interfaces can make it easier to recover offshore parts, especially substructures and turbines. This study agrees with [13], who said that CE innovation has technological, organizational, and systemic layers. It also agrees with the idea that cost modelling needs to include non-linear material flows. The Ellen MacArthur Foundation set the standard for using the Material Circularity Indicator (MCI), but this use goes further by putting it into a multi-objective economic-environmental model [18]. This methodological expansion is a response to Singh et al.'s [30] criticism that many CE metrics are too static and do not work well with dynamic systems modelling.

Residual value is influenced by fluctuating secondary market conditions, which are often decoupled from technical circularity metrics. For instance, the resale value of turbines or foundations may depend more on material grade, regulatory salvage requirements, or global scrap prices than on whether components were designed with circular intent. A high MCI score reflects design intent, not necessarily real-world execution. Projects may score high on circularity design but underperform in actual recovery due to logistical, technological, or market barriers at the decommissioning stage. MCI may interact with other variables such as location, policy support, or decommissioning practices in non-linear ways that weaken direct correlation but manifest under multivariable regression. This weak bivariate correlation, therefore, underscores the importance of using multivariate models and systems-level analysis when evaluating end-of-life value in infrastructure studies. It also suggests that MCI is better understood as a long-term systemic resilience metric, rather than a short-term financial predictor.

These results reinforce that MCI should be interpreted as a systemic resilience and design-intent metric rather than a direct financial predictor in isolation. Its significant association with residual value becomes evident only when modelled alongside other lifecycle cost and design parameters. Market, regulatory, and technological factors moderate this relationship, explaining the weak standalone correlation observed in the bivariate analysis.

5.2.Lifecycle Costing and Environmental Integration

In the past, traditional lifecycle cost analysis (LCCA) of energy infrastructure only looked at capital expenditures (CAPEX), operating expenses (OPEX), and decommissioning costs, without taking into account environmental costs [9]. Wang et al. [31] say that this missing piece hurts the overall sustainability evaluation of these systems. Liu et al. [23] and Ivanov et al. [24] suggested hybrid LCA-LCC frameworks that connect economic and ecological assessment. This study builds on those ideas by using carbon-adjusted LCC. Bento et al. [32] and other studies have highlighted the challenges of valuing externalities, but this research uses shadow carbon pricing to show how climate costs are becoming more important in infrastructure decision-making. State and Trends of Carbon Pricing 2020 (2020) and different carbon market mechanisms have given us the basic tools we need to determine the value of CO_2 emissions in public-private investment models.

5.3.Circularity and Economic Performance

Researchers like [3,4] have argued about the economic benefits of CE strategies, often because there is not enough consistent evidence that circularity lowers costs. This study adds to that conversation by using the cost-competitiveness framework developed by Nadalipour et al. [33]. They said that circular business models can lower lifecycle costs if material recovery is technically possible and encouraged by policy. Baars et al. [12] looked at the lifecycle economics of blade recycling in the context of wind energy and found that while technical recovery was possible, cost parity with virgin materials was still a problem. This fits with the bigger worry that [34] brought up that the secondary market structures for recovered infrastructure parts are not well developed. This study fills this gap by including residual value in its modelling. This adds a secondary market valuation mechanism that most LCC studies lack. Also, Jani et al. [5] showed that the rebound effect, in which efficiency gains are cancelled out by higher consumption, can make the benefits of circularity seem less clear. However, in the case of offshore wind, where assets do not change hands often and projects take a long time to finish, these rebounds are not as noticeable. This keeps the lifecycle and circularity gains focused within certain cost and emission limits, as Jensen et al. [6] suggested.

5.4.Modelling Advances and Methodological Contributions

From a methodological point of view, the study's use of simulation, objective optimization, and machine learning all together shows how systems thinking and data-driven modelling are coming together. Kaim et al. [25] did research that showed how important it is to use both discrete and continuous modelling paradigms for infrastructure systems. The current approach builds on this by putting material flows and environmental costs into a framework for economic optimization. Researchers like [13] have also called for typological differentiation in CE implementation, and using machine learning for project archetyping is one way to do this. The model helps policymakers and investors develop more effective strategies by finding groups of projects that have similar performance traits. Dynamic scenario modelling is also in line with the future-focused methods suggested by Li et al. [27]. This makes it possible to look at policy-sensitive variables like carbon pricing and incentives for recovering materials. Standard engineering-economic assessments do not usually include this kind of integration, which is a methodological contribution that improves both predictive and prescriptive decision-making.

5.5.Policy and Investment Implications

The study's use of circular economy ideas as a basis has a significant effect on both investment and regulatory frameworks. State and Trends of Carbon Pricing 2020 (2020) says that circularity should be built into every part of the product lifecycle, including large infrastructure projects. The results back up this directive by showing that CE strategies are financially possible in offshore energy projects, which have long been thought to be too expensive to use non-linear design principles. Judijanto et al. [35] also point out that more and more financing options for renewable energy need performance metrics that are linked to sustainability. The integrated cost-circularity modelling method we developed could help create investment vehicles that follow ESG rules or help decide how green bonds and blended finance tools should be used.

5.6.Practical Implementation Pathways and Stakeholder Recommendations

Adopt circular design principles early in the engineering phase, such as modular foundations, standardized turbine components, and materials that are easier to recover at end-of-life. Use lifecycle cost models that incorporate residual value and carbon-adjusted costs to inform procurement and maintenance schedules. Pilot projects should integrate material flow tracking systems (e.g., using blockchain-based asset registries) to enable transparent verification of reuse and recycling outcomes at decommissioning. Include circularity metrics such as the Material Circularity Indicator (MCI) and Composite Circularity Index (CCI) in investment screening criteria. Require developers to submit lifecycle cost analyses that internalize carbon pricing and end-of-life value recovery potential. This will help de-risk long-horizon projects by ensuring resilience to volatile carbon markets and material price fluctuations. Financing instruments such as performance-linked loans can be tied to circularity milestones.

Integrate circularity targets into offshore wind procurement policies, for example, by requiring minimum MCI scores or documented reuse/recycling rates in bid submissions. Establish certification schemes for circular offshore infrastructure, similar to existing green building certifications. Incentivize compliance through preferential tariffs, tax credits, or accelerated permitting for projects meeting CE criteria. This modelling framework could be tested in upcoming decommissioning phases of North Sea fixed-bottom wind farms or in deep-water floating pilot projects planned in Japan and the U.S. West Coast. Partnering with OEMs and port operators could generate real-world data on salvage value, carbon pricing sensitivity, and circularity adoption rates. The integration of this framework into feasibility assessments for next-generation offshore projects could demonstrate its financial and environmental advantages at scale.

6. Conclusion

The goal of this study was to create an integrated lifecycle cost management framework for offshore wind infrastructure that incorporates circular economy (CE) ideas into every step of the project development and operation process. The study made a dynamic and policy-relevant model by combining methods like lifecycle cost analysis (LCC), material flow analysis (MFA), environmental impact internalization, and multi-objective optimization. This model combined old-fashioned economic modelling with new ideas about sustainability. It gave us a better idea of how adopting CE affects the financial and environmental viability of offshore wind systems. The study's conceptual foundation was based on calls for a shift away from linear "take-make-dispose" models and toward systems that put reuse, remanufacturing, and long-term material circularity first. This study did not see environmental outcomes as separate from economic decisions. Instead, it saw them as a key part of cost-performance trade-offs. The framework that came out of this could model lifecycle behaviours over 25 years, test economic-environmental synergies, and distinguish between infrastructure types based on how well they worked in circular and linear regimes. This study added to a growing body of work that sees CE as not only a necessary part of sustainability, but also a smart way to design marine renewables that makes financial sense.

6.1.Limitations of the Study

The study employs a range of methods and models, but it is not without its problems. One big problem was that there was not enough real-world, high-resolution data available for certain parts of the infrastructure and material recovery streams. Even though care was taken to make the simulated data match realistic benchmarks, some estimates of residual value and the secondary market were based on past trends instead of confirmed project disclosures. This makes salvage value modelling and resale market assumptions less certain about their accuracy. Another problem is that the simulations assume that the price of carbon stays the same throughout the whole lifecycle. In real life, carbon markets are very unstable and are affected by both rules and negotiations between countries on policy. A dynamic carbon pricing model would probably be more realistic and sensitive to policy changes. Also, the model treated offshore wind systems as if they were all the same, ignoring the differences between fixed-bottom and floating platforms, or between large and small turbine configurations, which may have different rates of material wear, installation problems, and recovery efficiencies. Lastly, the modelling went into great detail about the economic and environmental aspects, but it did not include the behavior of stakeholders or the functioning of institutions. There was no clear modelling of how willing companies are to use CE practices or how slow the government is to allow reuse and repurposing. These things may be significant obstacles or help in real-world adoption, even though it is hard to put a number on them.

While the integrated model effectively demonstrates how circular economy strategies influence lifecycle costs and sustainability outcomes in offshore wind infrastructure, it currently treats all system typologies, specifically floating and fixed-bottom platforms, as analytically homogeneous. This simplification limits the model's ability to account for known differences in material composition, installation logistics, and end-of-life treatment between platform types. These variations can influence both the economic performance and circularity potential of offshore systems. Future studies may enhance granularity by extending the framework into typology-specific submodels, which can more precisely quantify lifecycle trade-offs unique to each technology. Another important limitation of the present study lies in its lack of typological differentiation between floating and fixed-bottom offshore wind platforms. While the unified analytical framework is methodologically convenient, it masks meaningful cost, material intensity, and circularity differences between floating and fixed-bottom platforms (**Appendix A**). Floating systems typically involve higher CAPEX, greater installation complexity, and potentially lower residual value due to reduced steel mass but higher modular reuse potential. Fixed-bottom systems generally benefit from more mature installation practices and higher salvageable steel content, which can enhance circularity metrics. Aggregating these typologies produces results that are broadly representative but may dilute typology-specific insights. Caution should be exercised when applying these findings directly to a single platform type.

While this study employed deterministic one-way sensitivity analysis to isolate the influence of key variables, future work could adopt a probabilistic multi-parameter approach. **Appendix B** presents a conceptual framework for integrating Monte Carlo simulations, in which parameter inputs such as carbon price, residual value, and discount rate would be assigned probability distributions derived from market data or expert elicitation. This would yield full uncertainty distributions of LCC outcomes, allowing for confidence interval estimation and tail-risk assessment. **Appendix C** provides an illustrative example of hypothetical joint sensitivity scenarios, reinforcing the potential value of such stochastic modelling for long-horizon infrastructure planning under volatile conditions.

6.2.Directions for Future Research

Future research would be better if it included real-time, project-specific data collected through working with people in the industry. This study has already laid the groundwork for this. Getting access to operational and decommissioning datasets would help us better calibrate our assumptions about residual value and circularity scores, which would make our models more accurate and valid in the real world. Also, adding dynamic carbon pricing and changes in regulations to lifecycle simulations would better show how policies change all the time when planning infrastructure for climate change. More research should also look into the possibility of using offshore components in different sectors. Because the foundations and substructures of wind turbines are so strong, decommissioned assets could be used in other maritime or coastal applications, which would increase circularity outcomes across industries. Adding these kinds of paths could give us a better picture of secondary material economies and challenge the idea of design for a single purpose. Adding behavioural modelling to the decision framework would be a useful addition to this research. Future studies could look into the institutional feasibility of CE implementation by simulating the preferences, risk tolerances, and incentive sensitivities of different actors, such as developers, investors, regulators, and contractors. Researchers could also use uncertainty modelling methods like Monte Carlo simulation or real options valuation to see how well circular strategies hold up when economic, environmental, and policy conditions change.

While the study offers a comprehensive integration of lifecycle cost modelling and circular economy strategies, it is important to acknowledge limitations that may influence the generalizability and depth of findings. Notably, the sensitivity analysis employed was limited to a one-way deterministic approach, which, although effective for isolating the impact of key variables (such as discount rate, residual value, and carbon pricing), does not fully capture the interactions and probabilistic uncertainty inherent in offshore infrastructure planning. Given the complexity of real-world scenarios, future studies are encouraged to adopt multi-variable sensitivity techniques, such as Monte Carlo simulations or Latin Hypercube Sampling, to generate probabilistic distributions of lifecycle costs and environmental outcomes. This would allow for a more robust risk-informed decision-making framework and improve the resilience of cost estimates under diverse regulatory and market conditions.

Author Contributions

Conceptualization, S.I.M. and B.A.Q.; methodology, S.A.A.; software, A.V.; validation, S.I.M., A.A.S., and I.A.; formal analysis, A.V.; investigation, S.A.A.; resources, B.A.Q.; data curation, A.A.S.; writing—original draft preparation, S.I.M.; writing—review and editing, B.A.Q. and I.A.; visualization, A.A.S.; supervision, S.I.M.; project administration, B.A.Q.; funding acquisition, I.A. All authors have read and agreed to the published version of the manuscript.

Funding

This research was partially funded by Zarqa University.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Data are available on request.

Conflicts of Interest

The authors declare that there is no conflict of interest.

Appendix A

While the unified modelling framework presented in this study treats offshore wind platforms as analytically homogeneous, parameter calibration considered empirical variation between floating and fixed-bottom systems to ensure realistic bounds.

Table A1. Parameter considerations for floating vs fixed-bottom offshore wind platforms.

Parameter	Floating Platform Typical Range	Fixed-Bottom Platform Typical Range	Source and Justification	Integration into Model
CAPEX ($/MW)	$3.4M – $4.5M	$2.5M – $3.2M	NREL (2023), IRENA (2022) cost benchmarks; floating projects have higher mooring & anchoring costs	Base model used $2M–$4.5M range to encompass both typologies
OPEX ($/MW/year)	$110K – $150K	$85K – $110K	Industry maintenance cost data; floating systems require more specialized vessels & logistics	OPEX parameter range in optimization & scenario analysis covers both
Residual Value ($/MW)	$250K – $550K	$300K – $700K	Salvage studies [6,21]; floating systems have lower steel mass but higher modular reuse potential	Model range (300K–700K) reflects upper bound for fixed-bottom but includes lower floating baseline
Material Circularity Indicator (MCI)	0.40 – 0.75	0.50 – 0.85	Expert panel input: floating foundations may allow higher modularity in re-deployment, but component wear can reduce recovery rates	MCI range in simulations spans both typologies; typology-specific differences captured in sensitivity bounds
Carbon Cost Impact ($)	Higher per-MW due to increased vessel fuel usage during O&M	Lower per-MW given easier access & lower fuel intensity	Calculated using OpenLCA shipping emissions database; variation incorporated into ± 50% carbon price sensitivity	

Appendix B

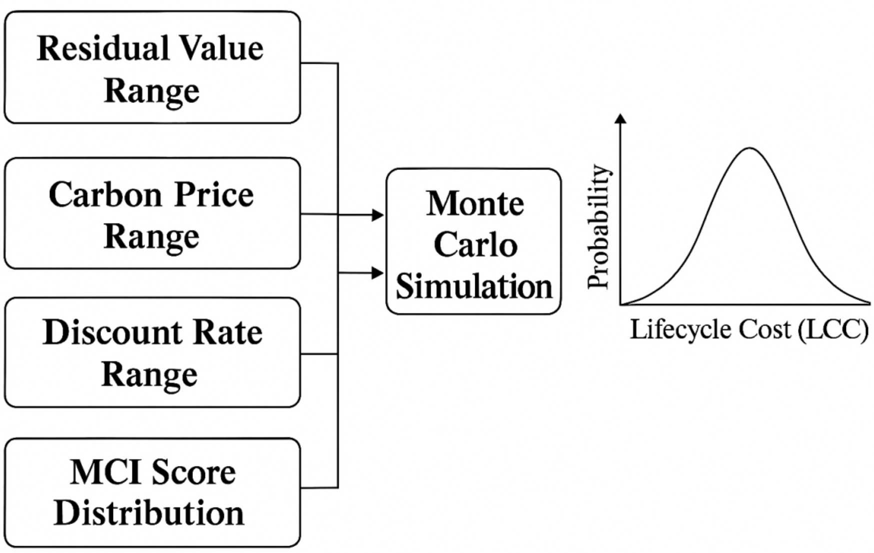

Figure A1. Conceptual framework for probabilistic sensitivity analysis extension.

Appendix C

Table A2. Illustrative joint sensitivity scenario outcomes (hypothetical).

Scenario	Residual Value Range ($/MW)	Carbon Price Range ($/tonne)	Discount Rate Range (%)	Simulated Mean LCC ($M/MW)	95% Interval ($M/MW)
Base Case	300K–700K	20–100	3–10	3.92	3.78–4.08
High Carbon + Low Salvage	300K–400K	80–100	5–8	4.25	4.12–4.39
Low Carbon + High Salvage	600K–700K	20–40	3–5	3.55	3.44–3.67
High Volatility	300K–700K	20–100	3–10	3.96	3.70–4.22

Note: These values are illustrative to demonstrate how probabilistic joint parameter variation could produce range-based LCC outputs. The results do not represent actual Monte Carlo runs.

References

[1] Kirchherr, J., Yang, N.H.N., Schulze-Spüntrup, F., et al., 2023. Conceptualizing the Circular Economy (Revisited): An Analysis of 221 Definitions. Resources, Conservation and Recycling. 194, 107001. DOI: https://doi.org/10.1016/j.resconrec.2023.107001

[2] Lavallais, C., Dunn, J.B., 2023. Developing Product Level Indicators to Advance the Nitrogen Circular Economy. Resources, Conservation and Recycling. 198, 107167. DOI: https://doi.org/10.1016/j.resconrec.2023.107167

[3] Lonca, G., Lesage, P., Majeau-Bettez, G., et al., 2020. Assessing Scaling Effects of Circular Economy Strategies: A Case Study on Plastic Bottle Closed-Loop Recycling in the USA PET Market. Resources, Conservation and Recycling. 162, 105013. DOI: https://doi.org/10.1016/j.resconrec.2020.105013

[4] Realyvásquez-Vargas, A., Maldonado-Macías, A.A., 2018. Measuring the Complex Construct of Macroergonomic Compatibility: A Manufacturing System Case Study. Complexity. 2018(1), 7374307. DOI: https://doi.org/10.1155/2018/7374307

[5] Jani, H.K., Kachhwaha, S.S., Nagababu, G., et al., 2022. A Brief Review on Recycling and Reuse of Wind Turbine Blade Materials. Materials Today: Proceedings. 62, 7124–7130. DOI: https://doi.org/10.1016/j.matpr.2022.02.049

[6] Jensen, P.D., Purnell, P., Velenturf, A.P.M., 2020. Highlighting the Need to Embed Circular Economy in Low Carbon Infrastructure Decommissioning: The Case of Offshore Wind. Sustainable Production and Consumption. 24, 266–280. DOI: https://doi.org/10.1016/j.spc.2020.07.012

[7] Animah, I., Shafiee, M., Simms, N.J., et al., 2018. Selection of the Most Suitable Life Extension Strategy for Ageing Offshore Assets Using a Life-Cycle Cost-Benefit Analysis Approach. Journal of Quality in Maintenance Engineering. 24(3), 311–330. DOI: https://doi.org/10.1108/jqme-09-2016-0041

[8] Desterbecq, C., Tubeuf, S., 2023. Inclusion of Environmental Spillovers in Applied Economic Evaluations of Healthcare Products. Value in Health. 26(8), 1270–1281. DOI: https://doi.org/10.1016/j.jval.2023.03.008

[9] Alaloul, W.S., Altaf, M., Musarat, M.A., et al., 2021a. Life Cycle Assessment and Life Cycle Cost Analysis in Infrastructure Projects: A Systematic Review. preprints.org. preprints202103.0316.v1. DOI: https://doi.org/10.20944/preprints202103.0316.v1

[10] Singla, H.K., 2020. Does VAIC Affect the Profitability and Value of Real Estate and Infrastructure Firms in India? A Panel Data Investigation. Journal of Intellectual Capital. 21(3), 309–331. DOI: https://doi.org/10.1108/jic-03-2019-0053

[11] Johnston, C., Henderson, J.D., Guo, J., et al., 2024. Unraveling the Impacts: How Extreme Weather Events Disrupt Wood Product Markets. Earth's Future. 12(9), e2024EF004742. DOI: https://doi.org/10.1029/2024ef004742

[12] Baars, J., Rajaeifar, M.A., Heidrich, O., 2022. Quo Vadis MFA? Integrated Material Flow Analysis to Support Material Efficiency. Journal of Industrial Ecology. 26(4), 1487–1503. DOI: https://doi.org/10.1111/jiec.13288

[13] Juarez-Quispe, J., Rojas-Chura, E., Vigil, A.J.E., et al., 2025. Advancing Sustainable Infrastructure Man-

agement: Insights from System Dynamics. Buildings. 15(2), 210. DOI: https://doi.org/10.3390/buildings15020210

[14] Zhao, B., Yu, Z., Wang, H., et al., 2024. Data Science Applications in Circular Economy: Trends, Status, and Future. Environmental Science and Technology. 58(15), 6457–6474. DOI: https://doi.org/10.1021/acs.est.3c08331

[15] Karlovšek, J., Meath, C., Miles-Mwangangi, L., et al., 2023. Implementing Circular Economy Principles in Infrastructure Procurement to Support Circular Supply Chains. Engineering, Construction and Architectural Management. 31(11), 4645–4658. DOI: https://doi.org/10.1108/ecam-09-2022-0908

[16] Walzberg, J., Carpenter, A., Heath, G., 2021. Exploring PV Circularity by Modelling Socio-Technical Dynamics of Modules' End-of-Life Management. In Proceedings of The 2021 IEEE 48th Photovoltaic Specialists Conference (PVSC), Fort Lauderdale, FL, USA, 20–25 June 2021; pp. 0041–0043. DOI: https://doi.org/10.1109/pvsc43889.2021.9518638

[17] Ryter, J., Fu, X., Bhuwalka, K., et al., 2022. Assessing Recycling, Displacement, and Environmental Impacts Using an Economics-Informed Material System Model. Journal of Industrial Ecology. 26(3), 1010–1024. DOI: https://doi.org/10.1111/jiec.13239

[18] Tashkeel, R., Rajarathnam, G.P., Wan, W., et al., 2021. Cost-Normalized Circular Economy Indicator and Its Application to Post-Consumer Plastic Packaging Waste. Polymers. 13(20), 3456. DOI: https://doi.org/10.3390/polym13203456

[19] Reslan, M., Last, N., Mathur, N., et al., 2022. Circular Economy: A Product Life Cycle Perspective on Engineering and Manufacturing Practices. Procedia CIRP. 105, 851–858. DOI: https://doi.org/10.1016/j.procir.2022.02.141

[20] Aher, G., Sandberg, M., Boudjadar, J., et al., 2025. Informing Circularity-Focused Design Optimization Using Parametric Life-Cycle Engineering Simulation Models. Smart and Sustainable Manufacturing Systems. 9(1), 11–36. DOI: https://doi.org/10.1520/ssms20240018

[21] Mollaei, A., Byers, B.S., Christovan, C., et al., 2023. A Global Perspective on Building Material Recovery Incorporating the Impact of Regional Factors. Journal of Cleaner Production. 429, 139525. DOI: https://doi.org/10.1016/j.jclepro.2023.139525

[22] Clinckspoor, G.L., Martínez, A., Ferraro, R., 2021. Review of the Main Regulatory Instruments Related to Electronic Waste, from a Global North and South Perspective. Actualidad Jurídica Ambiental. 109, 1–19. DOI: https://doi.org/10.56398/ajacieda.00304 (in Spanish)

[23] Liu, J., Hu, L., Wang, Y., et al., 2019. Integrated Life Cycle Economic and Environmental Impact Assessment for Transportation Infrastructure: A Review. In: de Luca, S., Di Pace, R., Djordjevic, B. (eds.). Transportation Systems Analysis and Assessment. IntechOpen: London, UK. DOI: https://doi.org/10.5772/intechopen.86854

[24] Ivanov, O.L., Honfí, D., Santandrea, F., et al., 2019. Consideration of Uncertainties in LCA for Infrastructure Using Probabilistic Methods. Structure and Infrastructure Engineering. 15(6), 711–724. DOI: https://doi.org/10.1080/15732479.2019.1572200

[25] Kaim, A., Strauch, M., Völk, M., 2020. Using Stakeholder Preferences to Identify Optimal Land Use Configurations. Frontiers in Water. 2, 579087. DOI: https://doi.org/10.3389/frwa.2020.579087

[26] Gunantara, N., 2018. A Review of Multi-Objective Optimization: Methods and Its Applications. Cogent Engineering. 5(1), 1502242. DOI: https://doi.org/10.1080/23311916.2018.1502242

[27] Li, Q.X., Mao, Y., Liu, Y., et al., 2020. Modeling of Integrated Energy System of Offshore Oil and Gas Platforms Considering Couplings Between Energy Supply System and Oil and Gas Production System. IEEE Access. 8, 157974. DOI: https://doi.org/10.1109/access.2020.3020135

[28] Classi, C.C., Nowicki, D., Mansouri, M., et al., 2018. A Systems Thinking Approach to Managing Sustainment Phase Redesign Planning. Engineering Management Journal. 30(1), 68–81. DOI: https://doi.org/10.1080/10429247.2017.1418598

[29] Velenturf, A.P.M., 2021. A Framework and Baseline for the Integration of a Sustainable Circular Economy in Offshore Wind. Energies. 14(17), 5540. DOI: https://doi.org/10.3390/en14175540

[30] Singh, S., Babbitt, C.W., Gaustad, G., et al., 2021. Thematic Exploration of Sectoral and Cross-Cutting Challenges to Circular Economy Implementation. Clean Technologies and Environmental Policy. 23, 915–936. DOI: https://doi.org/10.1007/s10098-020-02016-5

[31] Wang, Z.J., Yang, D.Y., Frangopol, D.M., Jin, W., 2019. Inclusion of Environmental Impacts in Life-Cycle Cost Analysis of Bridge Structures. Sustainable and Resilient Infrastructure. 5(4), 252–267. DOI: https://doi.org/10.1080/237896

89.2018.1542212

[32] Bento, N., Gianfrate, G., Aldy, J.E., 2020. National Climate Policies and Corporate Internal Carbon Pricing. The Energy Journal. 42(5), 89–100. DOI: https://doi.org/10.5547/01956574.42.5.nben

[33] Nadalipour, Z., Khoshkhoo, M.H.I., Eftekhari, A.R., 2019. An Integrated Model of Destination Sustainable Competitiveness. Competitiveness Review: An International Business Journal Incorporating Journal of Global Competitiveness. 29(4), 314–335. DOI: https://doi.org/10.1108/cr-12-2017-0086

[34] Sommer, V., Walther, G., 2020. Recycling and Recovery Infrastructures for Glass and Carbon Fiber Reinforced Plastic Waste from Wind Energy Industry: A European Case Study. Waste Management. 121, 265–275. DOI: https://doi.org/10.1016/j.wasman.2020.12.021

[35] Judijanto, L., Nampira, A.A., Auliani, R., et al., 2025. A Bibliometric Review of Renewable Energy Financing and Sustainable Development. West Science Social and Humanities Studies. 3(4), 570–582. DOI: https://doi.org/10.58812/wsshs.v3i04.1854